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Non-convergence of pitch and duration: Word-prosody of Garo

A Sangma, Cheman Baira

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Non-convergence of pitch and duration: Word-prosody of Garo

by

Cheman Baira A Sangma

A THESIS

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Abstract

Garó is an understudied Sino-Tibetan language spoken in Northeast India. There is currently only an impressionistic description of its word prosody by Burling (2003) which says that it is a stress final language. Recent studies have highlighted problems with impressionistic descriptions of prosody (de Lacy, 2014), and methodological problems with some acoustic studies which do not control for confounds of sentence prominence (Gordon, 2014; Roettger & Gordon, 2017). Edge prominent languages also have added complexity about whether prominence should be analysed as metrical prominence or boundary effect (Jun, 1998; Jun & Fougeron, 2000). Keeping all of these facts in mind, a production study was designed to elicit target words in carrier sentences which controlled for confounds of higher level prosody following Athanasopoulou et al. (2021) and Vogel et al. (2017).

Binary logistic regression conducted on the measurements of acoustic properties revealed that F0 is the cue for stress in Garó. I analysed the F0 pattern as an intonational pitch LH* where L associated to the first syllable and H* associates to the final syllable. The cue for stress in Garó is thus more specifically an association of intonational pitch accent. Due to the trisyllabic structure of the target words in this study, the foot structure could not be determined. The cues for stress were not found to be enhanced under focus and they were also found to be unaffected post-focally. The focus particle was found to add an IP boundary at the end of the focused constituent and additionally, it was found to upstep the L of the LH* intonational pitch accent. Therefore, the prosodic focus is present only with the focus particle in Garó.

The findings of this study thus confirm that Garó has word stress on the final syllable signaled by F0. What separates Garó from other edge prominent languages is that it has F0 events

on every prosodic word making it clear that it has stress. The prosodic expression of focus is also only present with the focus particle which makes it similar to other languages with morphosyntactic ways of expressing focus.

Preface

This thesis is an original, unpublished, independent work by the author, Cheman Baira A'gitok. The experiments reported in Chapters 5-10 were covered by Ethics Certificate number REB21-0041, issued by the University of Calgary Conjoint Faculties Research Ethics Board for the project "The sound system of Garo" on April 15, 2021.

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Dedicated to my late grandparents.

Abu, can you believe it? I made it!

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Chapter 1 – Introduction

Garo is an understudied Tibeto-Burman language spoken in Northeast India. In his grammar of Garo, Burling (2003) describes that Garo has word stress on the final syllable. The description is purely impressionistic, however, and additionally the description is based on the dialect of Garo spoken in Bangladesh, which is different from Standard Garo, which this thesis studies. The reliability of purely impressionistic descriptions have been called into question recently (de Lacy, 2014), so this study addresses this issue by doing a systematic acoustic study of production data collected from 8 native speakers of Garo. The author of this thesis is a native speaker of Standard Garo.

Stress or prominence at the word level arises from the metrical structure where the sound segments are organized into syllables, which in turn group into feet, and which in turn form the prosodic word (Hayes, 1995). There is a single head element at every level of the metrical structure and the stressed syllable is the head syllable of the head foot in a word (Gordon, 2011b; Gordon & van der Hulst, 2020; Hayes, 1995; Kager, 2010). The stressed syllable is typically signaled by having more of one or more acoustic properties compared to the unstressed syllables (Gordon, 2016; van Heuven & Turk, 2020; Remijsen & Heuven, 2005; Vogel et al., 2016, 2017). A care has to be taken when designing production experiments to test for the correlates of stress, however, as it has been reported that sentence prominence can change the phonetic properties of stress (Gordon, 2014; Sluijter & van Heuven, 1996; van der Hulst, 2010b). Thus, the present study aims to determine the acoustic cues of Garo stress, isolating the target word from the prominent position of the sentence following the methodology of Athanasopoulou et al. (2021) and Vogel et al. (2017).

Since focus affects word prosody by enhancing the acoustic properties of stress (Gordon & van der Hulst, 2020; van der Hulst, 2010b; Vogel et al., 2017), focus was also tested in this study to allow for a more definite identification of stress correlates. The prosody of focus was also of interest on its own because focus has been both proposed to add prosodic structure (Ladd, 2008; Nespor & Vogel, 1986), and has also been experimentally found to do so (Jeon & Nolan, 2017; Vogel et al., 2015). Of interest is also the Garo focus particle “-sa” since cross-linguistically, it has been found that languages that use a morphosyntactic strategy of marking focus do not normally have prosodic focus too (Mády & Kleber, 2010). In general, the prosody of focus particles is not well studied and often accounts are based on impressionistic descriptions (cf. Korean; Choe, 1995).

The same motivation applied to studying the post-focus condition. Acoustic properties have been found to be compressed in words that occur post-focally (Syed et al., 2022; Xu et al., 2012; Xu & Xu, 2005). Post-focal compression can also serve to isolate the acoustic correlates of stress since it reduces the correlates of stress. Just like the prosody of focus, and related to it, post-focus condition merits its own analysis since post-focal deaccenting has been found to be one of the strategies that languages generally use to signal focus prosodically (Rahmani et al., 2018; Syed et al., 2022; Xu et al., 2012).

The results in this study revealed that Garo has word stress, and that as Burling had described, the final syllable of the word is stressed. The stress is cued by an association of an LH* intonational pitch accent where the L associates to the first syllable and the H* to the final stressed syllable. Prosodic focus and post-focal compression were absent without the focus particle, so confirmation about the acoustic correlates of stress under focus was not found. The prosody of the word changes when the focus particle attaches to it as there is a fall on the final syllable of the word after the F0 peak. The focus particle also upsteps the L of the LH* pitch accent that associates

to the word such that the first syllable surfaces with a phonetic mid tone. All of these facts taken together reveal that Garo does not mark focus prosodically in the absence of the focus particle.

Chapter 2 – Background about Garo

Although the current study focuses specifically on the word prosody of Garo, the background chapter also includes information not related to the word prosody since the language is understudied. This background chapter thus includes information about its genetic classification and also about other aspects of its linguistic structure including morphology and syntax in addition to the more relevant background about its phonology.

2.1 Linguistic classification and dialects

Garo belongs to the Tibeto-Burman branch of the Sino-Tibetan language family (Grierson, 1908). Within the Tibeto-Burman group, Garo falls within the subgrouping known as either the Bodo-Garo group (Bradley, 1997; Thurgood, 2017), as Figure 1 shows, or the *Sal* group (Burling, 1983). It is mainly spoken in the western half of the Indian state of Meghalaya (Bradley, 1997; Burling, 2003), the area collectively known as the Garo Hills. There are, however, substantial number of Garo speakers in the neighbouring state of Assam and also the neighbouring country of Bangladesh (Burling, 2003).

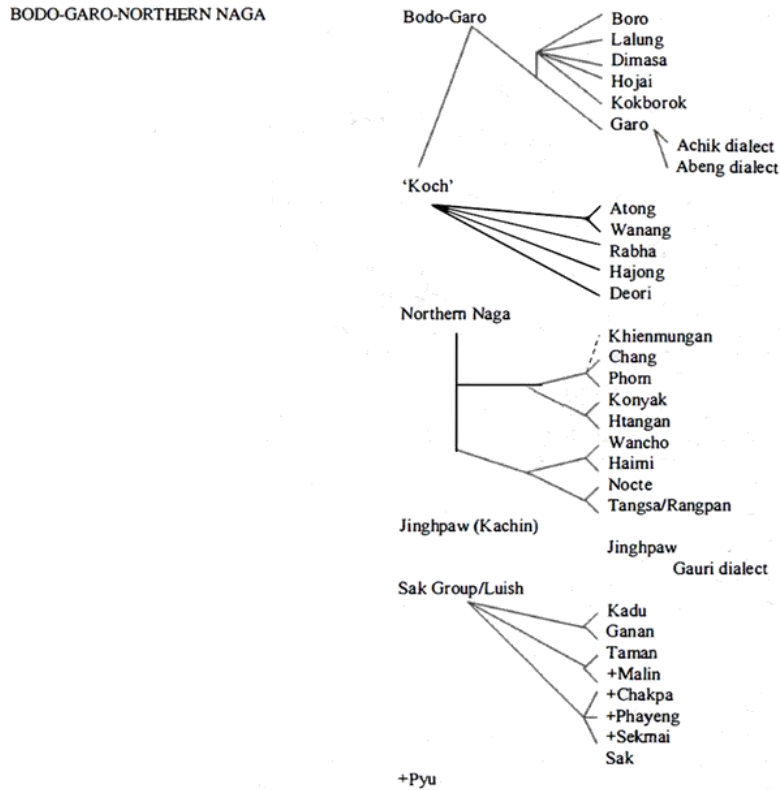


Figure 1: Bodo-Garo languages, including Garo from Bradley (1997).

The population census conducted by India's Office of the Registrar General & Census Commissioner (2011) puts the number of Garo speakers at a little over 1.45 million. The number of speakers in Bangladesh is not known, but Bradley (1997) reports based on old figures that about ten percent of Garo speakers live in Bangladesh.

Garo has eight dialects¹ that are mutually intelligible. The names of these dialects are: A'we or Standard A'we, A'beng or Am'beng, Chisak, Matchi, Dual, Gara Ganching, and Chibok. Of these dialects, Standard A'we is considered the standard dialect. It is used in teaching and writing, and is also the lingua franca among Garos. Although Standard A'we and A'we are the

¹ Traditionally, Garos count an extra of at least three more dialects, bringing the total to eleven. Linguistically speaking, however, these are not Garo languages but are more closely related to other Bodo-Garo languages. The names of these three dialects or languages are: Atong, Ruga, and Me'gam. These dialects may be more appropriately called the "cultural dialects" of Garo. The reason for this is because both the speakers of these languages and also the wider Garo community count the speakers of these three languages as an integral part of the Garo tribe.

same dialect for all intents and purposes, there are minor differences between the two. It might be more accurate to view the Standard A'we and A'we as being two varieties of the same dialect. The reason for their slight difference may have to do with the fact that although Standard A'we is only a standardized form of A'we, the two dialects are spoken in geographically disjointed areas of Garo Hills. The A'we dialect is mostly spoken in the North Garo Hills region, but Standard A'we is mostly associated with the town of Tura, which is in West Garo Hills. This study is only concerned with the Standard A'we dialect however.

2.2 Existing work

While the language is understudied, there has been some work done on the language. There is a language grammar by Keith (1874), which includes a preliminary description of the language. The morphology of Garo has been described by Ingty (2008), with Burling (1985) dealing with noun compounding. There have been a couple of papers on the phonology of Garo, including Burling (1981) which is a general description of Garo phonology along with its orthographic system, and Burling (1992) and Duanmu (1994) which deal specifically with the phonology of the glottal stop.

The most notable and the most comprehensive of these works is Burling (2003), which is the only descriptive grammar of Garo. It also culminates Burling's many years of work on the language. This grammar is not a description of the standard dialect however, as it describes the dialect that is spoken in Bangladesh.

2.3 Phonology of Garo

Garo has a fairly common inventory of 17 phonemic consonants (Figure 2). The phonemic status of these consonants is seen in the minimal pairs in Table 1.

	Bilabial	Alveolar	Velar	Glottal
Plosives	p b	t d	k g	ʔ
Nasals	m	n	ŋ	
Taps		r		
Fricatives		s		h
Approximants	w			
Lateral Approximants		l		
Affricates		ts dz		

Figure 2: Phonemic consonant of Garo.

Table 1: Consonant minimal pairs.

1.	[p ^h aʔ.a]	‘be daring’
2.	[baʔ.a]	‘bear/carry’
3.	[t ^h aʔ.a]	‘yam’
4.	[daʔ.a]	‘do not’
5.	[k ^h aʔ.a]	‘be bitter’
6.	[gaʔ.a]	‘step/stand on’
7.	[maʔ.a]	‘mother’
8.	[naʔ.a]	‘2 nd Sg.’
9.	[raʔ.a]	‘take’
10.	[saʔ.a]	‘nest (verb)’
11.	[waʔ.a]	‘bamboo’
12.	[ts ^h aʔ.a]	‘eat’
13.	[dzaʔ.a]	‘leg’
14.	[hai.da]	‘not sure’
15.	[bai.na]	‘to last’
16.	[mai.na]	‘why?’

17.	[sap _{na}]	‘to be capable’
18.	[sat _{na}]	‘to spray’
19.	[sak _{na}]	‘to braid’
20.	[ts ^h am _{na}]	‘to portion’
21.	[ts ^h an _{na}]	‘to count’
22.	[ts ^h aŋ _{na}]	‘to be able’
23.	[ts ^h a _{na}]	‘to germinate’
24.	[ts ^h aʔ _{na}]	‘to eat’
25.	[gam _{na}]	‘to pay’
26.	[gan _{na}]	‘to wear’
27.	[gal _{na}]	‘to discard’

The phonemes of Garo have distributional restrictions. Since the syllable is a central element in Garo phonology (Burling, 2017), the distributional restrictions are also defined based on the syllable position. Predictably, more of the consonants can occur and thus contrast in the onset positions of the syllable as compared to the coda positions. The segments that can occur and contrast in the onset positions of the syllable include: /p, b, t, d, k, ɡ, m, n, ɾ, s, h, w, ts̺, dʒ/ (Table 1: Examples 1-16). The smaller set of consonants that can occur and contrast in the coda positions are: /p, t, k, ʔ, m, n, ŋ, l/ (Table 1: Examples 17-27). Some consonants can only occur in either the onset or the coda positions. The segments: /ɾ, s, h, w, ts̺, dʒ/ can only occur in the onset positions, while the segments: /ʔ, ŋ, l/ occur exclusively in the coda positions. The voiceless plosives are realized differently in the onset and coda positions since they, along with the voiceless affricate are aspirated in the onset positions (aspirated sounds: /p, t, k, ts̺/).

While the distribution of the liquids /ɾ/ and /l/ could be analysed as being allophonic, i.e., analysed as /ɾ/ changing to [l] in the coda positions or vice versa, they are better treated as being

phonemic, with /r/ only occurring and contrasting in the onset positions and /l/ only occurring and contrasting in the coda positions. The same could be said about the distribution of voiced and voiceless plosives. While it could be analysed as a case of contextual neutralization of voicing contrast, whereby the voiced plosives turn voiceless in the coda position, voiced plosives are still better analysed as being restricted to only occurring and contrasting in the onset positions. The analysis of both cases as having to do with distributional restrictions at the phonemic level is due to an unusual syllabification process in the language. More on this below.

Consonant clusters are also possible in the language in both the onset and the coda positions. The type of possible clusters is highly restricted in the language, however. Both the onset and the coda clusters involve a template where one of the members in a cluster is constant. The onset clusters are of two configurations, the first of which is the [C₁r] configuration. The C₁ in this configuration represent the position where the segments: /p, b, t, d, k, ɡ, m, s, ^hts, ^hdz/ can go into to form a consonant cluster with /r/. The clusters of this configuration are seen in examples in Table 2.

Table 2: [C₁r] consonant clusters.

28.	[dɔk.p ^h ru.a]	‘smash through something’
29.	[nanŋ.b ^h rak.ka]	‘touch something by accident’
30.	[ok.d ^h rak.ka]	‘open by force’
31.	[dəŋʔ.k ^h rak.ka]	‘dry and hot’
32.	[dak.ɡ ^h rəm.ma]	‘do in unity’
33.	[nik.m ^h rak.ka]	‘see someone/something briefly’
34.	[s ^h rak.ka]	‘lick’
35.	[nək. ^h ts ^h rak.ka]	‘transparent’

36. [d͡ʒraŋ.ŋa] 'bright'

The second onset cluster configuration is [sC₂], where C₂ represents the position where the segments /p, t, k, ɾ/ can occur to form a cluster with /s/. The clusters of this configuration are seen in the examples in Table 3.

Table 3: [sC₂] consonant clusters.

37. [sp^hak.ka] 'shove'
 38. [st^hap.pa] 'stick (verb)'
 39. [sk^ho] 'head'
 40. [sɾoŋ.ŋa] 'be straight'

The coda position, unlike the onset position, only has one cluster configuration. The coda clusters involve the glottal stop /ʔ/ with which the sonorant sounds combine to form a cluster. The coda cluster is of the configuration: [Cʔ]. The segments: /m, n, ŋ, l/ can slot into the C position. The clusters of this configuration can be seen in the examples in Table 4.

Table 4: [Cʔ] consonant cluster.

41. [t^hemʔ.ma] 'fold'
 42. [denʔ.na] 'cut'
 43. [p^henʔ.ŋa] 'barricade (verb)'
 44. [salʔ.la] 'broom'

The inventory of Garo vowels is also a fairly common one. Garo has six phonemic vowels as can be seen in Figure 3. The phonemic status of these vowels can be seen in the minimal pairs in Table 5.

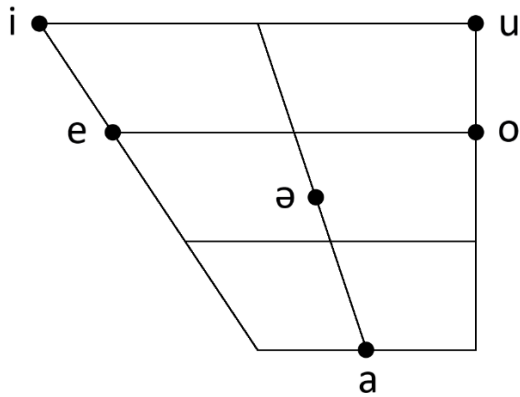


Figure 3: Phonemic vowels on Garo.

Table 5: Vowel minimal pairs.

45.	[s <u>i</u> .a]	‘die’
46.	[s <u>e</u> .a]	‘write’
47.	[s <u>a</u> .a]	‘be sick’
48.	[s <u>o</u> .a]	‘rot’
49.	[s <u>u</u> .a]	‘peck’
50.	[sə <u>l</u> .la]	‘be pretty’

There are no distributional restrictions for four vowels in the inventory: /e, a, o, u/. There is, however, a distributional restriction for /i/ and /ə/ vowels. The /i/ vowel is restricted to occur exclusively in open syllables and the /ə/ occurs exclusively in closed syllables. It would be possible to analyse the distribution of these vowels as being allophonic, i.e., /i/ changing to [ə] in closed

syllables or vice versa, but for the same reason that /ɾ/ and /l/ are better analysed as being phonemic, /i/ and /ə/ are also better analysed as phonemic. This has to do with an unusual syllabification process in the language. This will be elaborated on below.

Diphthongs are also possible in the language, but there is only one possible configuration. The two possible diphthongs involve the /a/ vowel and is of the configuration: /aV₂/. The vowels: /i/ and /u/ can slot into the V₂ position to form a diphthong with /a/. The two possible diphthongs can be seen in the examples in Table 6.

Table 6: Diphthongs.

51.	[ma <u>i</u> .na]	‘why’
52.	[sa <u>u</u> .na]	‘to swear’

The segmental inventory of Garo is similar to the inventory of its sister languages within the Boro-Garo group. All of the languages in the group have more or less the same inventory with only slight deviations (Burling & Joseph, 2006). Garo departs from its sister languages when it comes to prosody, however. All of the languages in the Boro-Garo subgroup have a two-way H vs. L tone system. Garo stands out in lacking tones entirely (Burling, 2003, 2017). What makes Garo’s atonality odder is the fact that the tone that marks particular morphemes in individual languages remarkable line up, e.g., Tiwa: /k^há/, Rabha: /k^há/, Boro: /k^há/, Kokborok: /k^há/ – ‘bitter,’ for which Garo has: /k^ha?/ (for more examples cf. Joseph & Burling, 2001). Due to this clear correspondence between the languages in terms of tonal contrast, the proto form of the language has been justifiably reconstructed as a tonal system (Burling & Joseph, 2006). Interestingly, the morphemes that are marked with a high tone in the related languages show contrast in terms of the glottal stop in Garo (Joseph & Burling, 2001). This has led Joseph & Burling (2001) to conclude

that the glottal stop in Garo corresponds to the H tone in its sister languages. This leads to the question of how Garo lost its tone and more importantly how it came to replace tone with the glottal stop. One possibility is that the proto language had a “stopped H tone” which Garo interpreted as a glottal stop in the course of its development. This is supported by the fact that in some of its sister languages the H tone is short and ends in a glottal stop (cf. Tiwa & Rabha; Joseph & Burling, 2001).

The syllable is the central element of Garo phonology (Burling, 2003, 2017). In terms of the possible syllable structure, the vowel is the only mandatory segment. Vowel-only syllables are possible as a consequence of this, vowel hiatuses are also not resolved in the language, e.g., [o.a] ‘open-Pre.’ The syllable is free to have either a coda or an onset, or both, so CV and VC syllables are possible in the language. Since consonant clusters are also possible in the language, the possible syllable shape in the language can be schematized as: (C)(C)V(C)(C).

Syllabification is not a straightforward process in Garo. When a morpheme that ends with a consonant combines with a morpheme that begins with a vowel, the final consonants of the first morpheme does not resyllabify as the onset of the following syllable. These morpheme final consonants instead geminate (A’gitok, 2022), i.e., in VC + V sequences, the syllabification pattern is VGV (where G is a geminate), and the expected syllabification *V.CV is not observed. Owing to this, it does not make sense to analyse the distribution of segments /ɾ/ and /l/, and also /i/ and /ə/ as being complementary. Since the morpheme final /l/ never resyllabifies, there are no instances where it turns to /ɾ/. The morpheme final /l/ always geminates when it is followed by a vowel initial morpheme, so a phonological rule that changes it to /ɾ/ cannot be defined. The issue is the same with distribution of /i/ and /ə/. Since the consonants that end the morphemes with /ə/ never resyllabify, a phonological rule that changes it to /i/ cannot be defined. Keeping these in mind, it

makes more sense to analyse these segments as phonemic even though their distributions appear to be complementary at first glance. The distribution of /ɾ/ needs to be defined as only beginning morphemes, while the distribution of /l/ as only ending morphemes. Also, the distribution of /ə/ needs to be defined as only occurring in morphemes that end in consonants, while the distribution of /i/ as only occurring in morphemes that does not end in consonants².

2.4 Morphology & syntax

In terms of morphology, Garo is a monosyllabic agglutinating language. Due to its agglutinating nature, it is common to find very long words with multiple syllables in the language. When it comes to the linearization of the morphemes, however, Garo favours suffixation rather than prefixation. Prefixes are virtually absent in the language, and one prefix that is possible, i.e., /daʔ-/ ‘Neg,’ is not very productive. Derivation is a productive word formation process in the language along with compounding and to a lesser degree, reduplication.

Syntactically, Garo is a verb final language and has an SOV word order. The subject and object DPs can be marked by case suffixes, but the case suffixes are not mandatory. Garo does not have much in terms of movement, e.g., Wh-movements are absent in the language. The language instead has syntactic particles that mark the various discourse structures.

² There is an exception in case of the glottal stop here. The glottal stop, however, has already been shown to not behave as other consonants in the language (Burling, 1992).

Chapter 3 – Background about Garo stress

Burling (2003) includes a preliminary description of Garo word prosody which makes clear that it does not have phonemic stress. The description is purely impressionistic, however, and also is based on words produced in isolation. The general stress pattern of Garo words according to Burling (2003) is that the final syllable is stressed. There are some exceptions to the general pattern reported in case of compounds however, and some suffixes are described as not attracting stress, leading to another class of exceptions (Table 7). The accuracy of these claims is hard to evaluate as there is no acoustic analysis to support the descriptions.

Table 7: Word-stress pattern according to Burling's (2003) description.

53.	[bi. 'gəl]	‘skin’
54.	[, bol.bi. 'd̥zak]	‘tree leaf’
55.	[na. 'tsʰəl.lo]	‘ear-Loc’
56.	[meʔ. 'tsʰək.ra.ra]	‘women all over the place’
57.	[meʔ.tsʰək. 'draŋ] ([meʔ.tsʰək. 'raŋ] in Standard Garo)	‘women-Pl’
58.	[soŋ. 'tʰaŋ]	‘own village’
59.	['reʔ.a]	‘go, come’
60.	[reʔ. 'aŋ.ŋa]	‘go away’
61.	[kʰat. 'pʰəl.la]	‘run back’
62.	[kʰat. 'pəl.ləŋ.ŋa] ([kʰat. 'pəl.ləŋ.ŋa] in Standard Garo)	‘running back’
63.	[kʰat.ba.pʰəlʔ. 'd̥zok]	‘has run back here’
64.	[kʰat.taŋ.pəlʔ. 'no.a]	‘will run back there’
65.	[iʔ.ba. 'pʰəl.le] ([reʔ.ba. 'pʰəl.le] in Standard Garo)	‘having come back’
66.	[kʰat. 'taŋ.gəp.pa]	‘the one who runs away’

67. [ʼaŋ.ŋa] ‘I’
 68. [gət.ʼtʰam] ‘three’
 69. [d͡zɛmʔ.ʼd͡zɛm] ‘constantly’
 70. [,hɛŋ.ŋɛ.ʼhɛŋ.ŋɛ] ([,ɛŋʔ.ŋɛ.ʼɛŋʔ.ŋɛ] in Standard Garo) ‘widely spaced’

Nouns in Garo, specifically disyllabic nouns are described as having mild stress on the second syllable, e.g., Table 7: 53. Although the pitch pattern is described as being level on the first syllable after which it rises on the second syllable before falling, no pitch track of any sort is provided, so, the description has to be taken as purely impressionistic. Other than pitch, the final syllable may also be slightly longer, but Burling (2003) is not certain about this characterization. Nouns longer than two-syllables are also described as having the strongest stress on the final syllable, but in case of compounds, the first member of the compound is also described as retaining its stress pattern, e.g., Table 7: 54, from [bol] ‘tree’ and [bi.ʼd͡zak] ‘leaf.’ How much of this description is accurate is difficult to gauge as there are no acoustic analyses provided to back up the assertions.

Some of the suffixes that attach to nouns are described as not drawing stress to themselves. This would leave the stress on the noun stem leading to a stress on a non-final syllable. Burling (2003) specifically points out the case suffix /-o/ ‘locative,’ /-ni/ ‘genitive,’ and /-t͡sa/ ‘instrumental’ (/t͡si/ in Standard Garo) and also another suffix /-rara/ ‘all over the place’ as leaving stress on the noun stem, e.g., (Table 7: 55, 56). Words with these suffixes are described as having the “strongest syllable,” which presumably means stress, on the final syllable of the noun stem and not on the suffix itself.

Some other suffixes are described as drawing stress to themselves. These suffixes include: /-draŋ/ ‘plural’ (/raŋ/ in Standard Garo) and /-taŋ/ ‘reflexive,’ e.g., Table 7: 57, 58. Burling (2003)

postulates that the difference in the behaviour of suffixes with regards to stress has to do with the syntax of the suffixes. Since the suffixes that do not attract stress are case suffixes, they are more or less clitics. Burling (2003) at the same time goes on to say that the difference in behaviour of the suffixes with regard to stress has to do with case suffixes being open syllables. There is no certainty on the part of Burling (2003) about what causes the suffixes to behave differently regarding stress. It has to be noted again at this point that there was no acoustic analysis to support the descriptions.

Verbs do not occur without suffixes in Garo (except in cases of negative imperatives), so it is not possible to establish the stress pattern of verb bases (Burling, 2003). What Burling calls principal verb suffixes: /-a/ ‘tense-present,’ /-əŋ/ ‘progressive’ and /-e/ ‘subordinative’ (Table 7: 59, 62, & 64) are described as not attracting stress. Another principal verb suffix which nominalizes verbs, i.e., /-gəpa/ (Table 8: 68) is also described as not attracting stress.

A group of suffixes identified as derivational suffixes, e.g., /-aŋ/ ‘movement away’ (Table 8: 60) and inflectional suffixes that can follow these derivational suffixes, e.g., /-pəlʔ/ ‘movement towards’ (Table 7: 62), are described as attracting stress (Burling, 2003). Some of the tense-aspect suffixes, /-dzok/ ‘perfective,’ and /-noa/ ‘immediate future,’ (Table 7: 63 & 64), are also described as attracting stress.

When it comes to the other word classes such as pronouns, Burling (2003) describes them as having a stress pattern similar to nouns (Table 7: 67). Since case suffixes do not attract stress, the first syllable is stressed in pronouns as per Burling. Numerals, which compose of a classifier and a number are describes as having stress on the second syllable, which is the number. Adverbs on the other hand can be formed by reduplication, and some of them end with /-e/ ‘subordinative.’

The general pattern in adverbs is also described as the final syllable being stressed (Table 7: 69), except in case of /-e/ (Table 7: 70).

The general pattern of word-stress that can be deduced from Burling's (2003) description is that the final syllable of words is stressed. There appears to be some exceptions to this general pattern due to some suffixes not attracting stress. It has to be noted however, that Burling's descriptions are purely impressionistic and that no acoustic analysis is provided in order to support the claims. It needs to be systematically tested therefore whether the general word-stress pattern in Garo is indeed stress on the final syllable. It also needs to be tested whether the exceptions that Burling describes really does exist in the stress system of Garo.

Chapter 4 – Word-stress: Background and theory

The term *stress* is defined as a prominence on a syllable in a word (Gordon & van der Hulst, 2020). The prominence refers to the difference of acoustic features that sets a particular syllable apart from other syllables in a word. The acoustic features that get enhanced under stressed, or to put it in other words, the features that stressed syllable have more of are in most cases: F0, vowel duration, intensity, the so called *stretchable properties* of sound segments according to van der Hulst (2010). Other studies such as Sluijter & van Heuven (1996) do report *spectral tilt* as being another cue of stress, but the most robust of the acoustic cues tend to be F0, vowel duration, and intensity.

4.1 Terminology

One thing that has to be kept in mind while studying stress is the fact that it can be difficult to determine what certain terms mean. There is no single terminological convention that researchers follow which can lead to a single term meaning different things in some cases and different terms meaning the exact same thing in other cases. The problem with lack of agreement in the usage of terms is by no means limited to studies in stress as it is regrettably a property of linguistics as a discipline, but it is certainly the case that discrepancies in the usage of terms is very common in prosodic studies, of which stress is a part. It is therefore imperative that even though a common ground for terminological practices cannot be established for stress, each study make explicit what different terms mean in their analysis.

The difference in terminology concerns even the phenomenon that is the subject matter of this study, i.e., prominence at the word-level. Although this thesis has used the terms *stress* and

word-stress interchangeably to describe this phenomenon, not every researcher describes the phenomenon using the same terms as this thesis. Some papers including and in particular van der Hulst (2010) uses the term *accent* for word-level prominence. The argument that these papers put forward for using *accent* instead of *stress* is that word-prominence is by nature abstract in that the prominence is signalled differently cross-linguistically. The argument proceeds that even if languages have prominence on the same syllable of the word, how that prominence is actually signalled can be different. What is common in these languages is then how the prominent syllable is calculated (discussed in section 4.2), which points to the fact that prominence is actually abstract and that it needs to be separated from how it is physically expressed in speech. Following this argument, van der Hulst (2010) goes on to classify languages according to how word-prominence is expressed, e.g., *pitch-accent* classification for languages that use pitch to express word-prominence, *stress-accent* classification for languages that use a combination of acoustic cues to express prominence.

As well-reasoned as van der Hulst's (2010) arguments are, there are objections to the usage of *accent* in place of the more common *stress*. One of the objections to the term *accent* comes from the fact that there is already a phenomenon in prosody that *accent* and more specifically *pitch-accent* describes. The prominence tones at the intonational level are also called *accent* (Arvaniti & Fletcher, 2020; Gordon, 2014; Gussenhoven, 2007), thus creating ambiguity. Due to this, some researchers reserve the term *accent* to mean prominence at the intonational level and instead use the term *stress* to describe prominence at the word level.

Another objection to the use of *accent* and more specifically *pitch-accent* for describing word-prominence comes from Hyman (2009), who argues that there is no need for a category of a *pitch-accent* system in classifying languages. Hyman's argument is against the use of the term

pitch-accent for languages where the position of the prominent syllable is contrastive and prominence is cued by pitch (Beckman & Pierrehumbert, 1986; Fikkert et al., 2020; Remijsen & Heuven, 2005; van der Hulst, 2010b). Hyman argues that it is not necessary to add a third category to the classification of word-prosody systems. The *pitch-accent* category was proposed due to languages like Japanese and Swedish having properties of both stress and tone systems due to the fact that even though pitch marks contrast in these languages, they can only occur on prominent syllables. Hyman says that the *pitch-accent* category is dispensable due to the fact that properties described for *pitch-accent* languages are also seen in canonical tone languages, i.e., there are tone languages where tone contrasts can only occur on prominent syllables. Hyman says that languages can be classified neatly into two categories – stress and tone and therefore the pitch-accent category can be dispensed.

Keeping the discussion in the preceding section in mind, this thesis will use the term *stress* instead of *accent* in order to denote word-prominence.

4.2 Metrical stress theory of word stress

Metrical stress theory assumes that stress is a manifestation of the rhythmic structure (Hayes, 1995). Metrical theory abandons the view that stress is a feature analogous to features like [round] and [nasal]. Instead, the theory represents stress as a hierarchically organized rhythmic structure. This rhythmic hierarchy is conceived differently by different researchers even within the metrical theory research program. Some conceive the rhythmic hierarchy in terms of trees while others use metrical grids instead (Gordon, 2011b; Hayes, 1995; Kager, 1995, 2010). Hayes (1995) himself adopts a hybrid of the two representational systems which he calls **bracketed grids** and is based on Halle & Vergnaud (1987).

The hierarchical view of stress as argued, succeeds in capturing certain properties of stress that is not possible when it is viewed as a feature (Hayes, 1995). These properties include: *rhythmic distribution* where syllables bearing equal levels of stress tend to occur spaced roughly equal distances, *stress hierarchies* where most languages have multiple degrees of stress corresponding to *primary*, *secondary*, and *tertiary*, and also the property of *lack of assimilation*, an exceptionless phonological universal where stress does not assimilate such that stressed syllables do not induce stress on adjacent syllables.

Metrical stress theory in general, whatever the representational convention is adopted, represents stress as a hierarchically organized rhythmic structure. This can be seen in the representation of the phrase in Figure 4.

(x (x)
 (x .)(x .)(x)
Mississippi mud

Figure 4: Hierarchical structure of the phrase “Mississippi mud” proposed by metrical stress theory (Hayes, 1995).

The rhythmic structure as can be seen in Figure 4 is hierarchical. Sequence of beats have multiple levels of strength (the x on the grid represents strength). Another thing to be noted about the structure is that there is a tendency for even spacing at all intervals of repetition or at all levels. The law of *downward implication* also applies to the grid where a beat (or x mark) on a higher layer must also have a beat on all the lower layers.

Another important feature of the rhythmic structure is that it is not just the columns that are important but also the rows. The rules of stress assignment of intonational pitch accent

association and rhythmic adjustment refer to notions such as *rightmost syllable with at least n degrees of stress* or *consecutive syllables bearing at least n degrees of stress* (Hayes, 1995).

One of the main proposals of the theory is that the best way to express stress rules is to state possible structures for the metrical constituents that segments could group into and then view stress placement as the parsing of a word into such constituents. The hierarchical rhythmic structure begins with grouping the sound segments into syllables (Blevins, 1996; Cooper & Zec, 2013; Gordon & van der Hulst, 2020; Hayes, 1995; Kager, 2010). The syllables are in turn grouped into *feet*, which are the smallest bracketed units posited by metrical theory (Hayes 1995; Kager, 1995, 2010). The syllables are basically grouped into feet and feet in turn group to form the *prosodic-word*. There is one grid mark assigned at every level of grouping such that feet and the prosodic-word both have one head or a prominent constituent and it is because of this hierarchical organization of the grid and grid or prominence marks at every level that syllables come to bear different degrees of stress - primary, secondary, and so on (Gordon, 2011b; Gordon & van der Hulst, 2020; Hayes, 1995; Hyman, 2009; van der Hulst, 2010b).

The constituent which is stressed or is the head of any given constituency depends on the language. Some languages stress the first syllable of the foot which are known as *trochaic* systems and other languages stress the second syllable of the foot which are known as *iambic* systems (Gordon, 2011b, 2011a, 2016; Gordon & van der Hulst, 2020; Hayes, 1995; van der Hulst, 2010b). This is true for the prosodic-word level as well since some languages place the primary stress on a particular foot close to the left-edge, while other languages place it on a foot near the right-edge (Gordon, 2011b, 2011a, 2016; Gordon & van der Hulst, 2020).

There are also some properties that are associated with the stress systems. These properties are theorized to hold for all stress languages and they are: *obligatoriness* by which every prosodic-

word must have a primary stress and *culminativity* by which a prosodic-word can have only one primary stress (Hyman, 2009). Some researchers also add *demarcation* as another property of stress systems where the primary stress serves to demarcate the domain of a prosodic-word (Gordon, 2016; van der Hulst, 2010b).

4.3 Primary accent first theory

Although the metrical stress theory of word stress is the most widely adopted theory of how stress is assigned at the word level, other researchers take a different view. In metrical stress theory, the assignment of rhythmic beats proceeds bottom-up such that there is one rhythmic beat at every level from the foot up to the word. The way that a syllable derives its prominent status at the word level is therefore by being the prominent syllable at the foot level and ultimately being the head syllable of the head foot of the word. The assignment of prominence very much proceeds from the bottom-up therefore. However, some other researchers propose that assignment of prominence at the word level proceeds top-down, i.e., they propose that the primary accent is assigned first in a word before the rhythmic structure at the lower level is determined (van der Hulst, 2010a, 2014).

One of the arguments that has been put forward for assignment of primary stress (accent for van der Hulst) before the rhythmic structure at the foot level is determined is that the rhythmic structure at the foot level is often defined by the head foot. What is meant by this is that far too often in languages that have iterative footing the foot that is formed first determines the rhythmic structure, i.e., iterative foot propagates away from the head foot. van der Hulst (2010a) argues that this is too much of a common occurrence for it to be just a coincidence. This is one of the reasons why he proposes that the primary stress is privileged in prominence assignments. What is basically being argued is that the head foot is in most cases the foot that is formed first and the iterative foot

formation ripples away from the head foot. Foot formation where the iterative feet start from the opposite edge to the head foot are much rarer.

Another argument that has been used to advance primary accent first models is that in case of clashes, the resolution is always in favour of the head foot (van der Hulst, 2010a). The argument is that when there is a clash in the rhythmic structure such that the rhythmic beat of the head foot is next to another rhythmic beat, the resolution, if one exists, is to delete the rhythmic beat that is not the beat of the head foot. All these point to the privileged status of the head foot, and consequently the primary stress as the argument proceeds.

One thing that has to be said about these proposals is that they are attractive. The purpose of this study is however, not to evaluate between the different theories of word stress. It is also unlikely that the data in this study is complex enough in its rhythmic structure to pick one theory over another. For these reasons this study will in its account of the stress pattern of Garo use the more conventional and more accepted metrical stress theory. It has to be pointed out that this is by no means a dismissal of the primary accent first theory. Future studies should definitely consider the rhythmic structure of Garo word more closely and pick between the two theories based on their explanatory adequacy and their power for predictions.

4.4 Acoustic cues of stress

With the question of how prominence relations hold between syllables at the word level, a natural question arises as to how prominence is actually signalled. While the acoustic cues that signal stress is as crosslinguistically varied as the rhythmic structures, there are particular acoustic cues that stand out as the most reliable cues of stress and these are: F0, duration, and intensity (Gordon & Roettger, 2017).

Some studies have pointed out duration being the most reliable cue for stress (Gordon, 2011a; Gordon & Roettger, 2017; van Heuven & Turk, 2020). These studies report that a vast majority of world's languages, e.g., English and Dutch increase the duration of a syllable that is stressed. In addition, some of the languages also simultaneously change the quality of the unstressed syllables by centralizing the vowel. Centralization is done to further highlight the prominent status of the stressed syllable.

Another important cue for stress is F0. Languages mark the stressed syllables by consistently producing it with either a low or a high F0 that sets it apart from the unstressed syllables. Some studies have sounded caution about the interpretation of F0 as a cue for stress as F0 is also used to signal sentence prominence (Gordon, 2014; Roettger & Gordon, 2017). Several recent studies that controlled for the confounds of word and sentence prominence have found however that in languages like Greek and Spanish F0 is a cue for word stress (Vogel et al., 2015, 2016, 2017).

While intensity is often included in a list of cues that signal stress in languages, it is not as reliable as duration and F0 (Gordon, 2016; Gordon & Roettger, 2017; van Heuven & Turk, 2020). In most cases intensity, if it plays a role in signaling stress, occurs with another acoustic property as a cue for word stress.

Duration, F0, and intensity are the acoustic cues usually seen on speech signal, i.e., production data that typically sets one of the syllables (stressed syllable) from the rest of the syllables in a word. While the pattern of these acoustic cues in the production data is the subject matter of this thesis, the perception of these properties which is equally important needs to be mentioned. The prosodic pattern seen in production studies need to be tested in perceptual experiments to ascertain that the pattern is perceptually salient (van Heuven & Turk, 2020; van

Zanten & van Heuven, 1998). Confirming the perceptual salience of the acoustic cues of stress in Garo is beyond the scope of this thesis however, and a perceptual experiment will have to be left for a future study.

4.4 Prosodic structure above the word

It is not only at the word level that the hierarchical rhythmic structure exists. The hierarchical structure extends to the sentence level where smaller units combine to form larger units much like at the word level (Nespor & Vogel, 1986; Selkirk, 2011; Vogel, 2009). The prosodic hierarchy is represented in Figure 5.

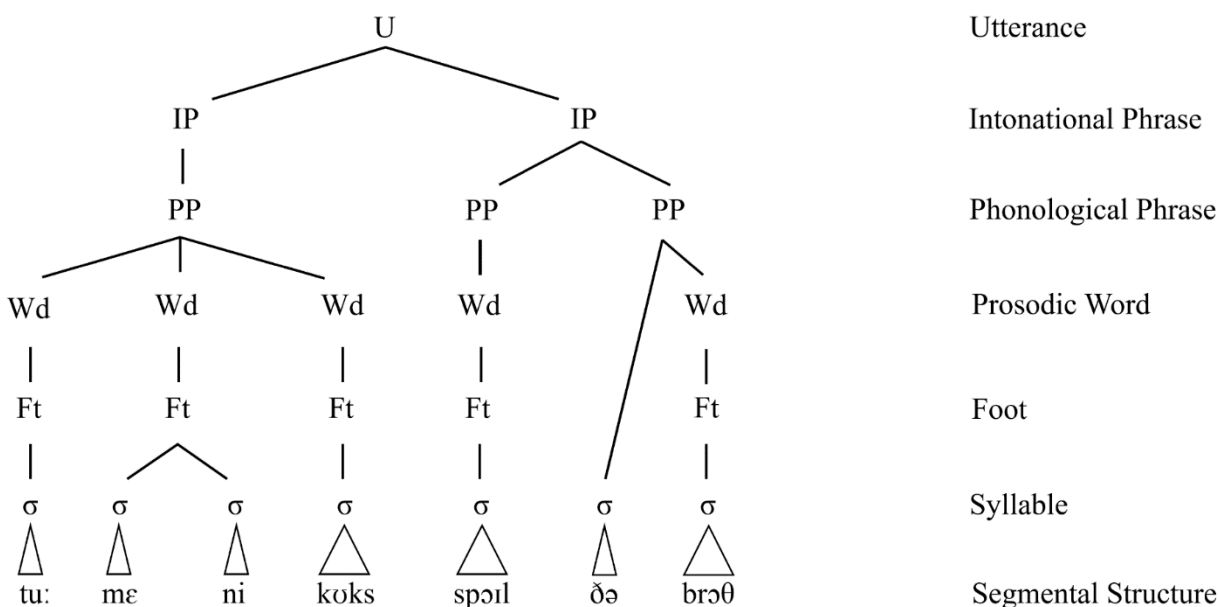


Figure 5: Prosodic structure of the sentence “too many cooks spoil the broth,” encompassing both the word level and the levels above the word.

The prosodic structure in Figure 5 shows the prosodic structure of the sentence “too many cooks spoil the broth.” The structure includes both the levels within and above the word. Each level of the hierarchy is made up of units that it immediately dominates. There are also prominence

relations that hold at each level of the hierarchy. There is also only one prominent unit at each level such that there is only one prominent unit in an utterance. This prominence at the sentence level serve to encode information structure of the utterance and is often expressed prosodically (Beckman & Pierrehumbert, 1986; Vogel et al., 2017). Typically, the prosodic expression of focus takes the form of enhancing the acoustic cues of word stress in addition to receiving intonational pitch accents (Arvaniti & Fletcher, 2020; Gussenhoven, 2007). There have also been proposals that focus adds additional prosodic structure to the focused item such that it alters the prosodic structure (Ladd, 2008; Nespor & Vogel, 1986).

Even without the addition of prosodic structure by focus, the higher levels of the prosodic hierarchy, i.e., the Phonological Phrase (PP) and the Intonational Phrase (IP) are often marked with F0 movements called *boundary tones* (Arvaniti, 2011; Arvaniti & Fletcher, 2020; Cole, 2015; Gussenhoven, 2007). These F0 movements serve to mark the prosodic domains and together with the prominence tones give rise to intonational contour of languages. It has to be noted that some languages do not have prominence tones and their intonational contours are composed entirely of boundary tones (Jun, 1998; Jun & Fougeron, 2000).

Focus, if it is prosodically expressed, involves the association of the sentence level prominence on the focused word (Arvaniti & Fletcher, 2020; Gussenhoven, 2007). When the sentence level prominence associates to the focused word it introduces F0 movement on the word if there is none or changes the existing F0 pattern. Languages like German have been found to change the F0 pattern of the word under focus (Roessig & Mücke, 2019). As has been mentioned previously, focus also adds prosodic structure to the focused constituent by adding a high level prosodic boundary which introduces boundary tones (Ladd, 2008; Nespor & Vogel, 1986). Addition of prosodic structure under focus have been found in experimental studies of languages

like Korean (Jeon & Nolan, 2017). In addition to adding or altering the F0 pattern, in languages like Arabic, focus has been found to enhance the acoustic correlates of stress on the focused word while simultaneously compressing the acoustic properties of words that occur after the focused word and also deaccenting them (collectively called post-focal compression; Lee et al., 2015; Vogel et al., 2017; Xu & Xu, 2005). Post-focal compression has been reported for languages like Persian (Rahmani et al., 2018). It is not only the prosody of the focused word that is affected by focus therefore, as the unfocused constituents are compressed in terms of their acoustic properties with the goal of further prosodically highlighting the focused word.

It has to be noted however, that the way that focus is marked prosodically is a little different in languages that employ morphosyntactic ways of marking focus. Garo also marks focus morphosyntactically by using the *-sa* focus particle (Burling, 2003). While morphosyntactic strategies of marking focus is not mutually exclusive with prosodic focus marking (Frota, 2000), languages like Hungarian and Korean, which mark focus morphosyntactically have been found to only have addition of prosodic structure under focus (Choe, 1995; Jeon & Nolan, 2017; Mády & Kleber, 2010; Vogel et al., 2015). There is no consistent enhancement of acoustic properties of stress under focus in languages like Hungarian and Korean, and neither is there any post-focal compression. These languages thus differ in not having the full range of prosodic effects typically seen under focus.

4.5 Typology of stress systems

Typologically, languages have either a *free* or a *fixed* stress. Free stress languages are those where stress is phonemic, e.g., Spanish. These languages have stress position as part of the lexical entry of the words (Hayes, 1995). Fixed stress languages on the other hand are those languages where

the stress position is predictable based on phonological factors. Fixed stress languages are the systems that can be explained by metrical theory due to their predictable nature (Hayes, 1995).

Even though all languages have the same metrical or rhythmic hierarchy, there is cross-linguistic variation in terms of which members of the constituents gets the stress. At the foot level, trochaic systems stress the first syllable of the foot while the iambic systems stress the second syllable. At the prosodic-word level the languages can also choose to stress either the initial or the final foot of the word. The combination of these two factors gives rise to four types of stress systems when it comes to primary stress. In trochaic systems if a language stresses the initial foot, the language has initial stress and if a language stresses the final foot, it has a penultimate stress. Similarly, in iambic systems, if a language stresses the initial foot, the language has peninitial stress and if a language stresses the final foot, it has a final stress (Gordon, 2011b; Gordon & van der Hulst, 2020; Kager, 2010). The structure in (Figure 6) shows the metrical structure of the word “horse” in Chickasaw which has final stress.

(x)
 (x) (. x)
 ,is so 'ba
 "horse"

Figure 6: Metrical structure of the word “horse” in Chickasaw.

Focusing the discussion on iambic systems since Garo is a final stress language (Burling, 2003), there can be variations even within iambic systems. Languages also vary in terms of the direction of the footing. In languages like Sirenikski, there is left to right footing so there is stress on every even-numbered syllable when counted from the left. Similarly, in languages like Chulupi,

there is right to left footing so there is stress on every odd-numbered syllable when counted from the right (Gordon, 2011b, 2016; Kager, 2010). If it is the case that Garo has a left to right footing like Sirenikski, it will be the foot that is formed at the end that will be promoted to the head foot of the word since Garo is a stress final language. Conversely, if Garo has a right to left footing like Chulupi, it will be the foot formed at the start that will be promoted to be the head foot.

In addition, predictable stress languages can also differ in terms of quantity sensitivity. Garo itself is not quantity sensitive (Burling, 2003), but the internal structure of syllables play a role in stress placement in languages like Chickasaw which are quantity sensitive systems (Gordon, 2011b; Gordon & van der Hulst, 2020; Hayes, 1995; van der Hulst, 2010b). Long vowels and syllable codas count towards making a syllable heavy in many languages. Heavy syllables preferentially attract stress in quantity sensitive systems, e.g., in Kabardian stress falls on the final syllable if it is heavy otherwise on penultimate syllable if it is light (Gordon, 2016). Heavy syllables can also disrupt the alternating stress pattern, attracting stress even if it is adjacent to a stressed syllable, e.g., in Chickasaw stress falls on every even numbered syllable and heavy syllables counting from left to right. Additionally, the final syllable is stressed which is the primary stressed syllable (Gordon, 2016).

It is quantity insensitive languages like Chulupi and Urubu Kaapor (Gordon, 2016) that Garo fits in with. Both Chulupi and Urubu Kaapor have stress on the final syllable of the word, so they have stress on odd-numbered syllables from right to left. It has to be noted that while Garo fits in with these languages in terms of having final stress, it is unclear if it has iterative footing. The existing description of Garo does not list any segmental processes that are sensitive to foot prominence, e.g., vowel centralization and also no secondary stress. Based on what is known about the foot structure of Garo, it is probably more reasonable to suggest that Garo is similar to

languages like Yawelmani, which has a main stress on the final syllable (Bakovic, 1998). The reason why languages like Yawelmani only have main stress and no iterativity is because these languages have unbounded feet. In these languages, all of the syllables group into a single foot and there is a rule to stress a particular syllable of a word, e.g., the final syllable as in Yawelmani. This is possibly the foot structure of Garo as well if the existing report of lack of iterative footing remains true. It has to be noted however, that the behaviour of the glottal stop hints at the presence of iterative footing, but it has not been formally analysed so it is not clear at the moment what the foot structure is, and it is beyond the scope of this thesis to do an analysis of the glottal stop pattern.

Another thing to note about final stress languages or edge-prominent language more generally is that there can be ambiguity about how the prominences must be interpreted. The classic cases are French and Korean. The most common interpretation of French and Korean is that these languages lack word level stress (Jun, 1998; Jun & Fougeron, 2000). Within this interpretation of Korean and French, these languages are taken to have prominence at the Accentual Phrase (AP) level (which is just a PP with phrasal tones), and not at the lexical level. The F0 movement seen on the words then are interpreted to arise from phrasal tones, and are not cues of word stress. There is another interpretation of the prominence in these languages however, e.g., Quebecois French in particular has been analysed as having a “dual” stress or a “hammock” stress where both the initial and the final syllables of a word are stressed (Gordon, 2011b). This interpretation is very different from analyses that propose that these languages do not have prominence at the word level and thus treat the F0 movement on the word as cues for word stress. It is possible that Garo could also end up with an ambiguous analysis if the acoustic properties of stress do not clearly signal prominence at the word level.

Based on the existing descriptions, therefore, Garo fits with languages like Yawelmani that has stress on the final syllable. It is very possible that Garo has unbounded feet as the existing description of the language does not report iterative footing, but it has to be repeated that the behaviour of the glottal stop does hint at the presence of iterative footing. It is just the case that the glottal stop pattern is unanalysed at the moment. Another thing that is quite clear about Garo is that even if it has unbounded feet, it likely has quantity insensitive unbounded feet since syllable weight has not been reported to play a role in stress assignment. These are statements based on impressionistic descriptions however, and it must be left open as to the possibility of Garo having iterative iambic footing. Additionally, due to being final stressed, it has to be entertained that Garo might have an ambiguous interpretation regarding its prominence.

Chapter 5 – Current study

Based on the problems highlighted about impressionistic descriptions of prosody, this study does a systematic acoustic study of Garo word prosody. Target words were elicited in carrier sentences and the confounds of word stress and sentence prominence were controlled for based on the concerns raised by the previous studies. In order to study the word prosody on its own, focus was placed away and after the target word. In addition to testing for the word prosody, this study also tested how focus affected prosody, how word prosody was affected in the post-focal condition, and also in a post-hoc analysis how focus particle affected the prosody of the focused word.

The first of the research questions of this study concerned stress. There are two research questions concerning stress:

- (i) Does Garo have word stress?
- (ii) How is stress signalled in Garo?

Based on the literature reviewed in the previous chapter, certain predictions can be made about the research questions. For question (i), no strong predictions can be made, but as per the existing description by Burling (2003) that Garo is a final stress language, it is probably the case that Garo does have word stress. It is also very common for languages to have word stress, so the null hypothesis should always be that a language has word stress. Consequently, it is being predicted that Garo has word stress.

A stronger prediction can be made about question (ii). If Garo does have word stress, it is predicted that it will be signalled either by duration or F0, or a combination of both. Intensity cannot be completely ruled out, but chances of intensity being the primary acoustic cue of stress is extremely low, so it is not predicted to be a cue for stress. So, for question (ii) it is predicted that

if duration is the cue, the stressed syllable will be significantly longer compared to the unstressed syllables. If, however F0 is the cue, then it is predicted that the stressed syllable will have either a consistently higher or lower F0 compared to the unstressed syllables.

The next set of research questions concern focus. Focus enhances the acoustic correlates of stress, so it is one way to confirm which acoustic properties actually cue stress in the language. It is not known however, whether there is even prosodic focus in the language, hence the need for research question (iii). The two research questions for focus are:

(iii) Is there prosodic focus in Garo?

(iv) How is focus signalled in Garo?

Some strong predictions can also be made about prosodic focus in Garo. For question (iii), it is predicted that Garo does have prosodic focus. Prosody is one of the most common ways that languages signal focus so it can be predicted that Garo will do the same.

Concerning question (iv), it can be predicted that if Garo does have prosodic focus, the way that focus will be signalled will either be by changing the F0 pattern associated with the word or by the enhancement of the acoustic cues of word stress, or both. Both the strategies of marking focus, i.e., changing the intonational pitch accent on the focused word and also enhancement of the properties of word stress are extremely common ways that languages express prosodic focus.

Taking into consideration that languages with morphosyntactic ways of expressing focus behave differently when it comes to prosodic expression of focus, this study also decided to analyse the prosody of the focus particle *-sa* in Garo. It has to be noted that this component of the study was added after the experiment design was completed and data was collected. The research question that concerns the focus particle of Garo is:

(v) Does the focus particle change the prosodic structure of the word that it attaches to?

It can be predicted for question (v) that the focus particle will add to the prosodic structure of the constituent that it attaches to. Morphosyntactic and prosodic strategies of marking focus are found to cooccur in languages so it is reasonable to predict that the same thing will happen in Garo.

There is also a research question concerning post-focal compression:

(vi) Is there post-focal compression in Garo?

For question (vi) it can be predicted that Garo does have post-focal compression. It is typical for languages to have prosodic focus, and post-focal compression, i.e., deaccenting and compression of acoustic properties of stress is one of the ways that languages signal prosodic focus. Post-focal compression serves to highlight the focused word by removing the prominence on other words in a sentence.

Chapter 6 – Methodology

Based on the motivations elaborated on the previous chapter, a production study was designed to answer the research questions also listed in the previous chapter (Chapter 5). The stimuli selection is based on my knowledge of the language as a native speaker. This study was approved by University of Calgary's Conjoint Faculties Research Ethics Board (REB21-0041).

This chapter includes information about the experiment design, participant information, technical details about the equipment used in the study and other related information.

6.1 Participant Information

The participants in this study were native speakers of Garo from the town of Tura in West Garo Hills. There was an added requirement that the parents of the participants should also have been born and brought up in Tura. The reason for this was to control for any influence of other dialects of Garo on the language development of the participants. The participants also speak Garo at home. They were between the ages of 18 to 25 during the time of recording. All of the participants were college educated. The participants also did not report any speech pathologies. 13 participants were recorded in total, but only the data from 8 speakers are being included in this study. The data collection was done in the music room of Hawakhana Baptist Church, Tura. The participants were compensated for their expenses related to their travel to the data collection centre. Additionally, the participants were given a small gift as a token of appreciation for their participation in the study. The price of the gifts given to the participants amounted to roughly CAD \$3.

All possible steps were taken to preserve the anonymity of the participants. They were given the option for their names to be included in the acknowledgement section of this thesis in the consent form they signed before the start of the experiment.

6.2 Data Collection

Data collection was done inside the music room of Hawakhana Baptist Church. Only the participant and the researcher were present inside the room during data collection. Since the data collection took place during the COVID-19 pandemic, all health protocols were followed to ensure the safety of both the participant and the researcher.

The participants were given a consent form and a language questionnaire before the beginning of the experiment. It was only after they had signed the consent form and filled in the questionnaire that the experiment was started. The participants were given instruction slides where they were given information about the study. They were also given practice slides so as to get them familiar with the carrier sentences, they were going to be reading out. They were told to repeat the practice slides if they felt they needed more warm-up. It was only after they were ready that the main experiment and thus the recording began. The participants had control of the pace of the experiment as they changed the slides on their own using an external keyboard connected to the computer. The participants were given a break after every thirty minutes during the recording in order to alleviate fatigue. They were also told before the recording that they can stop the experiment and the recording any time they wanted.

The test sentences were projected to an extension monitor Acer HA220Q connected via HDMI port to the main computer HP 14s. A single computer was used to run the experiment. The speech data was collected through a Logitech H390 head-worn microphone, connected via USB port to the main computer. Most of the data was recorded directly to Praat at 44.1 KHz, but a short

segment of the data from participant 3791 was recorded at 11.025 KHz by mistake. It was only one segment of the data from this particular participant that was recorded at a lower sampling rate however as the rest of the data for this participant and others were recorded at 44.1 KHz.

6.3 Experimental Design

A list of real trisyllabic Garo words was created for this experiment. Attempt was made to only include words with all open syllables, i.e., words of CVCVCV configuration, but this was not always possible. The target syllable, i.e., the syllable that would be measured in any target word was always CV, however. Two vowels were included in this study, the /a/ and the /i/ vowels, which were recorded in all three syllable positions of the word. The onsets were controlled for so as to have only either the voiced plosives, nasals, or the alveolar fricative as onsets. Examples of the words used in this study is given in Table 8. See Appendix G for the full list of target words.

Table 8: Examples of target words used in the study.

		Target Syllable 1	Target Syllable 2	Target Syllable 3
Target Vowel	/a/	[ba.bəl.si]	[ge.na.si]	[da.bi.na]
	/i/	[bi.ba.raŋ]	[^h o.gi.na]	[ma.ga.ni]

A carrier sentence was designed to elicit these target words. While the basic frame of the carrier sentence was the same throughout, the sentences differed slightly due to the different locations of the focus marker in different focal conditions of the experiment. The different focal conditions in the sentences were primed by an appropriate question. The dialogues for the different focal conditions are shown below.

Pre-focal condition:

Q: deran-ara X məŋgəppa k^hatt^ha-ni gəmən daʔal
 Derang-Top target-word called word-Gen about today
 ts^hants^hi-gen-na-ma
 think-Fut-Evi-Q

A: məhm, deran-ara X məŋgəppa k^hatt^ha-ni gəmən
 no Derang-Top target word called word-Gen about
 k^hnalo-sa ts^hants^hi-gen-na-ba
 tomorrow-Corrective think-Fut-Evi-?

Focal Condition:

Q: deran-ara k^haʔdoŋa məŋgəppa k^hatt^ha-ni gəmən k^hnalo
 Derang-Top confident called word-Gen about tomorrow
 ts^hants^hi-gen-na-ma
 think-Fut-Evi-Q

A: məhm, deran-ara X məŋgəppa k^hatt^ha-ni gəmən-sa
 no Derang-Top called word-Gen about-Corrective
 k^hnalo ts^hants^hi-gen-na-ba
 tomorrow think-Fut-Evi-?

Post-focal Condition

Q: dʒon-ara X məŋgəppa k^hatt^ha-ni gəmən k^hnalo

John-Top target-word called word-Gen about today

ts^hants^hi-gen-na-ma

think-Fut-Evi-Q

A: m̥hm̥, deran̥-sa X mən̥gəppa k^hatt^ha-ni ɣəmən

no Derang-Corrective target word called word-Gen about

k^hnalo ts^hants^hi-gen-na-ba

tomorrow think-Fut-Evi-?

These dialogues were presented on slides with a conversational format as seen below (Figure 7).



Figure 7: An example picture with dialogues used to elicit the data in this study. Translation of the dialogue: Q – “Is Derang going to think about the word called roba’a TODAY?” A – “No, Derang is going to think about the word called roba’a TOMORROW.”

³ Image: Freepik.com. This slide was designed using images from Freepik.com.

The reason why these dialogues were presented in a conversational format was to prevent the participants from developing a reading intonation. In addition, each dialogue slide was followed by a filler slide with pictures of everyday objects that the participants had to name. The intention of the filler slide was also to prevent the participants from developing some sort of rhythm when they were reading out the sentences.

6.4 Phonetic Analysis

The data was analysed using Praat (Boersma & Weenink, 2022). The target vowels were segmented with reference to both the waveform and the spectrogram. The beginnings and ends of the vowels were marked at the beginning of cycles on the zero-crossing line for consistency. When the waveform and the spectrographic information did not match, i.e., when the wave cycle looked like a vowel but the spectrogram did not show formant structure for that particular cycle, the ambiguity was resolved in favour of spectrographic information and the wave cycle was not included as part of the vowel. Since the boundary between vowels and nasals were often difficult to determine, nasal release was used to mark the boundary. When nasal release was not seen in the acoustic signal, the boundary was marked based on the intensity of the spectrogram, with the most intense part of the spectrogram for vowel and nasal sequences being marked as vowels. Due to the fact that vowels were consistently marked at the beginning of the cycle, cases when the beginning of a cycle had characteristics of a consonant but displayed vowel characteristics in terms of formant structure towards the end of the cycle were not included as part of the vowel, and the beginning of the vowel was marked from the immediately following cycle. In other cases, at the end of vowels, cases where a cycle had vowel characteristics towards the beginning and consonant characteristics towards the end were included as part of the vowel, and the end of the vowel was marked at the

beginning of the immediately following cycle. The picture in Figure 8 is an example of how the target vowels were segmented:

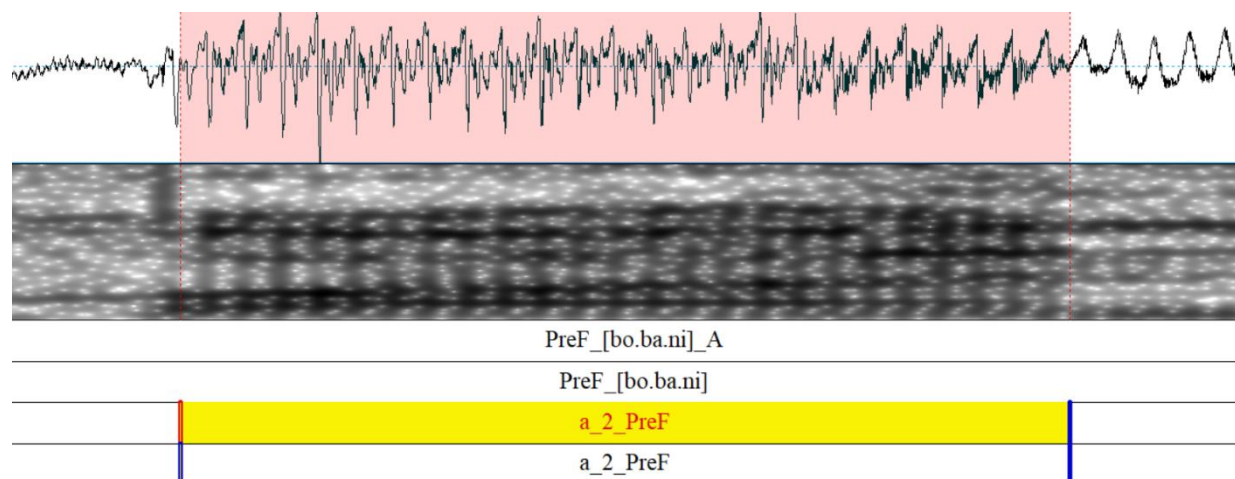


Figure 8: Screen shot from Praat showing how the /a/ vowel was segmented in the word [bobani] “mute-Gen.”

The vowel duration was split into four equal quarters (Q1 – Q4) and mean F0 and intensity were measured for each quarter. The mean F0 and intensity were also measured for the middle quarters of the vowel, i.e., for Q2 – Q3 and these are the measurement that are used as variables in the statistical analysis for F0 and intensity. Additionally, F0 change ($\Delta F0$) was calculated by subtracting the mean F0 at Q1 from the mean F0 at Q4 of the vowel. F0 range was calculated by subtracting the minimum F0 value of the whole vowel from the maximum F0 value of the whole vowel. The duration measurement was the entire length of the vowel. The vowels were also measured for the first and second formants (F1 & F2) in Q2-Q3 which were in turn used to calculate the Euclidean distance of the vowels from the centre of the vowel space.

While the segmentation of the target vowels was done manually, the measurement of the acoustic variables were done using a modified Praat script originally written by Crosswhite (2016).

The output produced by the script was used as the input data for the statistical analysis in R (R Core Team, 2021).

6.5 Data exclusions and data normalization

A total of 13 speakers were recorded for this study, but two male speakers (speakers 1437 and 5576) were excluded even before data segmentation since they did not fully meet the inclusion criteria set for this study. (Speaker 1437 has parents who were not born in Tura, and speaker 5576 did not meet the criteria for the educational level set for this study.) Another male participant (speaker 9638) was excluded from the study due to difficulty in producing the sentences. One female speaker (speaker 7589) was excluded during data segmentation since her speech was found to have unnatural prosodic emphasis on the focused words which is absent in other speakers. The final female speaker (speaker 7913) was excluded after visual inspection of the graphs since her word prosody was found to be too different from the other speakers as she produced the target words with very little F0 movement. Importantly, both of the female speakers (7589 and 7913) sounded like non-native speakers speaking Garo. With 5 exclusions, the data of the remaining 8 speakers (6 female, and 2 male) were used in the statistical analysis for this study. From this final data, 5 datapoints were excluded because these were clear outliers in terms of the F0 value.

The data included in the study were tested for normality (see Appendix B for the graphs and details of the distribution of the variables). The normality tests showed that F0 typically has a right skewed distribution. All of the other variables (duration and intensity) were found to have a normal distribution. Thus, F0 was first logarithmically transformed with base e before it was converted into z-scores for normalization. Duration and Intensity were directly converted into z-scores. F0 change and F0 range were also converted into z-scores.

F1 and F2 measurements were used to calculate the Euclidean distance (ED) of the vowel from the centre of the vowel space. The F1 and F2 were first converted into z-scores and the Euclidean distance (ED) was calculated using the formula:

$$ED = \sqrt{(X - 0)^2 + (Y - 0)^2}$$

Where, X is normalized F1 and Y is normalized F2.

The data z-transformation was done by speaker and by vowel, i.e., data for each vowel was normalized separately for each individual speaker before the data for all speakers were pooled to be fed into the statistical model. All of the data normalization was done in R.

The statistical models were run using the normalized scores, but in order to interpret the results the normalized scores were reconverted into the original units in order to better understand the magnitude of differences between the different categories. Reconversion was done using the mean and standard deviation (sd) (raw scores) of one of the participants picked at random (speaker 1687). So, e.g., duration is reconverted into milliseconds (ms) using the formula:

$$\text{Duration (ms)} = \text{mean (speaker 1687)} + (\text{mean (z-score duration)} * \text{sd (speaker 1687)})$$

Where, mean and sd (speaker 1687) are mean and standard deviation for duration for speaker 1687 in ms, and mean (z-score duration) is the mean of the normalized duration for a particular category.

It has to be noted that reconversion of F0 has to go through an extra step since it was log-transformed first before converting it into z-scores. The reconversion of F0 thus needs to proceed by exponentiating the z-scores first using the formula:

$$z\text{-F0} = e^{\text{mean (z-score of F0)}}$$

The output of the above formula is then fed to the formula:

$$\text{F0 (Hz)} = \text{mean (speaker 1687)} + (\text{mean (z-F0)} * \text{sd (speaker 1687)})$$

6.6 Statistical analysis and model

The statistical analysis in this study was done using the software R (R Core Team, 2021). Most of the coding for the statistical analysis in this study was done using the base package of R (R Core Team, 2021), which comes preinstalled with the software. There was one package that was used in this analysis however, which is not preinstalled. This package is *tidyverse* (Wickham et al., 2019). This package was needed to create the classification tables of the statistical models.

The statistical model used in this thesis is the *Binary Logistic Regression* (logistic regression henceforth). Logistic regression is a multivariate statistical technique in a broader family of *generalized linear models*. Logistic regression differs from other linear models, however, in that it does not predict a continuous variable but predicts a categorical variable. The predictors in logistic models can be both continuous and categorical.

Logistic regression predicts the log-odds of a datapoint being in the non-reference category. The *best fit line* of a model is calculated using *maximum likelihood estimate* and the line with the lowest *log-likelihood* is taken as the best fit line (Field et al., 2012). The reason why logistic regression is chosen for this thesis is because the data analysed in this study has categorical as well as continuous variables. The categorical variables include syllable positions, focal conditions, and words while the continuous variables include F0, intensity, duration, and the vowel formants.

Chapter 7 – Results: Stress

The analysis in this chapter concerns research questions (i) and (ii) about stress. Answering research questions (i) *does Garo have word stress?* and (ii) *how is stress signalled in Garo?* require an analysis of the data in the baseline focal condition (pre-focus). Since the pre-focus condition does not have the confound of focus, it isolates the word prosodic pattern and is thus chosen to determine the acoustic properties of stress in Garo. The statistical comparisons in this chapter employs binary logistic regression and comparisons are made between syllable positions in the baseline condition, i.e., syllable 1 vs syllable 2, syllable 2 vs syllable 3, and syllable 1 vs syllable 3. Syllable position is used the dependent variable and F0, F0 change ($\Delta F0$), Euclidean distance (ED), Duration, Intensity, are F0 range as the predictor variables.

It was observed during the visual inspection of the data that the speakers formed two groups with regards to the F0 pattern on the target word. One group of speakers had a rise on syllable 2 after the fall on syllable 1 – *early rise speakers*, while the other group of speakers had a relatively flat F0 contour on syllable 2 which was similar in F0 height to syllable 1 – *late rise speakers*. These two groups were statistically tested for the pattern and they were not found to be substantially different from each other. Since the two speaker groups were not distinct enough from each other, the data in this thesis was pooled for the statistical analysis. See Appendix A for a detailed discussion of the two speaker groups and the relevant statistical analysis.

The following pitch track in (Figure 9) shows the intonational contour of a sentence in the baseline condition. The target word is seen to have high F0 on the final syllable, but this needs to be tested statistically.

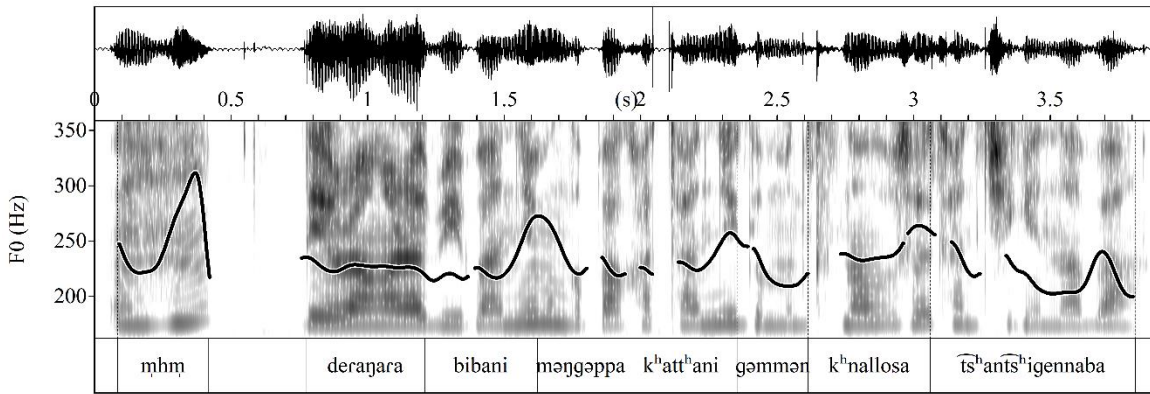


Figure 9: Pitch track of sentence in pre-focus condition. The word "bibani" is the target word.

The first section of this chapter includes a description of the prosodic pattern using graphs. The description is based on the graphs of F0, Duration, Intensity, and Formants (F1 & F2) and gives an overview of the word prosodic pattern, i.e., which of the syllables differ from other syllables based on the aforementioned acoustic properties. The second section of the chapter includes statistical analyses which tests whether the differences seen between the syllables in terms of the acoustic properties previously mentioned are statistically significant. This section includes the results of the statistical tests, the description of the results and also their interpretation. The third section of this chapter includes the discussion of the statistical results and connects it back to the pattern seen in the graphs. This chapter also interprets the pattern to state what the word prosodic pattern is like in Garo.

7.1 Descriptive statistics

The descriptive statistics examines the pattern of the aforementioned acoustic properties by using graphs. The F0 graphs are made using the mean of the normalized F0 at Q1 and Q4 of the vowel.

Duration and Intensity graphs are also made using the normalized Duration. Vowel quality graphs are made using the raw F1 and F2 in the Q2 and Q3 of the vowel.

7.2 F0 pattern

Since the duration of the target vowel was divided into four equal quarters during measurement, the mean F0 was measured on each of the quarters. The F0 graphs in this section are made with the mean F0 of the Q1 (first quarter) and the Q4 (fourth quarter) of the target vowel.

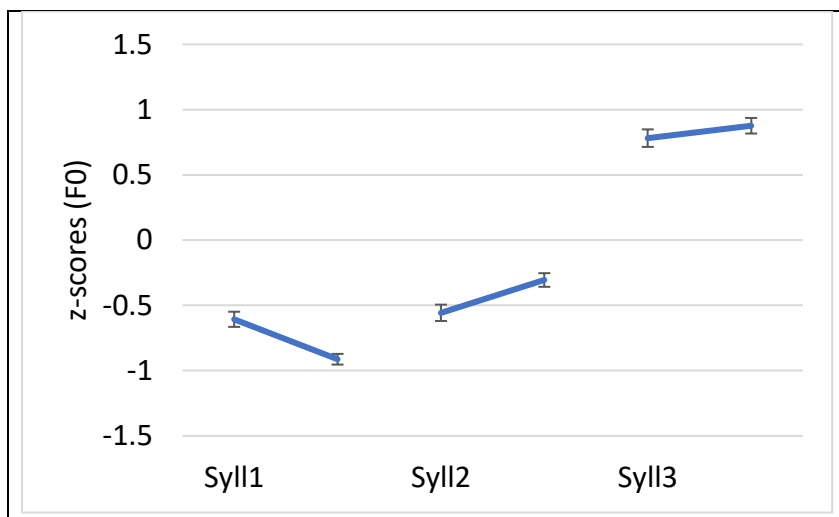


Figure 10: F0 track made with mean F0 at Q1 and Q4 of each syllable. Syllable positions are on the x-axis and z-scores(F0) are on the y-axis.

The F0 track in Figure 9 shows that there is a low falling F0 on syllable 1. There is a fall from Q1 to Q4 of syllable 1. The lowest F0 point is reached in Q4 of the syllable after which the F0 rises on syllable 2. The F0 rises from Q1 to Q4 of syllable 2 after which the highest F0 point is reached on syllable 3. The F0 pattern of syllable 3 is relatively level with very little change in F0 from Q1 to Q4 of syllable 3. The highest F0 point is reached on syllable 3 however. To summarize there is a low falling F0 on syllable 1 such that the lowest F0 point of the word is reached on

syllable 1. The F0 then rises to reach the highest F0 point on syllable 3. Syllable 1 therefore has the lowest F0 and syllable 3 has the highest F0.

7.3 Duration pattern

The Duration measurement measured how long the vowels were in each syllable position. The graphs for Duration pattern are made using the z-scores of Duration.

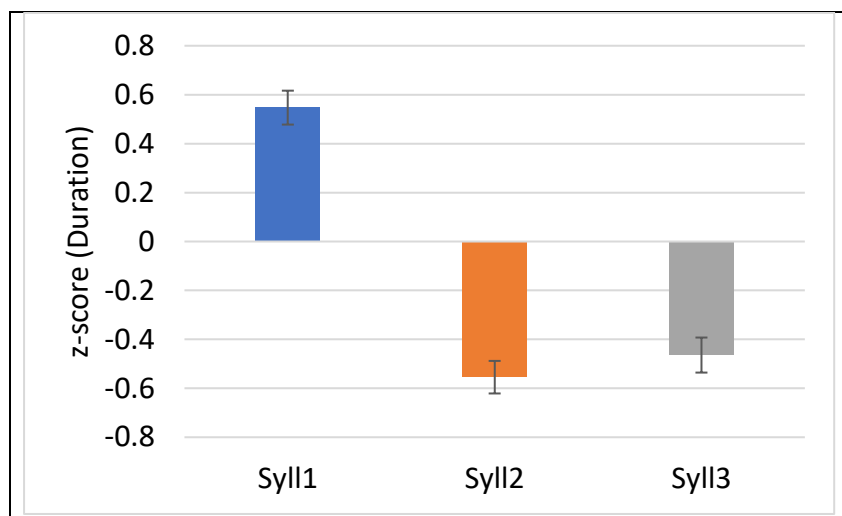


Figure 11: Graph of vowel duration pattern made with z-scores (Duration). Syllable positions are on the x-axis, and z-scores (Duration) are on the y-axis.

The vowel duration graph in (Figure 10) shows that syllable 1 has the longest duration compared to syllables 2 and 3. Syllable 3 seems to be slightly longer than syllable 2, but the difference between syllables 2 and 3 is very slight and syllable 1 is still much longer than syllable 3. Syllable 1 is therefore the longest syllable in a word.

7.4 Intensity pattern

The Intensity measurement measured the mean intensity in the middle part of the vowel (Q2 and Q3). The graphs for Intensity pattern are made using the z-score of Intensity.

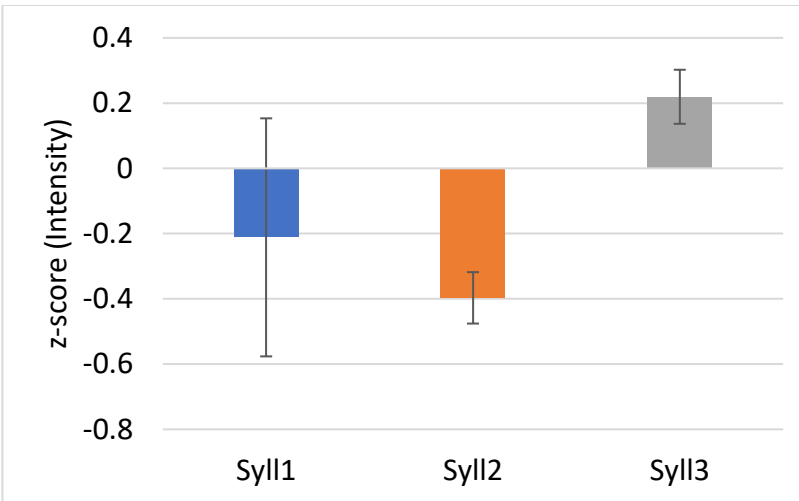


Figure 12: Vowel intensity graph made with z-scores (Intensity). Syllable positions are on the x-axis and z-scores (Intensity) is on the y-axis.

The vowel intensity graph in (Figure 11) shows that syllable 3 has the highest intensity compared to syllables 1 and 2 which are similar in intensity even though syllable 1 is much more variable. Syllable 3 therefore has the highest intensity in a word compared to syllables 1 and 2.

7.5 Vowel quality pattern

The vowel quality pattern is measured using the raw values of the first two formants (F1 and F2). The formant plot is plotted using the F1 and F2 values in Hertz in order to see if the vowel quality differed in the three syllable positions.

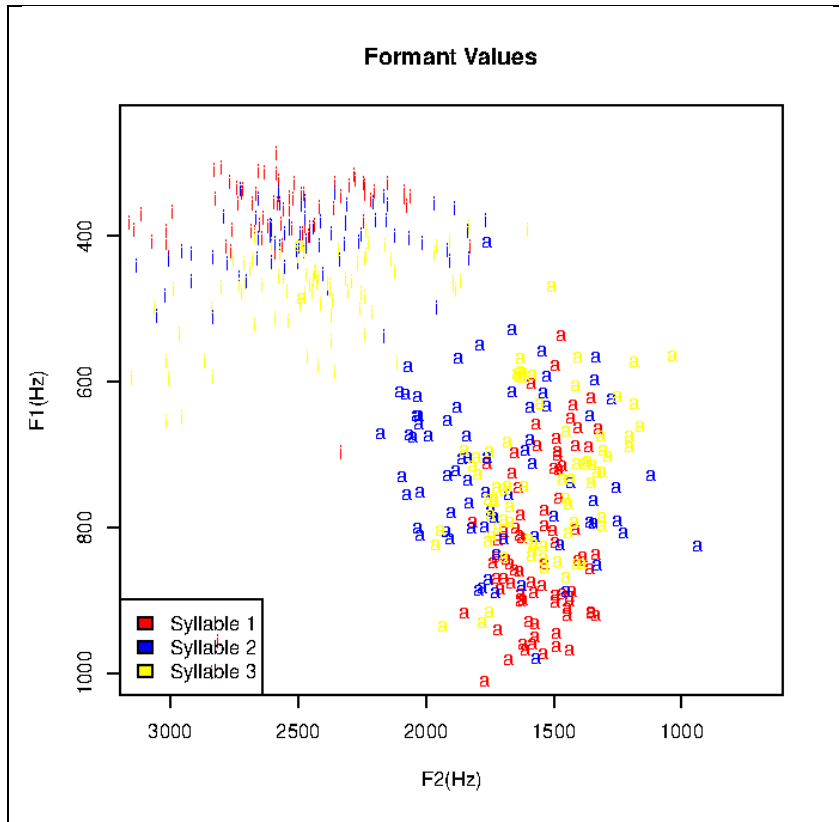


Figure 13: Vowel quality graph made with F1 and F2 values in Hertz. F2 (Hz) is on the x-axis and F1 (Hz) is on the y-axis. Syllable positions are coded in different colours (consult the legend).

The vowel quality graph in (Figure 12) shows that syllable 1 is most peripheral in the vowel space compared to syllables 2 and 3 for both /i/ and /a/. The two vowels differ in terms of whether syllable 2 or syllable 3 is more peripheral. For /i/ vowel, syllable 3 seems to be the most centralized compared to syllables 1 and 2. Syllable 2 lies somewhere in between syllables 1 and 3 in that while it is not as centralized as syllable 3, syllable 1 is overall relatively more peripheral. For /a/ vowel, there is no clear pattern for the syllable 2 and 3 in that they are equally centralized compared to syllable 1. Importantly however, there is no clustering of the vowel qualities (/i/ and /a/) in any of the syllable positions, i.e., the distinction between the vowel qualities is still maintained even though there is some centralization in syllable 2 and 3.

7.6 Statistical analysis

The statistical analysis of the data tests whether the differences seen between the syllables in terms of the acoustic properties seen in the graphs above are statistically significant. The statistical test used in this study is the *binary logistic regression*, so, the models will test how successful the acoustic properties (predictors) are in predicting the syllable positions (categorical variable).

Since this is a test for the effect of stress, i.e., to see which syllable is the most different from others, the logistic models compared two syllable positions at a time. The first of the models compared syllable 1 vs syllable 2, the second model compared syllable 2 vs syllable 3, and the third model compared syllable 1 vs syllable 3.

7.7 Syllable 1 vs syllable 2 comparison

This test checks how good the acoustic properties (predictors) are at predicting or differentiating between syllables 1 and 2 (categorical variable). A logistic regression was conducted with syllable as the categorical variable and Duration, Intensity, Euclidean distance (ED), F0, F0 change ($\Delta F0$), and F0 range as the predictor variables. Syllable 1 was set as the reference category for this test. The output of this model is given below (Output 1). F0, $\Delta F0$, Duration, and F0 range were found to be significant predictors. The overall classification rate of the model is 89.7%, and the chi-squared test statistics are: $\chi^2(6) = 233.807$, $p = 0$. The model had 135 datapoints for syllable 1 and 117 datapoints for syllable 2.

Output 1:

	Confidence interval
--	---------------------

Predictors	Estimate	Std. Error	z value	p-value	Odds- ratio	2.50%	97.50%	Classification rate
Intercept	0.96	0.62	1.54	0.12				
F0	1.85	0.58	3.15	0.001	6.36	2.13	21.71	69%
F0 change	3.37	0.56	5.94	< 0.001	29.17	10.8	101.52	83%
ED	0.57	0.44	1.3	0.19				
Duration	-1.93	0.34	-5.6	< 0.001	0.14	0.06	0.26	75%
Intensity	0.02	0.30	0.09	0.92				
F0 range	-0.79	0.38	-2.05	0.04	0.45	0.20	0.95	66%

glm(formula = Syllable ~ F0 + F0 change + ED + Duration + Intensity + F0range, family = "binomial")

Null deviance: 348.06 on 251 degrees of freedom

Residual deviance: 114.25 on 245 degrees of freedom

(54 observations deleted due to missingness)

AIC: 128.25

Number of Fisher Scoring iterations: 7

Since syllable 1 was the reference category for this comparison (so the model predicts the log-odds of items being in syllable 2) an examination of the estimated coefficients of the significant predictors reveals that while Duration and F0 range have a negative value, other significant predictors have a positive value. The negative coefficient indicates that syllable 1 has a longer duration (*mean* = 0.55, *sd* = 0.87) compared to syllable 2 (*mean* = -0.55, *sd* = 0.81) and is also supported by an odds-ratio < 1. The z-scores were reconverted into original units using the mean and standard deviation of one speaker, 1687 and syllable 1 (*mean* = 97.41 ms) is on average 17 ms longer than syllable 2 (*mean* = 80.4 ms).

F0 range also has a negative coefficient which indicates that syllable 1 has a wider F0 range (*mean* = 0.26, *sd* = 0.96) compared to syllable 2 (*mean* = -0.49, *sd* = 0.8). The z-scores were reconverted into original units using the mean and standard deviation of one speaker, 1687 and the difference between the max F0 (*mean* = 221 Hz) and min F0 (*mean* = 207.07 Hz) 13.93 Hz is greater compared to the difference seen on syllable 2 max F0 (*mean* = 223.4 Hz) and min F0 (*mean*

= 219 Hz) 4.4 Hz. This shows that there is a greater F0 movement on syllable 1 compared to syllable 2.

The coefficient is positive for F0 which means that syllable 2 has a higher mean F0 (*mean* = -0.37, *sd* = 0.57) compared to syllable 1 (*mean* = -0.84, *sd* = 0.51). This is also supported by an odds-ratio > 1. The z-scores were reconverted into original units using the mean and standard deviation of one speaker, speaker 1687 and syllable 2 (*mean* = 220.8 Hz) is on average 11 Hz higher than syllable 1 (*mean* = 209.2 Hz) in terms of F0.

The coefficient is also positive for $\Delta F0$, so syllable 2 has a rising F0 (*mean* = 0.26, *sd* = 0.67) compared to the falling F0 on syllable 1 (*mean* = -0.83, *sd* = 0.67). This is also supported by an odds-ratio > 1. The z-scores were reconverted into original units using the mean and standard deviation of one speaker and the F0 on syllable 1 falls from Q1 (*mean* = 217.24 Hz) to Q4 (*mean* = 207.94 Hz) while the F0 on syllable 2 rises from Q1 (*mean* = 218 Hz) to Q4 (*mean* = 223.3 Hz). A post hoc test was conducted with the significant predictors of this model where the individual significant predictors were the only predictor variable. The classification rate of the individual significant predictors is given in Output 1 – Classification rate.

7.8 Syllable 2 vs syllable 3 comparison

This test checks how good the acoustic properties (predictors) are at predicting or differentiating between syllables 2 and 3 (categorical variable). A logistic regression was conducted with syllable as the categorical variable and Duration, Intensity, Euclidean distance (ED), F0, F0 change ($\Delta F0$), and F0 range as the predictor variables. Syllable 2 was set as the reference category for this test. The output of this model is given below (Output 2). Only F0 was found to be the significant predictor. The overall classification rate of the model is 87%, and the chi-squared test statistics are:

$\chi^2(6) = 171.0073$, $p = 0$. The model had 117 datapoints for syllable 2 and 146 datapoints for syllable 3.

Output 2:

Predictors	Estimate	Std. Error	z-value	p-value	Odds- ratio	Confidence interval		Classification rate
						2.50%	97.50%	
Intercept	-0.31	0.34	-0.91	0.35				
F0	2.97	0.36	8.19	< 0.001	19.54	10.1	42.18	86%
F0 change	-0.2	0.26	-0.76	0.44				
ED	0.03	0.21	0.18	0.85				
Duration	0.26	0.23	1.11	0.26				
Intensity	-0.14	0.19	-0.74	0.45				
F0 range	-0.18	0.24	-0.73	0.46				

glm(formula = Syllable ~ F0 + F0 change + ED + Duration + Intensity + F0 range, family = "binomial")

Null deviance: 361.39 on 262 degrees of freedom

Residual deviance: 190.38 on 256 degrees of freedom

(39 observations deleted due to missingness)

AIC: 204.38

Number of Fisher Scoring iterations: 5

Since syllable 2 was the reference category for this comparison, an examination of the estimated coefficient reveals that it has positive value. The positive coefficient for F0 means that syllable 3 has a higher mean F0 ($mean = 0.92$, $sd = 0.72$) compared to syllable 2 ($mean = -0.37$, $sd = 0.57$). This is also supported by an odds-ratio > 1 . The z-scores were reconverted into original units using the mean and standard deviation of one speaker, 1687 and syllable 3 ($mean = 252$ Hz) is on average 31.19 Hz higher than syllable 2 ($mean = 220.81$ Hz) in terms of F0. As a follow up, a post hoc test was conducted with the significant predictor, which in this case is F0, as the only

predictor in the model classifying syllable 2 vs syllable 3. The percentage of the data correctly classified by this model is given in Output 2 – Classification rate.

7.9 Syllable 1 vs syllable 3 comparisons

This test checks how good the acoustic properties (predictors) are at predicting or differentiating between syllables 1 and 3 (categorical variable). A logistic regression was conducted with syllable as the categorical variable and Duration, Intensity, Euclidean distance (ED), F0, F0 change ($\Delta F0$), and F0 range as the predictor variables. Syllable 1 was set as the reference category for this test. The output of this model is given below (Output 3). F0, $\Delta F0$, and Duration were found to be significant predictors. The overall classification rate of the model is 95%, and the chi-squared test statistic is: $\chi^2(6) = 315.3048, p = 0$. The model had 135 datapoints for syllable 1 and 146 datapoints for syllable 3.

Output 3:

Predictors	Estimate	Std. Error	z-value	p-value	Odds- ratio	Confidence interval		Classification rate
						2.50%	97.50%	
Intercept	0.1	0.71	0.14	0.88				
F0	3.14	0.57	5.42	< 0.001	23.19	8.5	85.47	91%
F0 change	2.15	0.56	3.81	0.0001	8.6	3.29	29.43	86%
ED	0.79	0.58	1.35	0.17				
Duration	-0.76	0.32	-2.33	0.01	0.46	0.23	0.85	76%
Intensity	0.08	0.38	0.22	0.82				
F0 range	0.05	0.49	0.10	0.91				

glm(formula = Syllable ~ F0 + F0 change + ED + Duration + Intensity + F0 range, Family = "binomial")

Null deviance: 389.118 on 280 degrees of freedom

Residual deviance: 73.813 on 274 degrees of freedom

(33 observations deleted due to missingness)

AIC: 87.813

Number of Fisher Scoring iterations: 8

Since syllable 1 was the reference category for this comparison, an examination of the coefficients reveals that F0 and $\Delta F0$ has a positive value, while Duration has negative value. The negative coefficient indicates that syllable 1 has a longer duration ($mean = 0.55$, $sd = 0.87$) compared to syllable 3 ($mean = -0.46$, $sd = 0.89$) and is also supported by an odds-ratio < 1 . The z-scores were reconverted into original units using the mean and standard deviation of one speaker, 1687 and syllable 1 ($mean = 97.41\ ms$) is on average 15.61 ms longer than syllable 3 ($mean = 81.8\ ms$).

The coefficient is positive for F0 which means that syllable 3 has a higher mean F0 ($mean = 0.92$, $sd = 0.72$) compared to syllable 1 ($mean = -0.84$, $sd = 0.51$). This is also supported by an odds-ratio > 1 . The z-scores were reconverted into original units using the mean and standard deviation of one speaker, speaker 1687 and syllable 3 ($mean = 253\ Hz$) is in on average 43.8 Hz higher than syllable 1 ($mean = 209.2\ Hz$) in terms of F0.

The coefficient is also positive for $\Delta F0$, so syllable 3 has a rising F0 ($mean = 0.56$, $sd = 0.79$) compared to the falling F0 on syllable 1 ($mean = -0.83$, $sd = 0.67$). This is also supported by an odds-ratio > 1 . The z-scores were reconverted into original units using the mean and standard deviation of one speaker and the F0 on syllable 1 falls from Q1 ($mean = 217.24\ Hz$) to Q4 ($mean = 207.94\ Hz$) while the F0 on syllable 3 rises from Q1 ($mean = 246.3\ Hz$) to Q4 ($mean = 255\ Hz$). A post hoc test was conducted with the significant predictors of this model where the individual significant predictors were the only predictor variable. The classification rate of the individual significant predictors is given in Output 3 – Classification rate.

7.10 Summary and discussion of the results

The analysis in this chapter was specifically to answer research questions (i) and (ii). Statistical analysis of the data in baseline condition that compared the syllable positions to one another showed that in the baseline (pre-focus) condition, syllable 1 is longer in terms of duration compared to syllable 2 and also has a low falling F0 contour, while syllable 2 has a higher F0 compared to syllable 1. Syllable 3 has a higher F0 compared to syllable 2. Syllable 3 also has a higher F0 compared to syllable 1 making it the syllable with highest F0 in a word compared to syllables 1 and 2, and it also has a high rising or a flat high F0 contour compared to the low falling on syllable 1. Syllable 1 on the other hand is longer compared to syllable 3, making it the longest syllable in a word compared to syllables 2 and 3 which are similar in duration.

From the results it can be seen that the prosodic pattern seen on Garo words is that the final syllable has the highest F0 in a word which means that the stressed syllable has the highest F0. In addition to the high F0 on the final syllable, the initial syllable also has an F0 event. The initial syllable has a low falling F0 contour such that the lowest F0 point is reached on the initial syllable. Duration pattern is different from the F0 pattern, since the initial syllable is the longest in a word. Duration is not a cue of stress in Garo however, as it can be interpreted as a boundary phenomenon (more extensive discussion of duration is done in the General discussion chapter).

Chapter 8 – Results: Focus

The analysis in this chapter concerns the research questions (iii) and (iv) about focus. Answering research questions (iii) *is there prosodic focus in Garo?* and (iv) *how is focus signalled in Garo?* require an analysis of the data in both the focus and baseline conditions. Focus typically adds to the prosodic pattern of stress. In order to determine what the effects of focus are in Garo, two kinds of comparisons were done. In the first comparison the syllables positions in the focus condition were compared to each other, i.e., syllable 1 vs syllable 2, syllable 2 vs syllable 3, and syllable 1 vs syllable 3. A binary logistic regression with syllable position as the dependent variable and F0, F0 change ($\Delta F0$), Euclidean distance (ED), Duration, Intensity, and F0 range as predictor variables tested to determine whether focus changes the word prosodic pattern seen in the baseline condition.

The second set of comparisons compared the syllable positions between the focus and the baseline conditions, i.e., syllable 1 focus vs syllable 1 pre-focus, syllable 2 focus vs syllable 2 pre-focus, and syllable 3 focus vs syllable 3 pre-focus. A binary logistic regression with focus condition as the dependent variable and F0, F0 change ($\Delta F0$), Euclidean distance (ED), Duration, Intensity, and F0 range as the predictor variables tested whether the two focal conditions are similar or different.

The pitch track in (Figure 14) shows the intonational contour of the sentence in focus condition. The target word is seen to have a high F0 on the final syllable just like in the baseline condition, but this needs to be tested statistically.

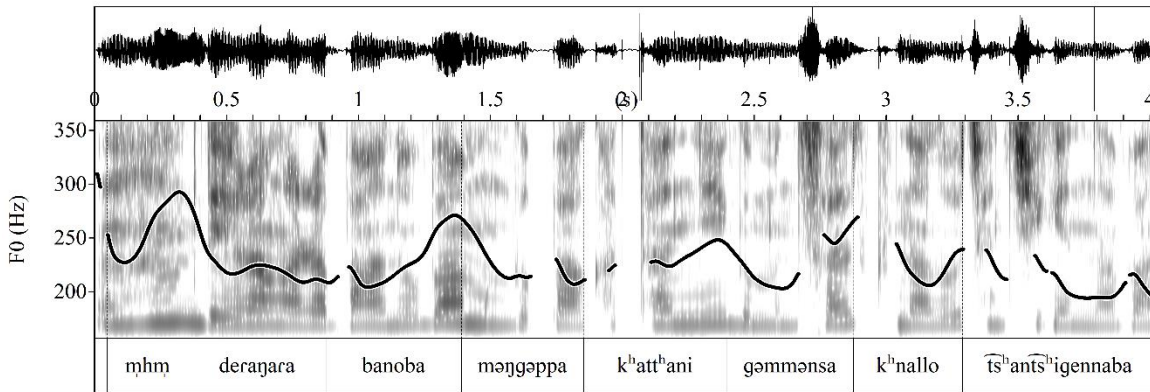


Figure 14: Pitch track of a sentence in focus condition. The word "banoba" is the target word.

The first section of the chapter includes a description of the prosodic pattern in the focus condition using graphs. The description is based on the graphs of F0, Duration, Intensity, and Formants (F1 & F2) and gives both an overall description of the word prosodic pattern in focus condition and also the comparison of the pattern in the focus and the baseline focal conditions. The description identifies which of the syllables differ from other syllables and if focus condition differs from the baseline condition based on the aforementioned acoustic properties. The second section of the chapter includes statistical analyses which tests whether the differences seen between the syllables and the focal conditions in terms of acoustic properties are statistically significant. This section also includes the results of the statistical tests, the description of the results and also their interpretation. The third section of the chapter includes the discussion of the statistical results and connects it back to the pattern seen in the graphs. This chapter also includes the pattern to state what the effect of focus in on the word prosody in Garo.

8.1 Descriptive statistics

The descriptive statistics examines the pattern of the aforementioned acoustic properties by using graphs. The F0 graphs are made using the mean of the normalized F0 at Q1 and Q4 of the vowel. Duration and Intensity graphs are also made using the normalized Duration. Vowel quality graphs are made using the normalized mean F1 and F2 in the Q2 and Q3 of the vowel.

8.2 F0 pattern

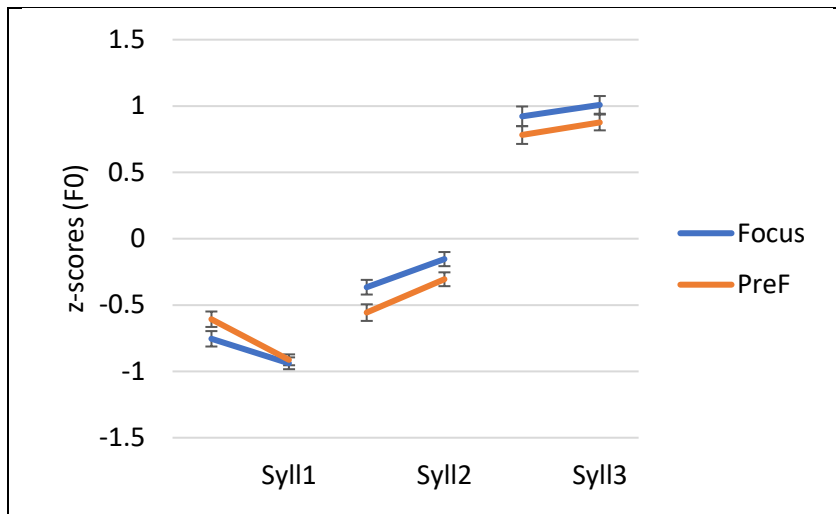


Figure 15: F0 track of focus and baseline conditions together made with mean of normalized F0 at Q1 and Q4 of each syllable. Syllable positions are on x-axis and z-scores (F0) on y-axis. Baseline F0 track is in orange and focus blue.

The vowel duration is split into four equal quarters so the F0 graph is made using the normalized mean F0 in the Q1 and the Q4 of the vowel.

The F0 track in Figure 13 shows that there is a low falling F0 on syllable 1 where the F0 falls slightly from the Q1 to Q4 of syllable 1. Conversely, there is a rising F0 on syllable 2 with the F0 rising from Q1 to Q4 of syllable 2. The rise in F0 on syllable 2 follows from the fall seen on syllable 1. The F0 peak is reached however on syllable 3, which has a relatively flat high F0.

There is very little change in the F0 from the Q1 to Q4 of syllable 3. To summarize the F0 pattern, the lowest point is reached on syllable 1 which has a low falling F0 pattern, and the highest F0 point is reached on syllable 3 which has a flat high F0. Crucially, this is identical to the F0 pattern seen in the baseline condition.

The two pre-focus and the focus conditions have the same overall F0 pattern and almost identical F0 levels. The falling low contour on syllable 1 is very similar in the two conditions. Both the high point and the low point of the fall is similar in the two conditions, i.e., the low F0 point does not get lower under focus. The F0 contour of syllable 2 is also almost identical as both the conditions have a rise on the syllable. The rise starts after the lowest F0 point seen on syllable 1 and the rise continues from Q1 to Q4 of syllable 2 in both the conditions. The highest F0 point on syllable 3 is also almost identical. In both the conditions the contour on syllable 3 is flat high as there is very little change in the F0 from Q1 to Q4 of the syllable. From these graphs it seems to be the case that focus does not affect the F0 pattern seen in the baseline condition.

8.3 Duration pattern

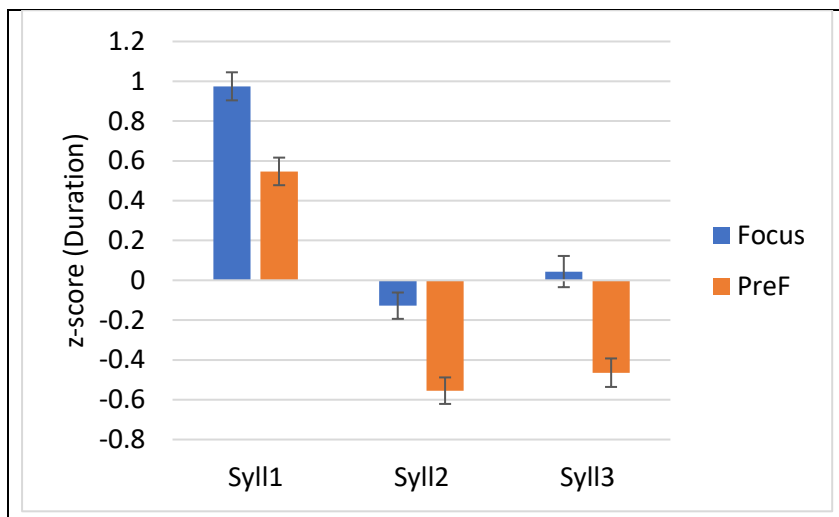


Figure 16: Duration patterns of the focus and baseline conditions made with means of normalized Duration. Syllable positions are on x-axis and z-score (Duration) on y-axis. Focus condition is in blue and baseline in orange.

The Duration graph is made with the normalized mean Durations of vowels. The Duration graph in Figure 14 shows that syllable 1 is the longest in the word in the focus condition compared to the other syllables. Syllable 2 is the shortest compared to syllable 1 and 3, but the difference between syllables 2 and 3 is not very big. The difference between syllable 1 and 2 is however substantial. Finally, syllable 3 is slightly longer compared to syllable 2, but the difference is very small. The difference between syllable 3 and syllable 1 looks to be substantial however, as syllable 1 is much longer compared to syllable 3. Crucially, the duration pattern seen in the graph is similar to the one seen in the baseline condition.

Although the pre-focus and the focus conditions have the same overall pattern, there is a slight increase in duration under focus. All of the syllables are lengthened under focus compared to the baseline condition. The basic pattern however is identical between the two conditions since syllable 1 is longest in both the conditions. Crucially, it has to be noted that although there is an increase in duration under focus, it was not a particular syllable that was targeted for lengthening. All of the syllables increased in length under focus.

8.4 Intensity pattern

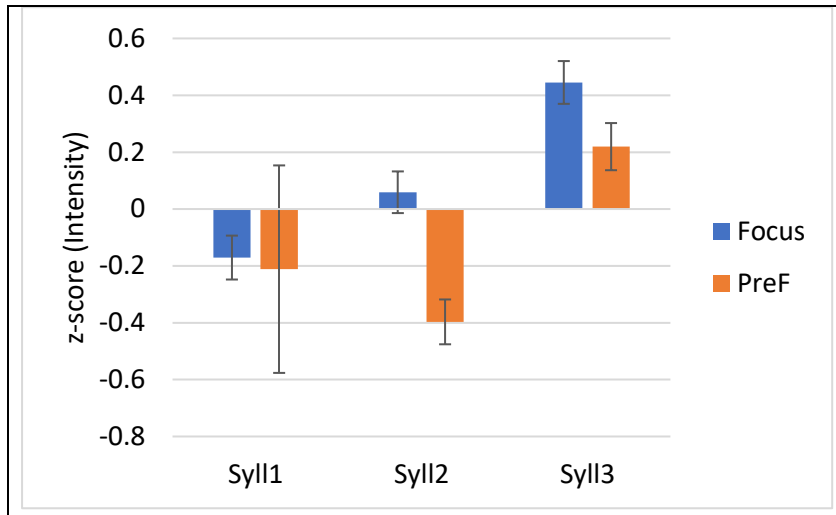


Figure 17: Intensity patterns of the focus and baseline conditions made with means of normalized Intensity. Syllable positions are on x-axis and z-score (Intensity) on y-axis. Focus condition is plotted in blue and baseline is plotted in orange.

The intensity graphs were made using the normalized mean Intensity in the middle portion of the vowels, i.e., the Q2 and Q3 of the vowel. The intensity graph in Figure 15 shows that syllable 3 is the loudest syllable in a word compared to syllable 1 and 2. Syllable 2 is louder compared to syllable 1, but syllable 3 still seems to be longer than syllable 2. Syllable 1 has the least intensity in a word. It has to be noted that this is slightly different from the pattern seen in the baseline condition where syllable 1 has higher intensity than syllable 2.

There is a slight change in the intensity under focus. Syllable 1 remains more or less the same in terms of loudness from the baseline condition. Syllable 2 and 3 however are seen to increase in loudness under focus. Syllable 2 of the focus condition seems to be significantly louder compared to the syllable 2 of the baseline condition. Syllable 3 also increases in Intensity under focus with syllable 3 of focus being louder than the syllable 3 of the baseline condition.

Importantly, there is a slight change in the basic Intensity pattern under focus compared to the baseline. In the baseline condition, syllable 2 is the least intense, but its Intensity increases under focus to be louder than syllable 1 under focus. The syllable position with the highest intensity is still preserved however, as syllable 3 still remains the loudest in a word under focus.

8.5 Vowel quality pattern

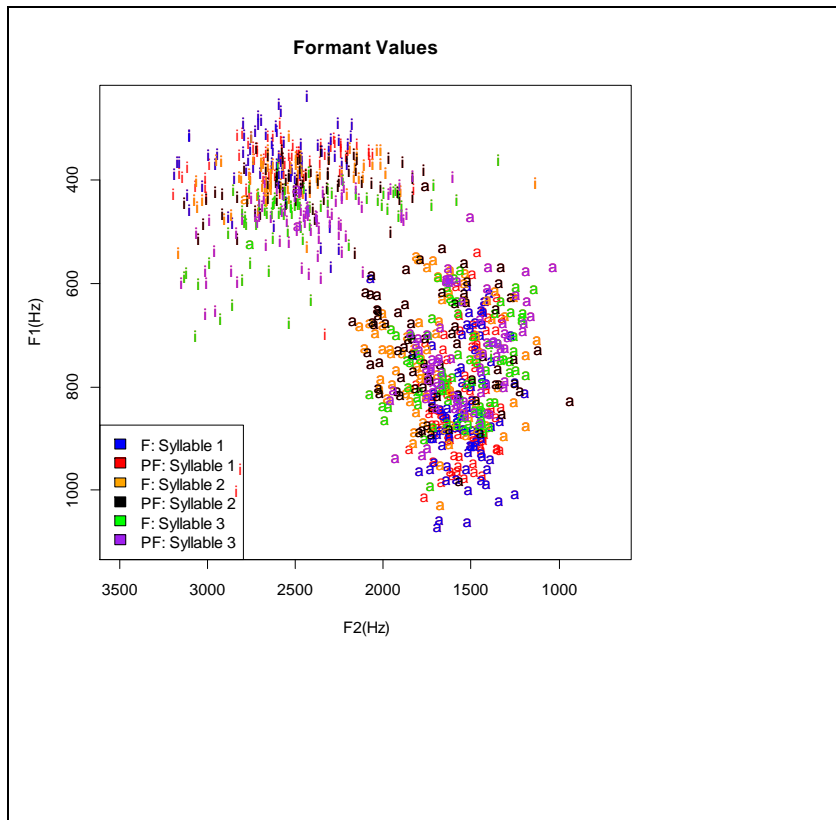


Figure 18: Vowel quality patterns of focus and baseline conditions made with F1 and F2 (Hz). F2 (Hz) is on x-axis and F1 (Hz) on y-axis. Focal conditions and syllable positions plotted in different colours (consult the legend). “F” is focus and “PF” is pre-focus.

The vowel quality pattern is measured using the values of the first two formants (F1 and F2). The formant plot is plotted using the F1 and F2 values in Hertz to see if the vowel qualities differed between the three syllable positions as well as between the two focal conditions. The vowel quality graph in Figure 16 shows that in focus condition syllable 1 is the most peripheral in

the vowel space compared to syllables 2 and 3. The two vowels differ in terms of whether syllable 2 or syllable 3 is more peripheral. For /i/ vowel, syllable 3 seems to be the most centralized compared to syllables 1 and 2. Syllable 2 lies somewhere in between syllables 1 and 3 in that while it is not as centralized as syllable 3, syllable 1 is overall relatively more peripheral. For /a/ vowel, there is no clear pattern for the syllable 2 and 3 in that they are equally centralized compared to syllable 1. Importantly however, there is no clustering of the vowel qualities (/i/ and /a/) in any of the syllable positions, i.e., the distinction between the vowel qualities is still maintained even though there is some centralization in syllable 2 and 3.

There is no drastic difference between the focus and the baseline condition. The overall pattern is similar between the two focal conditions and the vowels are not more peripheral under focus. Syllable 1 is the most peripheral in both conditions compared to syllable 2 and 3.

8.6 Statistical analysis

The statistical analysis of the data tests whether the differences seen between the syllables in terms of the acoustic properties seen in the graphs above are statistically significant. The statistical test conducted is the *binary logistic regression*, so, the models will test how successful the acoustic properties (predictors) are in predicting the syllable positions (categorical variable).

Since the goal of this testing focus was to see its effect on word-prosody, two kinds of comparisons were made with the focus data. First of the comparisons compared the syllables in the focus condition to one another, i.e., the first model compared syllable 1 to syllable 2, the second model compared syllable 2 vs syllable 3, and the third models compared syllable 1 vs syllable 3. This test was intended to see if the basic word-prosodic pattern seen in the baseline condition changed in any way under focus.

The second of the comparisons compared the syllables between the baseline and the focus condition, i.e., the first model in this comparison compared syllable 1 of baseline condition to the syllable 1 of the focus condition, second model compared syllable 2 of baseline to the syllable 2 of the focus, and the third model compared syllable 3 of baseline to the syllable 3 of the focus. This test was intended to see if the focus condition differed significantly from the baseline condition even if the basic pattern remained the same.

8.7 Syllable comparisons

This comparison tested the syllables in the focus condition to determine if the syllables were significantly different from each other.

8.7.1 Syllable 1 vs syllable 2 comparison

A logistic regression was conducted with syllable as the categorical variable and Duration, Intensity, Euclidean distance (ED), F0, F0 change ($\Delta F0$), and F0 range as the predictor variables. Syllable 1 was set as the reference category for this test. The output of this model is given below (Output 4). F0, $\Delta F0$, and Duration were found to be significant predictors. The overall classification rate of the model is 89% and the chi-squared test statistics are: $\chi^2(6) = 189.7151$, $p = 0$. The model had 129 datapoints for syllable 1 and 128 datapoints for syllable 2.

Output 4:

Predictors	Estimate	Std. Error	z-value	p-value	Odds- ratio	Confidence interval		Classification rate
						2.50%	97.50%	
Intercept	2.32	0.45	5.12	< 0.001				
F0	1.99	0.44	4.49	< 0.001	7.36	3.23	18.66	73%

F0 change	1.39	0.29	4.65	< 0.001	4.03	2.34	7.56	76%
ED	-0.32	0.23	-1.39	0.16				
Duration	-1.37	0.25	-5.36	< 0.001	0.25	0.14	0.4	76%
Intensity	-0.16	0.23	-0.68	0.49				
F0 range	-0.32	0.25	-1.29	0.19				

glm(formula = Syllable ~ F0 + F0 change + ED + Duration + Intensity + F0 range, family = "binomial")

Null deviance: 356.27 on 256 degrees of freedom

Residual deviance: 166.56 on 250 degrees of freedom

(44 observations deleted due to missingness)

AIC: 180.56

Number of Fisher Scoring iterations: 6

Since Syllable 1 was the reference category for this comparison, an examination of the estimated coefficients reveals that F0 and $\Delta F0$ have positive coefficients, while Duration has a negative coefficient. A positive coefficient as well as an odds ratio > 1 for F0 indicate that syllable 2 ($mean = -0.2$, $sd = 0.57$) has a higher average F0 compared to syllable 1 ($mean = -0.92$, $sd = 0.53$). The z-scores were reconverted into original units using the mean and standard deviation of speaker 1687 and the F0 on syllable 2 ($mean = 225$ Hz) is on average 17.8 Hz higher than syllable 1 ($mean = 207.2$ Hz).

The coefficient is also positive for $\Delta F0$ and the odds ratio > 1 indicate that syllable 2 ($mean = 0.31$, $sd = 0.75$) has a positive F0 change, i.e., the F0 rises on syllable 2 compared to the fall seen on syllable 1 ($mean = -0.63$, $sd = 0.8$). The z-scores were reconverted into original units using the mean and standard deviation of speaker 1687 and the F0 on syllable 1 falls from Q1 ($mean = 214.2$ Hz) to Q4 ($mean = 212$ Hz) while the F0 on syllable 2 rises from Q1 ($mean = 222$ Hz) to Q4 ($mean = 227.3$ Hz). A post hoc test was conducted with the significant predictors of this model where the individual significant predictors were the only predictor variable. The classification rate of the individual significant predictors is given in Output 4 – Classification rate.

The negative coefficient as well as an odds ratio < 1 indicate that syllable 1 ($mean = 1$, $sd = 0.9$) is longer compared to syllable 2 ($mean = -0.11$, $sd = 0.8$). The z-scores were reconverted into original units using the mean and standard deviation of one speaker, 1687 and syllable 1 ($mean = 104\ ms$) is on average 17 ms longer than syllable 2 ($mean = 87$).

8.7.2 Syllable 2 vs syllable 3 comparison

A logistic regression was conducted with syllable as the categorical variable and Duration, Intensity, Euclidean distance (ED), F0, F0 change ($\Delta F0$), and F0 range as the predictor variables. Syllable 1 was set as the reference category for this test. The output of this model is given below (Output 5). F0, and F0 range were found to be significant predictors. The overall classification rate of the model is 82% and the chi-squared test statistics are: $\chi^2(6) = 165.8802$, $p = 0$. The model had 128 datapoints for syllable 2 and 148 datapoints for syllable 3.

Output 5:

Predictors	Estimate	Std. Error	z-value	p-value	Odds- ratio	Confidence interval		Classification rate
						2.50%	97.50%	
Intercept	-0.9	0.33	-2.71	0.006				
F0	2.89	0.35	8.12	< 0.001	18.01	9.45	38.41	81%
F0 change	-0.18	0.27	-0.65	0.51				
ED	0.1	0.2	0.5	0.61				
Duration	0.21	0.21	0.97	0.32				
Intensity	-0.21	0.2	-1.05	0.29				
F0 range	-0.57	0.23	-2.4	0.01	0.56	0.34	0.88	58%

glm(formula = Syllable ~ F0 + F0 change + ED + Duration + Intensity + F0 range, family = "binomial")

Null deviance: 381.17 on 275 degrees of freedom

Residual deviance: 215.29 on 269 degrees of freedom

(23 observations deleted due to missingness)

AIC: 229.29

Number of Fisher Scoring iterations: 6

Since syllable 2 is the reference category for this comparison, an examination of the estimated coefficients reveal that F0 has a positive coefficient and F0 range has a negative coefficient. The positive coefficient for F0 as well as an odds ratio > 1 reveals that syllable 3 ($mean = 1.1, sd = 0.82$) has a higher F0 compared to syllable 2 ($mean = -0.22, sd = 0.6$). The z-scores were reconverted into original units using the mean and standard deviation of speaker 1687 and syllable 3 ($mean = 256\text{ Hz}$) is on average 31 Hz higher than syllable 2 ($mean = 225\text{ Hz}$) in terms of F0.

The negative coefficient for F0 range as well as an odds ratio < 1 reveals that syllable 2 ($mean = -0.21, sd = 1$) has a narrower F0 movement compared to syllable 3 ($mean = -0.01, sd = 1$). The z-scores were reconverted into original units using the mean and standard deviation of speaker 1687 and the difference between the max F0 ($mean = 229.2$) and min F0 ($mean = 221.2\text{ Hz}$) 8 Hz is smaller on syllable 2 compared to the difference seen on syllable 3 max F0 ($mean = 262\text{ Hz}$) and min F0 ($mean = 248\text{ Hz}$) 14 Hz. This shows that there is a greater F0 movement on syllable 3 compared to syllable 2.

8.7.3 Syllable 1 vs syllable 3 comparison

A logistic regression was conducted with syllable as the categorical variable and Duration, Intensity, Euclidean distance (ED), F0, F0 change ($\Delta F0$), and F0 range as the predictor variables. Syllable 1 was set as the reference category for this test. The output of this model is given below (Output 6). F0, $\Delta F0$, and F0 range were found to be significant predictors. The overall classification rate of the model is 95% and the chi-squared test statistics are: $\chi^2(6) = 312.1447, p = 0$. The model had 129 datapoints for syllable 1 and 148 datapoints for syllable 3.

Output 6:

Predictors	Estimate	Std. Error	z-value	p-value	Odds- ratio	Confidence interval		Classification rate
						2.50%	97.50%	
Intercept	1.22	0.64	1.89	0.05				
F0	4.67	0.89	5.24	< 0.001	107.21	24.82	861.86	93%
F0 change	1.11	0.48	2.32	0.02	3.05	1.26	8.38	81%
ED	-0.30	0.4	-0.75	0.45				
Duration	-0.12	0.34	-0.36	0.71				
Intensity	-0.35	0.32	-1.06	0.28				
F0 range	-1.31	0.5	-2.59	0.009	0.26	0.09	0.68	54%

glm(formula = Syllable ~ F0 + F0 change + ED + Duration + Intensity + F0 range, family = "binomial")

Null deviance: 382.699 on 276 degrees of freedom

Residual deviance: 70.555 on 270 degrees of freedom

(31 observations deleted due to missingness)

AIC: 84.555

Number of Fisher Scoring iterations: 8

Syllable 1 is the reference category for this comparison, and the examination of the estimated coefficients reveal that F0 and $\Delta F0$ have positive coefficients while F0 range has a negative coefficient. The positive coefficient as well as an odds ratio > 1 reveal that syllable 3 ($mean = 1.1$, $sd = 8.2$) has a higher F0 compared to syllable 1 ($mean = -0.92$, $sd = 0.53$). The z-scores were reconverted in to original units using the mean and standard deviation of speaker 1687 and syllable 2 ($mean = 256$ Hz) is on average 48.8 Hz higher in F0 compared to syllable 1 ($mean = 207.2$ Hz).

The positive coefficient for $\Delta F0$ as well as an odds ratio > 1 reveals that syllable 3 has a rising F0 ($mean = 0.63$, $sd = 0.8$) compared to the falling F0 on syllable 1 ($mean = -0.63$, $sd = 0.8$). The z-scores were reconverted into original units using the mean and standard deviation of

speaker 1687 and the F0 on syllable 1 falls from Q1 (*mean* = 214.2 Hz) to Q4 (*mean* = 207.3 Hz) while the F0 on syllable 2 rises from Q1 (*mean* = 250 Hz) to Q4 (*mean* = 259.1 Hz).

The negative coefficient for F0 range as well as an odds ratio < 1 reveals that syllable 1 (*mean* = 0.21, *sd* = 1) has a wider F0 movement compared to syllable 3 (*mean* = -0.01, *sd* = 1). The z-scores were reconverted into original units using the mean and standard deviation of speaker 1687 and the difference between the max F0 (*mean* = 221 Hz) and min F0 (*mean* = 205.4 Hz) 15.6 Hz is greater on syllable 1 compared to the difference seen on syllable 1 max F0 (*mean* = 257.3 Hz) and min F0 (*mean* = 248 Hz) 9.3 Hz. This shows that there is a greater F0 movement on syllable 2 compared to syllable 1.

8.8 Focus vs pre-focus comparisons

This comparison compared the syllables between the focus and the pre-focus condition to determine if the syllables were significantly different between the two focal conditions.

8.8.1 Syllable 1 pre-focus vs syllable 1 focus

A logistic regression was conducted with focal condition as the categorical variable and Duration, Intensity, Euclidean distance (ED), F0, F0 change ($\Delta F0$), and F0 range as the predictor variables. Pre-focus condition was set as the reference category for this test. The output of this model is given below (Output 7). $\Delta F0$, ED, and Duration were found to be significant predictors. The overall classification rate of the model is 63% and the chi-squared test statistics are: $\chi^2(6) = 24.89$, $p = 4.81188e-05$. The model had 135 datapoints for pre-focus condition and 129 datapoints for focus condition.

Output 7:

Predictors	Estimate	Std. Error	z-value	p-value	Odds- ratio	Confidence interval		Classification rate
						2.50%	97.50%	
Intercept	-0.8	0.4	-2.019	0.043				
F0	0.005	0.26	0.021	0.98				
F0 change	0.54	0.25	2.161	0.03	1.72	1.06	2.88	56%
ED	0.61	0.24	2.456	0.01	1.84	1.13	3.03	56%
Duration	0.54	0.16	3.388	0.0007	1.73	1.26	2.4	61%
Intensity	0.07	0.15	0.466	0.64				
F0 range	0.21	0.19	1.13	0.25				

glm(formula = Focus ~ F0 + F0 change + ED + Duration + Intensity + F0 range, family = "binomial")

Null deviance: 365.85 on 263 degrees of freedom

Residual deviance: 336.31 on 257 degrees of freedom

(50 observations deleted due to missingness)

AIC: 350.31

Number of Fisher Scoring iterations: 4

Pre-focus condition was the reference category for this comparison and an examination of the estimated coefficients reveal that $\Delta F0$, ED, and Duration have positive coefficients. The positive coefficient for $\Delta F0$ as well as an odds ratio > 1 reveals that syllable 1 focus has a rising F0 ($mean = 0.63$, $sd = 0.8$) compared to the falling F0 on syllable 1 ($mean = -0.63$, $sd = 0.8$). The z-scores were reconverted into original units using the mean and standard deviation of speaker 1687 and the F0 on syllable 1 falls from Q1 ($mean = 214.2$ Hz) to Q4 ($mean = 207.3$ Hz) while the F0 on syllable 2 rises from Q1 ($mean = 250$ Hz) to Q4 ($mean = 259.1$ Hz).

8.8.2 Syllable 2 pre-focus vs syllable 2 focus

A logistic regression was conducted with focal condition as the categorical variable and Duration, Intensity, Euclidean distance (ED), F0, F0 change ($\Delta F0$), and F0 range as the predictor variables.

Pre-focus condition was set as the reference category for this test. The output of this model is given

below (Output 8). Duration, and Intensity were found to be significant predictors. The overall classification rate of the model is 65%, and the chi-squared test statistics are: $\chi^2(6) = 35.44302$, $p = 3.536184e-06$. The model had 117 datapoints for the pre-focus condition and 128 datapoints for the focus condition.

Output 8:

Predictors	Estimate	Std. Error	z-value	p-value	Odds- ratio	Confidence interval		Classification rate
						2.50%	97.50%	
Intercept	0.54	0.27	1.94	0.05				
F0	0.41	0.27	1.52	0.12				
F0 change	-0.44	0.23	-1.91	0.05				
ED	0.12	0.17	0.71	0.47				
Duration	0.8	0.19	4.14	< 0.001	2.23	1.54	3.31	61%
Intensity	0.42	0.17	2.39	0.01	1.52	1.08	2.17	60%
F0 range	0.12	0.18	0.68	0.49				

glm(formula = Focus ~ F0 + F0 change + ED + Duration + Intensity + F0 range, family = "binomial")

Null deviance: 339.15 on 244 degrees of freedom

Residual deviance: 303.71 on 238 degrees of freedom

(48 observations deleted due to missingness)

AIC: 317.71

Number of Fisher Scoring iterations: 4

The pre-focal condition is the reference category for this comparison and an examination of the estimated coefficients reveal that Duration and Intensity have positive coefficients. The positive coefficient and an odds ratio > 1 indicate that syllable 2 of focus has a longer duration ($mean = -0.11$, $sd = 0.8$) compared to syllable 2 of pre-focus ($mean = -0.55$, $sd = 0.8$). The z-scores were reconverted into original units using the mean and standard deviation of one speaker,

6306 and syllable 2 focus ($mean = 87\ ms$) is on average 7 ms longer than syllable 2 pre-focus ($mean = 80\ ms$).

The positive coefficient for Intensity as well as an odds ratio > 1 also reveals that syllable 2 of focus ($mean = 0.06$, $sd = 0.9$) is louder compared to syllable 1 of focus ($mean = -0.2$, $sd = 1$). The z-scores were reconverted into original units using the mean and standard deviation of speaker 1687 and syllable 1 pre-focus ($mean = 66\ dB$) is on average 1 dB louder compared to syllable 1 focus ($mean = 65\ dB$).

8.8.3 Syllable 3 pre-focus vs syllable 3 focus

A logistic regression was conducted with focal condition as the categorical variable and Duration, Intensity, Euclidean distance (ED), F0, F0 change ($\Delta F0$), and F0 range as the predictor variables. Pre-focus condition was set as the reference category for this test. The output of this model is given below (Output 9). Duration was found to be the significant predictor. The overall classification rate of the model is 63% and the chi-squared test statistics are: $\chi^2(6) = 29.81913$, $p = 4.254587e-05$. The model had 146 datapoints for the pre-focus condition and 148 datapoints for the focus condition.

Output 9:

Predictors	Estimate	Std. Error	z-value	p-value	Odds- ratio	Confidence interval		Classification rate
						2.50%	97.50%	
Intercept	0.03	0.29	0.11	0.9				
F0	0.21	0.18	1.17	0.23				
F0 change	0.08	0.19	0.44	0.65				
ED	-0.16	0.16	-0.99	0.32				
Duration	0.67	0.14	4.55	< 0.001	1.95	1.48	2.65	61%
Intensity	0.15	0.13	1.18	0.23				

F0 range	-0.3	0.17	-1.79	0.07
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glm(formula = Focus ~ F0 + F0 change + ED + Duration + Intensity + F0 range, family = "binomial")

Null deviance: 426.97 on 307 degrees of freedom

Residual deviance: 404.41 on 306 degrees of freedom

AIC: 408.41

Number of Fisher Scoring iterations: 4

The pre-focus condition is the reference category for this comparison and an examination of the estimated coefficients reveal that Duration has a positive coefficient. The positive coefficient and an odds ratio > 1 indicate that syllable 3 of focus has a longer duration ($mean = 0.04$, $sd = 1$) compared to syllable 2 of pre-focus ($mean = -0.5$, $sd = 0.9$). The z-scores were reconverted into original units using the mean and standard deviation of one speaker, 6306 and syllable 2 focus ($mean = 90\ ms$) is on average 8 ms longer than syllable 2 pre-focus ($mean = 82\ ms$).

8.9 Summary and discussion of the results

The analysis in this chapter was to answer research questions (iii) and (iv) concerning focus. Statistical analysis comparing the syllable positions to one another in the focus condition showed that syllable 2 has a higher F0 compared to syllable 1 while syllable 1 is longer in duration compared to syllable 2 and also has a low falling F0 contour. Syllable 3 has a higher F0 compared to syllable 2. Syllable 3 also has a higher F0 compared to syllable 1 making it the syllable with the highest F0 in a word compared to syllables 1 and 2, and it also has a flat high or a high rising F0 contour compared to the low falling contour of syllable 1, whereas syllable 1 has a longer duration compared to syllable 3, which makes it the longest syllable in a word compared to syllables 2 and 3 which are similar in duration.

The statistical analysis comparing the syllable positions between the focus and the baseline conditions showed that the focus condition did not differ much in terms of the acoustic properties compared to the baseline condition. There was an increase in the duration under focus compared to the baseline condition, but it crucially increased on all of the syllables and did not only increase on syllable 1 which is the longest in the baseline condition.

The prosodic pattern under focus is identical to what is seen in the baseline condition. The final stressed syllable still has the highest F0 and initial syllable is still the longest in a word due to boundary effects. The initial syllable also still has a low falling contour under focus, identical to what is seen in the baseline condition. There is no real enhancement of the acoustic property of stress under focus since the F0 range is not increased. Duration did increase under focus, but it did not increase on only the first syllable as all of the syllables increased in duration in the focus condition.

Chapter 9 – Results: Post-focal Compression

The analysis in this chapter concerns the research question (vi) about post-focal compression. Answering research question (vi) *is there post-focal compression in Garo?* requires an analysis of the data from both the post-focus and the baseline conditions. There is typically a phenomenon known as post-focal compression which involves compression of the acoustic properties and also de-accenting (deletion of pitch-accents). In order to determine whether there is post-focal compression in Garo, two kinds of comparisons were done: the first comparison compared the syllable position in the post-focus condition with one another, i.e., syllable 1 vs syllable 2, syllable 2 vs syllable 3, and syllable 1 vs syllable 3. A binary logistic regression with syllable position as the dependent variable and F0, F0 change ($\Delta F0$), Euclidean distance (ED), Duration, Intensity, and F0 range as predictor variables tested to determine whether the basic word-prosodic pattern seen in the baseline condition changes post-focally

The second set of comparisons compared the syllable positions between the post-focus and the baseline conditions, i.e., syllable 1 post-focus vs syllable 1 pre-focus, syllable 2 post-focus vs syllable 2 pre-focus, and syllable 3 post-focus vs syllable 3 pre-focus. A binary logistic regression with focus condition as the dependent variable and F0, F0 change ($\Delta F0$), Euclidean distance (ED), Duration, Intensity, and F0 range as the predictor variables tested to determine whether the acoustic properties change between the focal conditions.

The pitch track in (Figure 19) shows the intonational contour of the sentence in post-focus condition. The target word is seen to have a high F0 on the final syllable just like in the baseline condition, but this needs to be tested statistically.

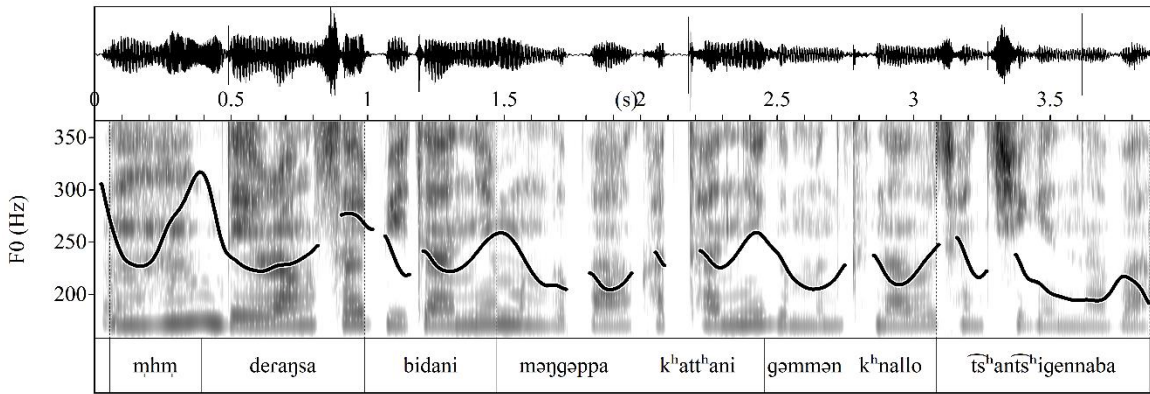


Figure 19: Pitch track of a sentence in post-focus condition. The word "bidani" is the target word.

The first section of the chapter includes a description of the prosodic pattern in the post-focus condition using graphs. The description is based on the graphs of F0, Duration, Intensity, and Formants (F1 & F2) and gives both an overall description of the word prosodic pattern in post-focus condition and also the comparison of the pattern in the post-focus and the baseline focal conditions. The description identifies which of the syllables differ from other syllables and if post-focus condition differs from the baseline condition based on the aforementioned acoustic properties. The second section of the chapter includes statistical analyses which tests whether the differences seen between the syllables and the focal conditions in terms of acoustic properties are statistically significant. This section also includes the results of the statistical tests, the description of the results and also their interpretation. The third section of the chapter includes the discussion of the statistical results and connects it back to the pattern seen in the graphs. This chapter also includes the pattern to state if there is an effect of post-focal compression in Garo.

9.1 Descriptive statistics

The descriptive statistics examines the pattern of the aforementioned acoustic properties by using graphs. The F0 graphs are made using the mean of the normalized F0 at Q1 and Q4 of the vowel. Duration and Intensity graphs are also made using the normalized Duration. Vowel quality graphs are made using the normalized mean F1 and F2 in the Q2 and Q3 of the vowel.

9.2 F0 pattern

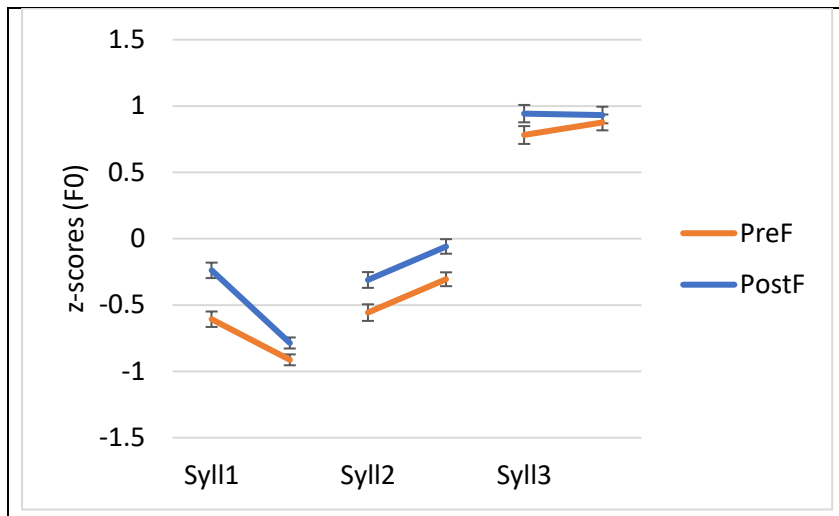


Figure 20: F0 track of post-focus and baseline conditions together made with mean of normalized F0 at Q1 and Q4 of each syllable. Syllable positions are on the x-axis and z-scores (F0) are on the y-axis. Baseline F0 track is in orange and post-focus in blue.

The vowel duration is split into four equal quarters so the F0 graph is made using the normalized mean F0 in the Q1 and the Q4 of the vowel. The F0 track in Figure 17 shows that in the post-focus condition there is a low falling on syllable 1 where F0 falls from Q1 to Q4 of syllable 1. The lowest F0 point in a word is reached on syllable 1. The F0 contour on syllable 2 is the opposite pattern however, as the F0 rises from the Q1 to Q4 of syllable 2. The rise on syllable 2

follows the fall that is seen on syllable 1. Syllable 3 has a high flat F0 contour with F0 changing very little from the Q1 to Q4 of syllable 3. The highest F0 point in a word is reached on syllable 3. To summarize the F0 pattern, the lowest F0 point in a word is reached on syllable 1 which has a low falling contour, and the highest F0 point in a word is reached on syllable 3 which has a high flat contour.

The baseline and the post-focus conditions have the same overall F0 pattern. The F0 levels on syllable 1 and 2 are higher in the post-focus condition, however. In syllable 1, the F0 level from which the fall starts in post-focal condition is slightly higher than the level that it falls from in the baseline condition. The lowest F0 point on syllable 1 is still similar between the two focal conditions. Similarly, the F0 level from which the rise starts on syllable 2 in the post-focus condition is slightly higher, and the highest F0 point reached on syllable 2 is also higher in the post-focus condition compared to the baseline. Both the F0 contour and the F0 level on syllable 3 are very similar between the post-focus and the baseline conditions, however.

9.3 Duration pattern

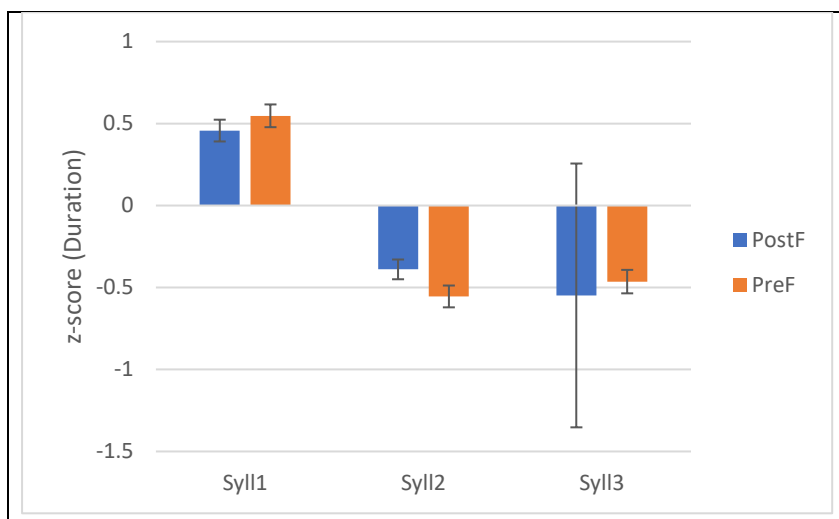


Figure 21: Duration patterns of the post-focus and baseline conditions made with means of normalized Duration. Syllable positions are on x-axis and z-score (Duration) on y-axis. Post-focus condition is plotted in blue and baseline in orange.

The Duration graph is made with the normalized mean Durations of vowels. The Duration graph in Figure 18 shows that in the post-focus condition that syllable 1 is the longest in the word in the post-focus condition compared to the other syllables. Syllable 2 is slightly longer compared to syllable 3 based on the graph, but it is still shorter than syllable 1. Syllable 3 is the shortest syllable in the post-focus condition, although it has to be noted that there is a lot of variability around the mean of Duration for syllable 3 as indicated by the large error bars in (Figure 18). To summarize, syllable 1 is the longest syllable in a word in the post-focus condition and syllable 3 is the shortest syllable in a word.

The baseline and the post-focus conditions have the same overall pattern for the most part. The only difference between the two focal conditions seems to be the slight increase in Duration of syllable 2 in the post-focus condition compared to the baseline condition. The increase in Duration on syllable 2 aside, the overall Duration pattern does not change between the focal condition since syllable 1 is still significantly longer compared to syllables 2 and 3. Critically, it has to be noted that Duration does not seem to either increase or decrease in the post-focus condition as the Duration remains pretty similar in the syllable positions barring the slight increase in Duration of syllable 2 in the post-focus condition.

9.4 Intensity pattern

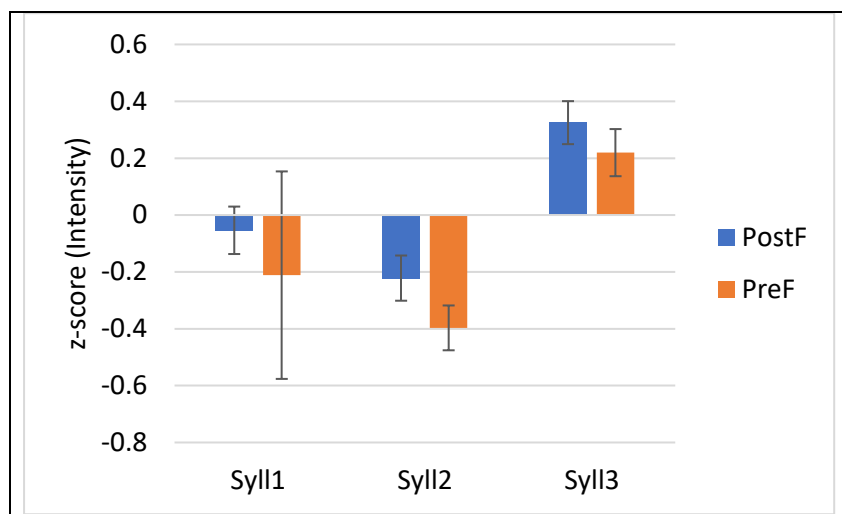


Figure 22: Intensity patterns of post-focus and baseline conditions made with means of normalized Intensity. Syllable positions are on x-axis and z-score (Intensity) on y-axis. Post-focus condition is plotted in blue and baseline in orange.

The intensity graphs were made using the normalized mean Intensity in the middle portion of the vowels, i.e., the Q2 and Q3 of the vowel. The intensity graph in Figure 19 shows that in the post-focus condition syllable 3 is the loudest syllable in a word compared to syllable 1 and 2. Syllable 1 is louder compared to syllable 2, but syllable 3 still seems to be significantly longer than syllable 1. Syllable 2 has the lowest intensity in a word. To summarize, syllable 3 clearly is the loudest in a word and syllable 2 the least intense.

There is a change in the intensity post-focally. All of the syllables increase in intensity in the post-focus condition compared to the baseline condition. The basic pattern remains the same however, as syllable 3 has the highest intensity and syllable 2 has the lowest intensity. In summary, even though there is a slight increase in the intensity of all the syllables in the post-focal condition, the basic pattern remains the same as syllable 3 is still the loudest and syllable 2 the least intense.

9.5 Vowel quality pattern

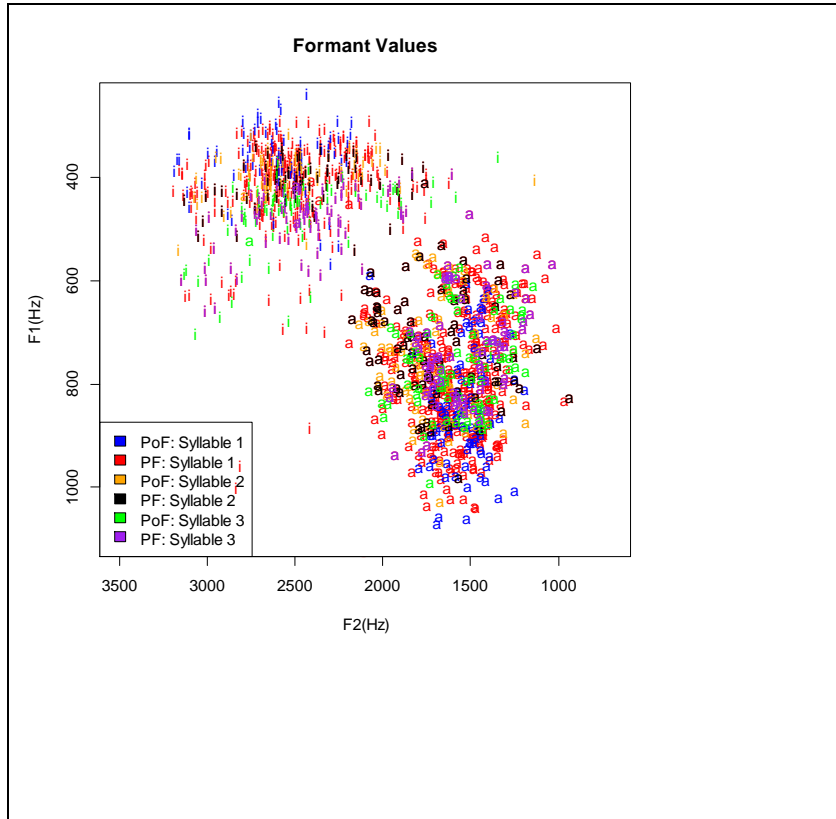


Figure 23: Vowel quality patterns of post-focus and baseline made with F1 and F2 (Hz). F2 (Hz) is on x-axis and F1 (Hz) on y-axis. Focal conditions and syllable positions are plotted in different colours (consult the legend). “F” is focus and “PF” pre-focus.

The vowel quality pattern is measured using the values of the first two formants (F1 and F2). The vowel quality graph in Figure 20 shows that in post-focus condition syllable 1 is the most peripheral in the vowel space compared to syllables 2 and 3. The two vowels differ in terms of whether syllable 2 or syllable 3 is more peripheral. For /i/ vowel, syllable 3 seems to be the most centralized compared to syllables 1 and 2. Syllable 2 lies somewhere in between syllables 1 and 3 in that while it is not as centralized as syllable 3, syllable 1 is overall relatively more peripheral. For /a/ vowel, there is no clear pattern for the syllable 2 and 3 in that they are equally centralized compared to syllable 1. Importantly however, there is no clustering of the vowel qualities (/i/ and

/a/) in any of the syllable positions, i.e., the distinction between the vowel qualities is still maintained even though there is some centralization in syllable 2 and 3.

There is no drastic difference between the post-focus and the baseline condition. The overall pattern is similar between the two focal conditions and the vowels are not more peripheral under focus. Syllable 1 is the most peripheral in both conditions compared to syllable 2 and 3.

9.6 Statistical analysis

The statistical analysis of the data tests whether the differences seen between the syllables in terms of the acoustic properties seen in the graphs above are statistically significant. The statistical test conducted is the *binary logistic regression*, so, the models will test how successful the acoustic properties (predictors) are in predicting the syllable positions (categorical variable).

Since the goal of this testing the post-focus condition was to see if there was any reduction in the acoustic properties of word-prosody, two kinds of comparisons were made with the post-focus data. The first comparison compared the syllables in the post-focus condition to one another, i.e., the first model compared syllable 1 vs syllable 2, the second model compared syllable 2 vs syllable 3, and the third models compared syllable 1 vs syllable 3. This test was intended to see if the basic word-prosodic pattern seen in the baseline condition, i.e., the difference between the syllables, is seen in the post-focal condition.

The second of the comparisons compared the syllables between the baseline and the post-focus condition, i.e., the first model in this comparison compared syllable 1 of baseline condition to the syllable 1 of the post-focus condition, second model compared syllable 2 of baseline to the syllable 2 of the post-focus, and the third model compared syllable 3 of baseline to the syllable 3

of the post-focus. This test was intended to see if the post-focus condition differed significantly from the baseline condition even if the basic pattern remained the same.

9.7 Syllable comparisons

This comparison tested the syllables in the post-focus condition to determine if the syllables were significantly different from each other.

9.7.1 Syllable 1 vs syllable 2 comparison

A logistic regression was conducted with syllable as the categorical variable and Duration, Intensity, Euclidean distance (ED), F0, F0 change ($\Delta F0$), and F0 range as the predictor variables. Syllable 1 was set as the reference category for this test. The output of this model is given below (Output 10). F0, $\Delta F0$, and Duration were found to be significant predictors. The overall classification rate of the model is 89% and the chi-squared test statistics are: $\chi^2(6) = 225.1005$, $p = 0$. The model had 131 datapoints for syllable 1 and 129 datapoints for syllable 2.

Output 10:

Predictors	Estimate	Std. Error	z-value	p-value	Odds- ratio	Confidence interval		Classification rate
						2.50%	97.50%	
Intercept	-1.46	0.53	-2.73	0.006				
F0	-1.1	0.46	-2.36	0.01	0.33	0.12	0.8	71%
F0 change	-2.55	0.45	-5.65	< 0.001	0.07	0.02	0.16	85%
ED	0.04	0.32	0.12	0.89				
Duration	1.52	0.31	4.82	< 0.001	4.58	0.82	2.44	75%
Intensity	0.34	0.27	1.27	0.2				
F0 range	0.24	0.37	0.66	0.5				

glm(formula = Syllable ~ F0 + F0 change + ED + Duration + Intensity + F0 range, family = "binomial")

Null deviance: 360.42 on 259 degrees of freedom

Residual deviance: 135.32 on 253 degrees of freedom
 (52 observations deleted due to missingness)
 AIC: 149.32
 Number of Fisher Scoring iterations: 6

Since Syllable 2 was the reference category for this comparison, an examination of the estimated coefficients reveals that F0 and $\Delta F0$ have negative coefficients, while Duration has a positive coefficient. The negative coefficient as well as an odds ratio < 1 reveal that syllable 2 ($mean = -0.16$, $sd = 0.6$) has a higher F0 compared to syllable 1 ($mean = -0.62$, $sd = 0.53$). The z-scores were reconverted into original units using the mean and standard deviation of speaker 1687 and syllable 2 ($mean = 226$ Hz) is on average 11 Hz higher in F0 compared to syllable 1 focus ($mean = 215$ Hz). This difference however is unlikely to be perceptually distinctive.

The negative coefficient for $\Delta F0$ as well as an odds ratio < 1 reveals that syllable 2 has a rising F0 ($mean = 0.4$, $sd = 0.84$) compared to the falling F0 on syllable 1 ($mean = -1.18$, $sd = 0.81$). The z-scores were reconverted into original units using the mean and standard deviation of speaker 1687 and the F0 on syllable 1 falls from Q1 ($mean = 225$ Hz) to Q4 ($mean = 211.1$ Hz) while the F0 on syllable 2 rises from Q1 ($mean = 223.1$ Hz) to Q4 ($mean = 230$ Hz).

The positive coefficient and an odds ratio > 1 indicate that syllable 1 has a longer duration ($mean = 0.5$, $sd = 0.83$) compared to syllable 2 ($mean = -0.2$, $sd = 0.74$). The z-scores were reconverted into original units using the mean and standard deviation of one speaker, 1687 and syllable 1 ($mean = 96$ ms) is on average 13 ms longer than syllable 3 ($mean = 83$ ms).

9.7.2 Syllable 2 vs syllable 3 comparison

A logistic regression was conducted with syllable as the categorical variable and Duration, Intensity, Euclidean distance (ED), F0, F0 change ($\Delta F0$), and F0 range as the predictor variables.

Syllable 1 was set as the reference category for this test. The output of this model is given below (Output 11). F0, and $\Delta F0$ were found to be significant predictors. The overall classification rate of the model is 82% and the chi-squared test statistics are: $\chi^2(6) = 168.1442$, $p = 0$. The model had 129 datapoints for syllable 2 and 143 datapoints for syllable 3.

Output 11:

Predictors	Estimate	Std. Error	z-value	p-value	Odds- ratio	Confidence interval		Classification rate
						2.50%	97.50%	
Intercept	-1.26	0.37	-3.36	0.0007				
F0	2.97	0.35	8.32	< 0.001	19.56	10.19	41.62	83%
F0 change	-0.78	0.25	-3.05	0.002	0.45	0.26	0.73	53%
ED	0.18	0.21	0.88	0.37				
Duration	-0.38	0.24	-1.58	0.11				
Intensity	-0.27	0.21	-1.29	0.19				
F0 range	-0.27	0.24	-1.12	0.26				

glm(formula = Syllable ~ F0 + F0 change + ED + Duration + Intensity + F0 range, family = "binomial")

Null deviance: 376.35 on 271 degrees of freedom

Residual deviance: 208.21 on 265 degrees of freedom

(37 observations deleted due to missingness)

AIC: 222.21

Number of Fisher Scoring iterations: 5

Since syllable 2 is the reference category for this comparison, an examination of the estimated coefficients reveal that F0 has a positive coefficient and $\Delta F0$ has a negative coefficient. The positive coefficient as well as an odds ratio > 1 reveal that syllable 3 ($mean = 1.03$, $sd = 0.8$) has a higher F0 compared to syllable 2 ($mean = -0.16$, $sd = 0.6$). The z-scores were reconverted in to original units using the mean and standard deviation of speaker 1687 and syllable 3 ($mean = 255$ Hz) is on average 29 Hz higher in F0 compared to syllable 2 focus ($mean = 226$ Hz).

The negative coefficient for $\Delta F0$ as well as an odds ratio < 1 reveals that syllable 2 has more of a rising F0 ($mean = 0.4$, $sd = 0.84$) compared to syllable 3 ($mean = 0.4$, $sd = 0.7$). The z-scores were reconverted into original units using the mean and standard deviation of speaker 1687 and the F0 on syllable 2 rises from Q1 ($mean = 223.1$ Hz) to Q4 ($mean = 230$ Hz) while the F0 on syllable 3 rises from Q1 ($mean = 250$ Hz) to Q4 ($mean = 257$ Hz).

9.7.3 Syllable 1 vs syllable 3 comparison

A logistic regression was conducted with syllable as the categorical variable and Duration, Intensity, Euclidean distance (ED), F0, F0 change ($\Delta F0$), and F0 range as the predictor variables. Syllable 1 was set as the reference category for this test. The output of this model is given below (Output 12). F0, $\Delta F0$, and Duration were found to be significant predictors. The overall classification rate of the model is 95% and the chi-squared test statistics are: $\chi^2(6) = 298.4429$, $p = 0$. The model had 131 datapoints for syllable 1 and 143 datapoints for syllable 3.

Output 12:

Predictors	Estimate	Std. Error	z-value	p-value	Odds- ratio	Confidence interval		Classification rate
						2.50%	97.50%	
Intercept	-0.17	0.5	-0.33	0.73				
F0	2.82	0.55	5.12	< 0.001	16.77	6.41	57.36	90%
F0 change	1.41	0.51	2.76	0.005	4.13	1.64	12.8	89%
ED	0.28	0.27	1.02	0.3				
Duration	-0.95	0.4	-2.37	0.01	0.38	0.16	0.8	77%
Intensity	-0.49	0.39	-1.27	0.2				
F0 range	-0.72	0.5	-1.44	0.14				

glm(formula = Syllable ~ F0 + F0 change + ED + Duration + Intensity + F0 range, family = "binomial")

Null deviance: 379.319 on 273 degrees of freedom

Residual deviance: 80.876 on 267 degrees of freedom

(39 observations deleted due to missingness)

AIC: 94.876

Number of Fisher Scoring iterations: 7

Syllable 1 is the reference category for this comparison, and the examination of the estimated coefficients reveal that F0 and $\Delta F0$ have positive coefficients while Duration has a negative coefficient. The positive coefficient as well as an odds ratio > 1 reveal that syllable 3 ($mean = 1.03, sd = 0.8$) has a higher F0 compared to syllable 1 ($mean = -0.62, sd = 0.53$). The z-scores were reconverted in to original units using the mean and standard deviation of speaker 1687 and syllable 3 ($mean = 255\text{ Hz}$) is on average 40 Hz higher in F0 compared to syllable 1 focus ($mean = 215\text{ Hz}$).

The positive coefficient for $\Delta F0$ as well as an odds ratio > 1 reveals that syllable 3 has a rising F0 ($mean = 0.4, sd = 0.7$) compared to the falling F0 on syllable 1 ($mean = -1.18, sd = 0.81$). The z-scores were reconverted into original units using the mean and standard deviation of speaker 1687 and the F0 on syllable 1 falls from Q1 ($mean = 225\text{ Hz}$) to Q4 ($mean = 211.1\text{ Hz}$) while the F0 on syllable 3 rises from Q1 ($mean = 250\text{ Hz}$) to Q4 ($mean = 257\text{ Hz}$).

The positive coefficient and an odds ratio > 1 indicate that syllable 1 has a longer duration ($mean = 0.5, sd = 0.83$) compared to syllable 3 ($mean = -0.54, sd = 0.8$). The z-scores were reconverted into original units using the mean and standard deviation of one speaker, 1687 and syllable 1 ($mean = 96\text{ ms}$) is on average 15.5 ms longer than syllable 3 ($mean = 80.5\text{ ms}$).

9.8 Post-focus vs pre-focus comparisons

This comparison compared the syllables between the focus and the pre-focus condition to determine if the syllables were significantly different between the two focal conditions.

9.8.1 Syllable 1 pre-focus vs syllable 1 post-focus

A logistic regression was conducted with focal condition as the categorical variable and Duration, Intensity, Euclidean distance (ED), F0, F0 change ($\Delta F0$), and F0 range as the predictor variables. Pre-focus condition was set as the reference category for this test. The output of this model is given below (Output 13). F0, and Intensity were found to be significant predictors. The overall classification rate of the model is 63% and the chi-squared test statistics are: $\chi^2(6) = 30.09499$, $p = 3.770719e-05$. The model had 135 datapoints for the pre-focus condition and 131 datapoints for the focus condition

Output 13:

Predictors	Estimate	Std. Error	z-value	p-value	Odds- ratio	Confidence interval		Classification rate
						2.50%	97.50%	
Intercept	-0.23	0.39	-0.6	0.54				
F0	0.64	0.27	2.36	0.01	1.91	1.13	3.33	71%
F0 change	-0.58	0.3	-1.89	0.05				
ED	0.18	0.22	0.81	0.41				
Duration	-0.19	0.16	-1.19	0.23				
Intensity	0.33	0.15	2.13	0.03	1.39	1.03	1.9	56%
F0 range	-0.01	0.22	-0.06	0.94				

glm(formula = Focus ~ F0 + F0 change + ED + Duration + Intensity + F0 range, family = "binomial")

Null deviance: 368.69 on 265 degrees of freedom

Residual deviance: 338.60 on 259 degrees of freedom

(51 observations deleted due to missingness)

AIC: 352.6

Number of Fisher Scoring iterations: 4

Pre-focus condition was the reference category for this comparison and an examination of the estimated coefficients reveal that both F0, and Intensity have positive coefficients. The positive coefficient as well as an odds ratio > 1 reveal that syllable 1 of post-focus ($mean = -0.62$, $sd = 0.53$) has a higher F0 compared to syllable 1 of pre-focus ($mean = -0.84$, $sd = 0.51$). The z-scores were reconverted in to original units using the mean and standard deviation of speaker 1687 and syllable 1 of post-focus ($mean = 215\text{ Hz}$) is on average 5.8 Hz higher in F0 compared to syllable 1 focus ($mean = 209.2\text{ Hz}$).

The positive coefficient for Intensity as well as an odds ratio > 1 also reveals that syllable 1 of post-focus ($mean = -0.05$, $sd = 1.04$) is louder compared to syllable 1 of pre-focus ($mean = -0.2$, $sd = 0.9$). The z-scores were reconverted into original units using the mean and standard deviation of speaker 1687 and syllable 1 pre-focus ($mean = 65.3\text{ dB}$) is on average 0.3 dB louder compared to syllable 1 focus ($mean = 65\text{ dB}$).

9.8.2 Syllable 2 pre-focus vs syllable 2 post-focus

A logistic regression was conducted with focal condition as the categorical variable and Duration, Intensity, Euclidean distance (ED), F0, F0 change ($\Delta F0$), and F0 range as the predictor variables. Pre-focus condition was set as the reference category for this test. The output of this model is given below (Output 14). Only F0, was found to be a significant predictor. The overall classification rate of the model is 59%, and the chi-squared test statistics are: $\chi^2(6) = 16.62098$, $p = 0.01078192$. The model had 117 datapoints for the pre-focus condition and 129 datapoints for the focus condition.

Output 14:

	Confidence interval
--	---------------------

Predictors	Estimate	Std. Error	z-value	p-value	Odds- ratio	2.50%	97.50%	Classification rate
Intercept	0.78	0.3	2.54	0.01				
F0	0.86	0.28	3	0.002	2.37	1.37	4.27	58%
F0 change	-0.09	0.2	-0.46	0.64				
ED	-0.24	0.19	-1.26	0.2				
Duration	0.3	0.18	1.67	0.09				
Intensity	-0.12	0.16	-0.74	0.45				
F0 range	0.07	0.18	0.41	0.67				

glm(formula = Focus ~ F0 + F0 change + ED + Duration + Intensity + F0 range, family = "binomial")

Null deviance: 340.44 on 245 degrees of freedom

Residual deviance: 323.82 on 239 degrees of freedom

(55 observations deleted due to missingness)

AIC: 337.82

Number of Fisher Scoring iterations: 4

The pre-focal condition is the reference category for this comparison and an examination of the estimated coefficients reveal that F0 has a positive coefficient. The positive coefficient as well as an odds ratio > 1 reveal that syllable 2 of post-focus ($mean = -0.62$, $sd = 0.53$) has a higher F0 compared to syllable 2 of pre-focus ($mean = -0.16$, $sd = 0.6$). The z-scores were reconverted in to original units using the mean and standard deviation of speaker 1687 and syllable 1 of post-focus ($mean = 226$ Hz) is on average 5 Hz higher in F0 compared to syllable 1 focus ($mean = 221$ Hz).

9.8.3 Syllable 3 pre-focus vs syllable 3 post-focus

A logistic regression was conducted with focal condition as the categorical variable and Duration, Intensity, Euclidean distance (ED), F0, F0 change ($\Delta F0$), and F0 range as the predictor variables. Pre-focus condition was set as the reference category for this test. The output of this model is given below (Output 15). $\Delta F0$ was found to be a significant predictor. The overall classification rate of the model is 63% and the chi-squared test statistics are: $\chi^2(6) = 11.7195$, $p = 0.06852707$. The

model had 146 datapoints for the pre-focus condition and 143 datapoints for the post-focus condition.

Output 15:

Predictors	Estimate	Std. Error	z-value	p-value	Odds- ratio	Confidence interval		Classification rate
						2.50%	97.50%	
Intercept	-0.39	0.3	-1.31	0.18				
F0	0.35	0.19	1.84	0.06				
F0 change	-0.35	0.17	-1.96	0.04	0.7	0.49	0.99	54%
ED	0.09	0.14	0.62	0.53				
Duration	-0.03	0.15	-0.22	0.81				
Intensity	0.12	0.13	0.92	0.35				
F0 range	-0.23	0.17	-1.38	0.16				

glm(formula = Focus ~ F0 + F0 change + ED + Duration + Intensity + F0 range, family = "binomial")

Null deviance: 400.61 on 288 degrees of freedom

Residual deviance: 388.89 on 282 degrees of freedom

(21 observations deleted due to missingness)

AIC: 402.89

Number of Fisher Scoring iterations: 4

The pre-focus condition is the reference category for this comparison and an examination of the estimated coefficients reveal that $\Delta F0$ has a positive coefficient. The positive coefficient for $\Delta F0$ as well as an odds ratio > 1 reveals that syllable 3 of post-focus has more of a rising F0 (*mean* = 0.63, *sd* = 0.8) compared to the F0 contour on syllable 3 of pre-focus (*mean* = 0.6, *sd* = 0.8). The z-scores were reconverted into original units using the mean and standard deviation of speaker 1687 and the F0 on syllable 3 of post-focus rises from Q1 (*mean* = 250 Hz) to Q4 (*mean* = 257 Hz) while the F0 on syllable 3 pre-focus rises from Q1 (*mean* = 253 Hz) to Q4 (*mean* = 255 Hz).

9.9 Summary and discussion of the results

The analysis in this chapter was to answer research question (vi) concerning post-focal compression. Statistical analysis comparing the syllable positions in post-focus condition to one another showed that syllable 2 has a higher F0 compared to syllable 1, whereas syllable 1 has a longer duration compared to syllable 2 and also has a low falling F0 contour. Syllable 3 has a higher F0 compared to syllable 2. Syllable 3 also has a higher F0 compared to syllable 1 making it the syllable with the highest F0 in the word, and it also has a flat high or a high rising F0 compared to the low falling F0 of syllable 1. Syllable 1 on the other hand has a longer duration compared to syllable 3 making it the longest syllable in the word.

The statistical analysis comparing the syllable positions between the post-focus and the baseline conditions showed that post-focus condition did not differ from the baseline condition substantially as the basic pattern in the post-focus condition remained the same as in the baseline. The acoustic cue of stress was also not compressed in the post-focus condition.

The prosodic pattern in the post-focus condition is identical to what is seen in the baseline condition. In the post-focus condition, the final stressed syllable has the highest F0 and the initial is still the longest in a word due to boundary effects. The initial syllable has a low falling contour in the post-focus condition, identical to what is seen in the baseline condition. There is no compression of the acoustic property of stress post-focally since the F0 range did not decrease.

Chapter 10 – Results: Focus particle

The analysis in the previous three chapters show that focal conditions have very little effect on the basic word-prosodic pattern. The pattern remained very similar across the three focal conditions – pre-focus (baseline), focus, and the post-focus conditions. While it could be concluded from these observations and analyses that there is no prosodic focus in Garo, one has to acknowledge the presence of the focus particle “-*sa*” in the language. The canonical and grammatical way of expressing focus in Garo is by using the focus particle “-*sa*.” There is no prosodic substitute for -*sa* such that the only grammatical way to express focus is by attaching the focus particle to the focused constituent. Keeping these points in mind, the *k^hnallo* word was chosen as a subject for a *post-hoc analysis* in order to determine the prosody of the -*sa* particle. The *k^hnallo* word carries the -*sa* particle in one of the focal conditions (pre-focus) and does not have the particle in the other two focal conditions (focus and post-focus).

Importantly, it also has to be noted that -*sa* does not attach to the target word in the focus condition even though the target word is within the focused constituent. The -*sa* attaches to the final word within the focused constituent, i.e., *gəmmən-sa* “about:”

Focus condition (Prosodic structure 1):

[[[m ^h m] _{PP}] _{IP} , [[derəŋara] _{PP}	[X	məŋgəppa] _{PP}	[k ^h att ^h ani	gəmmən-sa] _{PP}] _{IP}	[k ^h nallo] _{PP}
no	Derang-Top	X	called	word-Gen	about-Foc tomorrow

[ts^hants^hiɣennaba]_{PP}]_U⁴

think-Fut-Evi-?

“No, Derang is going to think about the word called X tomorrow.”

Prosodic structure 1: Prosodic structure of focus condition.

As can be seen in the prosodic structure of the focus condition in (Prosodic structure 1), -sa is attached to the word *gəmmən* which is the final word of the constituent that is focused. The target word (X) is in the focused constituent, but does not have the focus particle.

From these observations it seems a little premature to conclude that Garo does not have any prosodic focus. It is possible that the reason why no prosodic effect was not seen in the focus condition is due to the focus particle not attaching to the target word. It has been found for European Portuguese that even though it has a focus particle there is still prosodic focus in the language (Frota, 2000). Taking these facts into consideration, it will be premature to state that Garo lacks prosodic focus altogether without first examining the prosodic pattern of the word that carries the focus marker. One possibility was to test the word *gəmmən* itself which carries the -sa marker in the focus condition, but it was not an ideal candidate due to it having the reduced vowel [ə]. Instead, the word *k^hnallo* “tomorrow” is chosen since it carries the -sa in the pre-focus condition of this study and also because the vowels in the word are similar to the vowels included in the target words:

⁴ It has to be noted that the prosodic structure of the sentence given here is speculation as there has not been any study done on the prosodic structure and hierarchy of Garo. The structure given here is the best guess of the researcher based on his intuition as a native speaker.

Pre-focus condition (Prosodic structure 2):

[[m̥hm̥]_{PP}]_{IP}, [[deran̩ara]_{PP} [X m̩əŋgəppa]_{PP} [k^hatt^hani gəmmən]_{PP}]_{IP} [[k^hnallo-sa]_{PP}]_{IP}

no Derang-Top X called word-Gen about tomorrow-Foc

[ts^hants^hiɡennaba]_{PP}]_{IP}

think-Fut-Evi-?

“No, Derang is going to think about the word called X TOMORROW.”

Prosodic structure 2: Prosodic structure of pre-focus condition.

As can be seen in the prosodic structure of the pre-focus condition, *-sa* is attached to *k^hnallo*. In the focus condition (Prosodic structure 1) it does not carry the focus marker and comes after the focused word. The same is the case in the post-focus condition of this study (Prosodic structure 3):

Post-focus condition (Prosodic structure 3):

[[m̥hm̥]_{PP}]_{IP}, [[deran̩sa]_{PP}]_{IP} [[X m̩əŋgəppa]_{PP} [k^hatt^hani gəmmən]_{PP} [k^hnallo]_{PP}

no Derang-Foc X called word-Gen about tomorrow

[ts^hants^hiɡennaba]_{PP}]_{IP}

think-Fut-Evi-?

“No, DERANG is going to think about the word called X tomorrow.”

Prosodic structure 3: Prosodic structure of post-focus condition.

As can be seen in the prosodic structure of the post-focus condition (Prosodic structure 3) the word *k^hnallo* does not have *-sa* and it occurs after the focused word. Since the word *k^hnallo*

occurs in the data both with and without the *-sa* focus particle, it will allow for the determination of the word-prosodic pattern with and without *-sa*. The intended goal of this chapter is indeed to determine whether there is any difference in the prosodic pattern of the word *kʰnallo* when it occurs without the *-sa* compared to when it does occur with the *-sa*. One other comparison that this chapter does is the comparison of the word *kʰnallo* when it carries the *-sa*, i.e., *kʰnallosa* to the target word when it is focused. This comparison is to establish whether there is a significant difference between the word *kʰnallosa* and the focused target word.

The analysis in this chapter concerns the research question (v) about the prosody of the focus particle *-sa*. Answering the research question (v) *Does the focus particle change the prosodic structure of the word that it attaches to?* requires an establishment of the word-prosodic pattern of the word *kʰnallo* in the pre-focus condition where it has the *-sa* and is focused (*kʰnallo* with *-sa*) and in the focus and the post-focus conditions where it does not have the *-sa* and is unfocused (*kʰnallo* without *-sa*). The data analysed in this chapter is from the *knallo* word and also the /a/ vowel of the target word in focus condition. There are three kinds of statistical comparisons made in this chapter. The first comparison compared the syllable positions in *kʰnallo* without *-sa* in the focus condition (baseline for this analysis) with one another, i.e., syllable 1 vs syllable 2. A binary logistic regression with syllable position as a dependent variable and F0, F0 change ($\Delta F0$), Euclidean distance (ED), Duration, Intensity, and F0 range as predictor variable tested if the syllable positions are different in the *kʰnallo* without *-sa*.

The second of comparisons compared the syllable positions between the *kʰnallo* words with and without *-sa*, i.e., syllable 1 *kʰnallo* with *-sa* vs syllable 1 *kʰnallo* without *-sa*, syllable 2 *kʰnallo* with *-sa* vs syllable 2 *kʰnallo* without *-sa*, and syllable 3 *kʰnallo* with *-sa* vs syllable 2 *kʰnallo* without *-sa*. A binary logistic regression with focus condition as a dependent variable and F0, F0

change ($\Delta F0$), Euclidean distance (ED), Duration, Intensity, and F0 range as predictor variable tested if the prosody of the *k^hnallo* word is different with and without *-sa*.

The third set of comparisons compared the *k^hnallo* word with *-sa* to the focused target word, i.e., syllable 1 *k^hnallo* with *-sa* vs syllable 1 focused target word, syllable 2 *k^hnallo* with *-sa* vs syllable 2 focused target word, and syllable 3 *k^hnallo* with *-sa* vs syllable 3 focused target word. A binary logistic regression with *k^hnallo* word as a dependent variable and F0, F0 change ($\Delta F0$), Euclidean distance (ED), Duration, Intensity, and F0 range as predictor variable tested if the *k^hnallo* with *-sa* is different in prosody compared to the focused target word.

The pitch track in (Figures 24 & 25) shows the intonational contour of the sentence in focus and post-focus conditions. The *k^hnallo* word does not have the *-sa* in these focus conditions and is seen to have a high F0 on the final syllable just like in the target words, but this needs to be tested statistically.

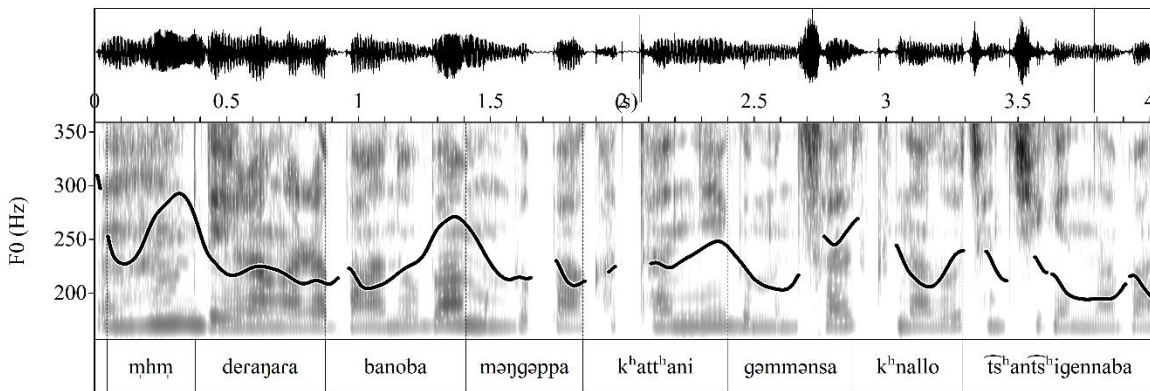


Figure 24: Pitch track of a sentence in focus condition. The *k^hnallo* word does not the *-sa* in this condition.

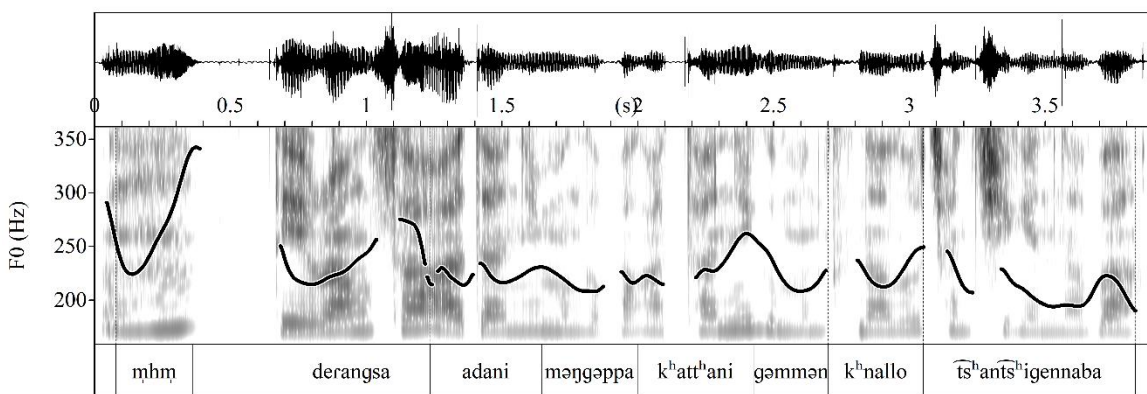


Figure 25: Pitch track of a sentence in post-focus condition. The *kʰnallo* word does not have the *-sa* in this condition.

The pitch track in (Figure 26) shows the intonational contour of a sentence in pre-focus condition. The *kʰnallo* word has the *-sa* particle in this condition and is seen to have a high falling contour on the final syllable, which is different from the contour seen on the final syllable of the *kʰnallo* without *-sa*, but this needs to be tested statistically.

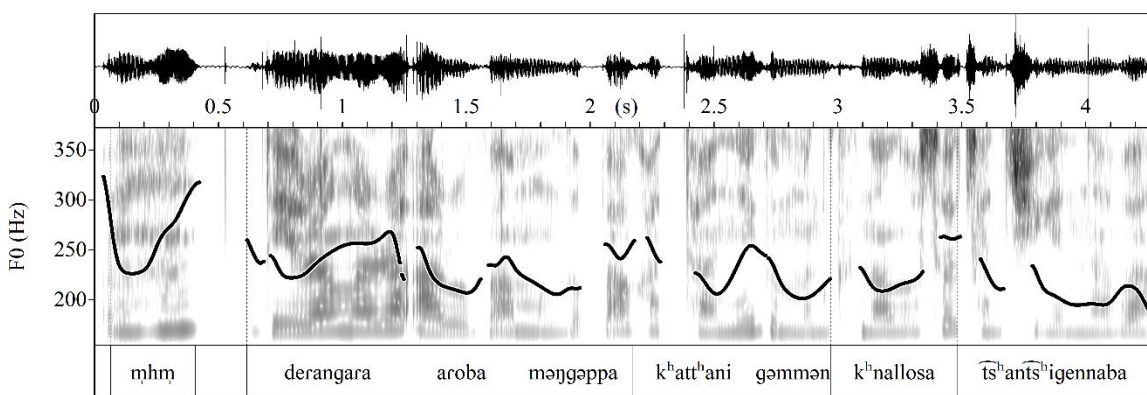


Figure 26: Pitch track of a sentence in the pre-focus condition. The *kʰnallo* word has the *-sa* in this condition.

The first part of this chapter will provide a description of the prosodic pattern using graphs. The description is based on the graphs of F0, Duration, Intensity, and Formants (F1 & F2) and gives an overview of the word prosodic pattern, i.e., which of the syllables differ from other syllables based on the aforementioned acoustic properties. There is also a comparison of the syllables between the *k^hnallosa* word and the target word to see if there is any meaningful difference between the two words. The second section of the chapter includes statistical analyses which tests whether the differences seen between the syllables in terms of the acoustic properties previously mentioned are statistically significant. The difference between the *k^hnallosa* word and the target word is also tested. This section includes the results of the statistical tests, the description of the results and also their interpretation. The third section of this chapter includes the discussion of the statistical results and connects it back to the pattern seen in the graphs. This chapter also interprets the pattern to state what the prosodic pattern is like with and without the focus marker “-sa.”

10.1 K^hnallo data

The data for this analysis is not the same as the data for the analyses in the preceding chapters. Additional participants had to be excluded for the analyses in this chapter due to too many missing data points for the *k^hnallo* vowels. Majority of the participants had missing F0 values in one or more vowel quarters. Only three participants were found to have enough F0 data and as a result only three participants are included for the analyses in this chapter – 1687, 6306, and 9761. The data norming was done by participant and only the [a] data was taken from the target word data, discussed in the previous chapters. The *k^hnallo* word data and the [a] data from the target word were normed together by participant. The reason why the *k^hnallo* word data and the [a] data were normed together was because it would allow for a more direct comparison between the *k^hnallo* and

the target word for the differences in the prosodic pattern. Since the *k^hnallo* word does not have the -sa in two focal conditions of this study, the *k^hnallo* without -sa in the focus condition is taken as the baseline condition for this analysis. The *k^hnallo* word was chosen to test the prosody of -sa over other words that carry -sa in other focal conditions of this study due to the fact that the vowels in *k^hnallo* are similar to the vowels included in the target word.

10.1 Descriptive statistics

The descriptive statistics examines the pattern of the aforementioned acoustic properties by using graphs. The F0 graphs are made using the mean of the normalized F0 at Q1 and Q4 of the vowel. Duration and Intensity graphs are also made using the normalized Duration. Vowel quality graphs are made using the normalized mean F1 and F2 in the Q2 and Q3 of the vowel.

10.2 F0 pattern

The vowel duration is split into four equal quarters so the F0 graph is made using the normalized mean F0 in the Q1 and the Q4 of the vowel.

10.2.1 F0 pattern in *k^hnallo* word

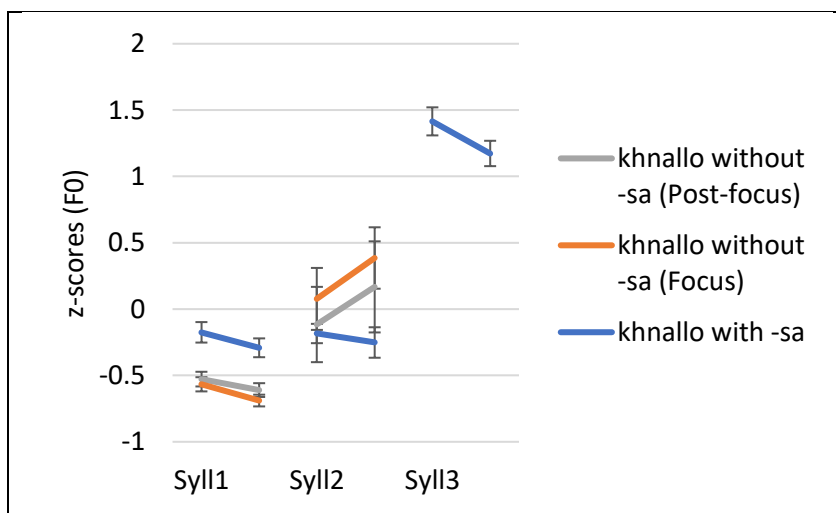


Figure 27: F0 track of *k^hnallo* words with and without *-sa* together made with mean of normalized F0 at Q1 and Q4 of each syllable. Syllable positions are on x-axis and z-scores (F0) on y-axis. *k^hnallo* words without *-sa* are in grey (post-focus) and orange (focus) and *k^hnallo* word with *-sa* is in blue.

The F0 track in Figure 21 shows that in *k^hnallo* words without *-sa* there is a low falling F0 on syllable 1 where the F0 falls slightly from the Q1 to Q4 of syllable 1. Conversely, there is a rising F0 on syllable 2 with the F0 rising from Q1 to Q4 of syllable 2. The rise in F0 on syllable 2 follows from the fall seen on syllable 1. The F0 peak is also reached on syllable 2. To summarize the F0 pattern, the lowest point is reached on syllable 1 which has a low falling F0 pattern, and the highest F0 point is reached on syllable 3 which has a flat high F0. Crucially, this is identical to the F0 pattern seen in the target word, i.e., in both the target word and the *k^hnallo* word without *-sa* the lowest F0 point is reached on the first syllable and the F0 peak is reached on the final syllable.

The two *k^hnallo* words without *-sa* are identical in terms of the F0 pattern. The effect of focal condition on F0 pattern is practically non-existent even in words that are situated towards the end of the sentence. This strengthens the observation that there is hardly any change under focus and also post-focally in the F0 pattern of the target word without the focus particle.

While the lowest F0 point in a word is also reached on the first syllable in the *k^hnallo* word with *-sa*, the lowest F0 point in the *k^hnallo* with *-sa* does not seem to be as low as the low point reached in the baseline *k^hnallo* word without *-sa* (in focus condition).

The F0 pattern on the final syllable is also different between the *k^hnallo* words with and without *-sa*. The final syllable (syllable 2) of *k^hnallo* without *-sa* has a rising F0 contour, i.e., the F0 rises from the Q1 to Q4 of the syllable, whereas the final syllable (syllable 3) of *k^hnallo* with *-sa* has a falling F0 pattern, i.e., the F0 falls from Q1 to Q4 of the syllable. It has to be noted however, that the highest F0 point in a word is still reached on the final syllable even in the *k^hnallo* word

with *-sa*. It does appear from Figure 21 that the *-sa* focus particle does cause a change in the F0 contour of a word that it attaches to. It appears to be the case that *-sa* causes a word to have a falling contour when it attaches to a word, i.e., instead of a word ending with a rising contour (usual pattern), the word has a falling F0 contour on the final syllable (which itself is the *-sa* particle) when the *-sa* particle attaches to it. From this comparison it can also be expected that the F0 contour on the final syllable will be different between the target word and the *k^hnallo* word with *-sa*, but a side-by-side comparison of the two word is still needed. This comparison is done in the following section.

10.2.2 Comparison of F0 patterns in *k^hnallo* with *-sa* and focused target words

This section compares the F0 pattern of the *k^hnallo* word with *-sa* and the target word in the focus condition, i.e., when the target word is within the focused constituent.

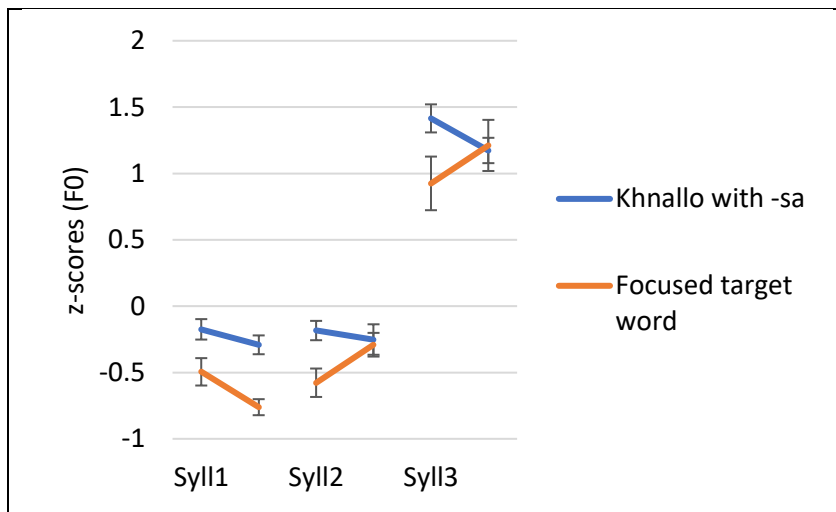


Figure 28: F0 track of *k^hnallo* with *-sa* and focused target words together made with mean of normalized F0 at Q1 and Q4 of each syllable. Syllable positions are on x-axis and z-scores (F0) on y-axis. F0 track for *k^hnallo* word is in blue and target word in orange.

The F0 track in Figure 32 shows that the F0 pattern is indeed different between the *k^hnallo* with *-sa* and the focused target words. The F0 contour on syllable 1 is low falling in the target word but is flatter on the *k^hnallo* word. The F0 falls from Q1 to Q4 of syllable 1 in the target word

but the F0 changes very little from the Q1 to Q4 of the *k^hnallo* word. The lowest F0 point is also not the same between the two words although the lowest F0 point is reached on syllable 1 in both the words. The F0 is lower on syllable 1 of the target word as compared to the syllable 1 of the *k^hnallo* word.

The F0 contour is also different between the two words on syllable 2. While the target word has a rising F0 contour, i.e., the F0 rises from the Q1 to Q4 of syllable 2 of the target word, the F0 contour is flat for the *k^hnallo* word, i.e., the F0 changes very little from Q1 to Q4 of syllable 2 of the *k^hnallo* word. The flat F0 level on syllable 2 of the *k^hnallo* word is also very similar to the F0 level on syllable 1 of the *k^hnallo* word.

As with the other two syllables, the F0 contour on syllable 3 is also very different between the two words. While the F0 contour of the target word is rising on the final syllable, i.e., the F0 rises from Q1 to Q4 of the syllable, the F0 contour on the *k^hnallo* word is falling instead, i.e., the F0 falls from Q1 to Q4 of the syllable. The point at which the highest F0 point is reached is different between the two words therefore. While the highest F0 point is reached at the end of the syllable, i.e., in Q4 in the target word, it is reached in Q1 in the *k^hnallo* word. The highest F0 point reached in the *k^hnallo* word also seems to be higher compared to the highest F0 point reached in the target word. Whether the difference is significant will have to be tested statistically, however.

10.3 Duration pattern

The Duration graphs are made with the normalized mean Durations of vowels.

10.3.1 Duration pattern in *k^hnallo* word

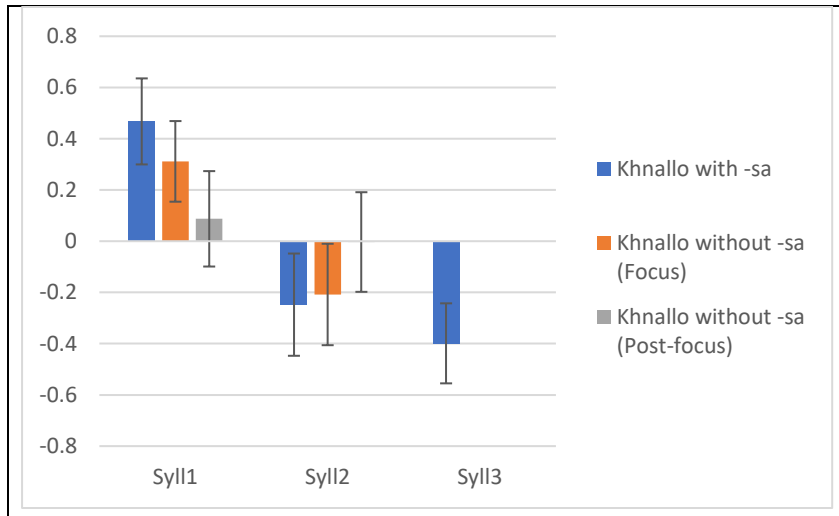


Figure 29: Duration patterns of the *k^hnallo* words with and without -sa. Syllable positions on x-axis and z-score (Duration) on y-axis.

The Duration graph in Figure 23 shows that in the *k^hnallo* words without -sa syllable 1 is the longest in the word compared to syllable 2. Crucially, this is identical to the pattern seen in the target word where syllable 1 is the longest syllable in a word. The basic duration pattern is the same in the two *k^hnallo* words without -sa but it has to be noted that the error bars overlap in the *k^hnallo* without -sa in the post-focus condition, so it is possible that the duration difference between the syllable positions is not statistically significant.

The basic duration pattern is similar in the *k^hnallo* word with -sa. Syllable 1 is the longest syllable compared to syllables 2 and 3. In the *k^hnallo* with -sa, which has three syllables, syllable 3 seems to be the shortest syllable in a word compared to syllables 1 and 2. Syllable 2 is in between syllables 1 and 3 in terms of duration. There does not seem to be a significant increase in duration when *k^hnallo* has the -sa as indicated by error bars that overlap compared to the baseline *k^hnallo* without -sa. From this comparison it seems to be the case that the duration pattern remains stable between the *k^hnallo* words with and without -sa. Another comparison that is necessary is the

comparison with the target word. While it is reasonable to expect that the basic pattern will remain the same, a comparison is still needed to confirm the pattern. This comparison is done in the following section.

10.3.2 Comparison of Duration patterns in *k^hnallo* with -sa and focused target words

This section compares the Duration pattern of the *k^hnallo* word with -sa with the target word in the focus condition, i.e., when the target word is within the focused constituent.

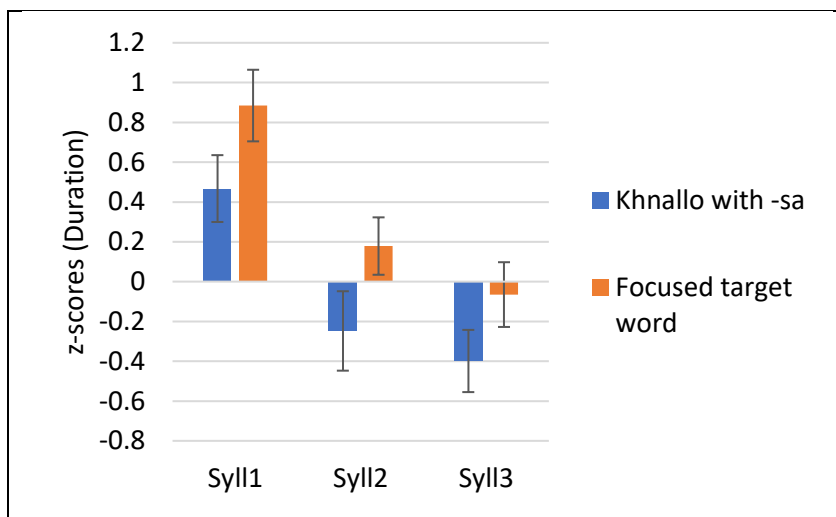


Figure 30: Duration patterns of *khnallo* with -sa and focused target words (normalized Duration). Syllable positions on x-axis and z-score (Duration) on y-axis. The *khnallo* word in blue and the target word in orange.

The Duration graph in Figure 24 shows that the basic pattern remains the same in both the words. Syllable 1 is the longest in both the words compared to syllables 2 and 3. Syllable 3 is the shortest in both the words compared to syllables 1 and 2. Syllable 2 lies somewhere in between syllables 1 and 3 in both the words. It is longer than syllable 3, but shorter than syllable 1. The target word does seem to have longer syllables as compared to the *k^hnallo* word with -sa. All of the syllable positions are longer in the target word compared to the *k^hnallo* word. It still needs to be statistically tested to say if the duration difference seen in the graph are significant.

10.4 Intensity pattern

The intensity graphs were made using the normalized mean Intensity in the middle portion of the vowels, i.e., the Q2 and Q3 of the vowel.

10.4.1 Intensity pattern in *k^hnallo* word

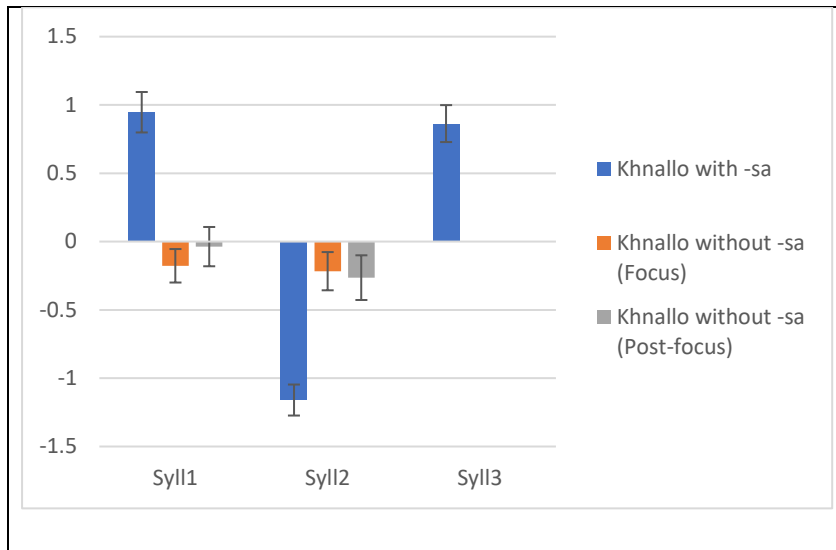


Figure 31: Intensity patterns of the *khnallo* words with and without -sa. Syllable positions on x-axis and z-score (Intensity) on y-axis.

The Intensity graph in Figure 25 shows that for *k^hnallo* words without -sa syllables 1 and 2 are very similar in intensity. The two *k^hnallo* words without -sa do not differ in terms of intensity pattern and level. While it might seem that syllable 1 of the *k^hnallo* word without -sa in post-focus condition has higher intensity, the overlap between the error bars is to such a degree that the difference is unlikely to be statistically significant.

The baseline *k^hnallo* without -sa and *k^hnallo* with -sa are different in their intensity patterns. While both the syllables have equal intensity in the baseline *k^hnallo* without -sa, in the *k^hnallo* with -sa syllable 2 has a lower intensity compared to syllables 1 and 3 which have similar intensity. The *k^hnallo* with -sa in general also has a higher intensity compared to the baseline *k^hnallo* without -

sa. Syllable 1 of the *k^hnallo* with *-sa* is more intense compared to the syllable 1 of the baseline *k^hnallo* without *-sa*. In syllable 2 however, the baseline *k^hnallo* without *-sa* has higher intensity compared to *k^hnallo* with *-sa*. There is no comparison for syllable 3 as the baseline *k^hnallo* without *-sa* only has two syllables. Another necessary comparison is that of *k^hnallo* with *-sa* with the focused target word. This comparison is done in the following section.

10.4.2 Comparison of Intensity pattern in *k^hnallo* with *-sa* and focused target words

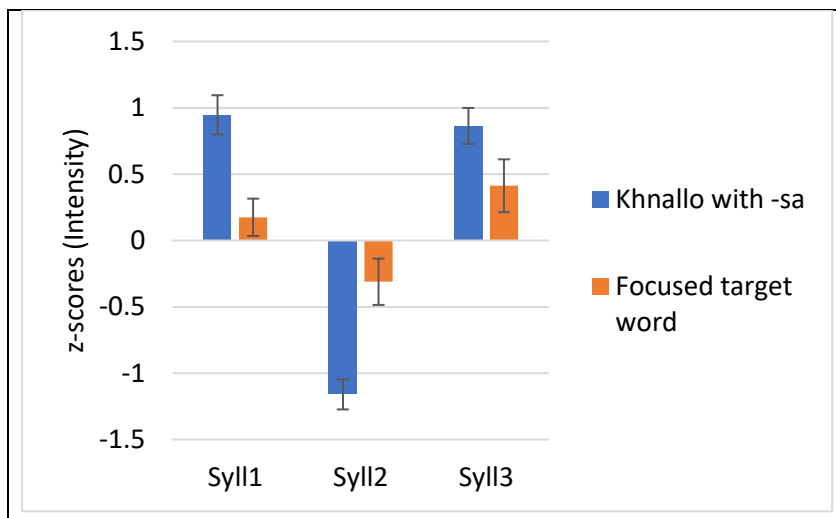


Figure 32: Intensity patterns of *khnallo* with *-sa* and focused target words. Syllable positions on x-axis and z-score (Intensity) on y-axis.

The Intensity graph in Figure 26 shows that the intensity pattern is different in the *k^hnallo* and the target words. The basic intensity pattern does remain the same between the two words, i.e., in both the words syllable 1 and 3 have similar intensities while syllable 2 has the lowest intensity compared to the other two syllables. The overall intensity is higher in the *k^hnallo* word compared to the target word, however. In syllables 1 and 3 the *k^hnallo* word has a higher intensity compared to the target word. In syllable 2 however the target word has a higher intensity compared to the target word. The differences between the two words will still need to be statistically tested, however.

10.5 Vowel quality pattern

The *k^hnallo* words without *-sa* only have two syllables. Additionally, the vowel qualities are fixed in each of the syllable positions since it is only the *k^hnallo* word that is the candidate word in this experiment. Due to these reasons, it does not make too much sense to examine the graphs for vowel centralization in the baseline and the post-focus conditions since the vowel qualities are entirely distinct in the two syllable positions. Nothing meaningful will come out of the examination. The pre-focus condition is different however, since *k^hnallo* has three syllables in this condition due to the presence of *-sa*. Additionally, syllables 1 and 3 have the same vowel quality, i.e., /a/ which opens up the possibility for examination for the presence of vowel centralization. The *k^hnallo* word with *-sa* can also be compared to the target in focus condition since only the /a/ data from the target word is included for analysis in this chapter. The vowel quality pattern is measured using the values of the first two formants (F1 and F2). The formant plot is plotted using the F1 and F2 values in Hertz to see if the vowel qualities differed between the three syllable positions as well as between the two focal conditions.

10.5.1 Vowel quality pattern in *k^hnallo* word with *-sa*

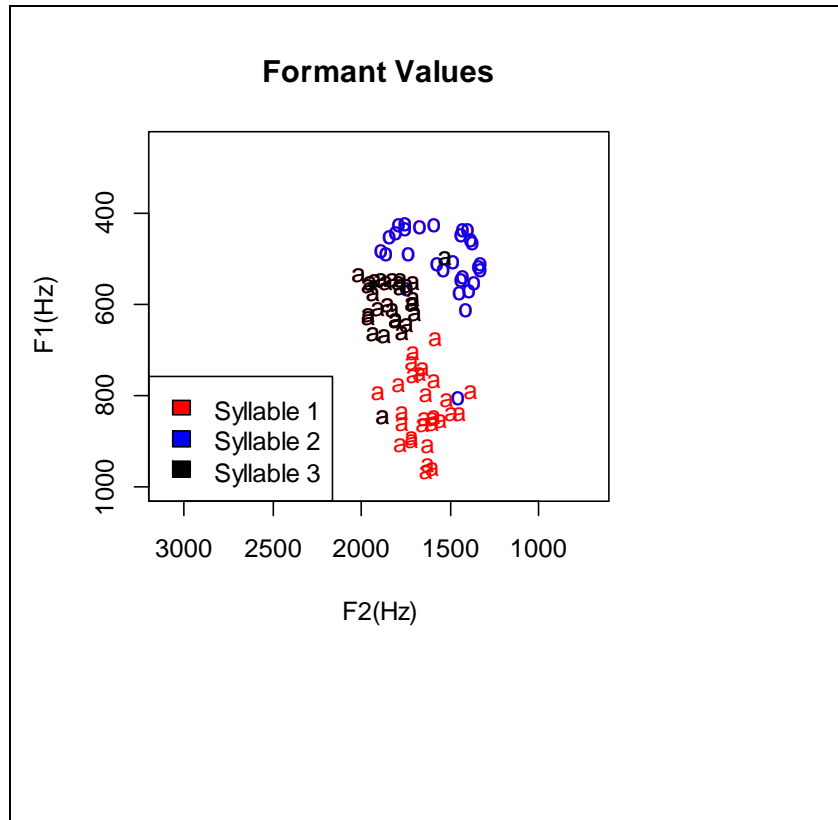


Figure 33: Vowel quality pattern in the *k^hnallo* with *-sa* made with *F1* and *F2* (Hz). *F2* (Hz) on *x*-axis and *F1* (Hz) on *y*-axis. Syllable positions are coded in different colours (consult the legend).

The vowel quality graph in (Figure 27) shows that syllable 1 is more peripheral compared to syllable 3. Nothing can be said about syllable 2 as it cannot be compared to anything else. The pattern of syllable 1 being the most peripheral is similar to the pattern seen in the target word. The *k^hnallo* word with *-sa* needs to be compared to the focused target word to determine if the two words are same in terms of their vowel quality. This comparison is done in the following section.

10.5.2 Comparison of vowel quality pattern in *k^hnallo* with -sa and focused target words

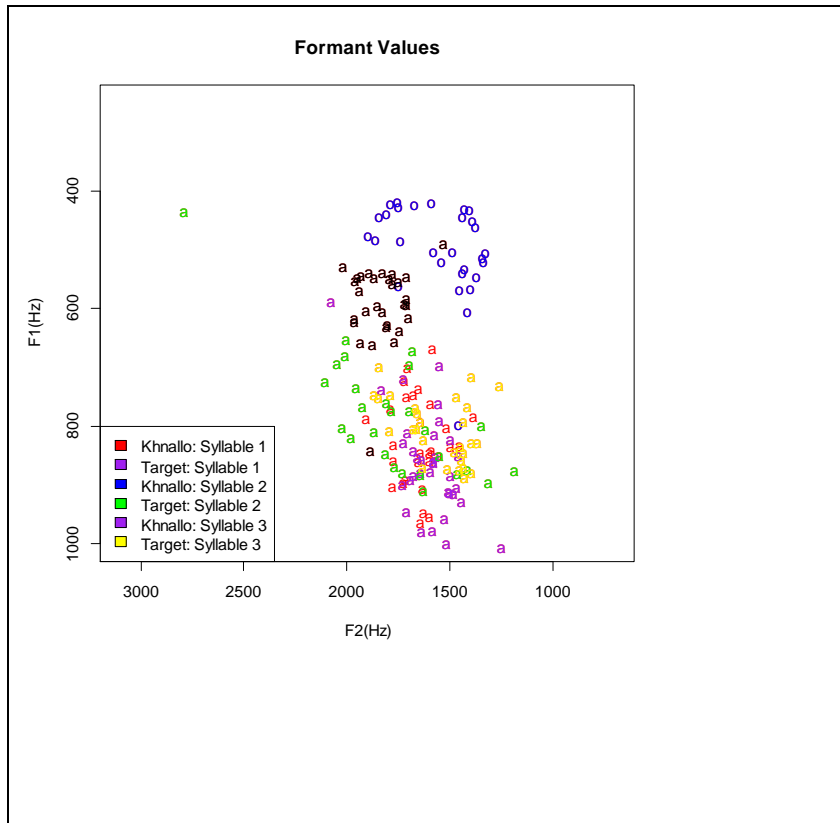


Figure 34: Vowel quality patterns of the *k^hnallo* with -sa and target (focus) words made with F1 and F2 (Hz). F2 (Hz) on x-axis and F1 (Hz) on y-axis. Focal conditions and syllable positions are plotted in different colours (consult the legend).

The vowel quality graph in Figure 28 shows that syllable 1 is equally peripheral in both the *k^hnallo* and the target words. In both the words syllable 1 is the most peripheral syllable in a word. Syllable 3 of *k^hnallo* word is relatively more centralized however. It is clearly more centralized compared to syllable 3 of the target word, but it is even more centralized compared to syllable 2 of the target word which is the most centralized syllable in the target word. This shows that syllable 3 of the *k^hnallo* word lies close to the center of the vowel space.

10.6 Statistical analysis

There are three types of comparisons made in this chapter. First of the comparisons compared the syllables of the focus (baseline) condition with each other to see if the difference between the syllables in terms of the acoustic properties seen in the graphs are statistically significant. In the interest of brevity, the baseline and the post-focus conditions are not compared in this chapter since they showed almost identical patterns.

In the second comparison, the syllables are compared between the baseline and the pre-focus conditions to see if some of the differences seen between the syllables in the two focal conditions are statistically significant. Since the baseline has only two syllables and the pre-focus has three syllables (due to the *-sa* particle), it was not only syllable 2 of the pre-focus but also syllable 3 of the pre-focus condition was compared to syllable 2 of the baseline condition. The rationale behind comparing syllable 3 of pre-focus and syllable 2 of baseline was that since these syllables were the final syllables in their respective focal conditions, their patterns should not be different if there is no prosodic focus. Comparing these syllables would allow for saying whether there is any difference in the patterns.

In the third comparison, the syllables are compared between the *k^hnallo* word (pre-focus condition) and the target word (focus condition). This comparison was also intended to provide answer to the question of whether there is any change in the prosodic pattern of a word in the presence of the focus particle *-sa*.

One important thing to note about the statistical analyses run in this chapter is that even though the kind of statistical test employed is the exact same as in the preceding chapters, the way the models are built is different. The data is still analysed using the *binary logistic regression* method. In the preceding chapters the models were built in such a way that all of the predictors

were fed into the model together and then post-hoc tests were conducted with the significant predictors. This way of model building did not work for the data in this chapter due to relatively fewer number of datapoints. The data in this chapter only includes three speaker and as a result the datapoints are fewer. Consequently, due to fewer number of datapoints the models with all of the predictors together did not converge. This is because there is complete separation of the data. In order to address this issue, the models in this chapter were run with single predictors instead, akin to how the post-hoc test was run for the models in the previous chapters.

The outputs of the models are also reported slightly differently in this chapter compared to the previous chapters. The details of the models are not provided in the test; see Appendix E for more information. Only the contents of the output table with the exception of the intercept estimates are included in the text.

10.7 Syllable comparison in the baseline *k^hnallo* without *-sa*

A logistic regression was conducted with syllable as the categorical variable. The predictor variables were: Duration, Intensity, Euclidean distance (ED), F0, F0 change ($\Delta F0$), and F0 range. Each of these predictor variables were tested individually for statistical significance. Syllable 1 was set as the reference category for this test. The output of this model is given below (Output 16). F0, $\Delta F0$, and F0 range were found to be significant predictors. For syllable 1 the model had 30 datapoints (F0, F0 range, ED, Duration, Intensity), 29 datapoints (F0 change), and for syllable 2 it had 26 datapoints (F0, F0 range, F0 change), 29 datapoints (ED, Duration, Intensity).

Output 16:

	Confidence interval
--	------------------------

Predictors	Estimate	Std. Error	z-value	p-value	Odds-ratio	2.50%	97.50%	Classification rate
F0	2.39	0.62	3.86	0.0001	11.01	3.68	43.7	98%
F0 change	5.44	1.72	3.16	0.001	232.63	18.44	23219.84	93%
ED	1	0.83	1.2	0.22				
Duration	-0.58	0.29	-1.94	0.051				
Intensity	-0.08	0.37	-0.21	0.82				
F0 range	3	0.8	3.73	0.0001	20.2	5.42	139.21	84%

An examination of the coefficients reveal that all three predictors have a positive coefficient. The positive coefficient as well as an odds ratio > 1 reveal that syllable 2 ($mean = 0.33$, $sd = 1.18$) has a higher F0 compared to syllable 1 ($mean = -0.66$, $sd = 0.27$). The z-scores were reconverted in to original units using the mean and standard deviation of speaker 1687 and syllable 2 ($mean = 241$ Hz) is on average 25 Hz higher in F0 compared to syllable 1 ($mean = 216$ Hz).

The positive coefficient for $\Delta F0$ as well as an odds ratio > 1 reveals that syllable 2 has a rising F0 ($mean = 1.23$, $sd = 1.1$) compared to a flat F0 on syllable 1 ($mean = -0.6$, $sd = 0.4$). The z-scores were reconverted into original units using the mean and standard deviation of speaker 1687 and the F0 on syllable 1 falls from Q1 ($mean = 207$ Hz) to Q4 ($mean = 209$ Hz) while the F0 on syllable 2 rises from Q1 ($mean = 228$ Hz) to Q4 ($mean = 245$ Hz).

The positive coefficient for F0 range as well as an odds ratio > 1 also reveals that syllable 2 ($mean = 1.22$, $sd = 1.42$) has a wider F0 movement compared to syllable 1 ($mean = -0.5$, $sd = 0.4$). The z-scores were reconverted into original units using the mean and standard deviation of speaker 1687 and the difference between the max F0 ($mean = 244$ Hz) and min F0 ($mean = 228$) 16 Hz is greater on syllable 2 compared to the difference seen on syllable 1 max F0 ($mean = 209.2$ Hz) and min F0 ($mean = 207.1$ Hz) 2.1 Hz. This shows that there is a greater F0 movement on syllable 2 compared to syllable 1.

10.8 Comparison of *k^hnallo* with and without -sa

This comparison compared the syllables between the focus and the pre-focus conditions to determine if the syllables were significantly different between the two focal conditions. Since the pre-focus condition has three syllables and the focus condition has only two syllables, syllable 3 of pre-focus is compared to syllable 2 of focus condition. Since both of these syllables are the final syllable in their respective focal conditions it makes for a reasonable comparison.

10.8.1 Syllable 1 *k^hnallo* without -sa vs syllable 1 *k^hnallo* with -sa

A logistic regression was conducted with focal condition as the categorical variable. The predictor variables were: Duration, Intensity, Euclidean distance (ED), F0, F0 change ($\Delta F0$), and F0 range. Each of these predictor variables were tested individually for statistical significance. Focus condition was set as the reference category for this test. The output of this model is given below (Output 17). F0, Euclidean distance (ED), Intensity, and F0 range were found to be significant predictors. For the of *k^hnallo* without -sa the model had 30 datapoints (F0, F0 range, ED, Duration, Intensity), and 29 datapoints (F0 change), and for the of *k^hnallo* with -sa the model had 29 datapoints (F0, F0 range, ED, Duration, Intensity), and 28 datapoints (F0 change).

Output 17:

Predictors	Estimate	Std. Error	z-value	p-value	Odds- ratio	Confidence interval		Classification rate
						2.50%	97.50%	
F0	3.67	1.03	3.57	0.0003	39.57	6.35	377.86	73%
F0 change	0.62	0.49	1.24	0.21				
ED	2.59	0.93	2.77	0.005	13.4	2.59	106.91	64%
Duration	0.2	0.3	0.68	0.49				
Intensity	2.01	0.51	3.88	0.0001	7.51	3.06	24.33	76%
F0 range	1.21	0.58	2.1	0.035	3.38	1.22	11.64	64%

An examination of the coefficients reveal that all three predictors have a positive coefficient. The positive coefficient as well as an odds ratio > 1 reveal that syllable 1 of *k^hnallo* with *-sa* ($mean = -0.25, sd = 0.4$) has a higher F0 compared to syllable 1 of *k^hnallo* without *-sa* ($mean = -0.66, sd = 0.27$). The z-scores were reconverted in to original units using the mean and standard deviation of speaker 1687 and syllable 1 of *k^hnallo* with *-sa* ($mean = 226.23\text{ Hz}$) is on average 10.23 Hz higher in F0 compared to syllable 1 of *k^hnallo* without *-sa* ($mean = 216\text{ Hz}$). This difference however is unlikely to be perceptually distinctive.

The positive coefficient for ED as well as an odds ratio > 1 reveals that syllable 1 of *k^hnallo* with *-sa* is more peripheral in the vowel space ($mean = 1.71, sd = 0.4$) compared to syllable 1 of *k^hnallo* without *-sa* ($mean = 1.1, sd = 0.3$). Syllable 1 of *k^hnallo* with *-sa* is 0.61 times farther away from the center of the vowel space compared to syllable 1 of *k^hnallo* without *-sa*.

The positive coefficient for Intensity as well as an odds ratio > 1 also reveals that syllable 1 of *k^hnallo* with *-sa* ($mean = 0.95, sd = 0.8$) is louder compared to syllable 1 of *k^hnallo* without *-sa* ($mean = -0.2, sd = 0.7$). The z-scores were reconverted into original units using the mean and standard deviation of speaker 1687 and syllable 1 of *k^hnallo* with *-sa* ($mean = 64\text{ dB}$) is on average 2.8 dB louder compared to syllable 1 of *k^hnallo* without *-sa* ($mean = 61.2\text{ dB}$).

The positive coefficient for F0 range as well as an odds ratio > 1 also reveals that syllable 1 of *k^hnallo* with *-sa* ($mean = -0.13, sd = 0.8$) has a wider F0 movement compared to syllable 1 of *k^hnallo* without *-sa* ($mean = -0.5, sd = 0.4$). The z-scores were reconverted into original units using the mean and standard deviation of speaker 1687 and the difference between the max F0 ($mean = 224\text{ Hz}$) and min F0 ($mean = 218\text{ Hz}$) 6 Hz is greater on syllable 1 of *k^hnallo* with *-sa* compared to the difference seen on syllable 1 of *k^hnallo* without *-sa* max F0 ($mean = 209.2\text{ Hz}$) and min F0

($mean = 207.1$ Hz) 2.1 Hz. This shows that there is a wider F0 movement on syllable 2 compared to syllable 1.

10.8.2 Syllable 2 of *k^hnallo* without -sa vs syllable 2 of *k^hnallo* with -sa

A logistic regression was conducted with focal condition as the categorical variable. The predictor variables were: Duration, Intensity, Euclidean distance (ED), F0, F0 change ($\Delta F0$), and F0 range. Each of these predictor variables were tested individually for statistical significance. Focus condition was set as the reference category for this test. The output of this model is given below (Output 18). F0, $\Delta F0$, Euclidean distance (ED), Intensity, and F0 range were found to be significant predictors. For the of *k^hnallo* without -sa the model had 26 datapoints (F0, F0 range, F0 change), and 29 datapoints (ED, Duration, Intensity), and for the of *k^hnallo* with -sa the model had 21 datapoints (F0), 23 datapoints (F0 range), 11 datapoints (F0 change), and 29 datapoints (ED, Duration, Intensity).

Output 18:

Predictors	Estimate	Std. Error	z-value	p-value	Odds- ratio	Confidence interval		Classification rate
						2.50%	97.50%	
F0	-1.35	0.62	-2.16	0.03	0.25	0.06	0.76	83%
F0 change	-5.97	2.78	-2.14	0.031	0.002			92%
ED	3.45	0.96	3.58	0.0003	31.61	5.91	270.59	74%
Duration	-0.03	0.24	-0.14	0.88				
Intensity	-1.98	0.54	-3.66	0.0002				
F0 range	-3.43	0.99	-3.43	0.0005	0.03			90%

An examination of the coefficients reveals that F0, $\Delta F0$, Intensity, and F0 range predictors have a negative coefficient and only ED has a positive coefficient. The negative coefficient as well as an odds ratio < 1 reveal that syllable 2 of *k^hnallo* without -sa ($mean = 0.32$, $sd = 1.17$) has a

higher F0 compared to syllable 2 of *k^hnallo* with *-sa* ($mean = -0.28, sd = 0.33$). The z-scores were reconverted in to original units using the mean and standard deviation of speaker 1687 and syllable 2 of *k^hnallo* without *-sa* ($mean = 241\text{ Hz}$) is on average 15.7 Hz higher in F0 compared to syllable 2 of *k^hnallo* with *-sa* ($mean = 225.3\text{ Hz}$).

The negative coefficient for $\Delta F0$ as well as an odds ratio < 1 reveals that syllable 2 of *k^hnallo* without *-sa* has a rising F0 ($mean = 1.23, sd = 1.1$) compared to the flatter F0 on syllable 2 of *k^hnallo* with *-sa* ($mean = -0.58, sd = 0.23$). The z-scores were reconverted into original units using the mean and standard deviation of speaker 1687 and the F0 on syllable 2 of *k^hnallo* with *-sa* stays relatively flat from Q1 ($mean = 218\text{ Hz}$) to Q4 ($mean = 224\text{ Hz}$) while the F0 on syllable 2 of *k^hnallo* without *-sa* rises from Q1 ($mean = 228\text{ Hz}$) to Q4 ($mean = 245\text{ Hz}$).

The positive coefficient for ED as well as an odds ratio > 1 reveals that syllable 2 of *k^hnallo* with *-sa* is more peripheral in the vowel space ($mean = 1.2, sd = 0.4$) compared to syllable 2 of *k^hnallo* without *-sa* ($mean = 1.7, sd = 0.4$). Syllable 2 of *k^hnallo* with *-sa* is 0.5 times farther away from the center of the vowel space compared to syllable 2 of *k^hnallo* without *-sa*.

The negative coefficient for Intensity as well as an odds ratio < 1 also reveals that syllable 2 of *k^hnallo* without *-sa* ($mean = -0.22, sd = 0.75$) is louder compared to syllable 2 of *k^hnallo* with *-sa* ($mean = -1.16, sd = 0.61$). The z-scores were reconverted into original units using the mean and standard deviation of speaker 1687 and syllable 2 of *k^hnallo* without *-sa* ($mean = 61.2\text{ dB}$) is on average 2 dB louder compared to syllable 2 of *k^hnallo* with *-sa* ($mean = 59.2\text{ dB}$).

The negative coefficient for F0 range as well as an odds ratio < 1 also reveals that syllable 2 of *k^hnallo* without *-sa* ($mean = 1.2, sd = 1.4$) has a wider F0 movement compared to syllable 2 of *k^hnallo* with *-sa* ($mean = -0.73, sd = 0.4$). The z-scores were reconverted into original units using the mean and standard deviation of speaker 1687 and the difference between the max F0

(*mean* = 244 Hz) and min F0 (*mean* = 228) 16 Hz is greater on syllable 2 of *k^hnallo* without -*sa* compared to the difference seen on syllable 2 of *k^hnallo* with -*sa* max F0 (*mean* = 219 Hz) and min F0 (*mean* = 218 Hz) 1 Hz. This shows that there is a wider F0 movement on syllable 2 of *k^hnallo* without -*sa* compared to syllable 2 of *k^hnallo* with -*sa*.

10.8.3 Syllable 2 of *k^hnallo* without -*sa* vs syllable 3 of *k^hnallo* with -*sa*

A logistic regression was conducted with focal condition as the categorical variable. The predictor variables were: Duration, Intensity, Euclidean distance (ED), F0, F0 change ($\Delta F0$), and F0 range. Each of these predictor variables were tested individually for statistical significance. Focus condition was set as the reference category for this test. The output of this model is given below (Output 19). F0, $\Delta F0$, Euclidean distance (ED), Intensity, and F0 range were found to be significant predictors. For of *k^hnallo* without -*sa* the model had 26 datapoints (F0, F0 range, F0 change), and 29 datapoints (ED, Duration, Intensity), and for of *k^hnallo* with -*sa* the model had 29 datapoints (F0, F0 range, F0 change), and 30 datapoints (ED, Duration, Intensity).

Output 19:

Predictors	Estimate	Std. Error	z-value	p-value	Odds- ratio	Confidence interval		Classification rate
						2.50%	97.50%	
F0	4.92	1.4	3.51	0.0004	137.68			80%
F0 change	-1.87	0.51	-3.66	0.0002	0.15	0.04	0.36	80%
ED	1.35	0.63	2.14	0.03	3.88	1.18	14.73	68%
Duration	-0.21	0.28	-0.76	0.44				
Intensity	2.91	0.82	3.52	0.0004	18.53	4.69	127.25	76%
F0 range	-1.39	0.43	-3.19	0.001	0.24	0.09	0.52	78%

An examination of the coefficients reveals that $\Delta F0$ and F0 range predictors have a negative coefficient and F0, ED, and Intensity have a positive coefficient. The positive coefficient as well

as an odds ratio > 1 reveal that syllable 3 of *k^hnallo* with *-sa* ($mean = 1.32, sd = 0.6$) has a higher F0 compared to syllable 2 of *k^hnallo* without *-sa* ($mean = 0.32, sd = 1.17$). The z-scores were reconverted in to original units using the mean and standard deviation of speaker 1687 and syllable 3 of *k^hnallo* with *-sa* ($mean = 266.6\text{ Hz}$) is on average 25.6 Hz higher in F0 compared to syllable 2 of *k^hnallo* without *-sa* ($mean = 241\text{ Hz}$).

The negative coefficient for $\Delta F0$ as well as an odds ratio < 1 reveals that syllable 2 of *k^hnallo* without *-sa* has a rising F0 ($mean = 1.23, sd = 1.1$) compared to the falling F0 on syllable 3 of *k^hnallo* with *-sa* ($mean = -0.29, sd = 0.84$). The z-scores were reconverted into original units using the mean and standard deviation of speaker 1687 and the F0 on syllable 2 of *k^hnallo* without *-sa* rises from Q1 ($mean = 228\text{ Hz}$) to Q4 ($mean = 245\text{ Hz}$) while the F0 on syllable 3 of *k^hnallo* with *-sa* falls from Q1 ($mean = 273\text{ Hz}$) to Q4 ($mean = 270\text{ Hz}$).

The positive coefficient for ED as well as an odds ratio > 1 reveals that syllable 3 of *k^hnallo* with *-sa* is more peripheral in the vowel space ($mean = 1.45, sd = 0.5$) compared to syllable 2 of *k^hnallo* without *-sa* ($mean = 1.2, sd = 0.4$). Syllable 3 of *k^hnallo* with *-sa* is 0.25 times farther away from the center of the vowel space compared to syllable 2 of *k^hnallo* with *-sa*.

The positive coefficient for Intensity as well as an odds ratio > 1 also reveals that syllable 3 of *k^hnallo* with *-sa* ($mean = 0.86, sd = 0.75$) is louder compared to syllable 2 of *k^hnallo* without *-sa* ($mean = -1.15, sd = 0.61$). The z-scores were reconverted into original units using the mean and standard deviation of speaker 1687 and syllable 3 of *k^hnallo* with *-sa* ($mean = 63.4\text{ dB}$) is on average 4.25 dB louder compared to syllable 2 of *k^hnallo* without *-sa* ($mean = 59.15\text{ dB}$).

The negative coefficient for F0 range as well as an odds ratio < 1 also reveals that syllable 2 of *k^hnallo* without *-sa* ($mean = 1.2, sd = 1.4$) has a wider F0 movement compared to syllable 3 of *k^hnallo* with *-sa* ($mean = -0.04, sd = 0.7$). The z-scores were reconverted into original units

using the mean and standard deviation of speaker 1687 and the difference between the max F0 (*mean* = 244 Hz) and min F0 (*mean* = 228) 16 Hz is greater on syllable 2 of *k^hnallo* without -*sa* compared to the difference seen on syllable 3 of *k^hnallo* with -*sa* max F0 (*mean* = 274 Hz) and min F0 (*mean* = 269 Hz) 5 Hz. This shows that there is a wider F0 movement on syllable 2 of *k^hnallo* without -*sa* compared to syllable 3 of *k^hnallo* with -*sa*.

10.9 *k^hnallo* word with -*sa* vs focused target word comparisons

This comparison compared the syllables between the *k^hnallo* word with -*sa* and the target word to determine if the syllables were significantly different between the two words.

10.9.1 Syllable 1 *k^hnallo* vs syllable 1 target word

A logistic regression was conducted with *k^hnallo* word (*k^hnallo* word coded 1, and target word coded 1) as the categorical variable. The predictor variables were: Duration, Intensity, Euclidean distance (ED), F0, F0 change ($\Delta F0$), and F0 range. Each of these predictor variables were tested individually for statistical significance. Target word (being coded 0) was set as the reference category for this test. The output of this model is given below (Output 20). F0, Euclidean distance (ED), and Intensity were found to be significant predictors. For the *k^hnallo* word the model had 29 datapoints (F0, F0 range, ED, Duration, Intensity), and 28 datapoints (F0 change), and for the target word the model had 34 datapoints (F0, F0 range, F0 change, ED, Duration, Intensity).

Output 20:

Predictors	Estimate	Std. Error	z-value	p-value	Odds- ratio	Confidence interval		Classification rate
						2.50%	97.50%	
F0	2.88	0.8	3.59	0.0003	17.83	4.27	102.2	70%

F0 change	0.51	0.39	1.3	0.19				
ED	1.27	0.54	2.31	0.02	3.57	1.3	11.58	60%
Duration	-0.43	0.26	-1.63	0.1				
Intensity	1.16	0.36	3.18	0.001	3.19	1.64	6.97	73%
F0 range	-0.47	0.31	-1.5	0.13				

An examination of the coefficients reveals that all of the predictors have a positive coefficient. The positive coefficient as well as an odds ratio > 1 reveal that syllable 1 of *k^hnallo* word ($mean = -0.74$, $sd = 0.5$) has a higher F0 compared to syllable 1 of the target word ($mean = -0.24$, $sd = 0.4$). The z-scores were reconverted in to original units using the mean and standard deviation of speaker 1687 and syllable 1 of *k^hnallo* word ($mean = 226.2$ Hz) is on average 14.2 Hz higher in F0 compared to syllable 1 of target word ($mean = 212$ Hz).

The positive coefficient for ED as well as an odds ratio > 1 reveals that syllable 1 of *k^hnallo* word is more peripheral in the vowel space ($mean = 1.42$, $sd = 0.45$) compared to syllable 1 of target word ($mean = 1.1$, $sd = 0.6$). Syllable 1 of *k^hnallo* word is 0.31 times farther away from the center of the vowel space compared to syllable 1 of target word.

The positive coefficient for Intensity as well as an odds ratio > 1 also reveals that syllable 1 of *k^hnallo* word ($mean = 0.95$, $sd = 0.8$) is louder compared to syllable 1 of target word ($mean = 0.2$, $sd = 0.61$). The z-scores were reconverted into original units using the mean and standard deviation of speaker 1687 and syllable 1 of *k^hnallo* word ($mean = 63.6$ dB) is on average 1.65 dB louder compared to syllable 1 focus ($mean = 61.95$ dB).

10.9.2 Syllable 2 *k^hnallo* vs syllable 2 target word

A logistic regression was conducted with *k^hnallo* word (*k^hnallo* word coded 1, and target word coded 1) as the categorical variable. The predictor variables were: Duration, Intensity, Euclidean distance (ED), F0, F0 change ($\Delta F0$), and F0 range. Each of these predictor variables were tested

individually for statistical significance. Target word (being coded 0) was set as the reference category for this test. The output of this model is given below (Output 21). $\Delta F0$, and Intensity were found to be significant predictors. For the *k^hnallo* word the model had 21 datapoints (F0), 23 datapoints (F0 range), 11 datapoints (F0 change), 29 datapoints (ED, Duration, Intensity), and for the target word the model had 27 datapoints (F0, F0 range, F0 change, ED, Duration, Intensity).

Output 21:

Predictors	Estimate	Std. Error	z-value	p-value	Odds- ratio	Confidence interval		Classification rate
						2.50%	97.50%	
F0	0.57	0.69	0.83	0.4				
F0 change	-6.59	2.28	-2.89	0.003				89%
ED	0.33	0.36	0.91	0.35				
Duration	-0.52	0.32	-1.63	0.1				
Intensity	-1.59	0.5	-3.17	0.001	0.2	0.06	0.48	77%
F0 range	-1.31	0.74	-1.75	0.07				

An examination of the coefficients reveals that both of the predictors have a negative coefficient. The negative coefficient for $\Delta F0$ as well as an odds ratio < 1 reveals that syllable 2 of target word has a rising F0 ($mean = 1.1$, $sd = 4.8$) compared to the flat F0 on syllable 2 of *k^hnallo* word ($mean = -1.73$, $sd = 3$). The z-scores were reconverted into original units using the mean and standard deviation of speaker 1687 and the F0 on syllable 2 *k^hnallo* word stays relatively flat from Q1 ($mean = 218$ Hz) to Q4 ($mean = 224$ Hz) while the F0 on syllable 2 target word rises from Q1 ($mean = 225$ Hz) to Q4 ($mean = 229$ Hz).

The positive coefficient for Intensity as well as an odds ratio > 1 also reveals that syllable 1 of target word ($mean = -0.31$, $sd = 0.91$) is louder compared to syllable 1 of *k^hnallo* word ($mean = -1.15$, $sd = 0.61$). The z-scores were reconverted into original units using the mean and standard

deviation of speaker 1687 and syllable 1 of target word (*mean* = 61 dB) is on average 1.85 dB louder compared to syllable 1 focus (*mean* = 59.15 dB).

10.9.3 Syllable 3 *k^hnallo* vs syllable 3 target word

A logistic regression was conducted with *k^hnallo* word (*k^hnallo* word coded 1, and target word coded 1) as the categorical variable. The predictor variables were: Duration, Intensity, Euclidean distance (ED), F0, F0 change ($\Delta F0$), and F0 range. Each of these predictor variables were tested individually for statistical significance. Target word (being coded 0) was set as the reference category for this test. The output of this model is given below (Output 22). $\Delta F0$, and ED were found to be significant predictors. For the *k^hnallo* word the model had 29 datapoints (F0, F0 range, F0 change), and 30 datapoints (ED, Duration, Intensity), and for the target word the model had 28 datapoints (F0, F0 range, F0 change, ED, Duration, Intensity).

Output 22:

Predictors	Estimate	Std. Error	z-value	p-value	Odds- ratio	Confidence interval		Classification rate
						2.50%	97.50%	
F0	0.27	0.33	0.82	0.41				
F0 change	-1.92	0.53	-3.61	0.0002	0.14	0.04	0.36	79%
ED	2.91	0.79	3.66	0.0002	18.5	4.6	111.07	81%
Duration	-0.49	0.34	-1.41	0.15				
Intensity	0.57	0.31	1.8	0.07				
F0 range	-0.31	0.26	-1.2	0.23				

An examination of the coefficients reveals that $\Delta F0$ has a negative coefficient and ED has a positive coefficient. The negative coefficient for $\Delta F0$ as well as an odds ratio < 1 reveals that syllable 3 target word has a rising F0 (*mean* = 1.05, *sd* = 1.05) compared to the falling F0 on syllable 3 pre-focus (*mean* = -0.29, *sd* = 0.84). The z-scores were reconverted into original units

using the mean and standard deviation of speaker 1687 and the F0 on syllable 3 *k^hnallo* word falls from Q1 (*mean* = 273 Hz) to Q4 (*mean* = 270 Hz) while the F0 on syllable 3 target word rises from Q1 (*mean* = 252 Hz) to Q4 (*mean* = 264 Hz). The positive coefficient for ED as well as an odds ratio > 1 reveals that syllable 3 of *k^hnallo* word is more peripheral in the vowel space (*mean* = 1.5, *sd* = 0.5) compared to syllable 3 of target word (*mean* = 0.9, *sd* = 0.4). Syllable 3 of *k^hnallo* word is 0.6 times farther away from the center of the vowel space compared to syllable 3 of target word.

10.10 Summary and discussion of the results

The analysis in this chapter was to answer the research question (v) concerning the prosody of the focus particle *-sa*. The statistical analysis comparing the syllable positions to one another in the *k^hnallo* without *-sa* showed that syllable 2 has a higher F0 compared to syllable 1 making it the syllable with the highest F0. Syllable 2 also has a high rising F0 compared to the low falling F0 on syllable 1.

The statistical analysis comparing the syllables between the *k^hnallo* with and without *-sa* showed that the prosodic pattern on *k^hnallo* with *-sa* is different from the *k^hnallo* without *-sa*. Syllable 1 of *k^hnallo* with *-sa* has a higher F0 compared to the syllable 1 of *k^hnallo* without *-sa* as it surfaces with a mid-level F0 instead of the usual low F0. The syllable 1 of *k^hnallo* with *-sa* also has a flat mid contour compared to the low falling contour seen on the syllable 1 of *k^hnallo* without *-sa*. Syllable 2 of *k^hnallo* without *sa* has a higher F0 compared to syllable 2 of *k^hnallo* with *-sa*. Syllable 2 of *k^hnallo* without *-sa* also has a high rising F0 contour as opposed to the syllable 2 of *k^hnallo* with *-sa* which has a flat mid contour that is identical in height and contour to the syllable 1. The final syllable of *k^hnallo* with *-sa* (syllable 3) has a higher F0 compared to the final syllable

of *k^hnallo* without *-sa* (syllable 2). The final syllable of *k^hnallo* with *-sa* also has a high falling contour compared to the final syllable of *k^hnallo* without *-sa* which has a high rising contour.

The statistical analysis comparing the syllable positions between the *k^hnallo* with *-sa* and the focused target words showed that the prosodic pattern of *k^hnallo* with *-sa* is also different compared to the focused target word. Syllable 1 of *k^hnallo* with *-sa* has a higher F0 compared to syllable 1 of focused target word. Syllable 1 of *k^hnallo* with *-sa* also has a flat mid F0 contour compared to the low falling on syllable 1 of the focused target word. Syllable 2 of the target word has a rising F0 contour compared to the flat mid F0 contour of the *k^hnallo* with *-sa*. Syllable 3 of the focused target word has a high rising F0 contour, whereas syllable 3 of *k^hnallo* with *-sa* has a high falling contour.

Interestingly, ED was also found to be different on syllable 3 between *k^hnallo* with *-sa* and the focused target word. The syllable 3 of *k^hnallo* with *-sa* is statistically more peripheral in the vowel space compared to syllable 3 of the focused target word. This result contradicts what is seen in the graph (Figure 28) however. In the graph it is seen that syllable 3 of *k^hnallo* with *-sa* is clearly more central compared to the syllable 3 of the target word. While interpreting this statistical result, it must be kept in mind that ED is calculated by basically adding the normalized F1 and F2 so it is entirely possible that syllable 3 of *k^hnallo* with *-sa* is more peripheral in terms of either F1 or F2 compared to syllable 3 of the target word even though it is really more central. This can be confirmed by plotting a graph using the normalized F1 and F2. Since normalization puts both F1 and F2 on same units, essentially centering the data, it can be seen whether syllable 3 of *k^hnallo* with *-sa* is more peripheral either along F1 or F2. This graph is plotted in (Figure 29):

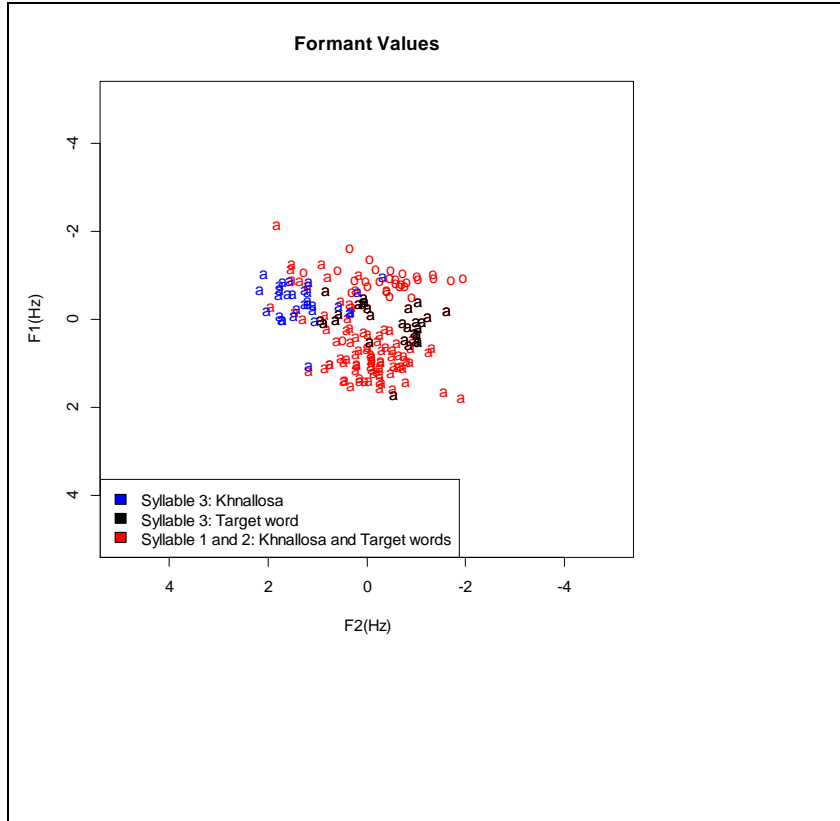


Figure 35: Formant plot made using the normalized F1 and F2. The F2 (z-scores) is on the x-axis and the F1 (z-scores) is on the y-axis. Datapoints in Red are not relevant for this comparison.

The formant plot in Figure 29 does confirm that the syllable 3 of *k^hnallo* with *-sa* is more peripheral along F2 compared to syllable 3 of the target word. Syllable 3 of both *k^hnallo* with *-sa* and target have similar values for F1. So, it is only because of higher F2 on syllable 3 of *k^hnallo* with *-sa* which means that it is more fronted in the vowel space that it ends up with a higher ED value.

The general observation is thus that in *k^hnallo* words without *-sa*, the pattern of the acoustic properties is very similar to what is seen in the target word. This is especially true for F0 and F0 contour which are identical, i.e., the initial syllable has a low falling F0 contour and lowest F0 point is reached on the first syllable and the final syllable has both a rising F0 contour and the highest F0 point. While the final syllable of target words does not usually have a steep F0 rise seen

on the final syllable of *k^hnallo* without *-sa*, it is explained by appealing to the fact that the *k^hnallo* word without *-sa* only has two syllables. If the lowest F0 point has to occur on the first syllable and the highest F0 point on the final syllable, there is inevitably going to be a rise on the final syllable of *k^hnallo* due to interpolation since there are only two syllables. The target word on the other hand has three syllables so the interpolation can happen on the second syllable, leaving the final syllable to have a flat high F0 contour.

The prosodic pattern of the *k^hnallo* word does change upon the introduction of *-sa* compared to both *k^hnallo* without *-sa* and the focused target word. The initial syllable changes its contour to have a flat mid-level F0 instead of the usual falling F0 contour of syllable 1 both *k^hnallo* words without *-sa* and the target words. This is probably a result of the upstepping of the L tone that aligns with the first syllable. The final syllable is also different in *k^hnallo* word with *-sa*. Instead of the usual high rising or flat high F0 seen on the final syllable of *k^hnallo* words without *-sa* and the target words, *k^hnallo* with *-sa* has a high falling contour instead even if the highest F0 point in the word is still reached on the final syllable. This fall seen on the final syllable of *k^hnallo* with *-sa* is probably due to an introduction of an additional L boundary tone by *-sa* particle that aligns with the final syllable of the word.

Chapter 11 – General discussion

This chapter both summarizes and discusses the results of the statistical analysis. The first part of the chapter discusses the prosody of word stress. The second part of the chapter discusses the effect of focus on word prosody. The third section discusses the effect of post-focal compression. Finally, the chapter also discusses the effect that the focus particle has on word prosody.

11.1 Prosody of Garo word stress

Two of the research questions of this study concern the word prosody. The first of the research questions is: (i) “*Does Garo have word stress?*” This question is worth asking because even if word stress is present in the majority of languages, there are some languages that have been found to lack word stress altogether (cf. Indonesian, French, & Korean: (Athanasopoulou et al., 2021; Jun, 2010; Jun & Fougeron, 2000)). The second one is (ii) “*How is stress signalled in Garo?*” The first of the questions will be answered if any of the syllables in a word stands out in terms of its acoustic properties. The answer to the second question is contingent on a positive answer to the first question. If the one syllable in a word does stand out from the rest in terms of its acoustic properties, the second question will be answered by identifying the acoustic property or properties that the stressed syllable possesses more of compared to the other syllables.

To answer the two questions above, the prosody of word stress was tested in the pre-focus condition. Pre-focus condition is appropriate to study the prosody of word stress on its own since it does not have any confounds of focus and because it is not affected by post-focal compression. The results of the statistical test confirm the observation from the graphs that the initial syllable is the longest in a word and the final syllable has the highest F0.

These results present a slight problem for interpretation. It is typically the case that the exponents of word stress surface on the same syllable (Gordon, 2014; Gordon & van der Hulst, 2020; Sluijter & van Heuven, 1996). This is not what is observed in Garo as the two acoustic properties affect two different syllables. In addition, the fact that the two syllables are marked by different acoustic properties makes the interpretation of the pattern more complicated. There have been analyses of languages like French in terms of “dual stress system” or a “hammock style stress” where there is high F0 on both edges of a word (Gordon, 2011b, 2016). Garo is still different from these languages with “dual stress” systems however, as the acoustic properties that mark the edge syllables of Garo words are different: duration marks the first syllable and high F0 marks the final syllable.

The problem of interpretation is resolved if duration is seen as a boundary level phenomenon instead of being a word level prosodic property. There are a couple of reasons to analyse duration as a boundary level phenomenon as opposed to a word level acoustic property. One of the reasons is an examination of the possible prosodic structure of the carrier sentences used in this study reveal that it lies at the edge of the phonological phrase. Granted that nothing definite can be said about the particulars of the prosodic hierarchy of Garo utterances due to absence of any studies done on Garo prosodic hierarchy, but based on how prosodic domains are typically formed (Nespor & Vogel, 1986), it can be said with relative confidence that the target word lies on the left edge of the phonological phrase:

Prosodic structure 4:

[[əhə]_{PP}]_{IP}, [[deɾaŋara]_{PP} [TARGET məŋgəppa]_{PP} [k^hatt^hani gəmmən]_{PP}]_{IP} [[k^hnallosa]_{PP}]_{IP}
 [ts^hants^hiɡennaba]_{PP}]_{IP}

“No, Derang is going to think about the word called X **TOMORROW**.”

Prosodic structure 4: Prosodic structure of the pre-focus condition.

The TARGET in (Prosodic structure 4) represents the target word. As can be seen in the speculated prosodic structure, the target word lies at the left edge of at least a phonological phrase. It therefore appears to be the case that Garo has initial lengthening instead of a more common final lengthening that is observed at the right edge of prosodic domains (Fougeron & Keating, 1997; Gussenhoven, 2007). A study on French reported some amount of domain initial lengthening of vowels (Georgeton & Fougeron, 2014)⁵, so it is not so off base to analyse the duration effect on the first syllable as being a boundary phenomenon rather than a word level effect. Another thing related to prosodic domains that seem to support this analysis of duration is that final lengthening does not seem to be very prominent in the language at least based on visual inspection of the speech signal. A strong caveat has to be emphasized for this statement about final lengthening however, as there was no attempt to do a quantitative analysis of the effect of final lengthening in this study.

Another set of evidence, or in the very least a circumstantial that point to duration being a boundary phenomenon come from the effect of focus on duration and the duration pattern seen in the word that is the subject of the post-hoc analysis in this study, i.e., the *k^hnallo* word. To break it down, focus does increase the duration, but it is not just the first syllable that increases in duration under focus, all the syllables increase in duration. In the *k^hnallo* word the duration differences between the syllables are not statistically significant, even though it has to be kept in mind that the post-hoc analysis was done with fewer datapoints, so the results are not as robust. These patterns

⁵ The study did report that lengthening effect was not consistent across vowels and speakers.

are discussed in detail in their respective sections of this chapter, but what these two patterns point to is that duration does not always reliably distinguish between syllables in a word.

Taking into consideration all of the points above, it is therefore reasonable to identify F0 as the acoustic property that expresses word stress in Garo. Intensity was not a significant predictor in majority of the models so it can be discarded as a cue of stress. F0 by far remains the most consistent cue to distinguish between syllables in a word. To summarize the F0 pattern again, the first syllable has low-falling F0 contour and the lowest F0 point in a word is also reached on the first syllable. After the low of the first syllable the F0 rises on the second syllable and continues to rise to the final syllable such that peak F0 is reached on the final syllable.

If F0 is taken as to signal stress in Garo, it can be seen that the final syllable has the highest F0 compared to the other syllables. It is therefore reasonable to analyse the final syllable as the stressed syllable in Garo. One of the things that point to the fact that the final syllable is the stressed syllable in the language is the consistent association of F0 peak with the final syllable in all the focal conditions and also in the *k^hnallo* word (more on these in the following sections). It can thus be clearly established that the final syllable is the stressed syllable in Garo and this validates Burling's (2003, 2017) description that Garo is a stress final language. Having said that Garo stresses the final syllable of words, the data in this study does not allow for a definitive statement about what the prosodic structure of the word level is. It is possible that the final syllable forms an iambic foot with the penultimate syllable as in as in (Prosodic structure 5):

Prosodic structure 5:

$[\sigma (\sigma ' \sigma)_{\text{Ft}}]_{\text{PW}}$

Prosodic structure 5: Proposed word prosodic structure with iambic foot.

In (Prosodic structure 5), the final two syllables of the word combine to form a foot and the second syllable of the foot is the head syllable. The foot type of Garo is therefore *bisyllabic iambic*. Additionally, it has to be stated that the final foot of the word is the head foot in Garo as it is always the final syllable of the word that is stressed.

It has to be noted at this point that even if the structure in (Prosodic structure 5) is correct, nothing could be said about whether the footing process is iterative based on the data. There is also no way to ascertain the directionality of the footing. The most reasonable proposal that can be forwarded based on the data if one goes down the route of proposing a bounded foot is that the final syllable forms an iambic foot with the penultimate syllable. Further research is needed to say anything concrete about the iterativity of the footing process and the directionality of the footing.

Alternative to the bounded iambic foot proposal, it could be proposed that Garo has an unbounded foot instead and that the final syllable regardless of syllable weight is stressed in a foot. If it is the case that Garo has unbounded feet, all of three syllables of the target word will form a single foot as in (Prosodic structure 6):

Prosodic structure 6:

$[(\sigma \ \sigma \ ' \sigma)_{\text{Ft}}]_{\text{PW}}$

Prosodic structure 6: Proposed word prosodic structure with unbounded foot.

In Prosodic structure 6, all three syllables in the trisyllabic target word forms a single foot and the final syllable within the foot is stressed with no regards for syllable weight. Either of the analysis, i.e., both the bounded iambic and the unbounded foot analysis fits the data in this study,

and it is left for the future research to determine which of the analysis is the correct one for the word prosodic structure of Garo.

The prosodic structures proposed in Prosodic structure 5 & 6 are proposed based on the principles of metrical stress theory laid out in (Hayes, 1995).

Having established that the final syllable is the stressed syllable in the language, the F0 as a cue to stress needs to be discussed. The F0 pattern seen on the target word could also have two interpretations. One of the interpretations of the F0 pattern is to say the high F0 is the exponent of stress and that the final syllable has a high F0 due to it being the stressed syllable. The logical end of this analysis of the F0 pattern is that in addition to the position of the abstract stressed syllable, the expression of stress on that syllable is also fixed in Garo.

The other slightly different analysis of the F0 pattern is to explain it in terms of intonational pitch accents. Since the F0 pattern is that the lowest F0 point is reached on the first syllable and the peak reached on the final syllable, an LH* intonational pitch-accent can be proposed for Garo (where L is an unstarred and H* is a starred tone). The L of LH* associates to the first syllable of the word and the H* of the LH* tonal complex by the virtue of it being a starred tone associates to the final syllable of the word since it is the stressed syllable in a word (Arvaniti & Fletcher, 2020; Beckman & Pierrehumbert, 1986; Gussenhoven, 2007). The logical end of this analysis is that only the position of the abstract stressed syllable is fixed or determined at the word level by the algorithm that builds the prosodic hierarchy. The F0 pattern itself is not defined at the word level but it instead arises due to intonation level pitch accents. One of the advantages of this analysis is that in addition to explaining the high F0 on the final syllable, it can also explain the low F0 on the first syllable. Under this analysis, the autosegmental-metrical structure of word stress can be represented as in (Prosodic structure 7):

Prosodic structure 7:

Prosodic structure 7: Proposed autosegmental-metrical structure of the word.

As the autosegmental metrical structure in Prosodic structure 7 shows, under the intonational pitch accent analysis, L of the LH* aligns with the first syllable of the word and the H* is aligned with the final stressed syllable.

To answer the research question (i) then, Garo does have stress. Garo either forms iambic feet and stresses the final foot of the word, or it has unbounded feet and the final syllable of the foot is stressed. The final syllable is the head syllable of a foot in both analyses and is therefore the stressed syllable. The prediction regarding question (i) that Garo will have word stress is thus confirmed. To answer research question (ii), either F0 is the exponent of stress or stress is expressed by association of the LH* intonational pitch-accent to the word where the H* tone of the LH* tone complex aligns with the stressed final syllable. The autosegmental-metrical structure of word stress can be represented as in (Prosodic structure 7). The prediction regarding question (ii) that the exponent of stress could be F0 is also confirmed by the results.

11.2 Focus and its prosody

Two further research questions in this study specifically concern focus. The first of the questions is: (iii) “*Is there any prosodic focus in Garo?*” This question will be answered in the positive if

the prosodic pattern of the focus condition is different in some way compared to the baseline condition. The second question related to focus is: (iv) “*How is focus signalled prosodically in Garo*” The answer to (iv) will be the acoustic property in which the focus condition differs from the baseline condition.

To summarize the basic pattern of the target word in the focus condition, it has the same prosodic pattern as the baseline (pre-focus) condition. In terms of duration, the pattern remained the same, i.e., the first syllable was the longest in the word, and even in terms of F0 the basic pattern is retained, i.e., the first syllable has the lowest F0 point and the final syllable has the F0 peak in the word. In the comparison between the focus and the baseline conditions, duration increase under focus compared to the baseline condition was statistically significant, but importantly, it is not a particular syllable that is singled out for the increase in duration. It also has to be highlighted that in comparisons between the focus and baseline conditions, classification rate of duration is just barely above the chance level.

The fact that the basic pattern in the focus condition is the same as the baseline condition indicates that focus does not alter the prosodic pattern of a word. This is somewhat unusual since languages usually signal focus prosodically by slightly altering the prosodic pattern under focus (Roessig & Mücke, 2019). One of the ways that languages usually signal focus is by changing the intonational pitch-accent on a word under focus condition. In German the pitch accent changes depending on the type of focus, i.e., the pitch accent that associate to a word changes depending on whether the focus being expressed is e.g., narrow or broad (Mücke & Grice, 2014). The narrow focus could therefore be differentiated from other type of focus conditions even if it is the case that the word receives broad focus by default. It is therefore totally conceivable that F0 pattern could unambiguously signal narrow focus on a word if it has it. This study did not find any change

in the F0 pattern of the target word in the focus condition however, which is already pointing to the fact that Garo does not have prosodic focus or at the very least not in the conventional sense.

In addition to the F0 pattern in the focus condition remaining identical to the baseline condition, Garo also does not have any additional F0 movement at the end of the focused word. If there was any additional F0 movement at the end of the target word under focus, it could be said that focus adds prosodic structure even if it does not change the pitch accent. Some researchers have proposed that focus not only introduces a pitch accent to the focused word, but also adds metrical structure to the focused word such that it carries a higher level prosodic boundary to the one that it would normally carry without the focus (Ladd, 2008; Nespor & Vogel, 1986). These proposals were initially theoretical in nature that were invoked to explain additional F0 movement seen at the end of the focused words, e.g., F0 fall at the end of focused words when it would normally end with a high F0. Another reason why addition of prosodic structure under focus was theoretically proposed was e.g., to address the problem of both words in a phrase like *FIVE FRANCS* being focused, which was left unresolved by the conventional explanation of focus affecting the *designated terminal element*. The problem is resolved by proposing two separate phrases for FIVE and FRANCS. This proposal also succeeds in capturing the F0 dip between FIVE and FRANCS since there is a prosodic boundary between the two words in this analysis (cf. Ladd, 2008; pp 273-280 for an in-depth discussion).

The prosodic structure addition under focus has not remained a purely theoretical proposal, however. An experimental study on Korean proved that focus does indeed add an intonational phrase boundary (Jeon & Nolan, 2017). Since Korean does not have lexical stress (Jun, 1996), it does not have the option to enhance the properties of word stress under focus. Instead, Jeon & Nolan (2017) found duration increases at the edge of the focused domains and also IP boundary

tones associating to the right edge of the focused word. It is clear then from both theoretical analyses and experimental evidence that focus can add prosodic structure which can in turn be detected by additional or different F0 movements at the edge of the focused item. Nothing of sort is observed in Garo, i.e., the F0 pattern does not change between baseline and the focus conditions indicating that there is no addition of prosodic structure under focus.

It is not only in the F0 pattern that the focus condition remains similar to the baseline condition. Even if there is a slight increase in the duration under focus, the increases happen on all of the syllables of the word and not on a particular syllable. Additionally, the F0 range does not change between the focus and the baseline. These points are crucial since languages have been found to enhance the acoustic properties of word stress under focus (Gordon, 2011a; Remijsen & Heuven, 2005; van der Hulst, 2010b; Vogel et al., 2017). Languages usually increase the F0 range under focus and also increase the duration and intensity (Ardali & Xu, 2012; Lee et al., 2015; Xu & Xu, 2005). The increase in the correlates of stress was certainly found in Greek and Spanish, where the F0 was higher on stressed syllables under focus (Vogel et al., 2016). There is also a reduction in F0 range seen on the words that occur before or after the focused word in many of the languages (Ardali & Xu, 2012; Xu & Xu, 2005). This process of reduction of F0 range comes broadly under the phenomenon of post-focal compression which will be discussed later in this chapter. The fact that Garo does not have any change in the F0 range between the baseline and the focus conditions further point towards absence of prosodic focus.

Even if the increase in duration under focus is considered more closely, it is crucial to note that the basic pattern of the property is still maintained. As in the baseline, the first syllable was still the longest under focus. Relatively speaking therefore, there was not real change to the pattern of duration. It is also important to repeat that the increase in duration happened on all of the

syllables of the word and not on a particular syllable. Additionally, the classification rate of duration when comparing the focus and baseline conditions was not very high as it was only slightly higher than the chance level. These results regarding duration ties back to what was said regarding the status of duration in the preceding section. The preceding section proposed to treat duration as a boundary phenomenon and thus leaving only F0 as a cue for stress. It is not only the fact that duration increase under focus is not substantial enough to set off focus clearly from the baseline condition, but also the fact that duration increases on all of the syllables that support the analysis that duration is not a cue for word stress.

From these results it can be proposed that the prosodic structure of the target word is identical between the baseline and the focus conditions. The correlate of stress is also the same under focus as in the baseline condition. The prosody of focus condition can therefore be represented as in (Prosodic structure 7), which is the prosodic structure for the baseline condition.

The results of the focus condition does not line up with what Burling (2003) described about focus in Garo. Burling impressionistically described two types of emphasis in Garo, what he calls “low-pitched emphasis” and “high-pitched emphasis.” The results of this study did not find evidence for either of the emphasis prosody that he described. It is possible though that the types of words that were used in this study does not allow for such prosodic emphases, as Burling did describe that these emphases are seen on very specific suffixes in Garo. Low-pitched emphasis is seen with tense suffixes and high-pitched emphasis with locative demonstratives. Further research is needed in order to say conclusively about whether Burling’s description of emphasis is correct. It also has to be noted that Burling describes a dialect of Garo that is spoken in Bangladesh which is different from the standard dialect.

To answer research question (iii), it is clear that Garo does not have prosodic focus. The basic pattern does not change under focus and remains the same as in the baseline condition. The prediction regarding question (iii) that Garo will have prosodic focus is thus disconfirmed. However, one has to leave open the possibility that the focus particle *-sa* does alter the prosodic structure of the constituent it attaches to. The post hoc analysis of *k^hnallo* word ought to provide a clearer answer as to whether the focus particle has any effect on the prosodic structure of the word that it attaches to. To answer research question (iv) then, there is no evidence to suggest that focus is expressed prosodically. The prediction for question (iv) that focus will either change the F0 pattern or enhance the properties of stress or both is also thus disconfirmed. As in the answer to research question (iii), it has to be left open for the possibility that the focus particle will introduce difference to the prosody of the constituent it attaches to.

One thing that has to be reiterated at this point is that the Garo has a focus particle and that the focus particle is not attached to the target word in the focus condition. The focus particle is attached to the final word of that phrase that contains the target word. In a sense this means that in the focus condition the focus on the target word is not a narrow focus but instead a broad focus where the entire constituent containing the target word is focused. It is entirely possible therefore that any prosodic expression of focus is tied to the focus particle *-sa*. It is possible that the *-sa* focus particle does add a prosodic structure to the constituent that it attaches to, it is just that this cannot be known from the target word under focus since it does not have the focus particle. This is the reason why the *k^hnallo* word was a subject of a post hoc test in this study since it has the focus particle in one of the focal conditions (pre-focus) of this study. The results of this post hoc test are discussed in the following section of this chapter.

One of the findings for languages that have focus particles is that it is that these languages can express focus prosodically in addition to the morphological marking of focus (Frota, 2000). Although these languages do not have the same prosodic expression of focus compared to languages that do not have focus particles i.e., they do not have e.g., different pitch accents to signal different kinds of focus, but they still have prosodic focus in terms of phrasing. Focus affects the phrase structure in these languages and therefore they have prosodic effects induced by phrase boundaries under focus (Frota, 2000; Kiss, 1995a). With these background about focus particles in mind, the prosody of the focus particle in Garo also needs to be studied. It is entirely possible as in these languages that the focus particle of Garo also alters the prosodic structure of the word that it attaches to. The analysis of the *k^hnallo* word data is in the following section.

11.3 Prosody of the focus particle

The research question that the post hoc analysis of the *k^hnallo* word looked to answer is: (v) “*Does the focus particle change the prosodic structure of the word that it attaches to?*” This question will be answered positively if there is any change to the prosodic pattern of the *k^hnallo* word when it has the focus particle (*k^hnallo* with *-sa*) as opposed to when it does not have the focus particle (*k^hnallo* without *-sa*). The prosodic pattern of the *k^hnallo* with *-sa* is also be compared to the focused target word to see if there is any difference between them in term of the prosodic structure.

To summarize the prosodic pattern of the *k^hnallo* without *-sa* (focus condition; baseline for this analysis) there is a low falling F0 on the first syllable and a high rising F0 on the final syllable. This pattern is identical to what is seen in the target word. This indicates that the low high F0 pattern seen on the target word stays consistent in across word within a sentence. This pattern seen on the *k^hnallo* word without *-sa* also lends credence to the analysis of the F0 pattern on target words in terms of intonational pitch accent since the alignment of both the low F0 point and the

high F0 point remains consistent across words, i.e., L aligns with the first syllable and H* aligns with the stressed final syllable. The prosodic structure of the *k^hnallo* without *-sa* will thus be the same as the target word in Prosodic structure 4 except without the middle syllable.

The F0 pattern of the *k^hnallo* word in the pre-focus condition of this study, i.e., *k^hnallo* with *-sa* is different from the baseline *k^hnallo* without *-sa*. Instead of the usual low falling on the first syllable, the *k^hnallo k^hnallo* with *-sa* has a flat mid level F0. Thus, *k^hnallo* with *-sa* and *k^hnallo* without *-sa* differ not only in terms of the average F0 on the first syllable, but also in terms of the F0 contour. The same distinction is also seen on the second syllable. While normally the F0 rises on the second syllable from the low F0 point on the first syllable, in the second syllable of *k^hnallo* with *-sa*, the F0 stays flat which matches the F0 level of the first syllable. It has to be noted however that a direct comparison cannot be made for the second syllables of *k^hnallo* words with and without *-sa* since the baseline *k^hnallo* without *-sa* is only disyllabic which makes its second syllable the final syllable. The second syllable of *k^hnallo* without *-sa* thus carry the prosody of the final syllable.

The F0 pattern of the final syllables also differed greatly between the two *k^hnallo* words. The baseline *k^hnallo* without *-sa* has, as noted above, a usual high rising F0 contour, but the *k^hnallo* with *-sa* has a high falling contour instead even though the F0 peak is still on the final syllable. The final syllables thus differ between the *k^hnallo* words.

In addition to the F0 pattern, there were other acoustic properties that the two *k^hnallo* words differed in. Intensity and F0 range also increased in *k^hnallo* with *-sa* indicating that the focus particle introduced more of these properties to the *k^hnallo* word. Of these two properties, intensity had the best classification rate indicating that there was more consistency in the intensity increase as compared to F0 range. For syllable 1, the *k^hnallo* with *-sa* has a higher intensity compared to *k^hnallo* without *-sa*, for syllable 2, the reverse is true as the syllable 2 of *k^hnallo* without *-sa* has a

higher intensity compared to *k^hnallo* with *-sa*. The comparison for syllable 3 was not as straightforward as syllable 3 of *k^hnallo* with *-sa* had to be compared to syllable 2 *k^hnallo* without *-sa*. This comparison does hold some merit however, as both of the syllables are the final syllables in the respective *k^hnallo* words.

The comparison of the *k^hnallo* with *-sa* with the focused target word showed that the F0 on the first syllable is significantly higher compared to the F0 seen on the first syllable of the focused target word. The fact that the F0 of the first syllable of *k^hnallo* with *-sa* is consistently higher than the usual F0 level seen on the first syllable points to the fact that *-sa* systematically raises the low F0 of the first syllable to mid. Intensity also seems to increase on the first syllable of *k^hnallo* with *-sa* relative to the intensity of the first syllable of the focused target word.

The F0 contour of the second syllable of *k^hnallo* with *-sa* is also different compared to the usual pattern. It is usual for the second syllable to have a rising F0 contour after the low on the first syllable and this is the pattern seen on the focused target word, however, in *k^hnallo* with *-sa*, the F0 contour is rather flat and it stays at the same level as the first syllable. The second syllable of *k^hnallo* with *-sa* also has a lower intensity compared to the second syllable of the focused target word.

The F0 contour of the final syllable is also significantly different between the *k^hnallo* with *-sa* and the focused target words. The usual pattern is to see a high rising or a high flat F0 contour on the final syllable as in the focused target word, but the pattern seen on *k^hnallo* with *-sa* is a falling F0 contour. It has to be noted however, that in both the words the F0 peak is reached on the final syllable, it is just the case that the *k^hnallo* with *-sa* displays an additional fall after the peak which is not seen on the target word.

A couple more interesting things to note about the prosodic pattern on the *k^hnallo* with *-sa* is that apart from the different F0 height of the first syllable compared to the target word, the F0 height and the range of the *k^hnallo* with *-sa* is overall the same. This indicates that there is no expansion of the F0 range even with the focus particle. Duration also remained unaffected in the *k^hnallo* with *-sa* compared to the target word. A caution must be exercised while interpreting the results of the post hoc analysis however, as the analysis was dealing with lot less data points compared to the main experiments of this study. The results still points to the fact that it is mostly the F0 pattern that is affected when the focus particle *-sa* is associated with a constituent.

The analysis of the *k^hnallo* words thus shows that the basic pattern seen at the word level without the *-sa* focus particle is that of a LH* F0 contour where the L associates to the first syllable and the H* associates to the final stressed syllable. This pattern remains consistent even in the baseline *k^hnallo* without *-sa* which is disyllabic. The consistency with which the L and H* tones associate to the first and the final syllables respectively lends more support to the analysis of the F0 pattern in terms of intonational pitch accents over the analysis of H on the final syllable as a cue to stress. The fact that duration remained unaffected in the *k^hnallo* with *-sa* also lends additional support to treating duration as a boundary phenomenon as opposed to being an acoustic correlate of word prosody. The acoustic pattern of the baseline *k^hnallo* word thus serve to confirm the analysis that was put forward based on the target word data.

The association of *-sa* to the *k^hnallo* word completely alters its prosody. The prosody of *k^hnallo* goes from having the usual F0 pattern without *-sa* to having a mid-level F0 on the first syllable as well as high fall on the final syllable with *-sa*. The difference in the F0 contour introduced by *-sa* also significantly distinguishes the *k^hnallo* word from the focused target word. The distinct pattern introduced by the focus particle points clearly to the phrasing effect introduced

by the focus particle. Morphosyntactic focus marking has been reported in the literature as clearly introducing prosodic structure (Frota, 2000). Prosodically, the reflex of this added prosodic structure has been reported in a couple of languages including Hungarian (Vogel et al., 2015). Hungarian has a morphosyntactic strategy to mark focus in that it moves the item to be focused to the specifier position of the Verb Phrase (Kiss, 1995b). The way that Hungarian marks focus in by no means purely prosodic (Frota, 2000), and even if though Hungarian does not have a focus particle, its strategy of marking focus more closely resembles how Garo marks focus. Even so, focused words were found to have a different F0 contour in Hungarian by Vogel et al. (2015). The usual F0 contour of Hungarian words is a H on the first syllable and a relatively flat F0 on the following syllables, i.e., the F0 does not drop substantially from the H on the first syllable in Hungarian words without focus. When the words are focused however, F0 fall is seen from the H on the initial syllable. The results reported by Vogel et al. (2015) for Hungarian is very similar to what is seen in Garo. The focus particle in Garo also introduces an F0 fall on the final syllable and the results from both Hungarian and Garo support the idea that focus marking introduces additional prosodic structure.

Similar pattern to Garo is also seen in Basque (Frota, 2000). In Basque, similar to Garo, focus introduces an additional F0 movement at the end of the focused constituent. Basque has lexical pitch accents so it has F0 movements associated with word by default. Focus only adds to the already existing F0 movement by introducing a H*L phrasal accent as Frota (2000) describes it. This H*L associates to the final syllable of the focused constituent. Frota makes it clear that this phrase accent is only seen under focus and has to do specifically with focus rather than syntactic phrasing because it is not seen in cases of topicalization which would form PPs on their own. The

way that Basque marks focus is therefore similar to what the focus particle does in Garo since there is an additional F0 movement introduced at the end of the focused constituent.

A more direct comparison of Garo data could be made with Korean. Korean is well known in the literature to have a particle *-nun* that signals contrastive focus (Choe, 1995; Frota, 2000). A description of the prosody of focus in Korean is that when the particle *-nun* attaches to a word to signal contrastive focus, it is not the focused word per se that is “accented,” but it is the particle itself that gets accented (Choe, 1995). It has to be kept in mind however, that this particular description on the prosody of focus was not based on an acoustic study but was likely an impressionistic description. This description thus needs to be interpreted in the light of what is known about Korean prosody. Jun (1998) makes it clear that Seoul Korean does not have lexical stress so it is very likely that the description of the prosody of focus in terms of “accent” is not accurate. Another study which even though it does not include the *-nun* particle, does report a difference in the F0 pattern introduced by focus (Jeon & Nolan, 2017). Jeon & Nolan (2017) found that in addition to the usual F0 pattern associated with the AP in Korean, which is in most cases LHLH (Jun, 1998), when the word is focused, there was an IP level boundary added to the word which consequently introduces IP level boundary tones, namely LH% or HL% causing extra F0 movement on the focused words (Jeon & Nolan, 2017).

When the descriptions about Korean focus prosody is considered holistically, it is found that the pattern is very similar to what is found in Garo. There is an introduction of additional prosodic structure under focus which inevitably introduces additional F0 movement in the form of boundary tones in both languages. The phenomenon of focus adding prosodic boundary to the focused constituent in Garo thus matches with what is seen in similar languages like Hungarian and Korean that also employ morphosyntactic strategies to mark focus.

From this discussion, it can be convincingly proposed that an IP level boundary is introduced by the focus particle in Garo which in turn introduces IP level boundary tones. This is different from what is seen on *k^hnallo* word without *-sa*. When the *k^hnallo* word occur without the *-sa* particle, the F0 pattern seen on it is the usual pattern which points to the fact that the prosodic structure is identical to what is seen on the target word. The prosodic structure for the baseline *k^hnallo* word without *-sa* can be represented as in (Prosodic structure 8):

Prosodic structure 8:

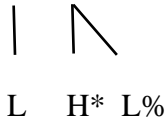
[k^hnallo]_{PW}

$\begin{array}{|c|c|} \hline | & | \\ \hline \end{array}$
 L H*

Prosodic structure 8: Proposed autosegmental-metrical structure of the k^hnallo without -sa.

The metrical structure proposed in (Prosodic structure 8) shows that the *k^hnallo* word forms a prosodic word just like the target word does. The intonational pitch accent that is associated with the baseline *k^hnallo* word at the autosegmental level is also still the same, i.e., it is still the LH* tone.

It can also be seen from the autosegmental-metrical structure of (Prosodic structure 8) that it is not enough to capture what happens under focus, i.e., when it has the focus particle *-sa*. There is additional prosodic structure needed on top of (Prosodic structure 8) in order to capture the changes in the F0 pattern introduced by the focus particle. This additional prosodic structure can be represented as in (Prosodic structure 9):

Prosodic structure 9:[[[k^hnallosa]_{PW}]_{PP}]_{IP}

Prosodic structure 9: Proposed autosegmental-metrical structure of k^hnallo with -sa.

The metrical structure proposed in (Prosodic structure 9) shows that the *k^hnallo* word with *-sa* does not have a simple prosodic word structure. The introduction of the focus particle *-sa* adds higher level prosodic boundaries to the constituent such that it has at least two more prosodic levels above the prosodic word. The addition of these prosodic structures invariably introduces extra elements at the autosegmental level as well. At the autosegmental level, there is still the LH* intonational pitch accent that associates to the prosodic word in Garo, but an additional intonational boundary tone L% is introduced. This L% boundary tone is what creates an extra F0 movement on the final syllable of *k^hnallo* with *-sa* and causes the F0 contour to fall from the H*.

While the autosegmental-metrical structure in (Prosodic structure 9) explains the F0 fall seen on the final syllable of *k^hnallo* with *-sa*, it does not explain the mid-level F0 seen on the first syllable. What exactly gives rise to this mid-level F0 on the first syllable needs to be explained even before a structural proposal can be put forward that modifies the structure in (Prosodic structure 9). It could be proposed that instead of the usual LH* intonational pitch accent the focus particle introduces a different pitch accent, perhaps a MH*, where the first tone of the complex is a mid tone. This proposal would certainly not be off base since as was discussed in the preceding section of this chapter, some languages do change the pitch accent to signal focus (Mücke & Grice, 2014; Roessig & Mücke, 2019). The objection to this proposal will instead come from the fact that

a phonological M tone is ad hoc for the prosody of Garo. A phonological M tone is unattested anywhere else in Garo prosody except for this case, so maybe an exploration of an alternative explanation is worthwhile.

A plausible alternative explanation for the mid-level F0 found on the first syllable is to propose that the F0 pattern arises out of upstepping the L of the usual LH* intonational pitch accent. This would mean that the mid-level F0 seen on the first syllable of *k^hnallosa* with *-sa* does not really arise out of a phonological mid tone but is instead a phonetic implementation of the upstepped L tone (\uparrow L). The advantage of this explanation is that it does not require a proposal of an ad hoc phonological category just to explain a single pattern and instead uses a widely attested phonological process to change a category that is necessary in the language. In this analysis of the F0 pattern of the first syllable, an additional statement needs to be added to the effect of the focus particle on the constituent it attaches to, namely that on top of adding metrical structure, it also affects the autosegmental level by upstepping the L of the pitch accent that associates to the word. Based on this analysis of the F0 pattern, the autosegmental-metrical structure of Prosodic structure 9 can be modified as in Prosodic structure 10:

Prosodic structure 10:

[[[k^hnallosa]_{PW}]_{PP}]_{IP}



*Prosodic structure 10: Revised autosegmental-metrical structure of the *k^hnallosa* with *-sa*.*

The autosegmental-metrical structure in (Prosodic structure 10) captures the F0 pattern seen on *k^hnallo* with *-sa*. The \uparrow L on the first syllable is phonetically realized as a mid tone and the fall on the final syllable is caused by the L% boundary tone at the end of the word by the intonational phrase boundary.

At the risk of going off in a tangent, the case of Garo focus particle not attaching to the target word in the focus condition, i.e., the fact that its position in the sentence was fixed is somewhat paralleled in how the focus particle works in Hausa (Inkelas & Zec, 1990). In Hausa the *-fa* particle signals focus on the immediately preceding word, but there are some constructions where its presence is ungrammatical. If e.g., in a Hausa sentence like “**He [BOUGHT-fa the table]_{PP}*,” the occurrence of the particle in the sentence is ungrammatical because “*the table*” follows it in the same phonological phrase. If, however the constituent “*the table*” is also focused such that it forms its own PP, the sentence becomes grammatical “*He [BOUGHT-fa]_{PP} [THE TABLE]_{PP}*.” The reason for this is that the *-fa* particle needs to occur at the end of a PP. Hausa facts have some parallel to the restriction of where *-sa* particle can occur in a sentence. From what can be determined the *-sa* particle in Garo is restricted to the specifier position of the phrase that contains the focused item. Admittedly the restrictions in Hausa and Garo regarding the position of the focus particles within the sentence do not match up one to one: Hausa has a phonological restriction, while Garo probably has a syntactic restriction, but the point is that restrictions on what constituent the focus particle can attach to are very much present in languages and it is simply not a quirk of Garo.

The answer to research question (v) then can finally be given after all these discussions. The focus particle *-sa* does change the prosodic structure of the constituent that it attaches to. For one it adds an IP level boundary to the constituent which in turn introduces a L% boundary tone

causing a fall on the final syllable after the peak of H*. Additionally, it also affects the autosegmental level of the constituent and changes the L of the LH* intonational pitch accent to \uparrow L causing the first syllable of the *k^hnallo* with *-sa* to surface with a phonetic mid-level F0. These findings tie back to the discussion about the focus condition where there was no evidence found for the prosodic expression of focus. The reason that focus and baseline conditions in the main experiment were identical can be understood in terms of prosodic effects of focus strictly affecting the word that the *-sa* particle attaches to. The prediction regarding question (v) that the focus particle will add prosodic structure to the word it attaches to is thus confirmed. Additionally, it was found that the focus particle also upsteps the L tone of the LH* pitch, which was not predicted to happen.

11.4 Post-focal compression

The question pertinent to the issue of post-focal compression is research question (vi): “*Is there post-focal compression in Garo?*” This question will be answered positively if there is any change to the prosody of the target word when it occurs post-focally in a sentence. Any change to the prosodic pattern and also any reduction to the acoustic properties post-focally will serve as evidence for the presence of post-focal compression.

One of the initial motivations behind looking at the post-focal compression in this study was to see whether there is any compression of the acoustic properties post-focally. The intention was to compare the pattern in the post-focal compression with what is seen in both the baseline and the focus conditions and identify the properties that change in the three focal conditions. The thinking was that identifying the properties that increased under focus compared to the baseline condition and decreased in the post-focal condition the acoustic correlates of stress could be more definitively identified.

To summarize and repeat the pattern seen in the post-focus condition, the basic pattern remained identical to the baseline. In terms of duration, syllable 1 is the longest in the target word and the F0 pattern is also identical, i.e., there is a low falling F0 on the first syllable and the lowest F0 point is also reached on the first syllable, and the F0 peak is reached on the final syllable. When the post-focus condition was compared to the pre-focus condition, syllable 1 of the post-focus condition is found to have higher F0 compared to the syllable 1 of baseline. It has to be noted however, that there is no change in the F0 contour of syllable 1 of post-focus compared to baseline. While syllable 2 of the post-focus is also found to be significantly higher in F0 compared to syllable 2 of the baseline, the classification rate of F0 is barely above the chance level so the difference is probably not as meaningful. Syllable 3 seemed to differ in terms of F0 where the baseline has a more rising F0 contour compared to the baseline, but again, the classification rate of $\Delta F0$ is so low that the difference in contour is unlikely to be meaningful. Besides mostly the F0 changing a little from the baseline to the post-focus, Intensity is also significantly different on syllable 1 where the post-focus condition has a louder syllable 1 compared to the baseline. Interestingly, duration was not affected at all in the post-focus condition.

The results of the post-focus experiment certainly does not provide evidence to support the presence of post-focal compression in Garo. There was no change to the basic prosodic pattern and neither was there any reduction in the acoustic properties of the vowels. This is certainly different from languages like Persian (Rahmani et al., 2018). One of the ways that languages usually signal focus prosodically is to not only enhance the acoustic properties of focused constituents and add prosodic structure to them, but languages also simultaneously change the prosody of surrounding constituents. The non-focused words, especially the words that occur post-focally lose their pitch accents such that they no longer have defined F0 movements. This is

certainly what happens in Persian (Rahmani et al., 2018). This process is known as *deaccentuation*. Rahmani et al. (2018) in fact show that post-focal deaccenting is the primary cue of prosodic focus in Persian as the increase in F0 under focus is not really consistent in Persian. If a language deaccentuates post-focally, there should be no defined F0 movement on words that follow the focused word. This is contrary to what is seen in Garo however, as the prosody of the target word does not change in the post-focal condition. To further provide evidence against deaccentuation in Garo, even the *k^hnallo* word, which is discussed in the preceding section (11.3), have the same prosody as the baseline target word.

Deaccentuation is also reported in German (Féry & Kügler, 2008). Similar to what happens in Persian, German also deaccentuates the words that occur post-focally. What is interesting about German is that unlike Persian, the F0 is heightened under focus but it still has post-focal deaccentuation. Similar phenomenon is also reported for Balochi (Syed et al., 2022) where there is deaccenting of the words that follow the focused word. The absence of such a phenomenon in Garo suggests that post-focal compression as a phonological process of marking prosodic focus is absent in the language.

Hungarian on the other hand is reported to lack any post-focal deaccentuation (Mády & Kleber, 2010). Hungarian words that follow the focused words still have F0 movements unlike German and Balochi. The Hungarian pattern thus resemble Garo very closely. Similarly, even though post-focal compression can occur in tonal languages, Xu et al. (2012) reports that Taiwanese Mandarin does not have any reduction of the F0 range post-focally. Considering Hungarian and Taiwanese Mandarin, it is not so surprising then that Garo does not have any post-focal compression. What is somewhat surprising perhaps that Garo does not employ any of the prosodic strategies usually seen in languages. Garo does not have any enhancement of the acoustic

properties under focus. Whatever prosodic effect is seen under focus only emerges when the focus particle attaches to the word as is discussed in the previous section of this chapter (11.3).

The fact that the post-focus conditions is identical to the baseline condition in its pattern indicates that the prosodic structure remains the same as the baseline target word. This statement is true not only for the target word in the post-focus condition, but also for the *k^hnallo* words so they have identical prosodic structures. Based on this, the autosegmental-metrical structure of the *k^hnallo* word without *-sa* (which applies for the target word as well) can be inferred to be identical to (Prosodic structures 7 & 8) and no new prosodic structure needs to be proposed for the post-focal condition. The structure in (Prosodic structure 8) is repeated below:

Prosodic structure 8:

[k^hnallo]_{PW}

$$\begin{array}{|c|c|} \hline | & | \\ \hline \end{array}$$
 L H*

Prosodic structure 11: Proposed autosegmental-metrical structure of the k^hnallo without -sa.

In (Prosodic structure 8) the L of the LH* pitch accent associates to the first syllable and the H* associates to the stressed final syllable. With the autosegmental-metrical structure identical to what is seen in the target word it is no wonder that the prosodic pattern does not change post-focally. The fact that even the focus condition has the same structure as in (Prosodic structure 7) also explains why there is not post-focal compression in Garo. The results tie together neatly as it can be stated that since focus does not really change the prosodic structure of the utterance (without the focus particle that is), there is no real avenue for post-focal compression to occur in Garo.

The results of the post-focal analysis even though there was nothing different about it compared to the baseline, allowed for a fuller understanding of the prosody of focus in Garo. Garo facts are interesting because there is complete absence of prosodic strategy to mark focus without the focus particle. Not only is there no enhancement of the acoustic properties under focus, there is not even a post-focal compression on the post-focal constituents in order to highlight the focused item. The lack of post-focal compression is observed not only on the target word in the post-focus condition, but also on the *k^hnallo* word which occurred post-focally in two of the focal conditions of this study. There was no evidence for post-focal compression on the *k^hnallo* word even in the two conditions where it does not have the focus particle. The prosody of a focused word only changes once the focus particle is attached to it.

The pattern completely changes once the focus particle attaches to the word however, as it not only adds an F0 fall at the end of the word, but it also upsteps the L of the LH* intonational pitch accent that associates to the prosodic word by default. All of these facts about word stress, focus, post-focus compression, and the prosody of the focus particle taken together gives a comprehensive picture about how the prosody of Garo works. It also adds to the understanding to how focus particles work prosodically in languages since there does not seem to be a lot of studies that directly tests the prosody of focus particles.

To answer the research question (v), there is no evidence for post-focal compression in Garo. The post-focus condition is identical to the baseline condition in its prosodic pattern. This is not only true for the target word but also for the *k^hnallo* word which occurs post-focally in two of the focal conditions. Not only does the pitch accent that associates to the prosodic word remain the same post-focally, but also, there does not seem to be any significant changes in the F0 range

which is typically what is affected post-focally. The prediction regarding question (vi) that Garo will have post-focal compression is thus disconfirmed.

Chapter 12 – Conclusion

Garo is an understudied language and nothing concrete is known about its prosody, so the aim of this study was to determine what the word stress pattern is in Garo with an acoustic study. Garo has been impressionistically described as a stress final language and there usually tends to be confounds of prominence and boundary related properties at the edges, so the study also aimed to answer the question of what the correlate of stress is in Garo by controlling for the boundary related properties. Additionally, the study also looked at the effect of focus and post-focal compression in Garo to see how these phenomena affect word stress, but these phenomena were also studied on their own. Finally, the prosody of the focus particle was also examined in this study by analysing the *k^hnallo* word in a post-hoc analysis since focus was not found to affect the prosody of the target word. In general, the prosody of focus particles is also not a well-studied area, so this study sought to add to the understanding of how focus particles work with prosody. With these aims in mind, this thesis did a production study by recording eight native speakers of Garo.

The study found that in terms of word stress, Garo does have final stress as has been described by Burling (2003). It could not be determined conclusively what the actual prosodic structure of the word level is in terms of the foot structure since the data in this study is not suited to answer this question. There are two possibilities of how the final syllable gets stressed in Garo: one possibility is that the final syllable and the penultimate syllable forms a quantity-insensitive iambic foot and the final syllable gets the stress by virtue of being the head syllable of the foot. The second possibility is that the language has unbounded feet and the final syllable of the unbounded foot is stressed regardless of the syllable weight. The stressed syllable is cued by an alignment of H* tone of the LH* intonational pitch accent. The L of the LH* aligns with the first

syllable of a word. The cue for stress in Garo is put simply therefore, the association of an intonational pitch accent.

Focus was not found to have any effect on the target word. The basic pattern in the focus condition stayed the same as in the non-focus condition. This showed that Garo does not change the intonational pitch accent under focus like some languages do. Additionally, the acoustic properties were not enhanced under focus. This showed that Garo also does not enhance the acoustic properties of stress under focus. The analysis of the focus particle on the *k^hnallo* word however, showed that the focus particle adds prosodic structure to the word it attaches to. The focus particle altered both the metrical and the autosegmental levels of the *k^hnallo* word when it attaches to it. At the metrical level it adds at least two high-level prosodic domains on the word, i.e., a PP and an IP thereby introducing an IP boundary to the word. The autosegmental level was also consequently affected as an additional tone in the form of a L% boundary tone was added to the tonal complex associating to the word. Additionally, the focus particle also upsteps the L of the LH* intonational pitch accent to [↑]L such that it is phonetically implemented as a mid tone. These additional prosodic structures invariably change the prosody of the *k^hnallo* word when it has the focus particle such that the first syllable of the *k^hnallo* with *-sa* surfaces with a phonetic mid tone instead of the usual low falling, and also there is an additional F0 fall on the final syllable instead of the usual high rising or high flat F0 contour. It is seen therefore that prosodic expression of focus only occurs when the focus particle attaches to a word.

Post-focal compression was also found to be absent in the language. Like in the focus condition, the basic prosodic pattern remained the same in the post-focal condition. The acoustic properties of stress are also not compressed post-focally. This lack of post-focal compression is not only seen on the target word but also on the *k^hnallo* word which was the subject of analysis for

the focus particle. Considering the focus and post-focus results together reveals that Garo does not mark focus prosodically in the absence of the focus particle.

This study therefore succeeds in providing a relatively comprehensive picture of at least the word prosody of an understudied language Garo. It adds to the typological understanding of how stress can be cued in languages. Its finding lines up with recent findings in stress studies that F0 is the primary cue to stress and disputes some claims that duration is the primary cue to stress. The findings of the focus, post-focal compression, and the focus particle analysis adds to the understanding of how focus is expressed prosodically in languages with morphosyntactic strategies of marking focus. The findings of lack of prosodic focus without the focus particle and the lack of post-focal compression in the language lines up with what has been found in similar languages. The analysis of the prosody of the focus particle has a standalone value and adds to the understanding of how a morphosyntactic way of marking focus functions together with prosody. This will hopefully open up an avenue for an acoustic analysis of the prosody of focus particles in other languages since there seems to be a lack of such investigations in the literature and Garo shows that focus particles can have very interesting prosodic properties. In closing, I would like to emphasize the fact that this study decided to go down the production study route not only because there has not been any acoustic study of Garo word prosody, but also to inform a future perception study. A perception study is still needed to confirm that the findings of this study are also perceptually salient.

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Appendix A – Two group of speakers

The participants in the study loosely formed two groups based on the F0 pattern on the target words. The two group of speakers differed in respect to the F0 pattern on the second syllable of the target words. A statistical analysis was done for the two groups of speakers which compared the syllable positions in pre-focus condition to one another, i.e., syllable 1 vs syllable 2, syllable 2 vs syllable 3, and syllable 1 vs syllable 3. These comparisons were done for the two groups separately to see whether the word prosodic pattern differed in the two groups. The results of the statistical tests revealed that these two groups did not differ significantly in terms of their F0 pattern however. Due to this, the data was pooled for the analyses in this study. The tests reported in this appendix were conducted just to confirm whether or not the two groups differed substantially in terms of F0. It will be worthwhile to still explore whether this divide in the prosodic pattern holds with larger datasets, this perhaps could be done in future studies. It will also be worthwhile to form an analysis for the difference seen in the prosodic pattern in the data collected for this study, but this is being left for the future as it is beyond the scope of this study.

The speakers roughly divided into two groups based on their F0 pattern. One group of speakers had a rising F0 on syllable 2, from the low fall on the syllable 1. The rise seen on the second syllable continues to a peak on syllable 3 in this group of speakers. The speakers that have this F0 pattern are: 9301, 6946, 7143, 3791, and 1687. This group of speakers is called *early rise speakers* hereon.

The second group of speakers have a different F0 pattern on the second syllable of the target words. This group of speakers have a relatively flat F0 on syllable 2 which is close to the lowest F0 point on syllable 1 which has a low falling F0. It is only on syllable 3 that the F0 rises

and reaches its peak in this group of speakers. So, the main difference of this group of speakers from the early rise speakers concerns the F0 pattern seen on syllable 2. The F0 pattern on syllable 1 and 3 are similar to the pattern seen on the other group of speakers. The speakers that have this F0 pattern are: 5793, 6306, and 9761. This group of speakers is called *late rise speakers* hereon.

The prosodic pattern of these two groups is thus described separately in order to capture what looks to be a difference between the two groups.

1. F0 pattern of early rise speakers

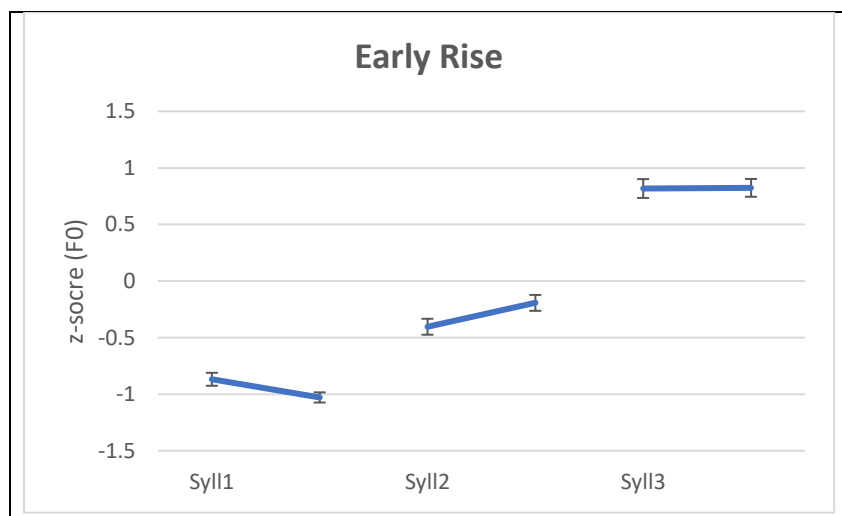
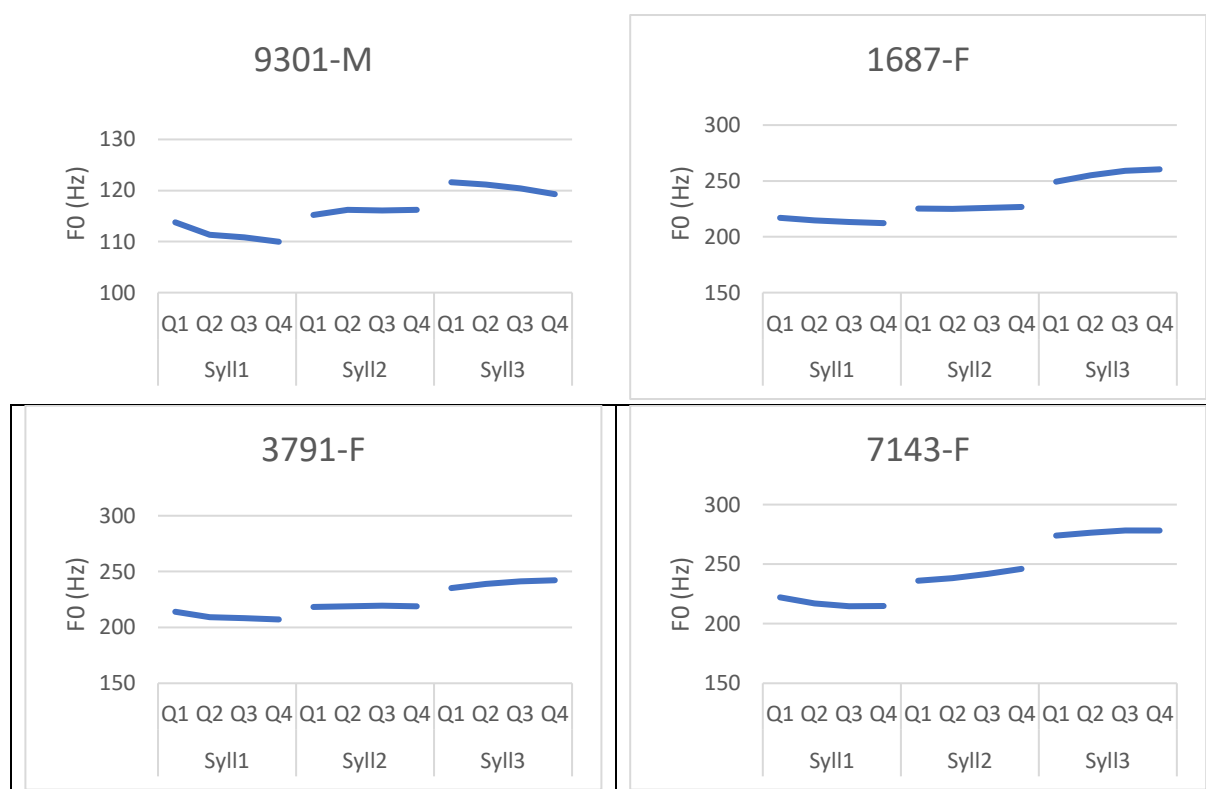


Figure 1: F0 track of Early rise speakers made with mean F0 at Q1 and Q4 of each syllable. Syllable positions are on the x-axis and z-scores(F0) are on the y-axis.

The F0 track in (Figure 1) shows that the *early rise speakers* have a low falling pitch on syllable 1. The F0 falls from Q1 to Q4 of syllable 1. The F0 then rises on syllable 2. The F0 rises from the low F0 on Q4 of syllable 1 and continues through the Q1 of syllable 2 to Q4 of syllable 2. The F0 peak is reached on syllable 3. The F0 on syllable 3 of *early rise speakers* is flat from the rise seen on syllable 2.

To summarize the pattern, there is a low falling F0 on syllable 1. The lowest F0 point in a word is reached in syllable 1, after which the F0 rises on syllable 2 to reach the peak on syllable 3. So, syllable 1 has the lowest F0 point and syllable 3 the highest F0 point.

The F0 track of individual speakers in this group is shown in (Figure 2). The F0 track for individual speakers is produced with the mean F0 in all four quarters instead of the track produced with the mean F0 of Q1 and Q4 for the whole group (Figure 1). The F0 track for individual speakers are also made using the raw F0 measurements in Hz instead of the z-scores. The general pattern is seen in the F0 track of individual speakers too, i.e., the lowest F0 point is on syllable 1 and the highest F0 point is seen on syllable 3.



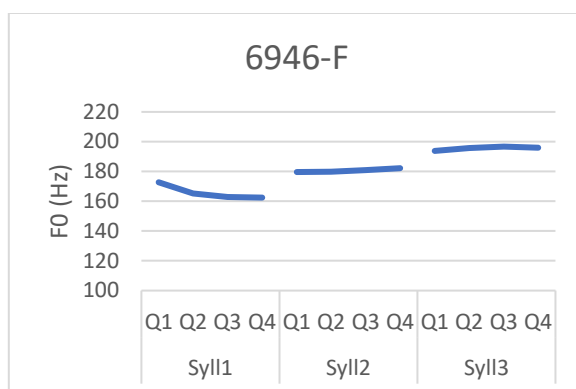


Figure 2: F0 track of each individual speaker in the early rise group made with mean F0 at all four quarters of the target vowel. Syllable positions are on the x-axis and F0 (Hz) in on the y-axis.

2. F0 pattern of late rise speakers

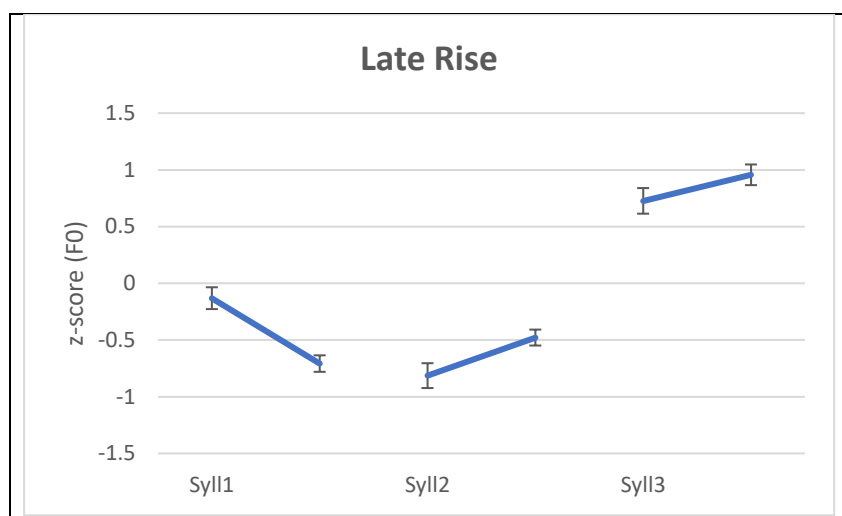


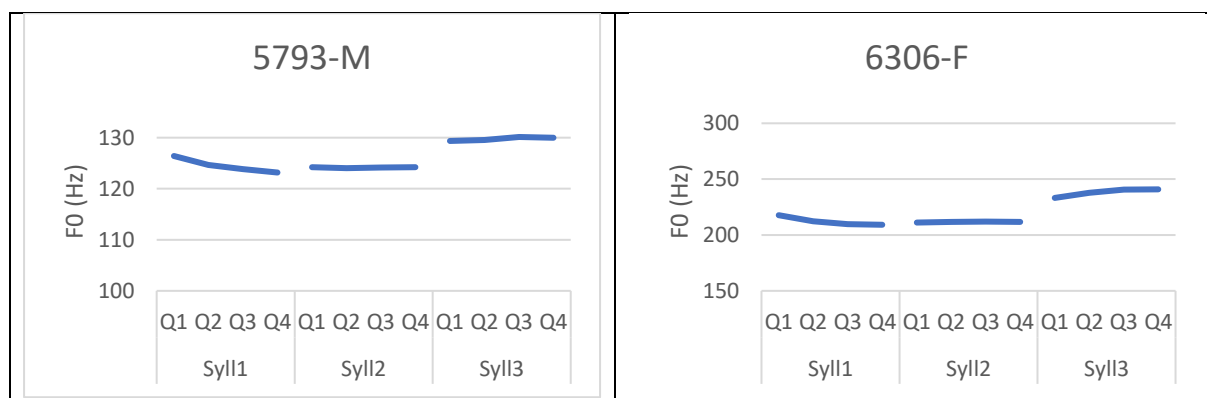
Figure 3: F0 track of Late rise speakers made with mean F0 at Q1 and Q4 of each syllable. Syllable positions are on the x-axis and z-scores(F0) are on the y-axis.

The F0 track in (Figure 3) shows that *late rise speakers* have a low falling F0 on syllable 1. The F0 falls from Q1 to Q4 of syllable 1. The F0 on syllable 2 stays relatively flat as there is very little change from Q1 to Q4 of syllable 2. The F0 level of syllable 2 is very close to the low

F0 point on syllable 1. The F0 peak is reached on syllable 3 with very little F0 movement on syllable 3 itself.

To summarize the pattern, there is a low falling F0 on syllable 1. The lowest F0 point in a word is reached on syllable 1, and the peak is reached on syllable 3. So, syllable 1 has the lowest F0 point and syllable 3 the highest F0 point. In this pattern, the two group of speakers (early and late rise) are exactly the same. The only difference seen between the two groups concern the F0 pattern on syllable 2. While early rise speakers have a rise on syllable 2 from the lowest point on syllable 1, the late rise speakers have a relatively flat F0 on syllable that is a continuation of the lowest F0 point on syllable 1.

The F0 track of individual speakers in late rise group is shown in (Figure 4). The F0 track for individual speakers is produced with the mean F0 in all four quarters instead of the track produced with the mean F0 of Q1 and Q4 for the whole group (Figure 1). The F0 track for individual speakers are also made using the raw F0 measurements in Hz instead of the z-scores. The general pattern is seen in the F0 track of individual speakers too, i.e., the lowest F0 point is on syllable 1 and the highest F0 point is seen on syllable 3.



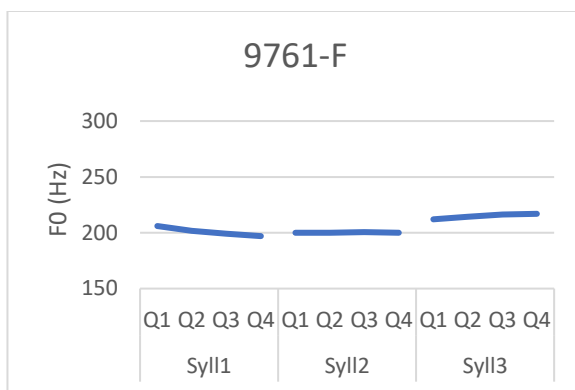


Figure 4: F0 track of each individual speaker in the late rise group made with mean F0 at all four quarters of the target vowel. Syllable positions are on the x-axis and F0 (Hz) is on the y-axis.

3. Vowel duration pattern of early rise speakers

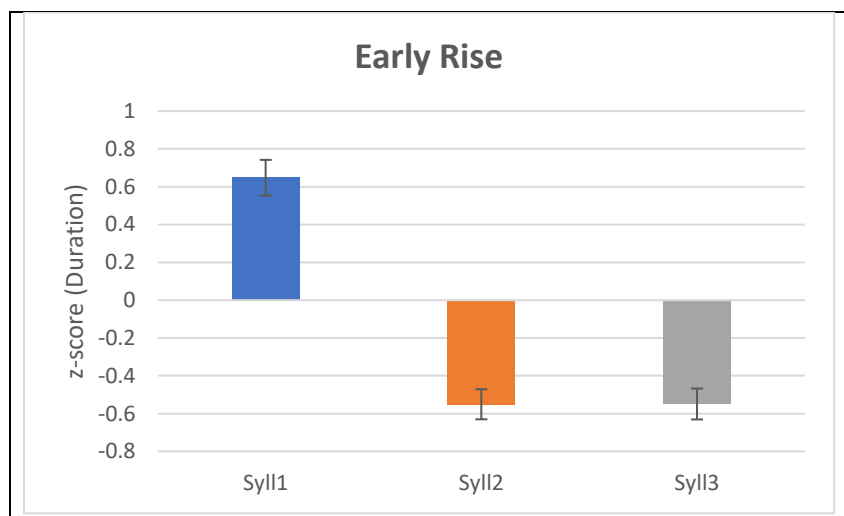


Figure 6: Graph of vowel duration pattern for early rise speakers made with z-scores (Duration). Syllable positions are on the x-axis, and z-scores (Duration) are on the y-axis.

The vowel duration graph in (Figure 6) shows that for early rise speakers, syllable 1 has the longest duration compared to syllables 2 and 3. The syllables 2 and 3 are similar in length. Syllable 1 is therefore the longest syllable in a word.

The vowel duration pattern for individual speakers in the early rise group is shown in (Figure 7). The general pattern is seen in all the individual speakers too, i.e., syllable 1 is the longest syllable in a word compared to syllables 2 and 3 which are similar in length.

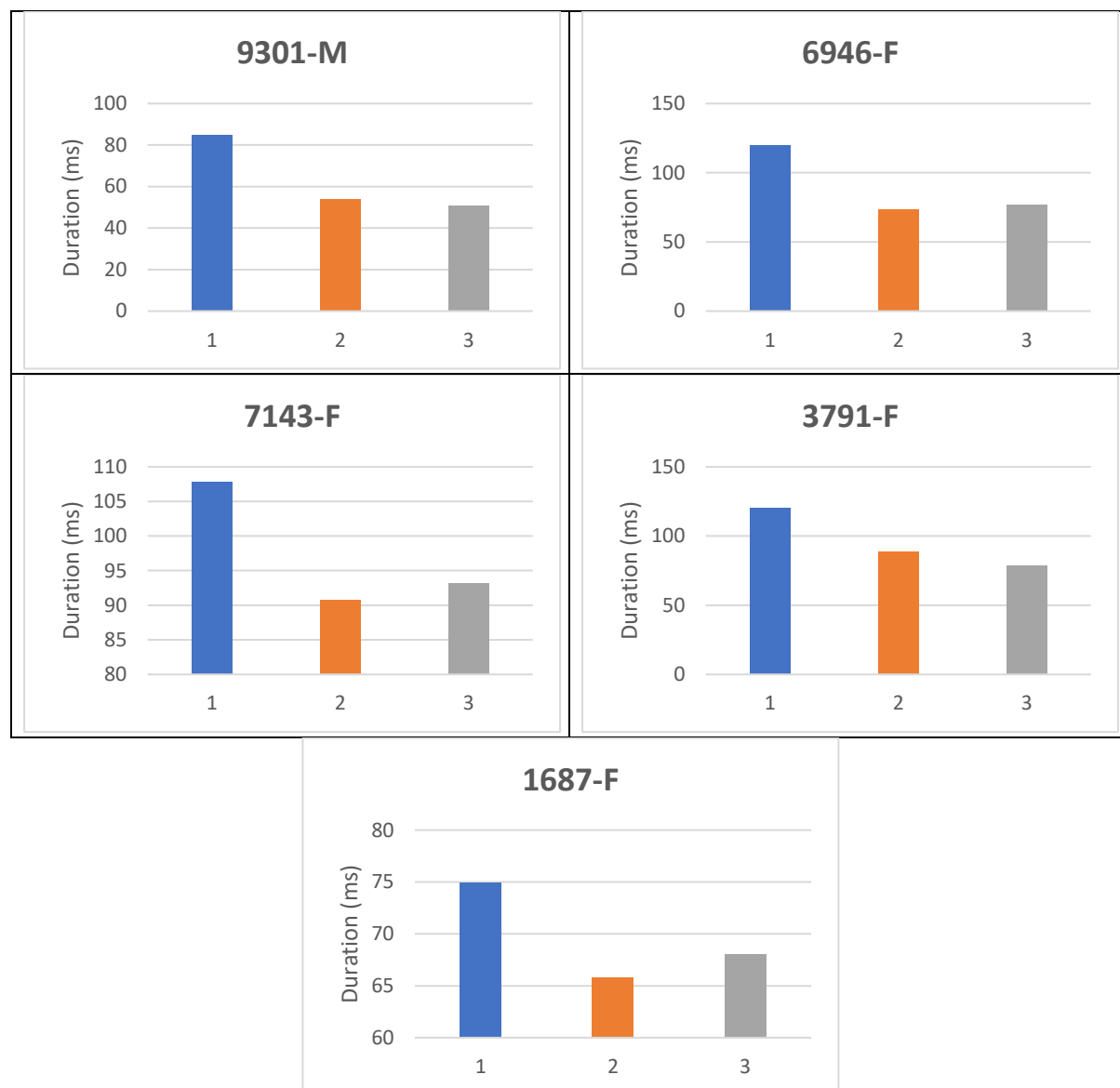


Figure 7: Duration pattern of each individual speaker in the early rise group made with mean Duration. Syllable positions are on the x-axis and Duration (ms) is on the y-axis.

4. Vowel duration pattern for late rise speakers

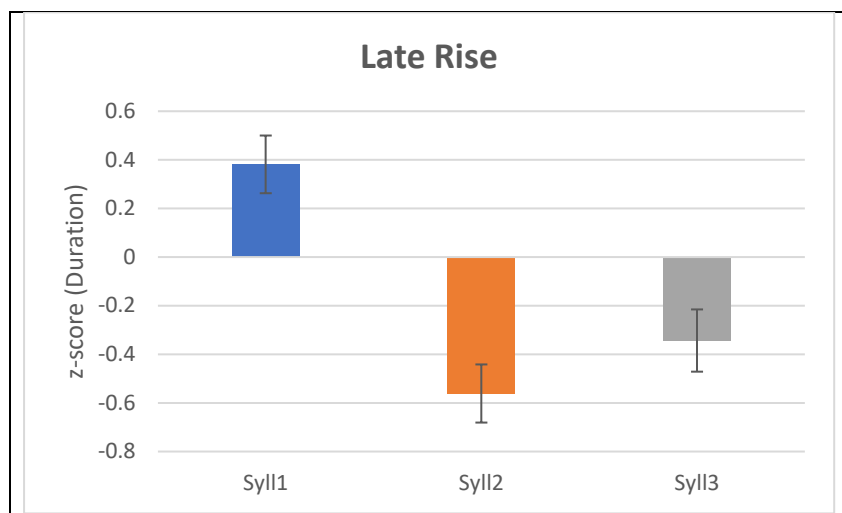
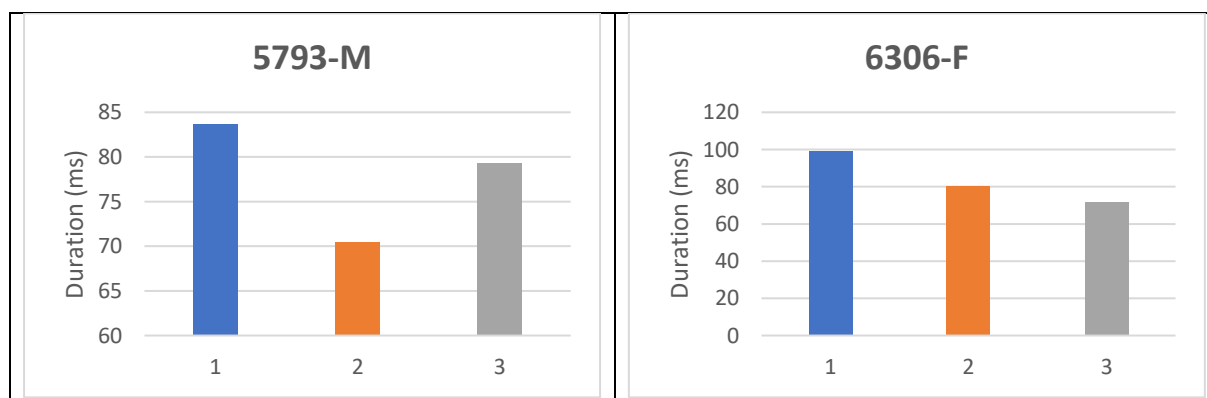


Figure 8: Graph of vowel duration pattern for late rise speakers made with z -scores (Duration). Syllable positions are on the x -axis, and z -scores (Duration) are on the y -axis.

The vowel duration graph in (Figure 8) shows that for late rise speakers, syllable 1 has the longest duration compared to syllables 2 and 3. Syllable 3 looks to be slightly longer compared to syllable 2, but the difference between syllable 2 and 3 is very small and they are both shorter than syllable 1. Syllable 1 is therefore the longest syllable in a word.

The vowel duration pattern for individual speakers in the late rise group is shown in (Figure 9). The general pattern is seen in all the individual speakers too, i.e., syllable 1 is the longest syllable in a word compared to syllables 2 and 3 which are similar in length.



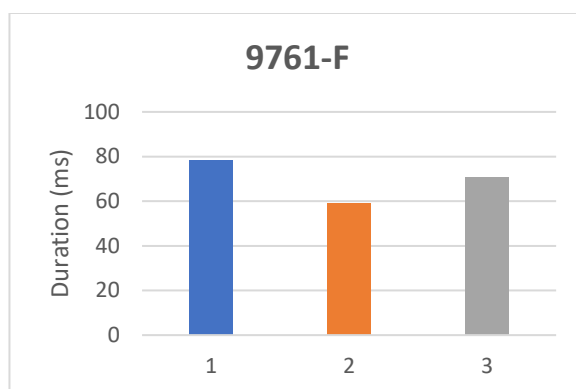


Figure 9: Duration pattern of each individual speaker in the late rise group made with mean Duration. Syllable positions are on the x-axis and Duration (ms) is on the y-axis.

5. Vowel intensity pattern for early rise speakers

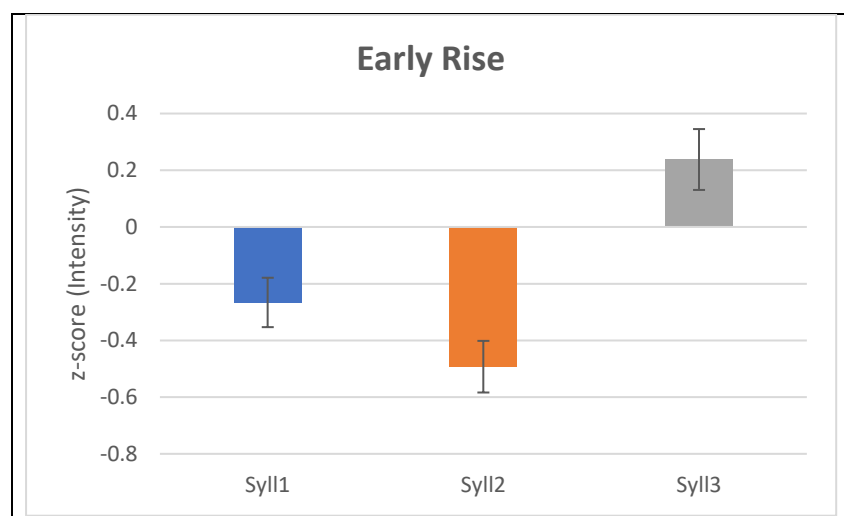


Figure 11: Graph of vowel intensity pattern for early rise speakers made with z-scores (Intensity). Syllable positions are on the x-axis, and z-scores (Intensity) are on the y-axis.

The vowel intensity graph in (Figure 11) shows that syllables 1 and 2 seems to have roughly the same intensity which is low compared to the intensity of syllable 3. Syllable 3 therefore have the highest intensity in a word and syllables 1 and 2 are similar in terms of intensity.

The vowel intensity pattern for individual speakers in the early rise group is shown in (Figure 12). The general pattern is seen in all but one individual speaker (7143 is an exception), i.e., syllable 3 has the highest intensity compared to syllables 1 and 2.

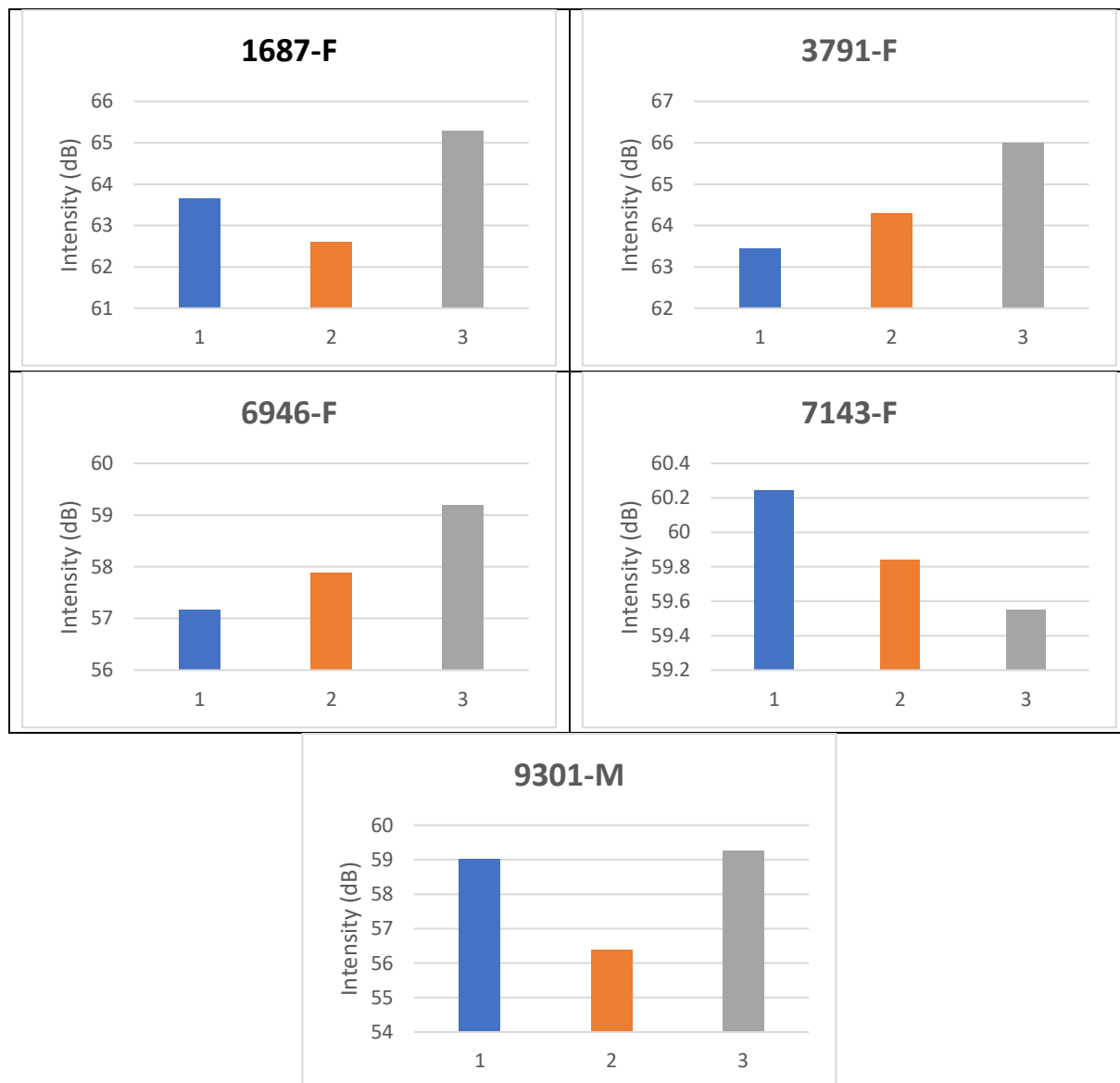


Figure 12: Vowel intensity pattern of each individual speaker in the early rise group made with mean Intensity. Syllable positions are on the x-axis and Intensity (dB) is on the y-axis.

6. Vowel intensity pattern for late rise speakers

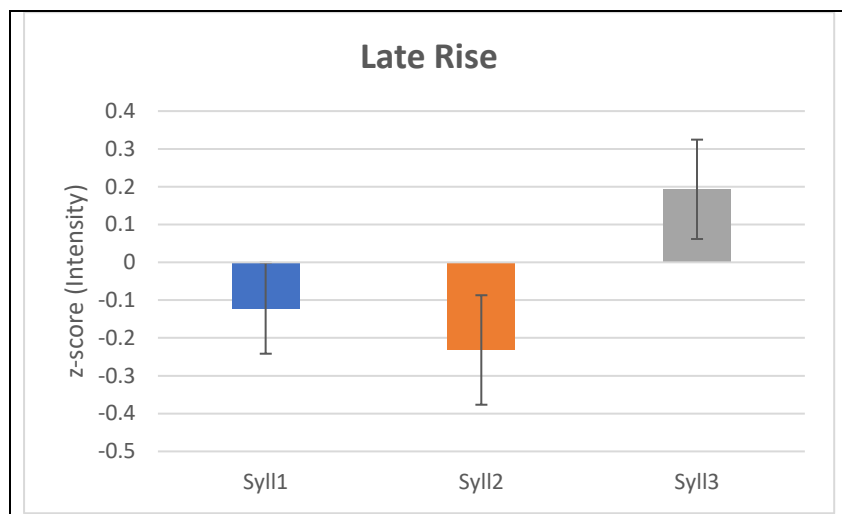
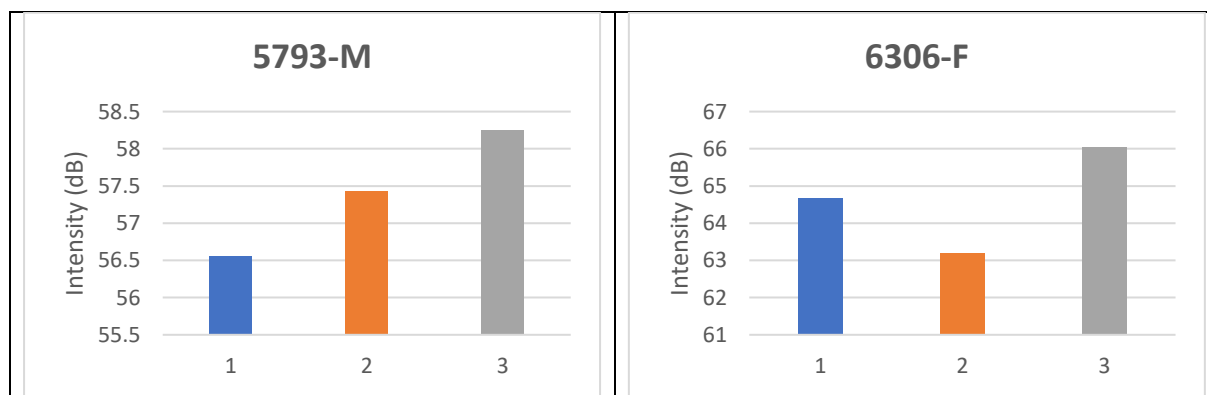


Figure 13: Graph of vowel intensity pattern for late rise speakers made with z -scores (Intensity). Syllable positions are on the x -axis, and z -scores (Intensity) are on the y -axis.

The vowel intensity graph in (Figure 13) shows that syllables 1 and 2 seems to have roughly the same intensity which is low compared to the intensity of syllable 3. Syllable 3 therefore have the highest intensity in a word and syllables 1 and 2 are similar in terms of intensity.

The vowel intensity pattern for individual speakers in the late rise group is shown in (Figure 14). The general pattern is seen in all but one individual speaker (9761 is an exception), i.e., syllable 3 has the highest intensity compared to syllables 1 and 2.



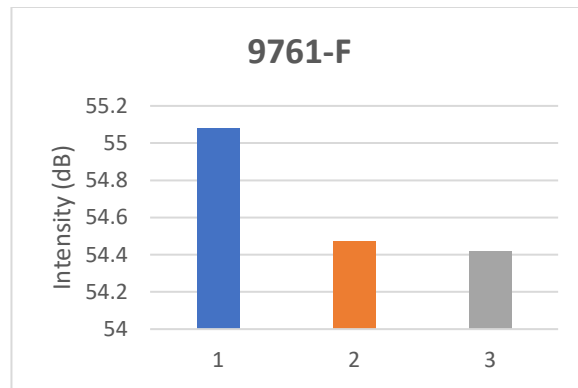


Figure 14: Vowel intensity pattern of each individual speaker in the late rise group made with mean Intensity. Syllable positions are on the x-axis and Intensity (dB) is on the y-axis.

7. Vowel quality pattern of early rise speakers

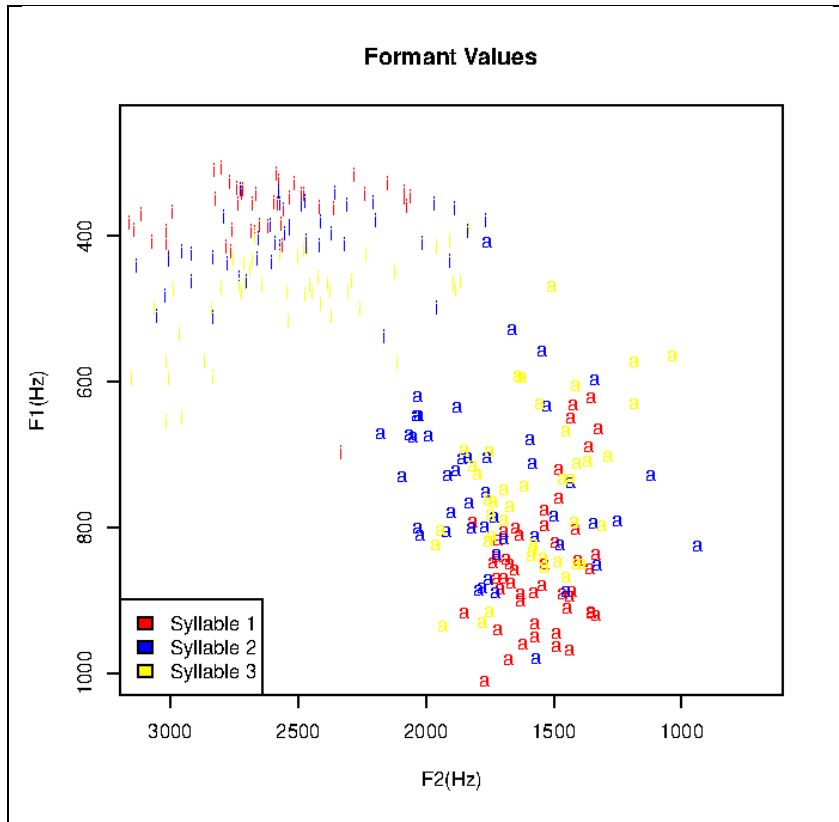


Figure 16: Vowel quality pattern for early rise speakers made with F1 and F2 values in Hertz. F2 (Hz) is on the x-axis and F1 (Hz) is on the y-axis. Syllable positions are coded in different colours (consult the legend).

The vowel quality graph in (Figure 16) shows that for the early rise speakers syllable 1 seems to be the most peripheral in the vowel space compared to syllables 2 and 3 for both /i/ and /a/. The two vowels differ in terms of whether syllable 2 or syllable 3 is more peripheral. For /i/ vowel, syllable 3 seems to be the most centralized compared to syllables 1 and 2. Syllable 2 lies somewhere in between syllables 1 and 3 in that while it is not as centralized as syllable 3, syllable 1 is overall more relatively more peripheral. For /a/ vowel, there is no clear pattern for the syllable 2 and 3 in that they are equally centralized compared to syllable 1. Importantly however, there is no clustering of the vowel qualities (/i/ and /a/) in any of the syllable positions, i.e., the distinction between the vowel qualities is still maintained even though there is some centralization in syllable

2 and 3. To summarize, even though syllable 2 and 3 are somewhat centralized compared to syllable 1, the centralization of vowels is not to a degree that the two vowel qualities are merged in either syllable 2 or 3.

8. Vowel quality pattern for late rise speakers

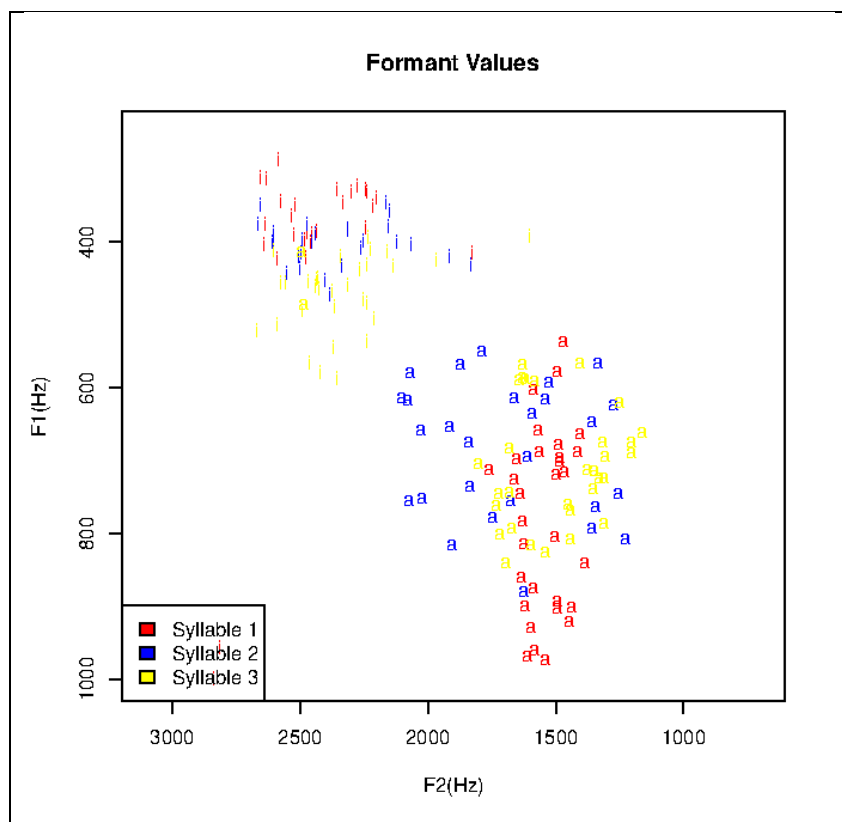


Figure 17: Vowel quality pattern for late rise speakers made with F1 and F2 values in Hertz. F2 (Hz) is on the x-axis and F1 (Hz) is on the y-axis. Syllable positions are coded in different colours (consult the legend).

The vowel quality graph in (Figure 17) shows that for the late rise speakers syllable 1 seems to be the most peripheral in the vowel space compared to syllables 2 and 3 for both /i/ and /a/. The two vowels differ in terms of whether syllable 2 or syllable 3 is more peripheral. For /i/ vowel, syllable 3 seems to be the most centralized compared to syllables 1 and 2. Syllable 2 lies

somewhere in between syllables 1 and 3 in that while it is not as centralized as syllable 3, syllable 1 is overall more relatively more peripheral. For /a/ vowel, there is no clear pattern for the syllable 2 and 3 in that they are equally centralized compared to syllable 1. Syllable 2 seems to be the most centralized compared to syllables 1 and 3. Importantly however, there is no clustering of the vowel qualities (/i/ and /a/) in any of the syllable positions, i.e., the distinction between the vowel qualities is still maintained even though there is some centralization in syllable 2 and 3. To summarize, even though syllable 2 and 3 are somewhat centralized compared to syllable 1, the centralization of vowels is not to a degree that the two vowel qualities are merged in either syllable 2 or 3. The same pattern is seen in the early rise speakers as well.

9. Statistical analysis

The statistical analysis of the data tests whether the differences seen between the syllables in terms of the acoustic properties seen in the graphs above are statistically significant. The statistical test used in this study is the *binary logistic regression*, so, the models will test how successful the acoustic properties (predictors) are in predicting the syllable positions (categorical variable).

Since this is a test for the effect of stress, i.e., to see which syllable is the most different from others, the logistic models compared two syllable positions at a time. The first of the models compared syllable 1 vs syllable 2, the second model compared syllable 2 vs syllable 3, and the third models compared syllable 1 vs syllable 3.

As it was done for the descriptive statistics in the preceding sections, the speakers are split into two groups and their analysed separately to see if there are any differences between the two groups in terms of the prediction made by the predictor variables.

9.1 Syllable 1 vs syllable 2 comparisons for early rise speakers

A logistic regression was conducted with syllable as the categorical variable and Duration, Intensity, Euclidean distance (ED), F0, F0 change ($\Delta F0$), and F0 range as the predictor variables. Syllable 1 was set as the reference category for this test. The output of this model is given below (Output 1).

For the model comparing syllable 1 vs syllable 2 for early rise speakers, F0, $\Delta F0$, and Duration were found to be the significant predictors (Output 1). The overall classification rate of the model comparing syllable 1 vs syllable 2 in pre-focal condition for early rise speakers is 92%, and the chi-squared test statistics are: $\chi^2(6) = 162.1317, p = 0$.

Output 1:

Predictors	Estimate	Std. Error	z-value	p-value	Odds- ratio	Confidence interval		Classification rate
						2.50%	97.50%	
Intercept	2.29	1.01	2.26	0.02				
F0	4.2	1.09	3.84	0.0001	67.23	9.98	800.58	82%
F0 change	3.3	0.78	4.18	< 0.001	27.17	7.27	167.91	81%
ED	0.79	0.64	1.23	0.21				
Duration	-2.35	0.55	-4.26	< 0.001	0.09	0.02	0.24	80%
Intensity	-0.39	0.49	-0.79	0.42				
F0 range	-0.16	0.57	-0.28	0.77				

glm(formula = Syllable ~ F0 + F0 change + ED + Duration + Intensity + F0 range, family = "binomial")

Null deviance: 217.792 on 157 degrees of freedom

Residual deviance: 55.661 on 151 degrees of freedom

(34 observations deleted due to missingness)

AIC: 69.661

Number of Fisher Scoring iterations: 8

In the above output table (output 1), the *Predictors* column lists the predictor variables in the model. The *Estimates* column contains the *coefficients* that were calculated for each predictor by the model. The *Std. Error* column contains the *standard error* calculated by the model for each predictor. The *z value* column contains the *z values* calculated for each predictor, and the *Pr(>|z|)* contains the *p-value* calculated for each predictor. The *Odds-ratio* column contains the *odds-ratio* estimates for each of the significant predictors. The *Confidence Interval* column contains the *upper* (97.5%) and the *lower* (2.5%) *limit* estimates for a 95% *confidence interval* for each significant predictor. Finally, the *Classification rate* column contains the percentage of correct classification by each significant predictor when they were tested as the only predictors in a post-hoc test (more on this below).

The model comparing syllable 1 vs syllable 2 yielded significant predictors of: F0, $\Delta F0$, and Duration. Since syllable 1 was the reference category for this comparison (so the model predicts the log-odds of items being in syllable 2) an examination of the estimated coefficients of the significant predictors reveals that while Duration has a negative value, other significant predictors have a positive value. The negative coefficient indicates that syllable 1 has a longer duration ($mean = 0.65$, $sd = 0.83$) compared to syllable 2 ($mean = -0.55$, $sd = 0.77$) and is also supported by an odds-ratio < 1 . The z-scores were reconverted into original units using the mean and standard deviation of one speaker, 1687 and syllable 1 ($mean = 99\ ms$) is on average 18.5 ms longer than syllable 2 ($mean = 80.5$).

The coefficient is positive F0 which means that syllable 2 has a higher mean F0 ($mean = 0.24$, $sd = 0.56$) compared to syllable 1 ($mean = -0.99$, $sd = 0.43$). This is also supported by an odds-ratio > 1 . The z-scores were reconverted into original units using the mean and standard

deviation of one speaker, 1687 and syllable 2 ($mean = 228\text{ Hz}$) is on average 18.7 Hz higher than syllable 2 ($mean = 209.3\text{ Hz}$) in terms of F0.

The coefficient is also positive for $\Delta F0$, so syllable 2 has a rising F0 ($mean = 0.3$, $sd = 0.8$) compared to the falling F0 on syllable 1 ($mean = -0.72$, $sd = 0.63$). This is also supported by an odds-ratio > 1 . The z-scores were reconverted into original units using the mean and standard deviation of one speaker, 1687 and the F0 on syllable 1 falls from Q1 ($mean = 212\text{ Hz}$) to Q4 ($mean = 205\text{ Hz}$) while the F0 on syllable 2 rises from Q1 ($mean = 221\text{ Hz}$) to Q4 ($mean = 226.1\text{ Hz}$). A post hoc test was conducted with the significant predictors of this model where the individual significant predictors were the only predictor variable. The classification rate of the individual significant predictors is given in (Output 1 – Classification rate).

9.2 Syllable 1 vs syllable 2 comparisons for late rise speakers

A logistic regression was conducted with syllable as the categorical variable and Duration, Intensity, Euclidean distance (ED), F0, F0 change ($\Delta F0$), and F0 range as the predictor variables. Syllable 1 was set as the reference category for this test. The output of this model is given below (Output 2).

For the model comparing syllable 1 vs syllable 2 for late rise speakers, Duration and $\Delta F0$, were found to be the significant predictors (Output 2). The overall classification rate of the model comparing syllable 1 vs syllable 2 in pre-focal condition for late rise speakers is 92%, and the chi-squared test statistics are: $\chi^2(6) = 97.30958$, $p = 0$.

Output 2:

Predictors	Estimate	Std. Error	z-value	p-value	Odds- ratio	Confidence interval		Classification rate
						2.50%	97.50%	
Intercept	1.38	1.33	1.03	0.29				
F0	-0.69	1.21	-0.57	0.56				
F0 change	4.33	1.43	3.02	< 0.001	76.41	7.12	2511.79	90%
ED	-0.93	0.92	-1.01	0.3				
Duration	-2.51	0.81	-3.1	<0.001	0.08	0.01	0.3	68%
Intensity	0.42	0.58	0.72	0.46				
F0 range	-1.42	0.73	-1.94	0.05				

glm(formula = Syllable ~ F0 + F0 change + ED + Duration + Intensity + F0 range, family = "binomial")

Null deviance: 130.141 on 93 degrees of freedom

Residual deviance: 32.832 on 87 degrees of freedom

(20 observations deleted due to missingness)

AIC: 46.832

Number of Fisher Scoring iterations: 8

The model comparing syllable 1 vs syllable 2 yielded significant predictors of: $\Delta F0$, and Duration. Since syllable 1 was the reference category for this comparison (so the model predicts the log-odds of items being in syllable 2) an examination of the estimated coefficients of the significant predictors reveals that while Duration has a negative value, $\Delta F0$ has a positive value. The negative coefficient indicates that syllable 1 has a longer duration ($mean = 0.38$, $sd = 0.92$) compared to syllable 2 ($mean = -0.56$, $sd = 0.88$) and is also supported by an odds-ratio < 1. The z-scores were reconverted into original units using the mean and standard deviation of one speaker, 6306 and syllable 1 ($mean = 107\ ms$) is on average 18 ms longer than syllable 2 ($mean = 89\ ms$).

The coefficient is positive for $\Delta F0$, so syllable 2 has a rising F0 ($mean = 0.19$, $sd = 0.41$) compared to the falling F0 on syllable 1 ($mean = -1.02$, $sd = 0.7$). This is also supported by an odds-ratio > 1. The z-scores were reconverted into original units using the mean and standard deviation of one speaker, 6306 and the F0 on syllable 1 falls from Q1 ($mean = 218\ Hz$) to Q4

(*mean* = 204.1 Hz) while the F0 on syllable 2 rises from Q1 (*mean* = 209 Hz) to Q4 (*mean* = 229 Hz). A post hoc test was conducted with the significant predictors of this model where the individual significant predictors were the only predictor variable. The classification rate of the individual significant predictors is given in (Output 2 – Classification rate).

10. Syllable 2 vs syllable 3 comparison

These tests check how good the acoustic properties (predictors) are at predicting or differentiating between syllables 2 and 3 (categorical variable). The data from the two groups are analysed separately to see if there was any difference in the prediction or differentiation made by the predictors in the different grouping of the speakers.

10.1 Syllable 2 vs syllable 3 comparisons for early rise speakers

A logistic regression was conducted with syllable as the categorical variable and Duration, Intensity, Euclidean distance (ED), F0, F0 change ($\Delta F0$), and F0 range as the predictor variables. Syllable 2 was set as the reference category for this test. The output of this model is given below (Output 3).

For the model comparing syllable 2 vs syllable 3 for early rise speakers, only F0 was found to be the significant predictor (Output 4). The overall classification rate of the model comparing syllable 2 vs syllable 3 in pre-focal condition for early rise speakers is 85%, and the chi-squared test statistics are: $\chi^2(6) = 94.78032, p = 0$.

Output 3:

Predictors	Estimate	Std. Error	z-value	p- value	Odds- ratio	Confidence interval		Classification rate
						2.50%	97.50%	
Intercept	-0.12	0.43	-0.29	0.76				
F0	2.95	0.45	6.44	< 0.001	19.15	8.41	51.28	84%
F0 change	-0.51	0.29	-1.72	< 0.001				
ED	-0.35	0.29	-1.2	0.22				
Duration	-0.09	0.3	-0.29	< 0.001				
Intensity	-0.08	0.28	-0.3	0.75				
F0 range	-0.35	0.29	-1.18	0.23				

glm(formula = Syllable ~ F0 + F0 change + ED + Duration + Intensity + F0 range , family = "binomial")

Null deviance: 221.40 on 160 degrees of freedom

Residual deviance: 126.61 on 154 degrees of freedom

(23 observations deleted due to missingness)

AIC: 140.61

Number of Fisher Scoring iterations: 5

The model comparing syllable 2 vs syllable 3 yielded a significant predictor of: F0. Since syllable 2 was the reference category for this comparison (so the model predicts the log-odds of items being in syllable 3) an examination of the estimated coefficients of the significant predictors reveals that F0 has a positive value. The coefficient is positive for F0 which means that syllable 3 has a higher mean F0 (*mean* = 0.9, *sd* = 0.71) compared to syllable 2 (*mean* = -0.25, *sd* = 0.6). This is also supported by an odds-ratio > 1. The z-scores were reconverted into original units using the mean and standard deviation of one speaker, 1687 and syllable 3 (*mean* = 256 Hz) is on average 28 Hz higher than syllable 2 (*mean* = 228 Hz) in terms of F0.

As a follow up, post-hoc tests were conducted with the significant predictor as the only predictor in the model classifying syllable 2 vs syllable 3. This was done in order to find out how successful the predictors were in classifying the data individually. The percentage of the data

correctly classified by the model when each F0 was the only predictor in the model is listed in the output table above (Output 3 – Classification rate).

10.2 Syllable 2 vs syllable 3 comparisons for late rise speakers

A logistic regression was conducted with syllable as the categorical variable and Duration, Intensity, Euclidean distance (ED), F0, F0 change ($\Delta F0$), and F0 range as the predictor variables. Syllable 2 was set as the reference category for this test. The output of this model is given below (Output 4).

For the model comparing syllable 2 vs syllable 3 for late rise speakers, only F0 was found to be the significant predictor (Output 4):

Output 4:

Predictors	Estimate	Std. Error	z-value	p-value	Odds- ratio	Confidence interval		Classification rate
						2.50%	97.50%	
Intercept	-0.8	0.76	-1.04	0.29				
F0	3.84	0.88	4.33	< 0.001	46.58	11.09	391.44	87%
F0 change	1.08	0.9	1.2	< 0.001				
ED	0.76	0.41	1.84	0.06				
Duration	0.73	0.46	1.56	< 0.001				
Intensity	-0.1	0.36	-0.28	0.77				
F0 range	0.79	0.62	1.26	0.2				

glm(formula = Syllable ~ F0 + F0 change + ED + Duration + Intensity + F0 range, family = "binomial")

Null deviance: 139.987 on 101 degrees of freedom

Residual deviance: 42.879 on 95 degrees of freedom

(16 observations deleted due to missingness)

AIC: 56.879

Number of Fisher Scoring iterations: 7

The overall classification rate of the model comparing syllable 2 vs syllable 3 in pre-focal condition for late rise speakers is 92%, and the chi-squared test statistics are: $\chi^2(6) = 97.10769$, $p = 0$.

The model comparing syllable 2 vs syllable 3 yielded a significant predictor of: F0. Since syllable 2 was the reference category for this comparison (so the model predicts the log-odds of items being in syllable 3) an examination of the estimated coefficient for F0 show that it is positive. The positive coefficient for F0 means that syllable 3 has a higher mean F0 ($mean = 1$, $sd = 0.74$) compared to syllable 2 ($mean = -0.6$, $sd = 0.53$). This is also supported by an odds-ratio > 1 . The z-scores were reconverted into original units using the mean and standard deviation of one speaker, 6306 and syllable 3 ($mean = 237.3$ Hz) is on average 29.3 Hz higher than syllable 2 ($mean = 208$ Hz) in terms of F0.

As a follow up, post-hoc tests were conducted with the significant predictor as the only predictor in the model classifying syllable 2 vs syllable 3. This was done in order to find out how successful the predictors were in classifying the data individually. The percentage of the data correctly classified by the model when each F0 was the only predictor in the model is listed in the output table above (Output 4 – Classification rate).

11. Syllable 1 vs syllable 3 comparisons

These tests check how good the acoustic properties (predictors) are at predicting or differentiating between syllables 1 and 3 (categorical variable). The data from the two groups are analysed separately to see if there was any difference in the prediction or differentiation made by the predictors in the different grouping of the speakers.

11.1 Syllable 1 vs syllable 3 comparisons for early rise speakers

A logistic regression was conducted with syllable as the categorical variable and Duration, Intensity, Euclidean distance (ED), F0, F0 change ($\Delta F0$), and F0 range as the predictor variables. Syllable 1 was set as the reference category for this test. The output of this model is given below (Output 5).

For the model comparing syllable 1 vs syllable 3 for early rise speakers, F0, $\Delta F0$, and Duration were found to be the significant predictors (Output 7). The overall classification rate of the model comparing syllable 1 vs syllable 3 in pre-focal condition for early rise speakers is 97%, and the chi-squared test statistics are: $\chi^2(6) = 211.1033$, $p = 0$. The confidence intervals could not be calculated for this model due to the presence of fitted probabilities equaling 0 or 1.

Output 5:

Predictors	Estimate	Std. Error	z-value	p-value	Odds- ratio	Confidence interval		Classification rate
						2.50%	97.50%	
Intercept	2.35	1.34	1.75	0.08	263.8			
F0	5.57	1.65	3.36	< 0.001	8			95%
F0 change	1.83	0.93	1.96	< 0.001	6.27			82%
ED	-0.24	0.67	-0.36	0.71				
Duration	-1.62	0.55	-2.94	< 0.001	0.19			81%
Intensity	-1.24	0.77	-1.61	0.1				
F0 range	0.52	0.69	0.76	0.44				

glm(formula = Syllable ~ F0 + F0 change + ED + Duration + Intensity + F0 range, family = "binomial")

Null deviance: 242.550 on 174 degrees of freedom

Residual deviance: 31.447 on 168 degrees of freedom

(15 observations deleted due to missingness)

AIC: 45.447

Number of Fisher Scoring iterations: 9

The model comparing syllable 1 vs syllable 3 yielded significant predictors of: F0, Δ F0, and Duration. Since syllable 1 was the reference category for this comparison (so the model predicts the log-odds of items being in syllable 3) an examination of the estimated coefficients of the significant predictors reveals that F0 and Δ F0 have a positive value, but Duration has a negative value. The negative coefficient indicates that syllable 1 has a longer duration (*mean* = 0.65, *sd* = 0.83) compared to syllable 3 (*mean* = -0.55, *sd* = 0.77) and is also supported by an odds-ratio < 1. The z-scores were reconverted into original units using the mean and standard deviation of one speaker, 1687 and syllable 1 (*mean* = 99 ms) is on average 18.5 ms longer than syllable 3 (*mean* = 80.5).

The coefficient is positive for F0 which means that syllable 3 has a higher mean F0 (*mean* = 0.9, *sd* = 0.71) compared to syllable 1 (*mean* = -0.99, *sd* = 0.43). This is also supported by an odds-ratio > 1. The z-scores were reconverted into original units using the mean and standard deviation of one speaker, 1687 and syllable 3 (*mean* = 256 Hz) is on average 46.7 Hz higher than syllable 1 (*mean* = 209.3 Hz) in terms of F0.

The coefficient is also positive for Δ F0, so syllable 3 has a rising F0 (*mean* = 0.5, *sd* = 0.82) compared to the falling F0 on syllable 1 (*mean* = -0.72, *sd* = 0.63). This is also supported by an odds-ratio > 1. The z-scores were reconverted into original units using the mean and standard deviation of one speaker, 1687 and the F0 on syllable 1 falls from Q1 (*mean* = 212 Hz) to Q4 (*mean* = 205 Hz) while the F0 on syllable 3 rises from Q1 (*mean* = 247.1 Hz) to Q4 (*mean* = 254 Hz). A post hoc test was conducted with the significant predictors of this model where the individual significant predictors were the only predictor variable. The classification rate of the individual significant predictors is given in (Output 5 – Classification rate).

11.2 Syllable 1 vs syllable 3 comparisons for late rise speakers

A logistic regression was conducted with syllable as the categorical variable and Duration, Intensity, Euclidean distance (ED), F0, F0 change ($\Delta F0$), and F0 range as the predictor variables. Syllable 1 was set as the reference category for this test. The output of this model is given below (Output 6).

The model comparing syllable 1 vs syllable 3 for early rise speakers did not converge (Output 6):

Output 6:

Predictors	Estimate	Std. Error	z-value	p-value	Odds-ratio	Confidence interval		Classification rate
						2.50%	97.50%	
Intercept								
F0								
F0 change								
ED								
Duration								
Intensity								
F0 range								
glm(formula = Syllable ~ F0 + F0 change + ED + Duration + Intensity + F0 range, family = "binomial")								
Null deviance: 1.4634e+02 on 105 degrees of freedom								
Residual deviance: 3.2836e-08 on 99 degrees of freedom								
(18 observations deleted due to missingness)								
AIC: 14								
Number of Fisher Scoring iterations: 25								

The overall classification rate of the model comparing syllable 1 vs syllable 3 in pre-focal condition for late rise speakers is 100%, and the chi-squared test statistics are: $\chi^2(6) = 146.3429$,

$p = 0$. The coefficients, odds-ratio, and the confidence intervals could not be calculated for this model since the model did not converge.

Due to the model not converging, the significant predictors for this comparison could not be determined.

12. Summary of the results

The speakers were split into two groups for both the descriptive statistics and the logistic regression due to the difference seen in the F0 pattern. The speakers roughly grouped into two groups regarding the F0 pattern. For one group of speakers, the early rise speakers, there was a rising F0 on syllable 2 from the low F0 of syllable 1. For the other group of speakers, the late rise group, the F0 on syllable 2 remains relatively flat, with the F0 level on syllable 2 being very close to the lowest F0 point on syllable 1.

In the statistical analysis, the two groups of speakers were analysed separately. The results of the statistical tests did not show a drastic difference between the two groups. In the early rise speakers syllable 2 had a higher F0 compared to syllable 1, but syllable 1 was longer in duration compared to syllable 2. Syllable 1 also had a low falling F0 compared to the rising F0 contour on syllable 2. Syllable 3 had a higher F0 compared to syllable 2. Syllable 3 also had a higher F0 compared to syllable 1, making it the syllable with the highest F0 in the word. Syllable 3 also had a flat high F0 contour compared to the low falling F0 contour on syllable 1. Syllable 1 on the other hand had a longer duration compared to syllable 2 making it the longest syllable in the word.

Similarly in the late rise speakers, even though syllable 1 and syllable 2 did not differ in terms of F0, syllable 1 was still longer in duration compared to syllable 2. Syllable 1 also had a low falling contour compared to the flat low contour on syllable 2. Syllable 3 had a higher F0

compared to syllable 2. While the model comparing syllable 1 and syllable 3 did not converge due to perfect separation of the data, it can be guessed from the graph that syllable 3 had a significantly higher F0 compared to syllable 1, making it the syllable with highest F0 in the word. Syllable 1 can also be guessed to be significantly longer than syllable 3, making it the syllable with the longest duration in the word.

The results of the statistical tests revealed that the two speaker groups did not differ substantially from one another in terms of their word prosodic pattern. Syllable 1 is the longest in terms of duration in both the speaker groups, and syllable 3 has the highest F0 in both the groups. One of the possibilities was that syllable 2 and syllable 3 would not be distinct enough in terms of F0 for the early rise speakers due to the rising F0 on syllable 2. This possibility was not borne out however, as syllable 3 has a higher F0 compared to syllable 2 in the early rise speakers. Since the pattern was not different enough between the two speaker groups, it was decided that continued separation of the data into two groups was not needed and the data was pooled for all the analyses in this thesis. The lack of difference between the two groups is also the reason why these tests are not included in the main body of the thesis. It has to be stressed however, that it will be worthwhile to see if this difference seen in the F0 pattern of early and late rise speakers hold in larger datasets with more speakers. The formal analysis also is still required to explain the different F0 pattern for early and late rise speakers, but such an analysis is beyond the scope of this study so it is left for the future.

Appendix B – Normality tests

```
## Subsetting the participants
> p6946 <- subset(df, ParticipantID==6946)
> p1687 <- subset(df, ParticipantID==1687)
> p3791 <- subset(df, ParticipantID==3791)
> p6306 <- subset(df, ParticipantID==6306)
> p7143 <- subset(df, ParticipantID==7143)
> p9761 <- subset(df, ParticipantID==9761)
> p5793 <- subset(df, ParticipantID==5793)
> p9301 <- subset(df, ParticipantID==9301)

## Subsetting out the vowels for each participant
> p6946.i <- subset(p6946, Vowel=="i")
> p6946.a <- subset(p6946, Vowel=="a")
> p1687.i <- subset(p1687, Vowel=="i")
> p1687.a <- subset(p1687, Vowel=="a")
> p3791.i <- subset(p3791, Vowel=="i")
> p3791.a <- subset(p3791, Vowel=="a")
> p6306.i <- subset(p6306, Vowel=="i")
> p6306.a <- subset(p6306, Vowel=="a")
> p7143.i <- subset(p7143, Vowel=="i")
> p7143.a <- subset(p7143, Vowel=="a")
> p9761.i <- subset(p9761, Vowel=="i")
> p9761.a <- subset(p9761, Vowel=="a")
> p5793.i <- subset(p5793, Vowel=="i")
> p5793.a <- subset(p5793, Vowel=="a")
> p9301.i <- subset(p9301, Vowel=="i")
> p9301.a <- subset(p9301, Vowel=="a")
>
> ##### Speaker 1687 #####
>
> ##### /i/ #####
> ## F0
> hist(p1687.i$F0_Q2Q3)
> ##Duration
> hist(p1687.i$Duration)
> ## intensity
> hist(p1687.i$Intensity_Q2Q3)
>
> ##### /a/ #####
> hist(p1687.a$F0_Q2Q3)
> p1687.a1 <- subset(p1687.a, F0_Q2Q3>150)
> hist(p1687.a1$F0_Q2Q3)
> ## Duration
> hist(p1687.a1$Duration)
> ## Intensity
> hist(p1687.a1$Intensity_Q2Q3)
>
> ##### Speaker 3791 #####
>
> ##### /i/ #####
> ## F0
```

```

> hist(p3791.i$F0_Q2Q3)
> ## Duration
> hist(p3791.i$Duration)
> ## Intensity
> hist(p3791.i$Intensity_Q2Q3)
>
> ##### /a/ #####
> ## F0
> hist(p3791.a$F0_Q2Q3)
> ## Duration
> hist(p3791.a$Duration)
> ## Intensity
> hist(p3791.a$Intensity_Q2Q3)
>
> ##### Speaker 6306 #####
>
> ##### /i/ #####
> ## F0
> hist(p6306.i$F0_Q2Q3)
> ## Intensity
> hist(p6306.i$Intensity_Q2Q3)
> ## Duration
> hist(p6306.i$Duration)
>
> ##### /a/ #####
> ## F0
> hist(p6306.a$F0_Q2Q3)
> ## Intensity
> hist(p6306.a$Intensity_Q2Q3)
> ## Duration
> hist(p6306.a$Duration)
>
> ##### Speaker 7143 #####
>
> ##### /i/ #####
> ## F0
> hist(p7143.i$F0_Q2Q3)
> p7143.il <- subset(p7143.i, F0_Q2Q3>200)
> hist(p7143.il$F0_Q2Q3)
> ## Intensity
> hist(p7143.il$Intensity_Q2Q3)
> ## Duration
> hist(p7143.il$Duration)
>
> ##### /a/ #####
> ## F0
> hist(p7143.a$F0_Q2Q3)
> p7143.al <- subset(p7143.a, F0_Q2Q3>150)
> hist(p7143.al$F0_Q2Q3)
> ## Intensity
> hist(p7143.al$Intensity_Q2Q3)
> ## Duration
> hist(p7143.al$Duration)
>
> ##### Speaker 7913 #####
>
> ##### /i/ #####

```

```

> ## F0
> hist(p7913.i$F0_Q2Q3)
> ## Intensity
> hist(p7913.i$Intensity_Q2Q3)
> ## Duration
> hist(p7913.i$Duration)
>
> ##### /a/ #####
> ## F0
> hist(p7913.a$F0_Q2Q3)
> ## Intensity
> hist(p7913.a$Intensity_Q2Q3)
> ## Duration
> hist(p7913.a$Duration)
>
> ##### Speaker 9761 #####
>
> ##### /i/ #####
> ## F0
> hist(p9761.i$F0_Q2Q3)
> ## Intensity
> hist(p9761.i$Intensity_Q2Q3)
> ## Duration
> hist(p9761.i$Duration)
>
> ##### /a/ #####
> ## F0
> hist(p9761.a$F0_Q2Q3)
> p9761.a1 <- subset(p9761.a, F0_Q2Q3>160)
> hist(p9761.a2$F0_Q2Q3)
> ## Intensity
> hist(p9761.a1$Intensity_Q2Q3)
> ## Duration
> hist(p9761.a1$Duration)
>
> ##### Speaker 5793 #####
>
> ##### /i/ #####
> ## F0
> hist(p5793.i$F0_Q2Q3)
> ## Intensity
> hist(p5793.i$Intensity_Q2Q3)
> ## Duration
> hist(p5793.i$Duration)
>
> ##### /a/ #####
> ## F0
> hist(p5793.a$F0_Q2Q3)
> ## Intensity
> hist(p5793.a$Intensity_Q2Q3)
> ## Duration
> hist(p5793.a$Duration)
>
> ##### Speaker 9301 #####
>
> ##### /i/ #####
> ## F0

```

```

> hist(p9301.i$F0_Q2Q3)
> ## Intensity
> hist(p9301.il$Intensity_Q2Q3)
> ## Duration
> hist(p9301.il$Duration)
>
> ##### /a/ #####
> ## F0
> hist(p9301.a$F0_Q2Q3)
> ## Intensity
> hist(p9301.al$Intensity_Q2Q3)
> ## Duration
> hist(p9301.al$Duration)
>
> ##### Speaker 6946 #####
>
> ##### /i/ #####
> ## F0
> hist(p6946.i$F0_Q2Q3)
> p6946.il <- subset(p6946.i, F0_Q2Q3>140)
> hist(p6946.il$F0_Q2Q3)
> ##Duration
> hist(p6946.il$Duration)
> ## intensity
> hist(p6946.il$Intensity_Q2Q3)
>
> ##### /a/ #####
> hist(p6946.a$F0_Q2Q3)
> ## Duration
> hist(p6946.a$Duration)
> ## Intensity
> hist(p6946.a$Intensity_Q2Q3)

```

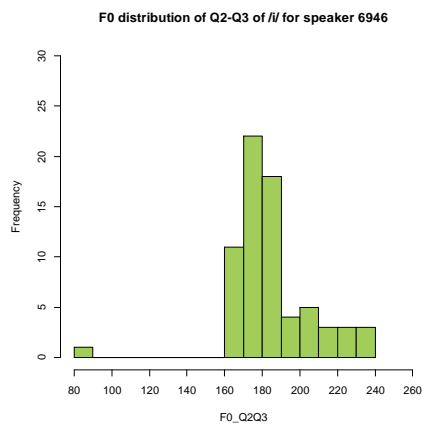
Test for normality:

FEMALE SPEAKERS

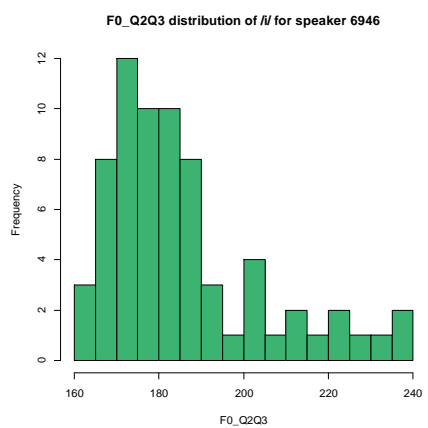
Speaker 6946

For /i/ vowel

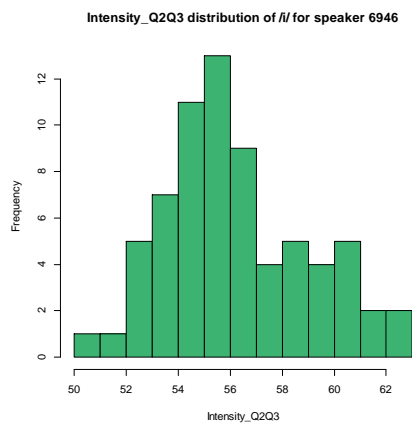
F0_Q2Q3



F0_Q2Q3 is not normally distributed for this speaker. The distribution also had outliers. The outlier was excluded and the distribution replotted.

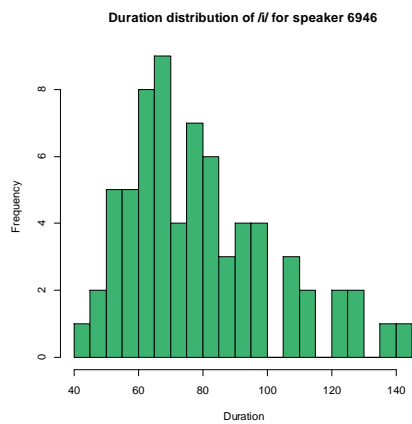


Intensity



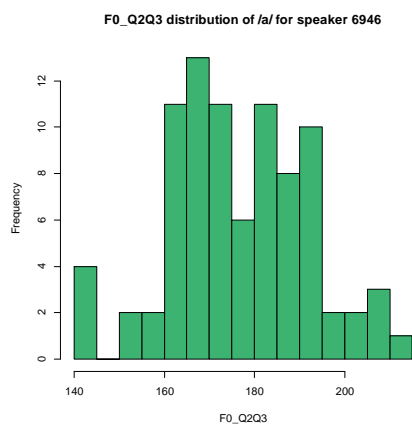
The intensity distribution is relatively normal.

Duration



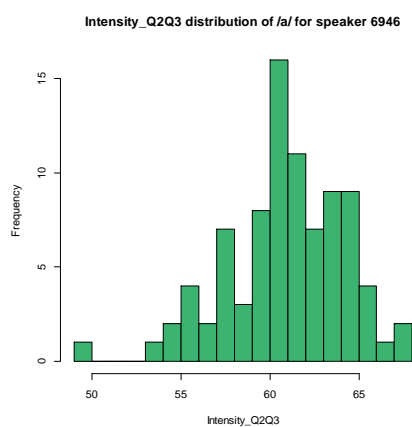
The duration distribution is also relatively normal.

For /a/ vowel



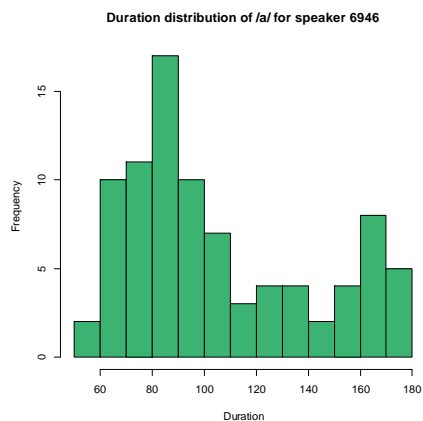
The F0_Q2Q3 is normally distributed.

Intensity



Intensity is relatively normal in its distribution.

Duration

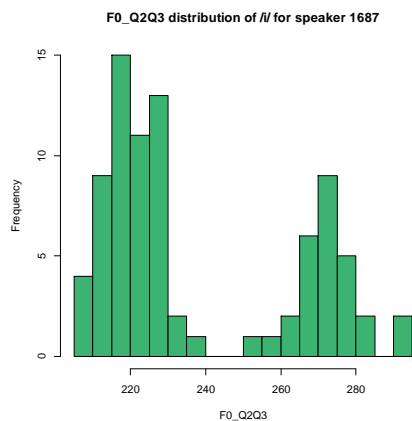


The distribution does not look very normal, it looks more like it is right-skewed.

Speaker 1687

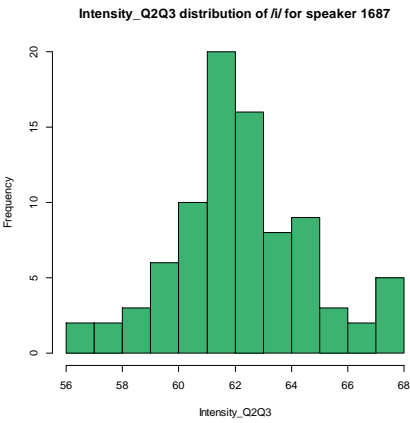
For /i/ vowel

F0_Q2Q3



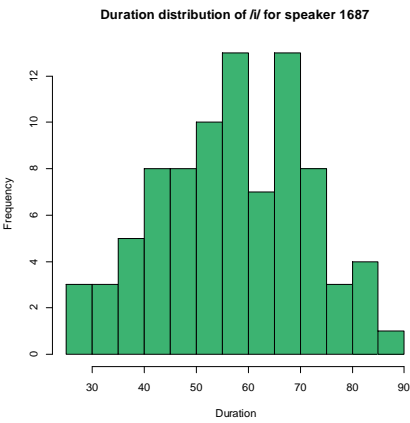
F0_Q2Q3 is not normally distributed, it looks more like a bimodal distribution

Intensity



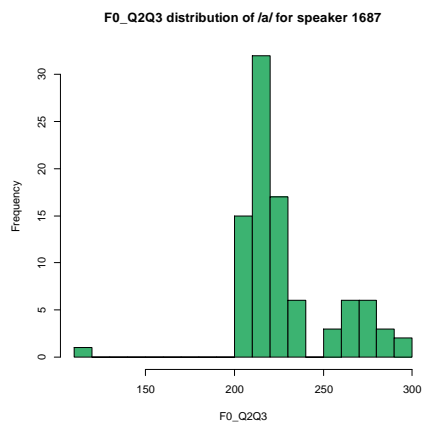
Intensity is normally distributed.

Duration

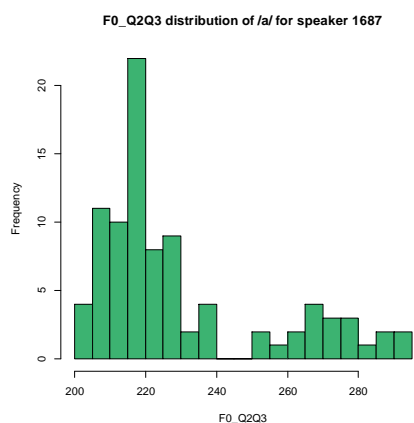


For /a/ vowel

F0_Q2Q3

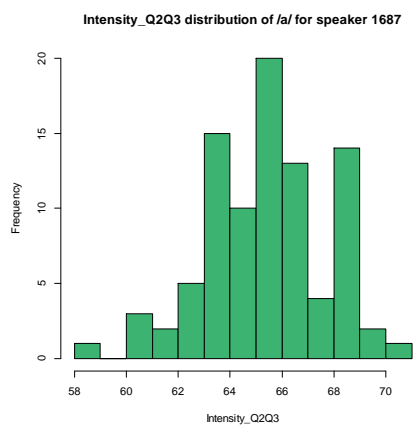


The F0 had a clear outlier. This was excluded and the distribution was replotted.



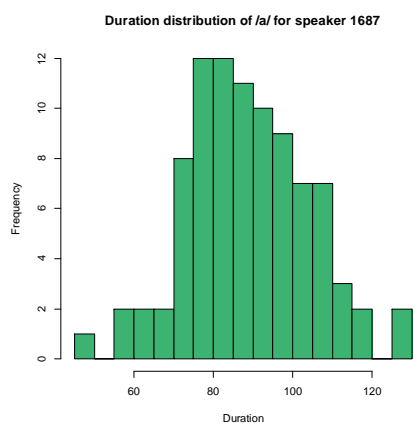
F0 is not normally distributed. It has a right skewed distribution.

Intensity



Intensity is relatively normally distributed.

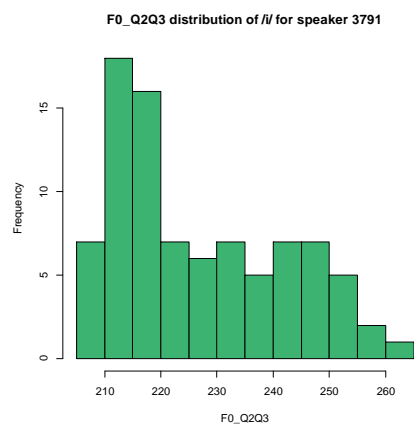
Duration



Duration is normally distributed.

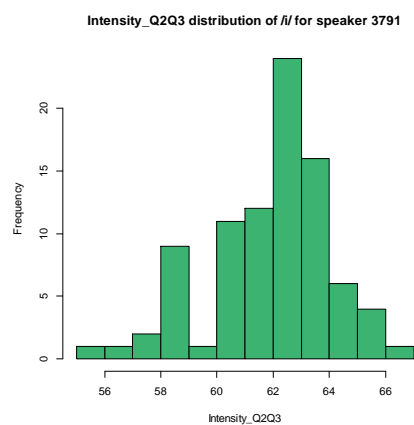
Speaker 3791

F0_Q2Q3



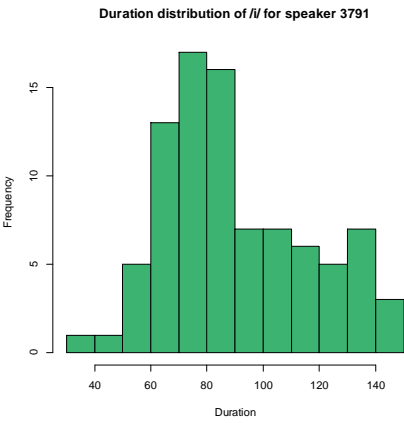
The F0 distribution is not normal, it is right skewed.

Intensity



Intensity is relatively normally distributed.

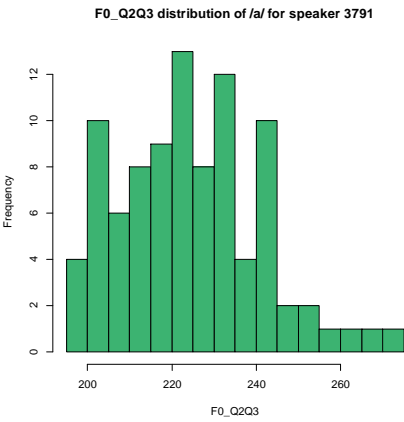
Duration



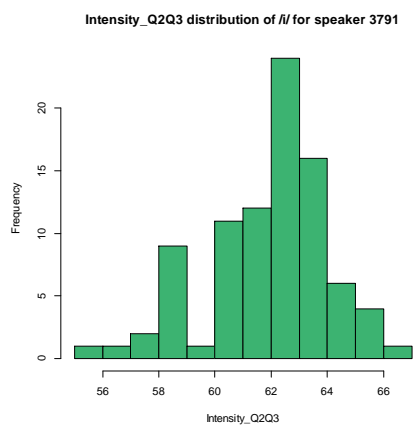
Duration is normally distributed.

For /a/ vowel

F0_Q2Q3

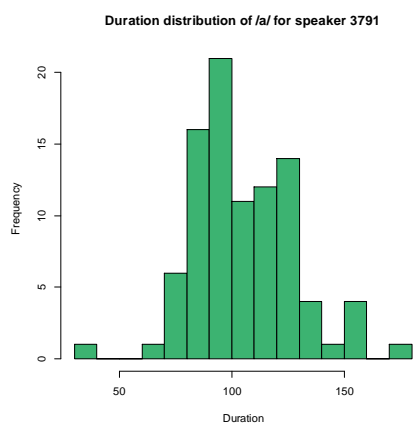


Intensity



Intensity is relatively normally distributed.

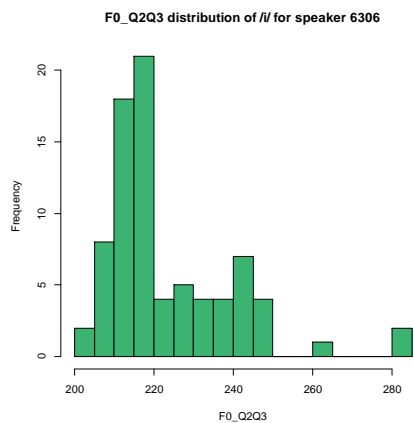
Duration



Duration is normally distributed.

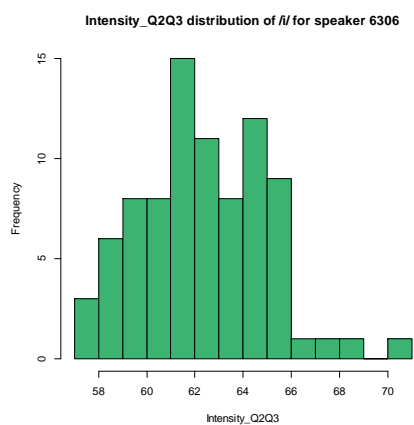
Speaker 6306

F0_Q2Q3



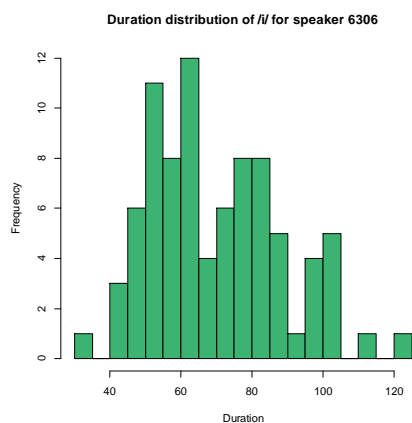
The F0 is not normally distributed, it has a right skewed distribution.

Intensity_Q2Q3



Intensity is relatively normally distributed.

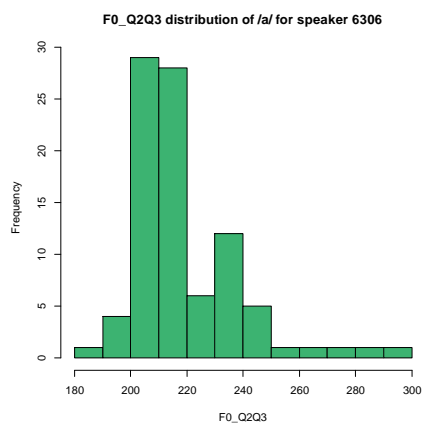
Duration



Duration is normally distributed.

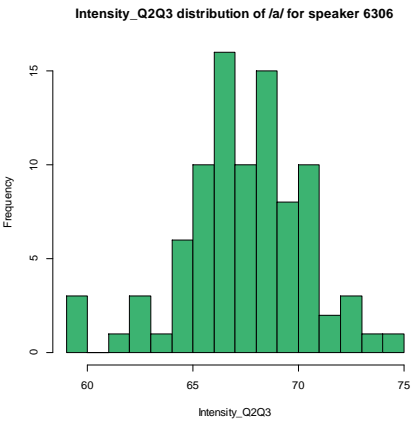
For /a/ vowel

F0_Q2Q3



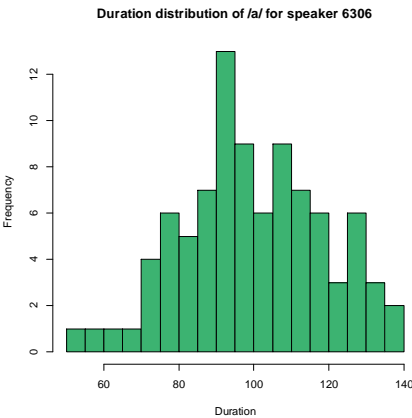
F0 is not normally distributed, it is right skewed.

Intensity_Q2Q3



Intensity is normally distributed.

Duration

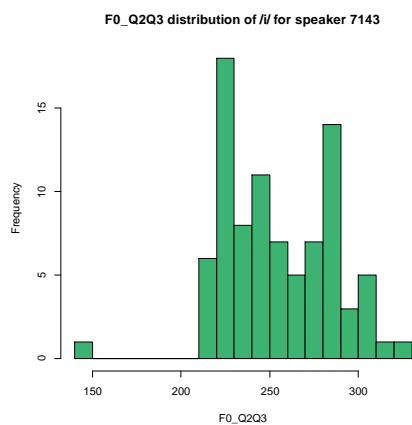


Duration is normally distributed.

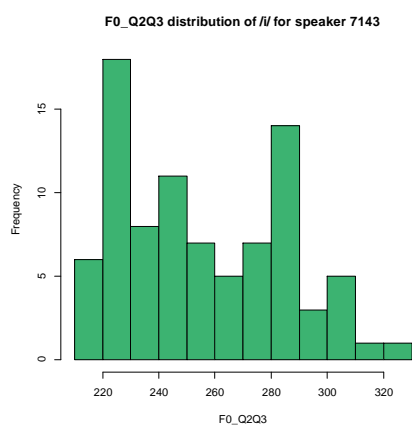
Speaker 7143

For /i/ vowel

F0_Q2Q3

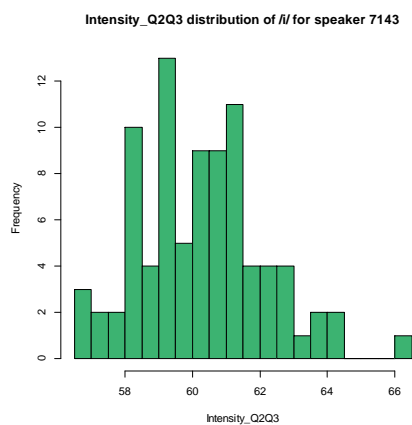


F0 has a clear outlier. It was excluded and the distribution was replotted.



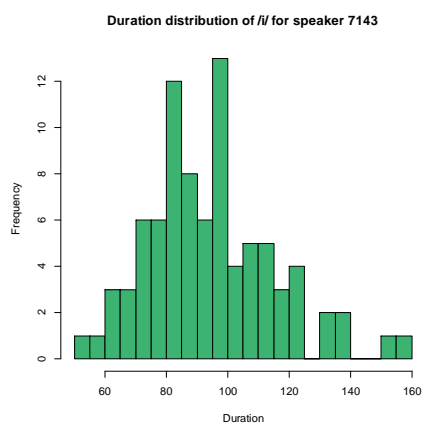
F0 has a relatively normal distribution.

Intensity_Q2Q3



Intensity is relatively normally distributed.

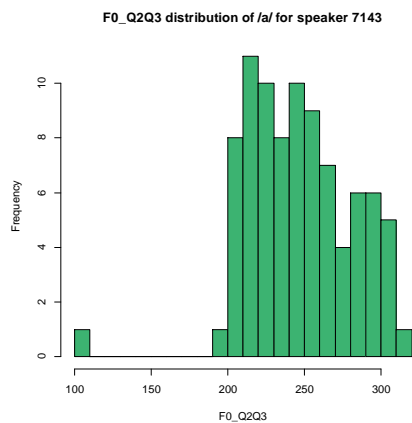
Duration



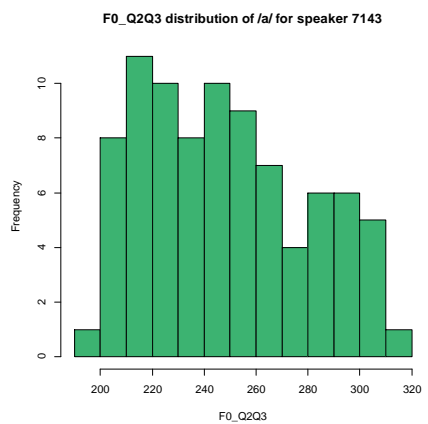
Duration is normally distributed.

For /a/ vowel

F0_Q2Q3

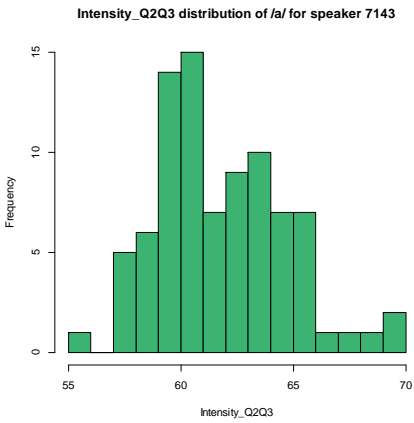


There is a clear outlier for F0 here. It was excluded and the distribution was replotted.



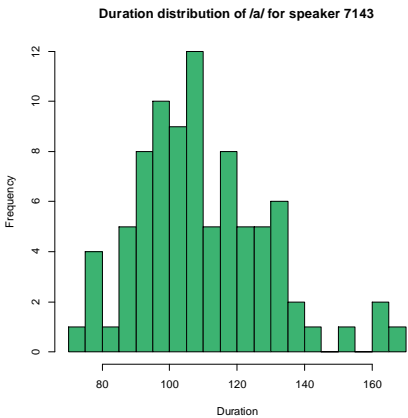
F0 is normally distributed.

Intensity_Q2Q3



Intensity is normally distributed.

Duration

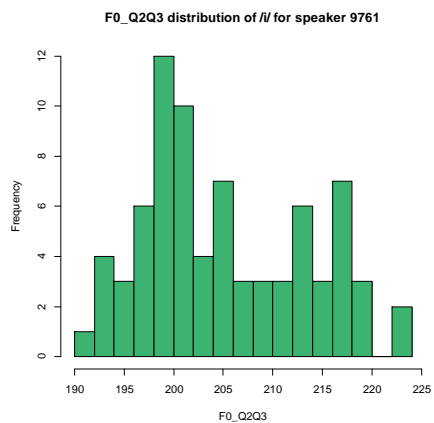


Duration is normally distributed.

Speaker 9761

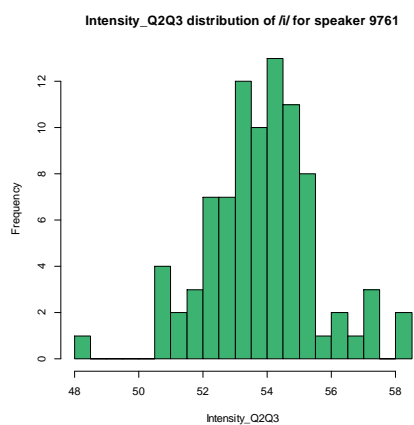
For /i/ vowel

F0_Q2Q3



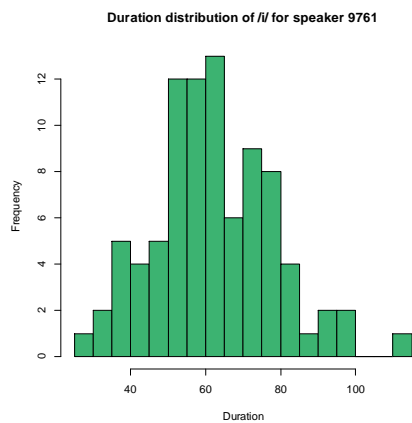
F0 is not normally distributed. It has a right skewed distribution.

Intensity_Q2Q3



Intensity is normally distributed.

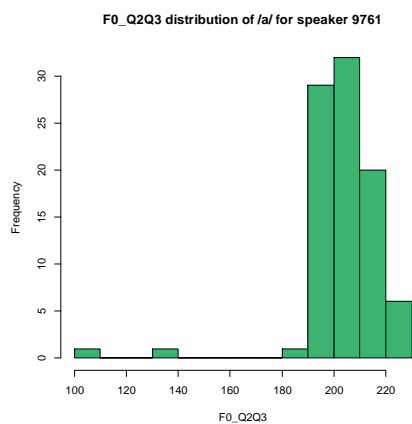
Duration



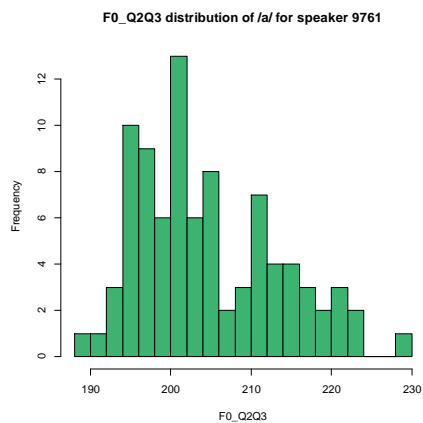
Duration is normally distributed.

For /a/ vowel

F0_Q2Q3

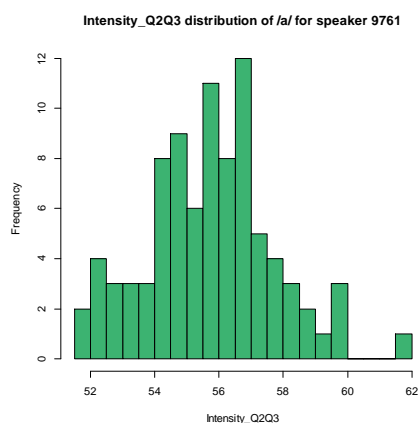


F0 has a couple of outliers. These were excluded and the distribution replotted.



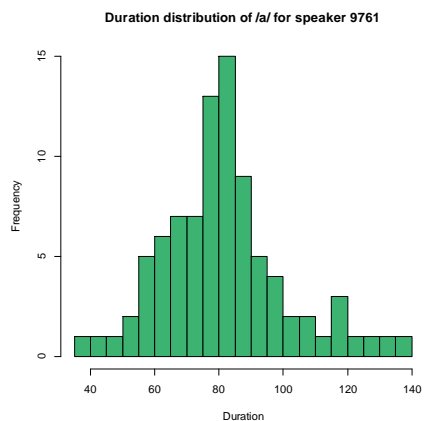
F0 is not very normal in its distribution. It has slightly right skewed distribution.

Intensity_Q2Q3



Intensity is normally distributed.

Duration



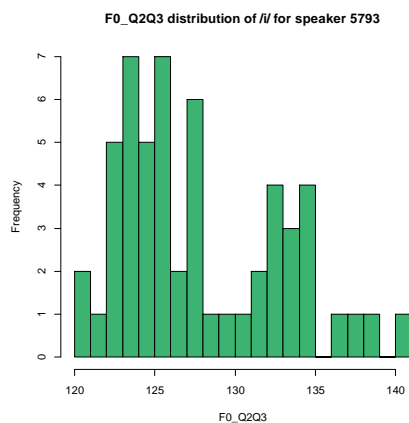
Duration is normally distributed.

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Speaker 5793

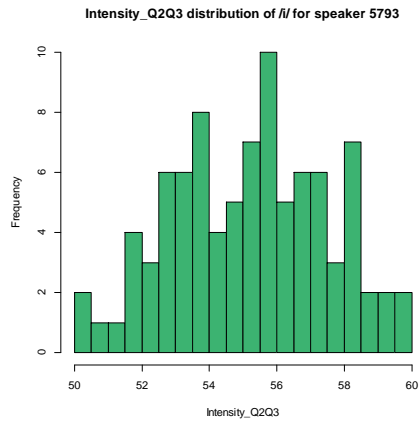
For /i/ vowel

F0_Q2Q3



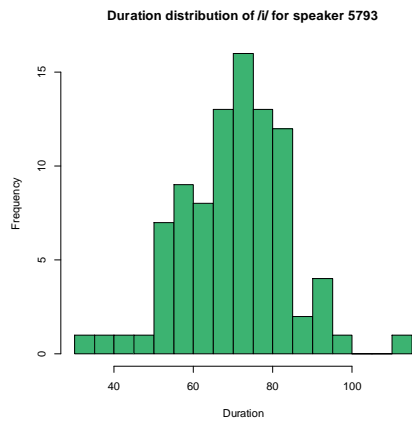
F0 is not normally distributed. It has a right skewed distribution.

Intensity_Q2Q3



Intensity is normally distributed.

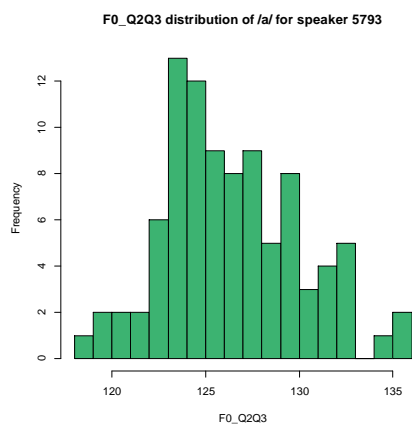
Duration



Duration is normally distributed.

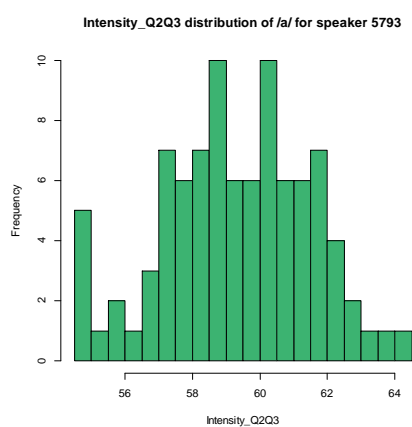
For /a/ vowel

F0_Q2Q3



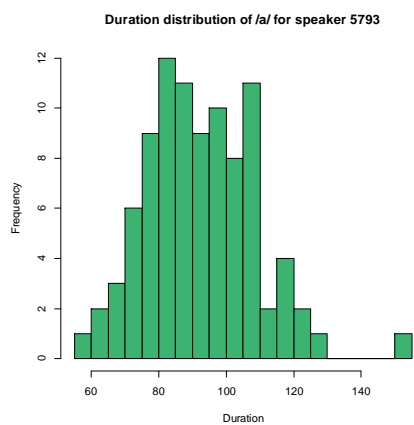
F0 distribution is relatively normal.

Intensity_Q2Q3



Intensity is normally distributed.

Duration

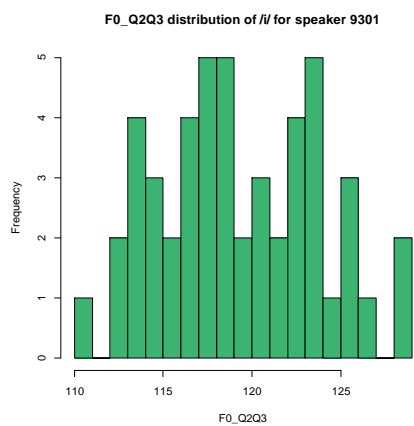


Duration is normally distributed.

Speaker 9301

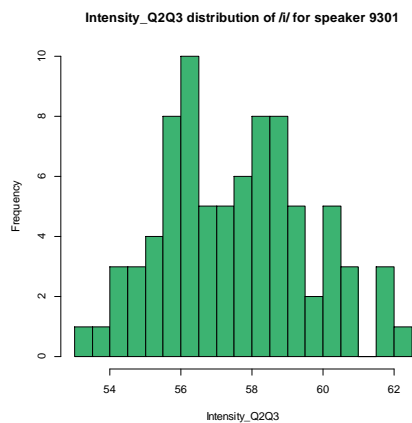
For /i/ vowel

F0_Q2Q3



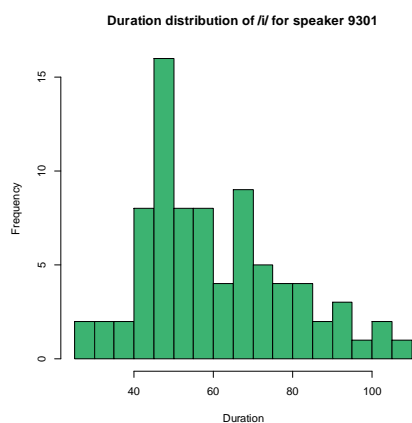
F0 is relatively normally distributed.

Intensity_Q2Q3



Intensity is normally distributed.

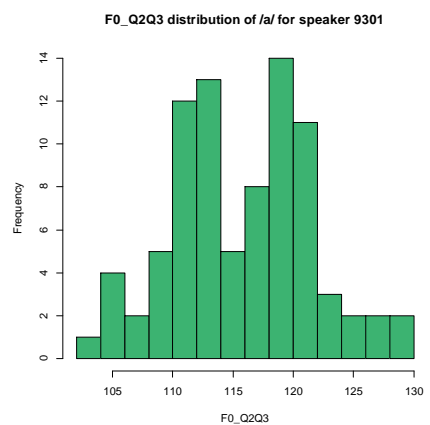
Duration



Duration is relatively normally distributed.

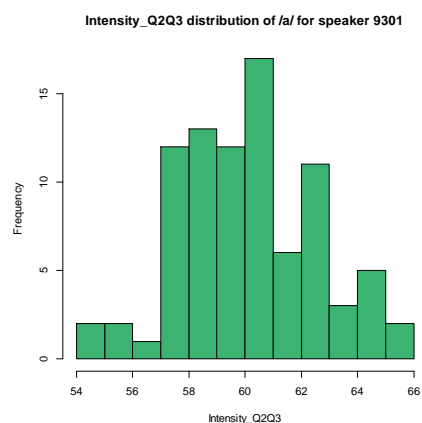
For /a/ vowel

F0_Q2Q3



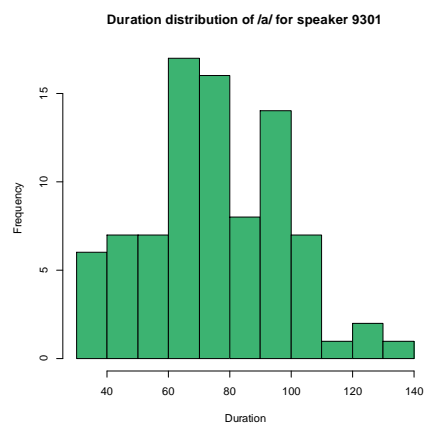
F0 is relatively normally distributed.

Intensity_Q2Q3



Intensity is normally distributed.

Duration



Duration is normally distributed.

Appendix C – Norming codes

```

> ## Subsetting the participants
> p6946 <- subset(df, ParticipantID==6946)
> p1687 <- subset(df, ParticipantID==1687)
> p3791 <- subset(df, ParticipantID==3791)
> p6306 <- subset(df, ParticipantID==6306)
> p7143 <- subset(df, ParticipantID==7143)
> p9761 <- subset(df, ParticipantID==9761)
> p5793 <- subset(df, ParticipantID==5793)
> p9301 <- subset(df, ParticipantID==9301)
>
> ## Subsetting out the vowels for each participant
> p6946.i <- subset(p6946, Vowel=="i")
> p6946.a <- subset(p6946, Vowel=="a")
> p1687.i <- subset(p1687, Vowel=="i")
> p1687.a <- subset(p1687, Vowel=="a")
> p3791.i <- subset(p3791, Vowel=="i")
> p3791.a <- subset(p3791, Vowel=="a")
> p6306.i <- subset(p6306, Vowel=="i")
> p6306.a <- subset(p6306, Vowel=="a")
> p7143.i <- subset(p7143, Vowel=="i")
> p7143.a <- subset(p7143, Vowel=="a")
> p9761.i <- subset(p9761, Vowel=="i")
> p9761.a <- subset(p9761, Vowel=="a")
> p5793.i <- subset(p5793, Vowel=="i")
> p5793.a <- subset(p5793, Vowel=="a")
> p9301.i <- subset(p9301, Vowel=="i")
> p9301.a <- subset(p9301, Vowel=="a")
>
> ## Subsetting out the outliers
> p1687.a1 <- subset(p1687.a, F0_Q2Q3>150)
> p6946.i1 <- subset(p6946.i, F0_Q2Q3>140)
> p7143.i1 <- subset(p7143.i, F0_Q2Q3>200)
> p7143.a1 <- subset(p7143.a, F0_Q2Q3>150)
> p9761.a1 <- subset(p9761.a, F0_Q2Q3>150)
>
> # Speaker 6946
> # /i/ data
> log.F0_Q1 <- log(p6946.i1$F0_Q1)
> log.F0_Q2 <- log(p6946.i1$F0_Q2)
> log.F0_Q3 <- log(p6946.i1$F0_Q3)
> log.F0_Q4 <- log(p6946.i1$F0_Q4)
> log.F0_ALL <- log(p6946.i1$F0_ALL)
> log.F0_Q2Q3 <- log(p6946.i1$F0_Q2Q3)
> log.maxF0_Q1 <- log(p6946.i1$maxF0_Q1)
> log.maxF0_Q2 <- log(p6946.i1$maxF0_Q2)
> log.maxF0_Q3 <- log(p6946.i1$maxF0_Q3)
> log.maxF0_Q4 <- log(p6946.i1$maxF0_Q4)

```

```

> log.maxF0_ALL <- log(p6946.i1$maxF0_ALL)
> log.maxF0_Q2Q3 <- log(p6946.i1$maxF0_Q2Q3)
> log.minF0_Q1 <- log(p6946.i1$minF0_Q1)
> log.minF0_Q2 <- log(p6946.i1$minF0_Q2)
> log.minF0_Q3 <- log(p6946.i1$minF0_Q3)
> log.minF0_Q4 <- log(p6946.i1$minF0_Q4)
> log.minF0_ALL <- log(p6946.i1$minF0_ALL)
> log.minF0_Q2Q3 <- log(p6946.i1$minF0_Q2Q3)
>
> # now transforing the log transformed values into z-scores
>
> z.log.F0_Q1 <- scale(log.F0_Q1, center = TRUE, scale = TRUE)
> z.log.F0_Q2 <- scale(log.F0_Q2, center=TRUE, scale=TRUE)
> z.log.F0_Q3 <- scale(log.F0_Q3, center=TRUE, scale=TRUE)
> z.log.F0_Q4 <- scale(log.F0_Q4, center=TRUE, scale=TRUE)
> z.log.F0_ALL <- scale(log.F0_ALL, center=TRUE, scale=TRUE)
> z.log.F0_Q2Q3 <- scale(log.F0_Q2Q3, center=TRUE, scale=TRUE)
> z.log.maxF0_Q1 <- scale(log.maxF0_Q1, center=TRUE, scale=TRUE)
> z.log.maxF0_Q2 <- scale(log.maxF0_Q2, center=TRUE, scale=TRUE)
> z.log.maxF0_Q3 <- scale(log.maxF0_Q3, center=TRUE, scale=TRUE)
> z.log.maxF0_Q4 <- scale(log.maxF0_Q4, center=TRUE, scale=TRUE)
> z.log.maxF0_ALL <- scale(log.maxF0_ALL, center=TRUE, scale=TRUE)
> z.log.maxF0_Q2Q3 <- scale(log.maxF0_Q2Q3, center=TRUE, scale=TRUE)
> z.log.minF0_Q1 <- scale(log.minF0_Q1, center=TRUE, scale=TRUE)
> z.log.minF0_Q2 <- scale(log.minF0_Q2, center=TRUE, scale=TRUE)
> z.log.minF0_Q3 <- scale(log.minF0_Q3, center=TRUE, scale=TRUE)
> z.log.minF0_Q4 <- scale(log.minF0_Q4, center=TRUE, scale=TRUE)
> z.log.minF0_ALL <- scale(log.minF0_ALL, center=TRUE, scale=TRUE)
> z.log.minF0_Q2Q3 <- scale(log.minF0_Q2Q3, center=TRUE, scale=TRUE)
>
> # formants into z-scores
> # F1
> z.F1_Q1 <- scale(p6946.i1$F1_Q1, center=TRUE, scale=TRUE)
> z.F1_Q2 <- scale(p6946.i1$F1_Q2, center=TRUE, scale=TRUE)
> z.F1_Q3 <- scale(p6946.i1$F1_Q3, center=TRUE, scale=TRUE)
> z.F1_Q4 <- scale(p6946.i1$F1_Q4, center=TRUE, scale=TRUE)
> z.F1_ALL <- scale(p6946.i1$F1_ALL, center=TRUE, scale=TRUE)
> z.F1_Q2Q3 <- scale(p6946.i1$F1_Q2Q3, center=TRUE, scale=TRUE)
>
> # F2
> z.F2_Q1 <- scale(p6946.i1$F2_Q1, center=TRUE, scale=TRUE)
> z.F2_Q2 <- scale(p6946.i1$F2_Q2, center=TRUE, scale=TRUE)
> z.F2_Q3 <- scale(p6946.i1$F2_Q3, center=TRUE, scale=TRUE)
> z.F2_Q4 <- scale(p6946.i1$F2_Q4, center=TRUE, scale=TRUE)
> z.F2_ALL <- scale(p6946.i1$F2_ALL, center=TRUE, scale=TRUE)
> z.F2_Q2Q3 <- scale(p6946.i1$F2_Q2Q3, center=TRUE, scale=TRUE)
>
> # F3
> z.F3_Q1 <- scale(p6946.i1$F3_Q1, center=TRUE, scale=TRUE)
> z.F3_Q2 <- scale(p6946.i1$F3_Q2, center=TRUE, scale=TRUE)
> z.F3_Q3 <- scale(p6946.i1$F3_Q3, center=TRUE, scale=TRUE)
> z.F3_Q4 <- scale(p6946.i1$F3_Q4, center=TRUE, scale=TRUE)
> z.F3_ALL <- scale(p6946.i1$F3_ALL, center=TRUE, scale=TRUE)
> z.F3_Q2Q3 <- scale(p6946.i1$F3_Q2Q3, center=TRUE, scale=TRUE)
>
> # Duration
> z.Duration <- scale(p6946.i1$Duration, center=TRUE, scale=TRUE)

```

```

>
> # Intensity
> z.Intensity_Q1 <- scale(p6946.il$Intensity_Q1, center=TRUE, scale=TRUE)
> z.Intensity_Q2 <- scale(p6946.il$Intensity_Q2, center=TRUE, scale=TRUE)
> z.Intensity_Q3 <- scale(p6946.il$Intensity_Q3, center=TRUE, scale=TRUE)
> z.Intensity_Q4 <- scale(p6946.il$Intensity_Q4, center=TRUE, scale=TRUE)
> z.Intensity_all <- scale(p6946.il$Intensity_all, center=TRUE, scale=TRUE)
> z.Intensity_Q2Q3 <- scale(p6946.il$Intensity_Q2Q3, center=TRUE, scale=TRUE)
>
> # F0change_Q4_minusQ1
> z.F0change_Q4_minusQ1 <- scale(p6946.il$F0change_Q4_minusQ1, center=TRUE,
scale=TRUE)
>
> #F0range_Max_minus_Min
> z.F0range_Max_minus_Min <- scale(p6946.il$F0range_Max_minus_Min,
center=TRUE, scale=TRUE)
>
> # combining the new dataframes with the main dataframe
>
> new2.p6946.il <-
cbind(p6946.il, log.F0_Q1, log.F0_Q2, log.F0_Q3, log.F0_Q4, log.F0_ALL, log.F0_Q2Q3
, log.maxF0_Q1, log.maxF0_Q2, log.maxF0_Q3, log.maxF0_Q4, log.maxF0_ALL, log.maxF0_
Q2Q3, log.minF0_Q1, log.minF0_Q2, log.minF0_Q3, log.minF0_Q4, log.minF0_ALL, log.mi
nF0_Q2Q3, z.log.F0_Q1, z.log.F0_Q2, z.log.F0_Q3, z.log.F0_Q4, z.log.F0_ALL, z.log.F
0_Q2Q3, z.log.maxF0_Q1, z.log.maxF0_Q2, z.log.maxF0_Q3, z.log.maxF0_Q4, z.log.maxF
0_ALL, z.log.maxF0_Q2Q3, z.log.minF0_Q1, z.log.minF0_Q2, z.log.minF0_Q3, z.log.min
F0_Q4, z.log.minF0_ALL, z.log.minF0_Q2Q3, z.F1_Q1, z.F1_Q2, z.F1_Q3, z.F1_Q4, z.F1_A
LL, z.F1_Q2Q3, z.F2_Q1, z.F2_Q2, z.F2_Q3, z.F2_Q4, z.F2_ALL, z.F2_Q2Q3, z.F3_Q1, z.F3_
Q2, z.F3_Q3, z.F3_Q4, z.F3_ALL, z.F3_Q2Q3, z.Duration, z.Intensity_Q1, z.Intensity_Q
2, z.Intensity_Q3, z.Intensity_Q4, z.Intensity_all, z.Intensity_Q2Q3, z.F0change_Q
4_minusQ1, z.F0range_Max_minus_Min)
>
> ## for /a/ vowel
> log.F0_Q1 <- log(p6946.a$F0_Q1)
> log.F0_Q2 <- log(p6946.a$F0_Q2)
> log.F0_Q3 <- log(p6946.a$F0_Q3)
> log.F0_Q4 <- log(p6946.a$F0_Q4)
> log.F0_ALL <- log(p6946.a$F0_ALL)
> log.F0_Q2Q3 <- log(p6946.a$F0_Q2Q3)
> log.maxF0_Q1 <- log(p6946.a$maxF0_Q1)
> log.maxF0_Q2 <- log(p6946.a$maxF0_Q2)
> log.maxF0_Q3 <- log(p6946.a$maxF0_Q3)
> log.maxF0_Q4 <- log(p6946.a$maxF0_Q4)
> log.maxF0_ALL <- log(p6946.a$maxF0_ALL)
> log.maxF0_Q2Q3 <- log(p6946.a$maxF0_Q2Q3)
> log.minF0_Q1 <- log(p6946.a$minF0_Q1)
> log.minF0_Q2 <- log(p6946.a$minF0_Q2)
> log.minF0_Q3 <- log(p6946.a$minF0_Q3)
> log.minF0_Q4 <- log(p6946.a$minF0_Q4)
> log.minF0_ALL <- log(p6946.a$minF0_ALL)
> log.minF0_Q2Q3 <- log(p6946.a$minF0_Q2Q3)
>
> # now transforing the log transformed values into z-scores
> z.log.F0_Q1 <- scale(log.F0_Q1, center = TRUE, scale = TRUE)
> z.log.F0_Q2 <- scale(log.F0_Q2, center=TRUE, scale=TRUE)
> z.log.F0_Q2 <- scale(log.F0_Q2, center=TRUE, scale=TRUE)
> z.log.F0_Q3 <- scale(log.F0_Q3, center=TRUE, scale=TRUE)

```

```

> z.log.F0_Q4 <- scale(log.F0_Q4, center=TRUE, scale=TRUE)
> z.log.F0_ALL <- scale(log.F0_ALL, center=TRUE, scale=TRUE)
> z.log.F0_Q2Q3 <- scale(log.F0_Q2Q3, center=TRUE, scale=TRUE)
> z.log.maxF0_Q1 <- scale(log.maxF0_Q1, center=TRUE, scale=TRUE)
> z.log.maxF0_Q2 <- scale(log.maxF0_Q2, center=TRUE, scale=TRUE)
> z.log.maxF0_Q3 <- scale(log.maxF0_Q3, center=TRUE, scale=TRUE)
> z.log.maxF0_Q4 <- scale(log.maxF0_Q4, center=TRUE, scale=TRUE)
> z.log.maxF0_ALL <- scale(log.maxF0_ALL, center=TRUE, scale=TRUE)
> z.log.maxF0_Q2Q3 <- scale(log.maxF0_Q2Q3, center=TRUE, scale=TRUE)
> z.log.minF0_Q1 <- scale(log.minF0_Q1, center=TRUE, scale=TRUE)
> z.log.minF0_Q2 <- scale(log.minF0_Q2, center=TRUE, scale=TRUE)
> z.log.minF0_Q3 <- scale(log.minF0_Q3, center=TRUE, scale=TRUE)
> z.log.minF0_Q4 <- scale(log.minF0_Q4, center=TRUE, scale=TRUE)
> z.log.minF0_ALL <- scale(log.minF0_ALL, center=TRUE, scale=TRUE)
> z.log.minF0_Q2Q3 <- scale(log.minF0_Q2Q3, center=TRUE, scale=TRUE)
>
> # formants into z-scores
> z.F1_Q1 <- scale(p6946.a$F1_Q1, center=TRUE, scale=TRUE)
> z.F1_Q2 <- scale(p6946.a$F1_Q2, center=TRUE, scale=TRUE)
> z.F1_Q3 <- scale(p6946.a$F1_Q3, center=TRUE, scale=TRUE)
> z.F1_Q4 <- scale(p6946.a$F1_Q4, center=TRUE, scale=TRUE)
> z.F1_ALL <- scale(p6946.a$F1_ALL, center=TRUE, scale=TRUE)
> z.F1_Q2Q3 <- scale(p6946.a$F1_Q2Q3, center=TRUE, scale=TRUE)
>
> # F2
> z.F2_Q1 <- scale(p6946.a$F2_Q1, center=TRUE, scale=TRUE)
> z.F2_Q2 <- scale(p6946.a$F2_Q2, center=TRUE, scale=TRUE)
> z.F2_Q3 <- scale(p6946.a$F2_Q3, center=TRUE, scale=TRUE)
> z.F2_Q4 <- scale(p6946.a$F2_Q4, center=TRUE, scale=TRUE)
> z.F2_ALL <- scale(p6946.a$F2_ALL, center=TRUE, scale=TRUE)
> z.F2_Q2Q3 <- scale(p6946.a$F2_Q2Q3, center=TRUE, scale=TRUE)
>
> # F3
> z.F3_Q1 <- scale(p6946.a$F3_Q1, center=TRUE, scale=TRUE)
> z.F3_Q2 <- scale(p6946.a$F3_Q2, center=TRUE, scale=TRUE)
> z.F3_Q3 <- scale(p6946.a$F3_Q3, center=TRUE, scale=TRUE)
> z.F3_Q4 <- scale(p6946.a$F3_Q4, center=TRUE, scale=TRUE)
> z.F3_ALL <- scale(p6946.a$F3_ALL, center=TRUE, scale=TRUE)
> z.F3_Q2Q3 <- scale(p6946.a$F3_Q2Q3, center=TRUE, scale=TRUE)
>
> # Duration
> z.Duration <- scale(p6946.a$Duration, center=TRUE, scale=TRUE)
>
> # Intensity
> z.Intensity_Q1 <- scale(p6946.a$Intensity_Q1, center=TRUE, scale=TRUE)
> z.Intensity_Q2 <- scale(p6946.a$Intensity_Q2, center=TRUE, scale=TRUE)
> z.Intensity_Q3 <- scale(p6946.a$Intensity_Q3, center=TRUE, scale=TRUE)
> z.Intensity_Q4 <- scale(p6946.a$Intensity_Q4, center=TRUE, scale=TRUE)
> z.Intensity_all <- scale(p6946.a$Intensity_all, center=TRUE, scale=TRUE)
> z.Intensity_Q2Q3 <- scale(p6946.a$Intensity_Q2Q3, center=TRUE, scale=TRUE)
>
> # F0change_Q4_minusQ1
> z.F0change_Q4_minusQ1 <- scale(p6946.a$F0change_Q4_minusQ1, center=TRUE,
scale=TRUE)
>
> # F0range_Max_minus_Min

```

```

> z.F0range_Max_minus_Min <- scale(p6946.i1$F0range_Max_minus_Min,
center=TRUE, scale=TRUE)
>
> new2.p6946.a <-
cbind(p6946.a, log.F0_Q1, log.F0_Q2, log.F0_Q3, log.F0_Q4, log.F0_ALL, log.F0_Q2Q3,
log.maxF0_Q1, log.maxF0_Q2, log.maxF0_Q3, log.maxF0_Q4, log.maxF0_ALL, log.maxF0_Q
2Q3, log.minF0_Q1, log.minF0_Q2, log.minF0_Q3, log.minF0_Q4, log.minF0_ALL, log.min
F0_Q2Q3, z.log.F0_Q1, z.log.F0_Q2, z.log.F0_Q3, z.log.F0_Q4, z.log.F0_ALL, z.log.F0
_Q2Q3, z.log.maxF0_Q1, z.log.maxF0_Q2, z.log.maxF0_Q3, z.log.maxF0_Q4, z.log.maxF0
_ALL, z.log.maxF0_Q2Q3, z.log.minF0_Q1, z.log.minF0_Q2, z.log.minF0_Q3, z.log.minF
0_Q4, z.log.minF0_ALL, z.log.minF0_Q2Q3, z.F1_Q1, z.F1_Q2, z.F1_Q3, z.F1_Q4, z.F1_AL
L, z.F1_Q2Q3, z.F2_Q1, z.F2_Q2, z.F2_Q3, z.F2_Q4, z.F2_ALL, z.F2_Q2Q3, z.F3_Q1, z.F3_Q
2, z.F3_Q3, z.F3_Q4, z.F3_ALL, z.F3_Q2Q3, z.Duration, z.Intensity_Q1, z.Intensity_Q2
, z.Intensity_Q3, z.Intensity_Q4, z.Intensity_all, z.Intensity_Q2Q3, z.F0change_Q4
_minusQ1, z.F0range_Max_minus_Min)
Error in data.frame(..., check.names = FALSE) :
arguments imply differing number of rows: 87, 69
>
> comp.p6946 <- rbind(new2.p6946.i1, new.p6946.a)
Error in rbind(deparse.level, ...) : object 'new.p6946.a' not found
> #F0range_Max_minus_Min
> z.F0range_Max_minus_Min <- scale(p6946.a$F0range_Max_minus_Min,
center=TRUE, scale=TRUE)
>
> new2.p6946.a <-
cbind(p6946.a, log.F0_Q1, log.F0_Q2, log.F0_Q3, log.F0_Q4, log.F0_ALL, log.F0_Q2Q3,
log.maxF0_Q1, log.maxF0_Q2, log.maxF0_Q3, log.maxF0_Q4, log.maxF0_ALL, log.maxF0_Q
2Q3, log.minF0_Q1, log.minF0_Q2, log.minF0_Q3, log.minF0_Q4, log.minF0_ALL, log.min
F0_Q2Q3, z.log.F0_Q1, z.log.F0_Q2, z.log.F0_Q3, z.log.F0_Q4, z.log.F0_ALL, z.log.F0
_Q2Q3, z.log.maxF0_Q1, z.log.maxF0_Q2, z.log.maxF0_Q3, z.log.maxF0_Q4, z.log.maxF0
_ALL, z.log.maxF0_Q2Q3, z.log.minF0_Q1, z.log.minF0_Q2, z.log.minF0_Q3, z.log.minF
0_Q4, z.log.minF0_ALL, z.log.minF0_Q2Q3, z.F1_Q1, z.F1_Q2, z.F1_Q3, z.F1_Q4, z.F1_AL
L, z.F1_Q2Q3, z.F2_Q1, z.F2_Q2, z.F2_Q3, z.F2_Q4, z.F2_ALL, z.F2_Q2Q3, z.F3_Q1, z.F3_Q
2, z.F3_Q3, z.F3_Q4, z.F3_ALL, z.F3_Q2Q3, z.Duration, z.Intensity_Q1, z.Intensity_Q2
, z.Intensity_Q3, z.Intensity_Q4, z.Intensity_all, z.Intensity_Q2Q3, z.F0change_Q4
_minusQ1, z.F0range_Max_minus_Min)
>
> comp.p6946 <- rbind(new2.p6946.i1, new2.p6946.a)
>
> ## Speaker 3791
>
> log.F0_Q1 <- log(p3791.i$F0_Q1)
> log.F0_Q2 <- log(p3791.i$F0_Q2)
> log.F0_Q3 <- log(p3791.i$F0_Q3)
> log.F0_Q4 <- log(p3791.i$F0_Q4)
> log.F0_ALL <- log(p3791.i$F0_ALL)
> log.F0_Q2Q3 <- log(p3791.i$F0_Q2Q3)
> log.maxF0_Q1 <- log(p3791.i$maxF0_Q1)
> log.maxF0_Q2 <- log(p3791.i$maxF0_Q2)
> log.maxF0_Q3 <- log(p3791.i$maxF0_Q3)
> log.maxF0_Q4 <- log(p3791.i$maxF0_Q4)
> log.maxF0_ALL <- log(p3791.i$maxF0_ALL)
> log.maxF0_Q2Q3 <- log(p3791.i$maxF0_Q2Q3)
> log.minF0_Q1 <- log(p3791.i$minF0_Q1)
> log.minF0_Q2 <- log(p3791.i$minF0_Q2)
> log.minF0_Q3 <- log(p3791.i$minF0_Q3)
> log.minF0_Q4 <- log(p3791.i$minF0_Q4)

```

```

> log.minF0_ALL <- log(p3791.i$minF0_ALL)
> log.minF0_Q2Q3 <- log(p3791.i$minF0_Q2Q3)
>
> # now transforming the log transformed values into z-scores
> z.log.F0_Q1 <- scale(log.F0_Q1, center = TRUE, scale = TRUE)
> z.log.F0_Q2 <- scale(log.F0_Q2, center=TRUE, scale=TRUE)
> z.log.F0_Q2 <- scale(log.F0_Q2, center=TRUE, scale=TRUE)
> z.log.F0_Q3 <- scale(log.F0_Q3, center=TRUE, scale=TRUE)
> z.log.F0_Q4 <- scale(log.F0_Q4, center=TRUE, scale=TRUE)
> z.log.F0_ALL <- scale(log.F0_ALL, center=TRUE, scale=TRUE)
> z.log.F0_Q2Q3 <- scale(log.F0_Q2Q3, center=TRUE, scale=TRUE)
> z.log.maxF0_Q1 <- scale(log.maxF0_Q1, center=TRUE, scale=TRUE)
> z.log.maxF0_Q2 <- scale(log.maxF0_Q2, center=TRUE, scale=TRUE)
> z.log.maxF0_Q3 <- scale(log.maxF0_Q3, center=TRUE, scale=TRUE)
> z.log.maxF0_Q4 <- scale(log.maxF0_Q4, center=TRUE, scale=TRUE)
> z.log.maxF0_ALL <- scale(log.maxF0_ALL, center=TRUE, scale=TRUE)
> z.log.maxF0_Q2Q3 <- scale(log.maxF0_Q2Q3, center=TRUE, scale=TRUE)
> z.log.minF0_Q1 <- scale(log.minF0_Q1, center=TRUE, scale=TRUE)
> z.log.minF0_Q2 <- scale(log.minF0_Q2, center=TRUE, scale=TRUE)
> z.log.minF0_Q3 <- scale(log.minF0_Q3, center=TRUE, scale=TRUE)
> z.log.minF0_Q4 <- scale(log.minF0_Q4, center=TRUE, scale=TRUE)
> z.log.minF0_ALL <- scale(log.minF0_ALL, center=TRUE, scale=TRUE)
> z.log.minF0_Q2Q3 <- scale(log.minF0_Q2Q3, center=TRUE, scale=TRUE)
>
> # formants into z-scores
> z.F1_Q1 <- scale(p3791.i$F1_Q1, center=TRUE, scale=TRUE)
> z.F1_Q2 <- scale(p3791.i$F1_Q2, center=TRUE, scale=TRUE)
> z.F1_Q3 <- scale(p3791.i$F1_Q3, center=TRUE, scale=TRUE)
> z.F1_Q4 <- scale(p3791.i$F1_Q4, center=TRUE, scale=TRUE)
> z.F1_ALL <- scale(p3791.i$F1_ALL, center=TRUE, scale=TRUE)
> z.F1_Q2Q3 <- scale(p3791.i$F1_Q2Q3, center=TRUE, scale=TRUE)
>
> # F2
> z.F2_Q1 <- scale(p3791.i$F2_Q1, center=TRUE, scale=TRUE)
> z.F2_Q2 <- scale(p3791.i$F2_Q2, center=TRUE, scale=TRUE)
> z.F2_Q3 <- scale(p3791.i$F2_Q3, center=TRUE, scale=TRUE)
> z.F2_Q4 <- scale(p3791.i$F2_Q4, center=TRUE, scale=TRUE)
> z.F2_ALL <- scale(p3791.i$F2_ALL, center=TRUE, scale=TRUE)
> z.F2_Q2Q3 <- scale(p3791.i$F2_Q2Q3, center=TRUE, scale=TRUE)
>
> # F3
> z.F3_Q1 <- scale(p3791.i$F3_Q1, center=TRUE, scale=TRUE)
> z.F3_Q2 <- scale(p3791.i$F3_Q2, center=TRUE, scale=TRUE)
> z.F3_Q3 <- scale(p3791.i$F3_Q3, center=TRUE, scale=TRUE)
> z.F3_Q4 <- scale(p3791.i$F3_Q4, center=TRUE, scale=TRUE)
> z.F3_ALL <- scale(p3791.i$F3_ALL, center=TRUE, scale=TRUE)
> z.F3_Q2Q3 <- scale(p3791.i$F3_Q2Q3, center=TRUE, scale=TRUE)
>
> # Duration
> z.Duration <- scale(p3791.i$Duration, center=TRUE, scale=TRUE)
>
> # Intensity
> z.Intensity_Q1 <- scale(p3791.i$Intensity_Q1, center=TRUE, scale=TRUE)
> z.Intensity_Q2 <- scale(p3791.i$Intensity_Q2, center=TRUE, scale=TRUE)
> z.Intensity_Q3 <- scale(p3791.i$Intensity_Q3, center=TRUE, scale=TRUE)
> z.Intensity_Q4 <- scale(p3791.i$Intensity_Q4, center=TRUE, scale=TRUE)
> z.Intensity_all <- scale(p3791.i$Intensity_all, center=TRUE, scale=TRUE)

```

```

> z.Intensity_Q2Q3 <- scale(p3791.i$Intensity_Q2Q3, center=TRUE, scale=TRUE)
>
> # F0change_Q4_minusQ1
> z.F0change_Q4_minusQ1 <- scale(p3791.i$F0change_Q4_minusQ1, center=TRUE,
scale=TRUE)
>
> #F0range_Max_minus_Min
> z.F0range_Max_minus_Min <- scale(p3791.i$F0range_Max_minus_Min,
center=TRUE, scale=TRUE)
>
> new2.p3791.i <-
cbind(p3791.i, log.F0_Q1, log.F0_Q2, log.F0_Q3, log.F0_Q4, log.F0_ALL, log.F0_Q2Q3,
log.maxF0_Q1, log.maxF0_Q2, log.maxF0_Q3, log.maxF0_Q4, log.maxF0_ALL, log.maxF0_Q
2Q3, log.minF0_Q1, log.minF0_Q2, log.minF0_Q3, log.minF0_Q4, log.minF0_ALL, log.min
F0_Q2Q3, z.log.F0_Q1, z.log.F0_Q2, z.log.F0_Q3, z.log.F0_Q4, z.log.F0_ALL, z.log.F0
_Q2Q3, z.log.maxF0_Q1, z.log.maxF0_Q2, z.log.maxF0_Q3, z.log.maxF0_Q4, z.log.maxF0
_ALL, z.log.maxF0_Q2Q3, z.log.minF0_Q1, z.log.minF0_Q2, z.log.minF0_Q3, z.log.minF
0_Q4, z.log.minF0_ALL, z.log.minF0_Q2Q3, z.F1_Q1, z.F1_Q2, z.F1_Q3, z.F1_Q4, z.F1_AL
L, z.F1_Q2Q3, z.F2_Q1, z.F2_Q2, z.F2_Q3, z.F2_Q4, z.F2_ALL, z.F2_Q2Q3, z.F3_Q1, z.F3_Q
2, z.F3_Q3, z.F3_Q4, z.F3_ALL, z.F3_Q2Q3, z.Duration, z.Intensity_Q1, z.Intensity_Q2
, z.Intensity_Q3, z.Intensity_Q4, z.Intensity_all, z.Intensity_Q2Q3, z.F0change_Q4
_minusQ1, z.F0range_Max_minus_Min)
>
>
> ## for /a/ vowel
> log.F0_Q1 <- log(p3791.a$F0_Q1)
> log.F0_Q2 <- log(p3791.a$F0_Q2)
> log.F0_Q3 <- log(p3791.a$F0_Q3)
> log.F0_Q4 <- log(p3791.a$F0_Q4)
> log.F0_ALL <- log(p3791.a$F0_ALL)
> log.F0_Q2Q3 <- log(p3791.a$F0_Q2Q3)
> log.maxF0_Q1 <- log(p3791.a$maxF0_Q1)
> log.maxF0_Q2 <- log(p3791.a$maxF0_Q2)
> log.maxF0_Q3 <- log(p3791.a$maxF0_Q3)
> log.maxF0_Q4 <- log(p3791.a$maxF0_Q4)
> log.maxF0_ALL <- log(p3791.a$maxF0_ALL)
> log.maxF0_Q2Q3 <- log(p3791.a$maxF0_Q2Q3)
> log.minF0_Q1 <- log(p3791.a$minF0_Q1)
> log.minF0_Q2 <- log(p3791.a$minF0_Q2)
> log.minF0_Q3 <- log(p3791.a$minF0_Q3)
> log.minF0_Q4 <- log(p3791.a$minF0_Q4)
> log.minF0_ALL <- log(p3791.a$minF0_ALL)
> log.minF0_Q2Q3 <- log(p3791.a$minF0_Q2Q3)
>
> # now transforming the log transformed values into z-scores
> z.log.F0_Q1 <- scale(log.F0_Q1, center = TRUE, scale = TRUE)
> z.log.F0_Q2 <- scale(log.F0_Q2, center=TRUE, scale=TRUE)
> z.log.F0_Q3 <- scale(log.F0_Q3, center=TRUE, scale=TRUE)
> z.log.F0_Q4 <- scale(log.F0_Q4, center=TRUE, scale=TRUE)
> z.log.F0_ALL <- scale(log.F0_ALL, center=TRUE, scale=TRUE)
> z.log.F0_Q2Q3 <- scale(log.F0_Q2Q3, center=TRUE, scale=TRUE)
> z.log.maxF0_Q1 <- scale(log.maxF0_Q1, center=TRUE, scale=TRUE)
> z.log.maxF0_Q2 <- scale(log.maxF0_Q2, center=TRUE, scale=TRUE)
> z.log.maxF0_Q3 <- scale(log.maxF0_Q3, center=TRUE, scale=TRUE)
> z.log.maxF0_Q4 <- scale(log.maxF0_Q4, center=TRUE, scale=TRUE)
> z.log.maxF0_ALL <- scale(log.maxF0_ALL, center=TRUE, scale=TRUE)

```



```

> z.log.maxF0_Q2Q3 <- scale(log.maxF0_Q2Q3, center=TRUE, scale=TRUE)
> z.log.minF0_Q1 <- scale(log.minF0_Q1, center=TRUE, scale=TRUE)
> z.log.minF0_Q2 <- scale(log.minF0_Q2, center=TRUE, scale=TRUE)
> z.log.minF0_Q3 <- scale(log.minF0_Q3, center=TRUE, scale=TRUE)
> z.log.minF0_Q4 <- scale(log.minF0_Q4, center=TRUE, scale=TRUE)
> z.log.minF0_ALL <- scale(log.minF0_ALL, center=TRUE, scale=TRUE)
> z.log.minF0_Q2Q3 <- scale(log.minF0_Q2Q3, center=TRUE, scale=TRUE)
>
> # formants into z-scores
> z.F1_Q1 <- scale(p3791.a$F1_Q1, center=TRUE, scale=TRUE)
> z.F1_Q2 <- scale(p3791.a$F1_Q2, center=TRUE, scale=TRUE)
> z.F1_Q3 <- scale(p3791.a$F1_Q3, center=TRUE, scale=TRUE)
> z.F1_Q4 <- scale(p3791.a$F1_Q4, center=TRUE, scale=TRUE)
> z.F1_ALL <- scale(p3791.a$F1_ALL, center=TRUE, scale=TRUE)
> z.F1_Q2Q3 <- scale(p3791.a$F1_Q2Q3, center=TRUE, scale=TRUE)
>
> # F2
> z.F2_Q1 <- scale(p3791.a$F2_Q1, center=TRUE, scale=TRUE)
> z.F2_Q2 <- scale(p3791.a$F2_Q2, center=TRUE, scale=TRUE)
> z.F2_Q3 <- scale(p3791.a$F2_Q3, center=TRUE, scale=TRUE)
> z.F2_Q4 <- scale(p3791.a$F2_Q4, center=TRUE, scale=TRUE)
> z.F2_ALL <- scale(p3791.a$F2_ALL, center=TRUE, scale=TRUE)
> z.F2_Q2Q3 <- scale(p3791.a$F2_Q2Q3, center=TRUE, scale=TRUE)
>
> # F3
> z.F3_Q1 <- scale(p3791.a$F3_Q1, center=TRUE, scale=TRUE)
> z.F3_Q2 <- scale(p3791.a$F3_Q2, center=TRUE, scale=TRUE)
> z.F3_Q3 <- scale(p3791.a$F3_Q3, center=TRUE, scale=TRUE)
> z.F3_Q4 <- scale(p3791.a$F3_Q4, center=TRUE, scale=TRUE)
> z.F3_ALL <- scale(p3791.a$F3_ALL, center=TRUE, scale=TRUE)
> z.F3_Q2Q3 <- scale(p3791.a$F3_Q2Q3, center=TRUE, scale=TRUE)
>
> # Duration
> z.Duration <- scale(p3791.a$Duration, center=TRUE, scale=TRUE)
>
> # Intensity
> z.Intensity_Q1 <- scale(p3791.a$Intensity_Q1, center=TRUE, scale=TRUE)
> z.Intensity_Q2 <- scale(p3791.a$Intensity_Q2, center=TRUE, scale=TRUE)
> z.Intensity_Q3 <- scale(p3791.a$Intensity_Q3, center=TRUE, scale=TRUE)
> z.Intensity_Q4 <- scale(p3791.a$Intensity_Q4, center=TRUE, scale=TRUE)
> z.Intensity_all <- scale(p3791.a$Intensity_all, center=TRUE, scale=TRUE)
> z.Intensity_Q2Q3 <- scale(p3791.a$Intensity_Q2Q3, center=TRUE, scale=TRUE)
>
> # F0change_Q4_minusQ1
> z.F0change_Q4_minusQ1 <- scale(p3791.a$F0change_Q4_minusQ1, center=TRUE,
scale=TRUE)
>
> #F0range_Max_minus_Min
> z.F0range_Max_minus_Min <- scale(p3791.a$F0range_Max_minus_Min,
center=TRUE, scale=TRUE)
>
> new2.p3791.a <-
cbind(p3791.a, log.F0_Q1, log.F0_Q2, log.F0_Q3, log.F0_Q4, log.F0_ALL, log.F0_Q2Q3,
log.maxF0_Q1, log.maxF0_Q2, log.maxF0_Q3, log.maxF0_Q4, log.maxF0_ALL, log.maxF0_Q
2Q3, log.minF0_Q1, log.minF0_Q2, log.minF0_Q3, log.minF0_Q4, log.minF0_ALL, log.min
F0_Q2Q3, z.log.F0_Q1, z.log.F0_Q2, z.log.F0_Q3, z.log.F0_Q4, z.log.F0_ALL, z.log.F0
_Q2Q3, z.log.maxF0_Q1, z.log.maxF0_Q2, z.log.maxF0_Q3, z.log.maxF0_Q4, z.log.maxF0

```

```

_ALL, z.log.maxF0_Q2Q3, z.log.minF0_Q1, z.log.minF0_Q2, z.log.minF0_Q3, z.log.minF
0_Q4, z.log.minF0_ALL, z.log.minF0_Q2Q3, z.F1_Q1, z.F1_Q2, z.F1_Q3, z.F1_Q4, z.F1_AL
L, z.F1_Q2Q3, z.F2_Q1, z.F2_Q2, z.F2_Q3, z.F2_Q4, z.F2_ALL, z.F2_Q2Q3, z.F3_Q1, z.F3_Q
2, z.F3_Q3, z.F3_Q4, z.F3_ALL, z.F3_Q2Q3, z.Duration, z.Intensity_Q1, z.Intensity_Q2
, z.Intensity_Q3, z.Intensity_Q4, z.Intensity_all, z.Intensity_Q2Q3, z.F0change_Q4
_minusQ1, z.F0range_Max_minus_Min)
>
> comp.p3791 <- rbind(new.p3791.i, new.p3791.a)
Error in rbind(new.p3791.i, new.p3791.a) : object 'new.p3791.i' not found
> comp.p3791 <- rbind(new2.p3791.i, new.p3791.a)
Error in rbind(deparse.level, ...) : object 'new.p3791.a' not found
> comp.p3791 <- rbind(new2.p3791.i, new2.p3791.a)
>
> ##### For speaker 6306
>
>
> log.F0_Q1 <- log(p6306.i$F0_Q1)
> log.F0_Q2 <- log(p6306.i$F0_Q2)
> log.F0_Q3 <- log(p6306.i$F0_Q3)
> log.F0_Q4 <- log(p6306.i$F0_Q4)
> log.F0_ALL <- log(p6306.i$F0_ALL)
> log.F0_Q2Q3 <- log(p6306.i$F0_Q2Q3)
> log.maxF0_Q1 <- log(p6306.i$maxF0_Q1)
> log.maxF0_Q2 <- log(p6306.i$maxF0_Q2)
> log.maxF0_Q3 <- log(p6306.i$maxF0_Q3)
> log.maxF0_Q4 <- log(p6306.i$maxF0_Q4)
> log.maxF0_ALL <- log(p6306.i$maxF0_ALL)
> log.maxF0_Q2Q3 <- log(p6306.i$maxF0_Q2Q3)
> log.minF0_Q1 <- log(p6306.i$minF0_Q1)
> log.minF0_Q2 <- log(p6306.i$minF0_Q2)
> log.minF0_Q3 <- log(p6306.i$minF0_Q3)
> log.minF0_Q4 <- log(p6306.i$minF0_Q4)
> log.minF0_ALL <- log(p6306.i$minF0_ALL)
> log.minF0_Q2Q3 <- log(p6306.i$minF0_Q2Q3)
>
> # now transforming the log transformed values into z-scores
> z.log.F0_Q1 <- scale(log.F0_Q1, center = TRUE, scale = TRUE)
> z.log.F0_Q2 <- scale(log.F0_Q2, center=TRUE, scale=TRUE)
> z.log.F0_Q2 <- scale(log.F0_Q2, center=TRUE, scale=TRUE)
> z.log.F0_Q3 <- scale(log.F0_Q3, center=TRUE, scale=TRUE)
> z.log.F0_Q4 <- scale(log.F0_Q4, center=TRUE, scale=TRUE)
> z.log.F0_ALL <- scale(log.F0_ALL, center=TRUE, scale=TRUE)
> z.log.F0_Q2Q3 <- scale(log.F0_Q2Q3, center=TRUE, scale=TRUE)
> z.log.maxF0_Q1 <- scale(log.maxF0_Q1, center=TRUE, scale=TRUE)
> z.log.maxF0_Q2 <- scale(log.maxF0_Q2, center=TRUE, scale=TRUE)
> z.log.maxF0_Q3 <- scale(log.maxF0_Q3, center=TRUE, scale=TRUE)
> z.log.maxF0_Q4 <- scale(log.maxF0_Q4, center=TRUE, scale=TRUE)
> z.log.maxF0_ALL <- scale(log.maxF0_ALL, center=TRUE, scale=TRUE)
> z.log.maxF0_Q2Q3 <- scale(log.maxF0_Q2Q3, center=TRUE, scale=TRUE)
> z.log.minF0_Q1 <- scale(log.minF0_Q1, center=TRUE, scale=TRUE)
> z.log.minF0_Q2 <- scale(log.minF0_Q2, center=TRUE, scale=TRUE)
> z.log.minF0_Q3 <- scale(log.minF0_Q3, center=TRUE, scale=TRUE)
> z.log.minF0_Q4 <- scale(log.minF0_Q4, center=TRUE, scale=TRUE)
> z.log.minF0_ALL <- scale(log.minF0_ALL, center=TRUE, scale=TRUE)
> z.log.minF0_Q2Q3 <- scale(log.minF0_Q2Q3, center=TRUE, scale=TRUE)
>
> # formants into z-scores

```

```

> z.F1_Q1 <- scale(p6306.i$F1_Q1, center=TRUE, scale=TRUE)
> z.F1_Q2 <- scale(p6306.i$F1_Q2, center=TRUE, scale=TRUE)
> z.F1_Q3 <- scale(p6306.i$F1_Q3, center=TRUE, scale=TRUE)
> z.F1_Q4 <- scale(p6306.i$F1_Q4, center=TRUE, scale=TRUE)
> z.F1_ALL <- scale(p6306.i$F1_ALL, center=TRUE, scale=TRUE)
> z.F1_Q2Q3 <- scale(p6306.i$F1_Q2Q3, center=TRUE, scale=TRUE)
>
> # F2
> z.F2_Q1 <- scale(p6306.i$F2_Q1, center=TRUE, scale=TRUE)
> z.F2_Q2 <- scale(p6306.i$F2_Q2, center=TRUE, scale=TRUE)
> z.F2_Q3 <- scale(p6306.i$F2_Q3, center=TRUE, scale=TRUE)
> z.F2_Q4 <- scale(p6306.i$F2_Q4, center=TRUE, scale=TRUE)
> z.F2_ALL <- scale(p6306.i$F2_ALL, center=TRUE, scale=TRUE)
> z.F2_Q2Q3 <- scale(p6306.i$F2_Q2Q3, center=TRUE, scale=TRUE)
>
> # F3
> z.F3_Q1 <- scale(p6306.i$F3_Q1, center=TRUE, scale=TRUE)
> z.F3_Q2 <- scale(p6306.i$F3_Q2, center=TRUE, scale=TRUE)
> z.F3_Q3 <- scale(p6306.i$F3_Q3, center=TRUE, scale=TRUE)
> z.F3_Q4 <- scale(p6306.i$F3_Q4, center=TRUE, scale=TRUE)
> z.F3_ALL <- scale(p6306.i$F3_ALL, center=TRUE, scale=TRUE)
> z.F3_Q2Q3 <- scale(p6306.i$F3_Q2Q3, center=TRUE, scale=TRUE)
>
> # Duration
> z.Duration <- scale(p6306.i$Duration, center=TRUE, scale=TRUE)
>
> # Intensity
> z.Intensity_Q1 <- scale(p6306.i$Intensity_Q1, center=TRUE, scale=TRUE)
> z.Intensity_Q2 <- scale(p6306.i$Intensity_Q2, center=TRUE, scale=TRUE)
> z.Intensity_Q3 <- scale(p6306.i$Intensity_Q3, center=TRUE, scale=TRUE)
> z.Intensity_Q4 <- scale(p6306.i$Intensity_Q4, center=TRUE, scale=TRUE)
> z.Intensity_all <- scale(p6306.i$Intensity_all, center=TRUE, scale=TRUE)
> z.Intensity_Q2Q3 <- scale(p6306.i$Intensity_Q2Q3, center=TRUE, scale=TRUE)
>
> # F0change_Q4_minusQ1
> z.F0change_Q4_minusQ1 <- scale(p6306.i$F0change_Q4_minusQ1, center=TRUE,
scale=TRUE)
>
> # F0range_Max_minus_Min
> z.F0range_Max_minus_Min <- scale(p6306.i$F0range_Max_minus_Min,
center=TRUE, scale=TRUE)
>
> new.p6306.i <-
cbind(p6306.i, log.F0_Q1, log.F0_Q2, log.F0_Q3, log.F0_Q4, log.F0_ALL, log.F0_Q2Q3,
log.maxF0_Q1, log.maxF0_Q2, log.maxF0_Q3, log.maxF0_Q4, log.maxF0_ALL, log.maxF0_Q
2Q3, log.minF0_Q1, log.minF0_Q2, log.minF0_Q3, log.minF0_Q4, log.minF0_ALL, log.min
F0_Q2Q3, z.log.F0_Q1, z.log.F0_Q2, z.log.F0_Q3, z.log.F0_Q4, z.log.F0_ALL, z.log.F0
_Q2Q3, z.log.maxF0_Q1, z.log.maxF0_Q2, z.log.maxF0_Q3, z.log.maxF0_Q4, z.log.maxF0
_ALL, z.log.maxF0_Q2Q3, z.log.minF0_Q1, z.log.minF0_Q2, z.log.minF0_Q3, z.log.minF
0_Q4, z.log.minF0_ALL, z.log.minF0_Q2Q3, z.F1_Q1, z.F1_Q2, z.F1_Q3, z.F1_Q4, z.F1_AL
L, z.F1_Q2Q3, z.F2_Q1, z.F2_Q2, z.F2_Q3, z.F2_Q4, z.F2_ALL, z.F2_Q2Q3, z.F3_Q1, z.F3_Q
2, z.F3_Q3, z.F3_Q4, z.F3_ALL, z.F3_Q2Q3, z.Duration, z.Intensity_Q1, z.Intensity_Q2
, z.Intensity_Q3, z.Intensity_Q4, z.Intensity_all, z.Intensity_Q2Q3, z.F0change_Q4
_minusQ1, z.F0range_Max_minus_Min)
>
>
>

```

```

>
> ## for /a/ vowel
>
> log.F0_Q1 <- log(p6306.a$F0_Q1)
> log.F0_Q2 <- log(p6306.a$F0_Q2)
> log.F0_Q3 <- log(p6306.a$F0_Q3)
> log.F0_Q4 <- log(p6306.a$F0_Q4)
> log.F0_ALL <- log(p6306.a$F0_ALL)
> log.F0_Q2Q3 <- log(p6306.a$F0_Q2Q3)
> log.maxF0_Q1 <- log(p6306.a$maxF0_Q1)
> log.maxF0_Q2 <- log(p6306.a$maxF0_Q2)
> log.maxF0_Q3 <- log(p6306.a$maxF0_Q3)
> log.maxF0_Q4 <- log(p6306.a$maxF0_Q4)
> log.maxF0_ALL <- log(p6306.a$maxF0_ALL)
> log.maxF0_Q2Q3 <- log(p6306.a$maxF0_Q2Q3)
> log.minF0_Q1 <- log(p6306.a$minF0_Q1)
> log.minF0_Q2 <- log(p6306.a$minF0_Q2)
> log.minF0_Q3 <- log(p6306.a$minF0_Q3)
> log.minF0_Q4 <- log(p6306.a$minF0_Q4)
> log.minF0_ALL <- log(p6306.a$minF0_ALL)
> log.minF0_Q2Q3 <- log(p6306.a$minF0_Q2Q3)
>
> # now transforming the log transformed values into z-scores
> z.log.F0_Q1 <- scale(log.F0_Q1, center = TRUE, scale = TRUE)
> z.log.F0_Q2 <- scale(log.F0_Q2, center=TRUE, scale=TRUE)
> z.log.F0_Q3 <- scale(log.F0_Q3, center=TRUE, scale=TRUE)
> z.log.F0_Q4 <- scale(log.F0_Q4, center=TRUE, scale=TRUE)
> z.log.F0_ALL <- scale(log.F0_ALL, center=TRUE, scale=TRUE)
> z.log.F0_Q2Q3 <- scale(log.F0_Q2Q3, center=TRUE, scale=TRUE)
> z.log.maxF0_Q1 <- scale(log.maxF0_Q1, center=TRUE, scale=TRUE)
> z.log.maxF0_Q2 <- scale(log.maxF0_Q2, center=TRUE, scale=TRUE)
> z.log.maxF0_Q3 <- scale(log.maxF0_Q3, center=TRUE, scale=TRUE)
> z.log.maxF0_Q4 <- scale(log.maxF0_Q4, center=TRUE, scale=TRUE)
> z.log.maxF0_ALL <- scale(log.maxF0_ALL, center=TRUE, scale=TRUE)
> z.log.maxF0_Q2Q3 <- scale(log.maxF0_Q2Q3, center=TRUE, scale=TRUE)
> z.log.minF0_Q1 <- scale(log.minF0_Q1, center=TRUE, scale=TRUE)
> z.log.minF0_Q2 <- scale(log.minF0_Q2, center=TRUE, scale=TRUE)
> z.log.minF0_Q3 <- scale(log.minF0_Q3, center=TRUE, scale=TRUE)
> z.log.minF0_Q4 <- scale(log.minF0_Q4, center=TRUE, scale=TRUE)
> z.log.minF0_ALL <- scale(log.minF0_ALL, center=TRUE, scale=TRUE)
> z.log.minF0_Q2Q3 <- scale(log.minF0_Q2Q3, center=TRUE, scale=TRUE)
>
> # formants into z-scores
> z.F1_Q1 <- scale(p6306.a$F1_Q1, center=TRUE, scale=TRUE)
> z.F1_Q2 <- scale(p6306.a$F1_Q2, center=TRUE, scale=TRUE)
> z.F1_Q3 <- scale(p6306.a$F1_Q3, center=TRUE, scale=TRUE)
> z.F1_Q4 <- scale(p6306.a$F1_Q4, center=TRUE, scale=TRUE)
> z.F1_ALL <- scale(p6306.a$F1_ALL, center=TRUE, scale=TRUE)
> z.F1_Q2Q3 <- scale(p6306.a$F1_Q2Q3, center=TRUE, scale=TRUE)
>
> # F2
> z.F2_Q1 <- scale(p6306.a$F2_Q1, center=TRUE, scale=TRUE)
> z.F2_Q2 <- scale(p6306.a$F2_Q2, center=TRUE, scale=TRUE)
> z.F2_Q3 <- scale(p6306.a$F2_Q3, center=TRUE, scale=TRUE)
> z.F2_Q4 <- scale(p6306.a$F2_Q4, center=TRUE, scale=TRUE)
> z.F2_ALL <- scale(p6306.a$F2_ALL, center=TRUE, scale=TRUE)

```

```

> z.F2_Q2Q3 <- scale(p6306.a$F2_Q2Q3, center=TRUE, scale=TRUE)
>
> # F3
> z.F3_Q1 <- scale(p6306.a$F3_Q1, center=TRUE, scale=TRUE)
> z.F3_Q2 <- scale(p6306.a$F3_Q2, center=TRUE, scale=TRUE)
> z.F3_Q3 <- scale(p6306.a$F3_Q3, center=TRUE, scale=TRUE)
> z.F3_Q4 <- scale(p6306.a$F3_Q4, center=TRUE, scale=TRUE)
> z.F3_ALL <- scale(p6306.a$F3_ALL, center=TRUE, scale=TRUE)
> z.F3_Q2Q3 <- scale(p6306.a$F3_Q2Q3, center=TRUE, scale=TRUE)
>
> # Duration
> z.Duration <- scale(p6306.a$Duration, center=TRUE, scale=TRUE)
>
> # Intensity
> z.Intensity_Q1 <- scale(p6306.a$Intensity_Q1, center=TRUE, scale=TRUE)
> z.Intensity_Q2 <- scale(p6306.a$Intensity_Q2, center=TRUE, scale=TRUE)
> z.Intensity_Q3 <- scale(p6306.a$Intensity_Q3, center=TRUE, scale=TRUE)
> z.Intensity_Q4 <- scale(p6306.a$Intensity_Q4, center=TRUE, scale=TRUE)
> z.Intensity_all <- scale(p6306.a$Intensity_all, center=TRUE, scale=TRUE)
> z.Intensity_Q2Q3 <- scale(p6306.a$Intensity_Q2Q3, center=TRUE, scale=TRUE)
>
> # F0change_Q4_minusQ1
> z.F0change_Q4_minusQ1 <- scale(p6306.a$F0change_Q4_minusQ1, center=TRUE,
scale=TRUE)
>
> #F0range_Max_minus_Min
> z.F0range_Max_minus_Min <- scale(p6306.a$F0range_Max_minus_Min,
center=TRUE, scale=TRUE)
>
> new.p6306.a <-
cbind(p6306.a, log.F0_Q1, log.F0_Q2, log.F0_Q3, log.F0_Q4, log.F0_ALL, log.F0_Q2Q3,
log.maxF0_Q1, log.maxF0_Q2, log.maxF0_Q3, log.maxF0_Q4, log.maxF0_ALL, log.maxF0_Q
2Q3, log.minF0_Q1, log.minF0_Q2, log.minF0_Q3, log.minF0_Q4, log.minF0_ALL, log.min
F0_Q2Q3, z.log.F0_Q1, z.log.F0_Q2, z.log.F0_Q3, z.log.F0_Q4, z.log.F0_ALL, z.log.F0
_Q2Q3, z.log.maxF0_Q1, z.log.maxF0_Q2, z.log.maxF0_Q3, z.log.maxF0_Q4, z.log.maxF0
_ALL, z.log.maxF0_Q2Q3, z.log.minF0_Q1, z.log.minF0_Q2, z.log.minF0_Q3, z.log.minF
0_Q4, z.log.minF0_ALL, z.log.minF0_Q2Q3, z.F1_Q1, z.F1_Q2, z.F1_Q3, z.F1_Q4, z.F1_AL
L, z.F1_Q2Q3, z.F2_Q1, z.F2_Q2, z.F2_Q3, z.F2_Q4, z.F2_ALL, z.F2_Q2Q3, z.F3_Q1, z.F3_Q
2, z.F3_Q3, z.F3_Q4, z.F3_ALL, z.F3_Q2Q3, z.Duration, z.Intensity_Q1, z.Intensity_Q2
, z.Intensity_Q3, z.Intensity_Q4, z.Intensity_all, z.Intensity_Q2Q3, z.F0change_Q4
_minusQ1, z.F0range_Max_minus_Min)
>
>
> ## combining /i/ and /a/ data
>
> comp.p6306 <- rbind(new.p6306.i, new.p6306.a)
>
>
> ##### Speaker 7143 #####
>
> ## For /i/ vowel
>
>
> log.F0_Q1 <- log(p7143.i1$F0_Q1)
> log.F0_Q2 <- log(p7143.i1$F0_Q2)
> log.F0_Q3 <- log(p7143.i1$F0_Q3)
> log.F0_Q4 <- log(p7143.i1$F0_Q4)

```

```

> log.F0_ALL <- log(p7143.i1$F0_ALL)
> log.F0_Q2Q3 <- log(p7143.i1$F0_Q2Q3)
> log.maxF0_Q1 <- log(p7143.i1$maxF0_Q1)
> log.maxF0_Q2 <- log(p7143.i1$maxF0_Q2)
> log.maxF0_Q3 <- log(p7143.i1$maxF0_Q3)
> log.maxF0_Q4 <- log(p7143.i1$maxF0_Q4)
> log.maxF0_ALL <- log(p7143.i1$maxF0_ALL)
> log.maxF0_Q2Q3 <- log(p7143.i1$maxF0_Q2Q3)
> log.minF0_Q1 <- log(p7143.i1$minF0_Q1)
> log.minF0_Q2 <- log(p7143.i1$minF0_Q2)
> log.minF0_Q3 <- log(p7143.i1$minF0_Q3)
> log.minF0_Q4 <- log(p7143.i1$minF0_Q4)
> log.minF0_ALL <- log(p7143.i1$minF0_ALL)
> log.minF0_Q2Q3 <- log(p7143.i1$minF0_Q2Q3)
>
> # now transforming the log transformed values into z-scores
> z.log.F0_Q1 <- scale(log.F0_Q1, center = TRUE, scale = TRUE)
> z.log.F0_Q2 <- scale(log.F0_Q2, center=TRUE, scale=TRUE)
> z.log.F0_Q2 <- scale(log.F0_Q2, center=TRUE, scale=TRUE)
> z.log.F0_Q3 <- scale(log.F0_Q3, center=TRUE, scale=TRUE)
> z.log.F0_Q4 <- scale(log.F0_Q4, center=TRUE, scale=TRUE)
> z.log.F0_ALL <- scale(log.F0_ALL, center=TRUE, scale=TRUE)
> z.log.F0_Q2Q3 <- scale(log.F0_Q2Q3, center=TRUE, scale=TRUE)
> z.log.maxF0_Q1 <- scale(log.maxF0_Q1, center=TRUE, scale=TRUE)
> z.log.maxF0_Q2 <- scale(log.maxF0_Q2, center=TRUE, scale=TRUE)
> z.log.maxF0_Q3 <- scale(log.maxF0_Q3, center=TRUE, scale=TRUE)
> z.log.maxF0_Q4 <- scale(log.maxF0_Q4, center=TRUE, scale=TRUE)
> z.log.maxF0_ALL <- scale(log.maxF0_ALL, center=TRUE, scale=TRUE)
> z.log.maxF0_Q2Q3 <- scale(log.maxF0_Q2Q3, center=TRUE, scale=TRUE)
> z.log.minF0_Q1 <- scale(log.minF0_Q1, center=TRUE, scale=TRUE)
> z.log.minF0_Q2 <- scale(log.minF0_Q2, center=TRUE, scale=TRUE)
> z.log.minF0_Q3 <- scale(log.minF0_Q3, center=TRUE, scale=TRUE)
> z.log.minF0_Q4 <- scale(log.minF0_Q4, center=TRUE, scale=TRUE)
> z.log.minF0_ALL <- scale(log.minF0_ALL, center=TRUE, scale=TRUE)
> z.log.minF0_Q2Q3 <- scale(log.minF0_Q2Q3, center=TRUE, scale=TRUE)
>
> # formants into z-scores
> z.F1_Q1 <- scale(p7143.i1$F1_Q1, center=TRUE, scale=TRUE)
> z.F1_Q2 <- scale(p7143.i1$F1_Q2, center=TRUE, scale=TRUE)
> z.F1_Q3 <- scale(p7143.i1$F1_Q3, center=TRUE, scale=TRUE)
> z.F1_Q4 <- scale(p7143.i1$F1_Q4, center=TRUE, scale=TRUE)
> z.F1_ALL <- scale(p7143.i1$F1_ALL, center=TRUE, scale=TRUE)
> z.F1_Q2Q3 <- scale(p7143.i1$F1_Q2Q3, center=TRUE, scale=TRUE)
>
> # F2
> z.F2_Q1 <- scale(p7143.i1$F2_Q1, center=TRUE, scale=TRUE)
> z.F2_Q2 <- scale(p7143.i1$F2_Q2, center=TRUE, scale=TRUE)
> z.F2_Q3 <- scale(p7143.i1$F2_Q3, center=TRUE, scale=TRUE)
> z.F2_Q4 <- scale(p7143.i1$F2_Q4, center=TRUE, scale=TRUE)
> z.F2_ALL <- scale(p7143.i1$F2_ALL, center=TRUE, scale=TRUE)
> z.F2_Q2Q3 <- scale(p7143.i1$F2_Q2Q3, center=TRUE, scale=TRUE)
>
> # F3
> z.F3_Q1 <- scale(p7143.i1$F3_Q1, center=TRUE, scale=TRUE)
> z.F3_Q2 <- scale(p7143.i1$F3_Q2, center=TRUE, scale=TRUE)
> z.F3_Q3 <- scale(p7143.i1$F3_Q3, center=TRUE, scale=TRUE)
> z.F3_Q4 <- scale(p7143.i1$F3_Q4, center=TRUE, scale=TRUE)

```

```

> z.F3_ALL <- scale(p7143.il$F3_ALL, center=TRUE, scale=TRUE)
> z.F3_Q2Q3 <- scale(p7143.il$F3_Q2Q3, center=TRUE, scale=TRUE)
>
> # Duration
> z.Duration <- scale(p7143.il$Duration, center=TRUE, scale=TRUE)
>
> # Intensity
> z.Intensity_Q1 <- scale(p7143.il$Intensity_Q1, center=TRUE, scale=TRUE)
> z.Intensity_Q2 <- scale(p7143.il$Intensity_Q2, center=TRUE, scale=TRUE)
> z.Intensity_Q3 <- scale(p7143.il$Intensity_Q3, center=TRUE, scale=TRUE)
> z.Intensity_Q4 <- scale(p7143.il$Intensity_Q4, center=TRUE, scale=TRUE)
> z.Intensity_all <- scale(p7143.il$Intensity_all, center=TRUE, scale=TRUE)
> z.Intensity_Q2Q3 <- scale(p7143.il$Intensity_Q2Q3, center=TRUE, scale=TRUE)
>
> # F0change_Q4_minusQ1
> z.F0change_Q4_minusQ1 <- scale(p7143.il$F0change_Q4_minusQ1, center=TRUE,
scale=TRUE)
>
> #F0range_Max_minus_Min
> z.F0range_Max_minus_Min <- scale(p7143.il$F0range_Max_minus_Min,
center=TRUE, scale=TRUE)
>
> new.p7143.il <-
cbind(p7143.il, log.F0_Q1, log.F0_Q2, log.F0_Q3, log.F0_Q4, log.F0_ALL, log.F0_Q2Q3
, log.maxF0_Q1, log.maxF0_Q2, log.maxF0_Q3, log.maxF0_Q4, log.maxF0_ALL, log.maxF0_
Q2Q3, log.minF0_Q1, log.minF0_Q2, log.minF0_Q3, log.minF0_Q4, log.minF0_ALL, log.mi
nF0_Q2Q3, z.log.F0_Q1, z.log.F0_Q2, z.log.F0_Q3, z.log.F0_Q4, z.log.F0_ALL, z.log.F
0_Q2Q3, z.log.maxF0_Q1, z.log.maxF0_Q2, z.log.maxF0_Q3, z.log.maxF0_Q4, z.log.maxF
0_ALL, z.log.maxF0_Q2Q3, z.log.minF0_Q1, z.log.minF0_Q2, z.log.minF0_Q3, z.log.min
F0_Q4, z.log.minF0_ALL, z.log.minF0_Q2Q3, z.F1_Q1, z.F1_Q2, z.F1_Q3, z.F1_Q4, z.F1_A
LL, z.F1_Q2Q3, z.F2_Q1, z.F2_Q2, z.F2_Q3, z.F2_Q4, z.F2_ALL, z.F2_Q2Q3, z.F3_Q1, z.F3_
Q2, z.F3_Q3, z.F3_Q4, z.F3_ALL, z.F3_Q2Q3, z.Duration, z.Intensity_Q1, z.Intensity_Q
2, z.Intensity_Q3, z.Intensity_Q4, z.Intensity_all, z.Intensity_Q2Q3, z.F0change_Q
4_minusQ1, z.F0range_Max_minus_Min)
>
>
> ## for /a/ vowel
>
> log.F0_Q1 <- log(p7143.a1$F0_Q1)
> log.F0_Q2 <- log(p7143.a1$F0_Q2)
> log.F0_Q3 <- log(p7143.a1$F0_Q3)
> log.F0_Q4 <- log(p7143.a1$F0_Q4)
> log.F0_ALL <- log(p7143.a1$F0_ALL)
> log.F0_Q2Q3 <- log(p7143.a1$F0_Q2Q3)
> log.maxF0_Q1 <- log(p7143.a1$maxF0_Q1)
> log.maxF0_Q2 <- log(p7143.a1$maxF0_Q2)
> log.maxF0_Q3 <- log(p7143.a1$maxF0_Q3)
> log.maxF0_Q4 <- log(p7143.a1$maxF0_Q4)
> log.maxF0_ALL <- log(p7143.a1$maxF0_ALL)
> log.maxF0_Q2Q3 <- log(p7143.a1$maxF0_Q2Q3)
> log.minF0_Q1 <- log(p7143.a1$minF0_Q1)
> log.minF0_Q2 <- log(p7143.a1$minF0_Q2)
> log.minF0_Q3 <- log(p7143.a1$minF0_Q3)
> log.minF0_Q4 <- log(p7143.a1$minF0_Q4)
> log.minF0_ALL <- log(p7143.a1$minF0_ALL)
> log.minF0_Q2Q3 <- log(p7143.a1$minF0_Q2Q3)
>

```

```

> # now transforming the log transformed values into z-scores
> z.log.F0_Q1 <- scale(log.F0_Q1, center = TRUE, scale = TRUE)
> z.log.F0_Q2 <- scale(log.F0_Q2, center=TRUE, scale=TRUE)
> z.log.F0_Q2 <- scale(log.F0_Q2, center=TRUE, scale=TRUE)
> z.log.F0_Q3 <- scale(log.F0_Q3, center=TRUE, scale=TRUE)
> z.log.F0_Q4 <- scale(log.F0_Q4, center=TRUE, scale=TRUE)
> z.log.F0_ALL <- scale(log.F0_ALL, center=TRUE, scale=TRUE)
> z.log.F0_Q2Q3 <- scale(log.F0_Q2Q3, center=TRUE, scale=TRUE)
> z.log.maxF0_Q1 <- scale(log.maxF0_Q1, center=TRUE, scale=TRUE)
> z.log.maxF0_Q2 <- scale(log.maxF0_Q2, center=TRUE, scale=TRUE)
> z.log.maxF0_Q3 <- scale(log.maxF0_Q3, center=TRUE, scale=TRUE)
> z.log.maxF0_Q4 <- scale(log.maxF0_Q4, center=TRUE, scale=TRUE)
> z.log.maxF0_ALL <- scale(log.maxF0_ALL, center=TRUE, scale=TRUE)
> z.log.maxF0_Q2Q3 <- scale(log.maxF0_Q2Q3, center=TRUE, scale=TRUE)
> z.log.minF0_Q1 <- scale(log.minF0_Q1, center=TRUE, scale=TRUE)
> z.log.minF0_Q2 <- scale(log.minF0_Q2, center=TRUE, scale=TRUE)
> z.log.minF0_Q3 <- scale(log.minF0_Q3, center=TRUE, scale=TRUE)
> z.log.minF0_Q4 <- scale(log.minF0_Q4, center=TRUE, scale=TRUE)
> z.log.minF0_ALL <- scale(log.minF0_ALL, center=TRUE, scale=TRUE)
> z.log.minF0_Q2Q3 <- scale(log.minF0_Q2Q3, center=TRUE, scale=TRUE)
>
> # formants into z-scores
> z.F1_Q1 <- scale(p7143.a1$F1_Q1, center=TRUE, scale=TRUE)
> z.F1_Q2 <- scale(p7143.a1$F1_Q2, center=TRUE, scale=TRUE)
> z.F1_Q3 <- scale(p7143.a1$F1_Q3, center=TRUE, scale=TRUE)
> z.F1_Q4 <- scale(p7143.a1$F1_Q4, center=TRUE, scale=TRUE)
> z.F1_ALL <- scale(p7143.a1$F1_ALL, center=TRUE, scale=TRUE)
> z.F1_Q2Q3 <- scale(p7143.a1$F1_Q2Q3, center=TRUE, scale=TRUE)
>
> # F2
> z.F2_Q1 <- scale(p7143.a1$F2_Q1, center=TRUE, scale=TRUE)
> z.F2_Q2 <- scale(p7143.a1$F2_Q2, center=TRUE, scale=TRUE)
> z.F2_Q3 <- scale(p7143.a1$F2_Q3, center=TRUE, scale=TRUE)
> z.F2_Q4 <- scale(p7143.a1$F2_Q4, center=TRUE, scale=TRUE)
> z.F2_ALL <- scale(p7143.a1$F2_ALL, center=TRUE, scale=TRUE)
> z.F2_Q2Q3 <- scale(p7143.a1$F2_Q2Q3, center=TRUE, scale=TRUE)
>
> # F3
> z.F3_Q1 <- scale(p7143.a1$F3_Q1, center=TRUE, scale=TRUE)
> z.F3_Q2 <- scale(p7143.a1$F3_Q2, center=TRUE, scale=TRUE)
> z.F3_Q3 <- scale(p7143.a1$F3_Q3, center=TRUE, scale=TRUE)
> z.F3_Q4 <- scale(p7143.a1$F3_Q4, center=TRUE, scale=TRUE)
> z.F3_ALL <- scale(p7143.a1$F3_ALL, center=TRUE, scale=TRUE)
> z.F3_Q2Q3 <- scale(p7143.a1$F3_Q2Q3, center=TRUE, scale=TRUE)
>
> # Duration
> z.Duration <- scale(p7143.a1$Duration, center=TRUE, scale=TRUE)
>
> # Intensity
> z.Intensity_Q1 <- scale(p7143.a1$Intensity_Q1, center=TRUE, scale=TRUE)
> z.Intensity_Q2 <- scale(p7143.a1$Intensity_Q2, center=TRUE, scale=TRUE)
> z.Intensity_Q3 <- scale(p7143.a1$Intensity_Q3, center=TRUE, scale=TRUE)
> z.Intensity_Q4 <- scale(p7143.a1$Intensity_Q4, center=TRUE, scale=TRUE)
> z.Intensity_all <- scale(p7143.a1$Intensity_all, center=TRUE, scale=TRUE)
> z.Intensity_Q2Q3 <- scale(p7143.a1$Intensity_Q2Q3, center=TRUE, scale=TRUE)
>
> # F0change_Q4_minusQ1

```



```

> z.F0change_Q4_minusQ1 <- scale(p7143.a1$F0change_Q4_minusQ1, center=TRUE,
scale=TRUE)
>
> #F0range_Max_minus_Min
> z.F0range_Max_minus_Min <- scale(p7143.a1$F0range_Max_minus_Min,
center=TRUE, scale=TRUE)
>
> new.p7143.a1 <-
cbind(p7143.a1, log.F0_Q1, log.F0_Q2, log.F0_Q3, log.F0_Q4, log.F0_ALL, log.F0_Q2Q3
, log.maxF0_Q1, log.maxF0_Q2, log.maxF0_Q3, log.maxF0_Q4, log.maxF0_ALL, log.maxF0_
Q2Q3, log.minF0_Q1, log.minF0_Q2, log.minF0_Q3, log.minF0_Q4, log.minF0_ALL, log.mi
nF0_Q2Q3, z.log.F0_Q1, z.log.F0_Q2, z.log.F0_Q3, z.log.F0_Q4, z.log.F0_ALL, z.log.F
0_Q2Q3, z.log.maxF0_Q1, z.log.maxF0_Q2, z.log.maxF0_Q3, z.log.maxF0_Q4, z.log.maxF
0_ALL, z.log.maxF0_Q2Q3, z.log.minF0_Q1, z.log.minF0_Q2, z.log.minF0_Q3, z.log.min
F0_Q4, z.log.minF0_ALL, z.log.minF0_Q2Q3, z.F1_Q1, z.F1_Q2, z.F1_Q3, z.F1_Q4, z.F1_A
LL, z.F1_Q2Q3, z.F2_Q1, z.F2_Q2, z.F2_Q3, z.F2_Q4, z.F2_ALL, z.F2_Q2Q3, z.F3_Q1, z.F3_
Q2, z.F3_Q3, z.F3_Q4, z.F3_ALL, z.F3_Q2Q3, z.Duration, z.Intensity_Q1, z.Intensity_Q
2, z.Intensity_Q3, z.Intensity_Q4, z.Intensity_all, z.Intensity_Q2Q3, z.F0change_Q
4_minusQ1, z.F0range_Max_minus_Min)
>
> ## combining /i/ and /a/ data
>
> comp.7143 <- rbind(new.p7143.i1, new.p7143.a1)
>
>
> ##### Speaker 9301 #####
>
>
> log.F0_Q1 <- log(p9301.i$F0_Q1)
> log.F0_Q2 <- log(p9301.i$F0_Q2)
> log.F0_Q3 <- log(p9301.i$F0_Q3)
> log.F0_Q4 <- log(p9301.i$F0_Q4)
> log.F0_ALL <- log(p9301.i$F0_ALL)
> log.F0_Q2Q3 <- log(p9301.i$F0_Q2Q3)
> log.maxF0_Q1 <- log(p9301.i$maxF0_Q1)
> log.maxF0_Q2 <- log(p9301.i$maxF0_Q2)
> log.maxF0_Q3 <- log(p9301.i$maxF0_Q3)
> log.maxF0_Q4 <- log(p9301.i$maxF0_Q4)
> log.maxF0_ALL <- log(p9301.i$maxF0_ALL)
> log.maxF0_Q2Q3 <- log(p9301.i$maxF0_Q2Q3)
> log.minF0_Q1 <- log(p9301.i$minF0_Q1)
> log.minF0_Q2 <- log(p9301.i$minF0_Q2)
> log.minF0_Q3 <- log(p9301.i$minF0_Q3)
> log.minF0_Q4 <- log(p9301.i$minF0_Q4)
> log.minF0_ALL <- log(p9301.i$minF0_ALL)
> log.minF0_Q2Q3 <- log(p9301.i$minF0_Q2Q3)
>
> # now transforing the log transformed values into z-scores
> z.log.F0_Q1 <- scale(log.F0_Q1, center = TRUE, scale = TRUE)
> z.log.F0_Q2 <- scale(log.F0_Q2, center=TRUE, scale=TRUE)
> z.log.F0_Q2 <- scale(log.F0_Q2, center=TRUE, scale=TRUE)
> z.log.F0_Q3 <- scale(log.F0_Q3, center=TRUE, scale=TRUE)
> z.log.F0_Q4 <- scale(log.F0_Q4, center=TRUE, scale=TRUE)
> z.log.F0_ALL <- scale(log.F0_ALL, center=TRUE, scale=TRUE)
> z.log.F0_Q2Q3 <- scale(log.F0_Q2Q3, center=TRUE, scale=TRUE)
> z.log.maxF0_Q1 <- scale(log.maxF0_Q1, center=TRUE, scale=TRUE)
> z.log.maxF0_Q2 <- scale(log.maxF0_Q2, center=TRUE, scale=TRUE)

```

```

> z.log.maxF0_Q3 <- scale(log.maxF0_Q3, center=TRUE, scale=TRUE)
> z.log.maxF0_Q4 <- scale(log.maxF0_Q4, center=TRUE, scale=TRUE)
> z.log.maxF0_ALL <- scale(log.maxF0_ALL, center=TRUE, scale=TRUE)
> z.log.maxF0_Q2Q3 <- scale(log.maxF0_Q2Q3, center=TRUE, scale=TRUE)
> z.log.minF0_Q1 <- scale(log.minF0_Q1, center=TRUE, scale=TRUE)
> z.log.minF0_Q2 <- scale(log.minF0_Q2, center=TRUE, scale=TRUE)
> z.log.minF0_Q3 <- scale(log.minF0_Q3, center=TRUE, scale=TRUE)
> z.log.minF0_Q4 <- scale(log.minF0_Q4, center=TRUE, scale=TRUE)
> z.log.minF0_ALL <- scale(log.minF0_ALL, center=TRUE, scale=TRUE)
> z.log.minF0_Q2Q3 <- scale(log.minF0_Q2Q3, center=TRUE, scale=TRUE)
>
> # formants into z-scores
> z.F1_Q1 <- scale(p9301.i$F1_Q1, center=TRUE, scale=TRUE)
> z.F1_Q2 <- scale(p9301.i$F1_Q2, center=TRUE, scale=TRUE)
> z.F1_Q3 <- scale(p9301.i$F1_Q3, center=TRUE, scale=TRUE)
> z.F1_Q4 <- scale(p9301.i$F1_Q4, center=TRUE, scale=TRUE)
> z.F1_ALL <- scale(p9301.i$F1_ALL, center=TRUE, scale=TRUE)
> z.F1_Q2Q3 <- scale(p9301.i$F1_Q2Q3, center=TRUE, scale=TRUE)
>
> # F2
> z.F2_Q1 <- scale(p9301.i$F2_Q1, center=TRUE, scale=TRUE)
> z.F2_Q2 <- scale(p9301.i$F2_Q2, center=TRUE, scale=TRUE)
> z.F2_Q3 <- scale(p9301.i$F2_Q3, center=TRUE, scale=TRUE)
> z.F2_Q4 <- scale(p9301.i$F2_Q4, center=TRUE, scale=TRUE)
> z.F2_ALL <- scale(p9301.i$F2_ALL, center=TRUE, scale=TRUE)
> z.F2_Q2Q3 <- scale(p9301.i$F2_Q2Q3, center=TRUE, scale=TRUE)
>
> # F3
> z.F3_Q1 <- scale(p9301.i$F3_Q1, center=TRUE, scale=TRUE)
> z.F3_Q2 <- scale(p9301.i$F3_Q2, center=TRUE, scale=TRUE)
> z.F3_Q3 <- scale(p9301.i$F3_Q3, center=TRUE, scale=TRUE)
> z.F3_Q4 <- scale(p9301.i$F3_Q4, center=TRUE, scale=TRUE)
> z.F3_ALL <- scale(p9301.i$F3_ALL, center=TRUE, scale=TRUE)
> z.F3_Q2Q3 <- scale(p9301.i$F3_Q2Q3, center=TRUE, scale=TRUE)
>
> # Duration
> z.Duration <- scale(p9301.i$Duration, center=TRUE, scale=TRUE)
>
> # Intensity
> z.Intensity_Q1 <- scale(p9301.i$Intensity_Q1, center=TRUE, scale=TRUE)
> z.Intensity_Q2 <- scale(p9301.i$Intensity_Q2, center=TRUE, scale=TRUE)
> z.Intensity_Q3 <- scale(p9301.i$Intensity_Q3, center=TRUE, scale=TRUE)
> z.Intensity_Q4 <- scale(p9301.i$Intensity_Q4, center=TRUE, scale=TRUE)
> z.Intensity_all <- scale(p9301.i$Intensity_all, center=TRUE, scale=TRUE)
> z.Intensity_Q2Q3 <- scale(p9301.i$Intensity_Q2Q3, center=TRUE, scale=TRUE)
>
> # F0change_Q4_minusQ1
> z.F0change_Q4_minusQ1 <- scale(p9301.i$F0change_Q4_minusQ1, center=TRUE,
scale=TRUE)
>
> #F0range_Max_minus_Min
> z.F0range_Max_minus_Min <- scale(p9301.i$F0range_Max_minus_Min,
center=TRUE, scale=TRUE)
>
> new.p9301.i <-
cbind(p9301.i, log.F0_Q1, log.F0_Q2, log.F0_Q3, log.F0_Q4, log.F0_ALL, log.F0_Q2Q3,
log.maxF0_Q1, log.maxF0_Q2, log.maxF0_Q3, log.maxF0_Q4, log.maxF0_ALL, log.maxF0_Q

```

```

2Q3, log.minF0_Q1, log.minF0_Q2, log.minF0_Q3, log.minF0_Q4, log.minF0_ALL, log.min
F0_Q2Q3, z.log.F0_Q1, z.log.F0_Q2, z.log.F0_Q3, z.log.F0_Q4, z.log.F0_ALL, z.log.F0
_Q2Q3, z.log.maxF0_Q1, z.log.maxF0_Q2, z.log.maxF0_Q3, z.log.maxF0_Q4, z.log.maxF0
_ALL, z.log.maxF0_Q2Q3, z.log.minF0_Q1, z.log.minF0_Q2, z.log.minF0_Q3, z.log.minF
0_Q4, z.log.minF0_ALL, z.log.minF0_Q2Q3, z.F1_Q1, z.F1_Q2, z.F1_Q3, z.F1_Q4, z.F1_AL
L, z.F1_Q2Q3, z.F2_Q1, z.F2_Q2, z.F2_Q3, z.F2_Q4, z.F2_ALL, z.F2_Q2Q3, z.F3_Q1, z.F3_Q
2, z.F3_Q3, z.F3_Q4, z.F3_ALL, z.F3_Q2Q3, z.Duration, z.Intensity_Q1, z.Intensity_Q2
, z.Intensity_Q3, z.Intensity_Q4, z.Intensity_all, z.Intensity_Q2Q3, z.F0change_Q4
_minusQ1, z.F0range_Max_minus_Min)
>
>
> ## for /a/ vowel
>
> log.F0_Q1 <- log(p9301.a$F0_Q1)
> log.F0_Q2 <- log(p9301.a$F0_Q2)
> log.F0_Q3 <- log(p9301.a$F0_Q3)
> log.F0_Q4 <- log(p9301.a$F0_Q4)
> log.F0_ALL <- log(p9301.a$F0_ALL)
> log.F0_Q2Q3 <- log(p9301.a$F0_Q2Q3)
> log.maxF0_Q1 <- log(p9301.a$maxF0_Q1)
> log.maxF0_Q2 <- log(p9301.a$maxF0_Q2)
> log.maxF0_Q3 <- log(p9301.a$maxF0_Q3)
> log.maxF0_Q4 <- log(p9301.a$maxF0_Q4)
> log.maxF0_ALL <- log(p9301.a$maxF0_ALL)
> log.maxF0_Q2Q3 <- log(p9301.a$maxF0_Q2Q3)
> log.minF0_Q1 <- log(p9301.a$minF0_Q1)
> log.minF0_Q2 <- log(p9301.a$minF0_Q2)
> log.minF0_Q3 <- log(p9301.a$minF0_Q3)
> log.minF0_Q4 <- log(p9301.a$minF0_Q4)
> log.minF0_ALL <- log(p9301.a$minF0_ALL)
> log.minF0_Q2Q3 <- log(p9301.a$minF0_Q2Q3)
>
> # now transforming the log transformed values into z-scores
> z.log.F0_Q1 <- scale(log.F0_Q1, center = TRUE, scale = TRUE)
> z.log.F0_Q2 <- scale(log.F0_Q2, center=TRUE, scale=TRUE)
> z.log.F0_Q2 <- scale(log.F0_Q2, center=TRUE, scale=TRUE)
> z.log.F0_Q3 <- scale(log.F0_Q3, center=TRUE, scale=TRUE)
> z.log.F0_Q4 <- scale(log.F0_Q4, center=TRUE, scale=TRUE)
> z.log.F0_ALL <- scale(log.F0_ALL, center=TRUE, scale=TRUE)
> z.log.F0_Q2Q3 <- scale(log.F0_Q2Q3, center=TRUE, scale=TRUE)
> z.log.maxF0_Q1 <- scale(log.maxF0_Q1, center=TRUE, scale=TRUE)
> z.log.maxF0_Q2 <- scale(log.maxF0_Q2, center=TRUE, scale=TRUE)
> z.log.maxF0_Q3 <- scale(log.maxF0_Q3, center=TRUE, scale=TRUE)
> z.log.maxF0_Q4 <- scale(log.maxF0_Q4, center=TRUE, scale=TRUE)
> z.log.maxF0_ALL <- scale(log.maxF0_ALL, center=TRUE, scale=TRUE)
> z.log.maxF0_Q2Q3 <- scale(log.maxF0_Q2Q3, center=TRUE, scale=TRUE)
> z.log.minF0_Q1 <- scale(log.minF0_Q1, center=TRUE, scale=TRUE)
> z.log.minF0_Q2 <- scale(log.minF0_Q2, center=TRUE, scale=TRUE)
> z.log.minF0_Q3 <- scale(log.minF0_Q3, center=TRUE, scale=TRUE)
> z.log.minF0_Q4 <- scale(log.minF0_Q4, center=TRUE, scale=TRUE)
> z.log.minF0_ALL <- scale(log.minF0_ALL, center=TRUE, scale=TRUE)
> z.log.minF0_Q2Q3 <- scale(log.minF0_Q2Q3, center=TRUE, scale=TRUE)
>
> # formants into z-scores
> z.F1_Q1 <- scale(p9301.a$F1_Q1, center=TRUE, scale=TRUE)
> z.F1_Q2 <- scale(p9301.a$F1_Q2, center=TRUE, scale=TRUE)
> z.F1_Q3 <- scale(p9301.a$F1_Q3, center=TRUE, scale=TRUE)

```

```

> z.F1_Q4 <- scale(p9301.a$F1_Q4, center=TRUE, scale=TRUE)
> z.F1_ALL <- scale(p9301.a$F1_ALL, center=TRUE, scale=TRUE)
> z.F1_Q2Q3 <- scale(p9301.a$F1_Q2Q3, center=TRUE, scale=TRUE)
>
> # F2
> z.F2_Q1 <- scale(p9301.a$F2_Q1, center=TRUE, scale=TRUE)
> z.F2_Q2 <- scale(p9301.a$F2_Q2, center=TRUE, scale=TRUE)
> z.F2_Q3 <- scale(p9301.a$F2_Q3, center=TRUE, scale=TRUE)
> z.F2_Q4 <- scale(p9301.a$F2_Q4, center=TRUE, scale=TRUE)
> z.F2_ALL <- scale(p9301.a$F2_ALL, center=TRUE, scale=TRUE)
> z.F2_Q2Q3 <- scale(p9301.a$F2_Q2Q3, center=TRUE, scale=TRUE)
>
> # F3
> z.F3_Q1 <- scale(p9301.a$F3_Q1, center=TRUE, scale=TRUE)
> z.F3_Q2 <- scale(p9301.a$F3_Q2, center=TRUE, scale=TRUE)
> z.F3_Q3 <- scale(p9301.a$F3_Q3, center=TRUE, scale=TRUE)
> z.F3_Q4 <- scale(p9301.a$F3_Q4, center=TRUE, scale=TRUE)
> z.F3_ALL <- scale(p9301.a$F3_ALL, center=TRUE, scale=TRUE)
> z.F3_Q2Q3 <- scale(p9301.a$F3_Q2Q3, center=TRUE, scale=TRUE)
>
> # Duration
> z.Duration <- scale(p9301.a$Duration, center=TRUE, scale=TRUE)
>
> # Intensity
> z.Intensity_Q1 <- scale(p9301.a$Intensity_Q1, center=TRUE, scale=TRUE)
> z.Intensity_Q2 <- scale(p9301.a$Intensity_Q2, center=TRUE, scale=TRUE)
> z.Intensity_Q3 <- scale(p9301.a$Intensity_Q3, center=TRUE, scale=TRUE)
> z.Intensity_Q4 <- scale(p9301.a$Intensity_Q4, center=TRUE, scale=TRUE)
> z.Intensity_all <- scale(p9301.a$Intensity_all, center=TRUE, scale=TRUE)
> z.Intensity_Q2Q3 <- scale(p9301.a$Intensity_Q2Q3, center=TRUE, scale=TRUE)
>
> # F0change_Q4_minusQ1
> z.F0change_Q4_minusQ1 <- scale(p9301.a$F0change_Q4_minusQ1, center=TRUE,
scale=TRUE)
>
> #F0range_Max_minus_Min
> z.F0range_Max_minus_Min <- scale(p9301.a$F0range_Max_minus_Min,
center=TRUE, scale=TRUE)
>
> new.p9301.a <-
cbind(p9301.a, log.F0_Q1, log.F0_Q2, log.F0_Q3, log.F0_Q4, log.F0_ALL, log.F0_Q2Q3,
log.maxF0_Q1, log.maxF0_Q2, log.maxF0_Q3, log.maxF0_Q4, log.maxF0_ALL, log.maxF0_Q
2Q3, log.minF0_Q1, log.minF0_Q2, log.minF0_Q3, log.minF0_Q4, log.minF0_ALL, log.min
F0_Q2Q3, z.log.F0_Q1, z.log.F0_Q2, z.log.F0_Q3, z.log.F0_Q4, z.log.F0_ALL, z.log.F0
_Q2Q3, z.log.maxF0_Q1, z.log.maxF0_Q2, z.log.maxF0_Q3, z.log.maxF0_Q4, z.log.maxF0
_ALL, z.log.maxF0_Q2Q3, z.log.minF0_Q1, z.log.minF0_Q2, z.log.minF0_Q3, z.log.minF
0_Q4, z.log.minF0_ALL, z.log.minF0_Q2Q3, z.F1_Q1, z.F1_Q2, z.F1_Q3, z.F1_Q4, z.F1_AL
L, z.F1_Q2Q3, z.F2_Q1, z.F2_Q2, z.F2_Q3, z.F2_Q4, z.F2_ALL, z.F2_Q2Q3, z.F3_Q1, z.F3_Q
2, z.F3_Q3, z.F3_Q4, z.F3_ALL, z.F3_Q2Q3, z.Duration, z.Intensity_Q1, z.Intensity_Q2
, z.Intensity_Q3, z.Intensity_Q4, z.Intensity_all, z.Intensity_Q2Q3, z.F0change_Q4
_minusQ1, z.F0range_Max_minus_Min)
>
> ## combining /i/ and /a/ data
>
> comp.p9301 <- rbind(new.p9301.i, new.p9301.a)
>
>

```

```

> ##### Speaker 9761 #####
>
> log.F0_Q1 <- log(p9761.i$F0_Q1)
> log.F0_Q2 <- log(p9761.i$F0_Q2)
> log.F0_Q3 <- log(p9761.i$F0_Q3)
> log.F0_Q4 <- log(p9761.i$F0_Q4)
> log.F0_ALL <- log(p9761.i$F0_ALL)
> log.F0_Q2Q3 <- log(p9761.i$F0_Q2Q3)
> log.maxF0_Q1 <- log(p9761.i$maxF0_Q1)
> log.maxF0_Q2 <- log(p9761.i$maxF0_Q2)
> log.maxF0_Q3 <- log(p9761.i$maxF0_Q3)
> log.maxF0_Q4 <- log(p9761.i$maxF0_Q4)
> log.maxF0_ALL <- log(p9761.i$maxF0_ALL)
> log.maxF0_Q2Q3 <- log(p9761.i$maxF0_Q2Q3)
> log.minF0_Q1 <- log(p9761.i$minF0_Q1)
> log.minF0_Q2 <- log(p9761.i$minF0_Q2)
> log.minF0_Q3 <- log(p9761.i$minF0_Q3)
> log.minF0_Q4 <- log(p9761.i$minF0_Q4)
> log.minF0_ALL <- log(p9761.i$minF0_ALL)
> log.minF0_Q2Q3 <- log(p9761.i$minF0_Q2Q3)
>
> # now transforming the log transformed values into z-scores
> z.log.F0_Q1 <- scale(log.F0_Q1, center = TRUE, scale = TRUE)
> z.log.F0_Q2 <- scale(log.F0_Q2, center=TRUE, scale=TRUE)
> z.log.F0_Q3 <- scale(log.F0_Q3, center=TRUE, scale=TRUE)
> z.log.F0_Q4 <- scale(log.F0_Q4, center=TRUE, scale=TRUE)
> z.log.F0_ALL <- scale(log.F0_ALL, center=TRUE, scale=TRUE)
> z.log.F0_Q2Q3 <- scale(log.F0_Q2Q3, center=TRUE, scale=TRUE)
> z.log.maxF0_Q1 <- scale(log.maxF0_Q1, center=TRUE, scale=TRUE)
> z.log.maxF0_Q2 <- scale(log.maxF0_Q2, center=TRUE, scale=TRUE)
> z.log.maxF0_Q3 <- scale(log.maxF0_Q3, center=TRUE, scale=TRUE)
> z.log.maxF0_Q4 <- scale(log.maxF0_Q4, center=TRUE, scale=TRUE)
> z.log.maxF0_ALL <- scale(log.maxF0_ALL, center=TRUE, scale=TRUE)
> z.log.maxF0_Q2Q3 <- scale(log.maxF0_Q2Q3, center=TRUE, scale=TRUE)
> z.log.minF0_Q1 <- scale(log.minF0_Q1, center=TRUE, scale=TRUE)
> z.log.minF0_Q2 <- scale(log.minF0_Q2, center=TRUE, scale=TRUE)
> z.log.minF0_Q3 <- scale(log.minF0_Q3, center=TRUE, scale=TRUE)
> z.log.minF0_Q4 <- scale(log.minF0_Q4, center=TRUE, scale=TRUE)
> z.log.minF0_ALL <- scale(log.minF0_ALL, center=TRUE, scale=TRUE)
> z.log.minF0_Q2Q3 <- scale(log.minF0_Q2Q3, center=TRUE, scale=TRUE)
>
> # formants into z-scores
> z.F1_Q1 <- scale(p9761.i$F1_Q1, center=TRUE, scale=TRUE)
> z.F1_Q2 <- scale(p9761.i$F1_Q2, center=TRUE, scale=TRUE)
> z.F1_Q3 <- scale(p9761.i$F1_Q3, center=TRUE, scale=TRUE)
> z.F1_Q4 <- scale(p9761.i$F1_Q4, center=TRUE, scale=TRUE)
> z.F1_ALL <- scale(p9761.i$F1_ALL, center=TRUE, scale=TRUE)
> z.F1_Q2Q3 <- scale(p9761.i$F1_Q2Q3, center=TRUE, scale=TRUE)
>
> # F2
> z.F2_Q1 <- scale(p9761.i$F2_Q1, center=TRUE, scale=TRUE)
> z.F2_Q2 <- scale(p9761.i$F2_Q2, center=TRUE, scale=TRUE)
> z.F2_Q3 <- scale(p9761.i$F2_Q3, center=TRUE, scale=TRUE)
> z.F2_Q4 <- scale(p9761.i$F2_Q4, center=TRUE, scale=TRUE)
> z.F2_ALL <- scale(p9761.i$F2_ALL, center=TRUE, scale=TRUE)
> z.F2_Q2Q3 <- scale(p9761.i$F2_Q2Q3, center=TRUE, scale=TRUE)

```

```

>
> # F3
> z.F3_Q1 <- scale(p9761.i$F3_Q1, center=TRUE, scale=TRUE)
> z.F3_Q2 <- scale(p9761.i$F3_Q2, center=TRUE, scale=TRUE)
> z.F3_Q3 <- scale(p9761.i$F3_Q3, center=TRUE, scale=TRUE)
> z.F3_Q4 <- scale(p9761.i$F3_Q4, center=TRUE, scale=TRUE)
> z.F3_ALL <- scale(p9761.i$F3_ALL, center=TRUE, scale=TRUE)
> z.F3_Q2Q3 <- scale(p9761.i$F3_Q2Q3, center=TRUE, scale=TRUE)
>
> # Duration
> z.Duration <- scale(p9761.i$Duration, center=TRUE, scale=TRUE)
>
> # Intensity
> z.Intensity_Q1 <- scale(p9761.i$Intensity_Q1, center=TRUE, scale=TRUE)
> z.Intensity_Q2 <- scale(p9761.i$Intensity_Q2, center=TRUE, scale=TRUE)
> z.Intensity_Q3 <- scale(p9761.i$Intensity_Q3, center=TRUE, scale=TRUE)
> z.Intensity_Q4 <- scale(p9761.i$Intensity_Q4, center=TRUE, scale=TRUE)
> z.Intensity_all <- scale(p9761.i$Intensity_all, center=TRUE, scale=TRUE)
> z.Intensity_Q2Q3 <- scale(p9761.i$Intensity_Q2Q3, center=TRUE, scale=TRUE)
>
> # F0change_Q4_minusQ1
> z.F0change_Q4_minusQ1 <- scale(p9761.i$F0change_Q4_minusQ1, center=TRUE,
scale=TRUE)
>
> #F0range_Max_minus_Min
> z.F0range_Max_minus_Min <- scale(p9761.i$F0range_Max_minus_Min,
center=TRUE, scale=TRUE)
>
> new.p9761.i <-
cbind(p9761.i, log.F0_Q1, log.F0_Q2, log.F0_Q3, log.F0_Q4, log.F0_ALL, log.F0_Q2Q3,
log.maxF0_Q1, log.maxF0_Q2, log.maxF0_Q3, log.maxF0_Q4, log.maxF0_ALL, log.maxF0_Q
2Q3, log.minF0_Q1, log.minF0_Q2, log.minF0_Q3, log.minF0_Q4, log.minF0_ALL, log.min
F0_Q2Q3, z.log.F0_Q1, z.log.F0_Q2, z.log.F0_Q3, z.log.F0_Q4, z.log.F0_ALL, z.log.F0
_Q2Q3, z.log.maxF0_Q1, z.log.maxF0_Q2, z.log.maxF0_Q3, z.log.maxF0_Q4, z.log.maxF0
_ALL, z.log.maxF0_Q2Q3, z.log.minF0_Q1, z.log.minF0_Q2, z.log.minF0_Q3, z.log.minF
0_Q4, z.log.minF0_ALL, z.log.minF0_Q2Q3, z.F1_Q1, z.F1_Q2, z.F1_Q3, z.F1_Q4, z.F1_AL
L, z.F1_Q2Q3, z.F2_Q1, z.F2_Q2, z.F2_Q3, z.F2_Q4, z.F2_ALL, z.F2_Q2Q3, z.F3_Q1, z.F3_Q
2, z.F3_Q3, z.F3_Q4, z.F3_ALL, z.F3_Q2Q3, z.Duration, z.Intensity_Q1, z.Intensity_Q2
, z.Intensity_Q3, z.Intensity_Q4, z.Intensity_all, z.Intensity_Q2Q3, z.F0change_Q4
_minusQ1, z.F0range_Max_minus_Min)
>
>
>
> ## for /a/ vowel
>
> log.F0_Q1 <- log(p9761.a1$F0_Q1)
> log.F0_Q2 <- log(p9761.a1$F0_Q2)
> log.F0_Q3 <- log(p9761.a1$F0_Q3)
> log.F0_Q4 <- log(p9761.a1$F0_Q4)
> log.F0_ALL <- log(p9761.a1$F0_ALL)
> log.F0_Q2Q3 <- log(p9761.a1$F0_Q2Q3)
> log.maxF0_Q1 <- log(p9761.a1$maxF0_Q1)
> log.maxF0_Q2 <- log(p9761.a1$maxF0_Q2)
> log.maxF0_Q3 <- log(p9761.a1$maxF0_Q3)
> log.maxF0_Q4 <- log(p9761.a1$maxF0_Q4)
> log.maxF0_ALL <- log(p9761.a1$maxF0_ALL)
> log.maxF0_Q2Q3 <- log(p9761.a1$maxF0_Q2Q3)

```

```

> log.minF0_Q1 <- log(p9761.a1$minF0_Q1)
> log.minF0_Q2 <- log(p9761.a1$minF0_Q2)
> log.minF0_Q3 <- log(p9761.a1$minF0_Q3)
> log.minF0_Q4 <- log(p9761.a1$minF0_Q4)
> log.minF0_ALL <- log(p9761.a1$minF0_ALL)
> log.minF0_Q2Q3 <- log(p9761.a1$minF0_Q2Q3)
>
> # now transforming the log transformed values into z-scores
> z.log.F0_Q1 <- scale(log.F0_Q1, center = TRUE, scale = TRUE)
> z.log.F0_Q2 <- scale(log.F0_Q2, center=TRUE, scale=TRUE)
> z.log.F0_Q3 <- scale(log.F0_Q3, center=TRUE, scale=TRUE)
> z.log.F0_Q4 <- scale(log.F0_Q4, center=TRUE, scale=TRUE)
> z.log.F0_ALL <- scale(log.F0_ALL, center=TRUE, scale=TRUE)
> z.log.F0_Q2Q3 <- scale(log.F0_Q2Q3, center=TRUE, scale=TRUE)
> z.log.maxF0_Q1 <- scale(log.maxF0_Q1, center=TRUE, scale=TRUE)
> z.log.maxF0_Q2 <- scale(log.maxF0_Q2, center=TRUE, scale=TRUE)
> z.log.maxF0_Q3 <- scale(log.maxF0_Q3, center=TRUE, scale=TRUE)
> z.log.maxF0_Q4 <- scale(log.maxF0_Q4, center=TRUE, scale=TRUE)
> z.log.maxF0_ALL <- scale(log.maxF0_ALL, center=TRUE, scale=TRUE)
> z.log.maxF0_Q2Q3 <- scale(log.maxF0_Q2Q3, center=TRUE, scale=TRUE)
> z.log.minF0_Q1 <- scale(log.minF0_Q1, center=TRUE, scale=TRUE)
> z.log.minF0_Q2 <- scale(log.minF0_Q2, center=TRUE, scale=TRUE)
> z.log.minF0_Q3 <- scale(log.minF0_Q3, center=TRUE, scale=TRUE)
> z.log.minF0_Q4 <- scale(log.minF0_Q4, center=TRUE, scale=TRUE)
> z.log.minF0_ALL <- scale(log.minF0_ALL, center=TRUE, scale=TRUE)
> z.log.minF0_Q2Q3 <- scale(log.minF0_Q2Q3, center=TRUE, scale=TRUE)
>
> # formants into z-scores
> z.F1_Q1 <- scale(p9761.a1$F1_Q1, center=TRUE, scale=TRUE)
> z.F1_Q2 <- scale(p9761.a1$F1_Q2, center=TRUE, scale=TRUE)
> z.F1_Q3 <- scale(p9761.a1$F1_Q3, center=TRUE, scale=TRUE)
> z.F1_Q4 <- scale(p9761.a1$F1_Q4, center=TRUE, scale=TRUE)
> z.F1_ALL <- scale(p9761.a1$F1_ALL, center=TRUE, scale=TRUE)
> z.F1_Q2Q3 <- scale(p9761.a1$F1_Q2Q3, center=TRUE, scale=TRUE)
>
> # F2
> z.F2_Q1 <- scale(p9761.a1$F2_Q1, center=TRUE, scale=TRUE)
> z.F2_Q2 <- scale(p9761.a1$F2_Q2, center=TRUE, scale=TRUE)
> z.F2_Q3 <- scale(p9761.a1$F2_Q3, center=TRUE, scale=TRUE)
> z.F2_Q4 <- scale(p9761.a1$F2_Q4, center=TRUE, scale=TRUE)
> z.F2_ALL <- scale(p9761.a1$F2_ALL, center=TRUE, scale=TRUE)
> z.F2_Q2Q3 <- scale(p9761.a1$F2_Q2Q3, center=TRUE, scale=TRUE)
>
> # F3
> z.F3_Q1 <- scale(p9761.a1$F3_Q1, center=TRUE, scale=TRUE)
> z.F3_Q2 <- scale(p9761.a1$F3_Q2, center=TRUE, scale=TRUE)
> z.F3_Q3 <- scale(p9761.a1$F3_Q3, center=TRUE, scale=TRUE)
> z.F3_Q4 <- scale(p9761.a1$F3_Q4, center=TRUE, scale=TRUE)
> z.F3_ALL <- scale(p9761.a1$F3_ALL, center=TRUE, scale=TRUE)
> z.F3_Q2Q3 <- scale(p9761.a1$F3_Q2Q3, center=TRUE, scale=TRUE)
>
> # Duration
> z.Duration <- scale(p9761.a1$Duration, center=TRUE, scale=TRUE)
>
> # Intensity
> z.Intensity_Q1 <- scale(p9761.a1$Intensity_Q1, center=TRUE, scale=TRUE)

```

```

> z.Intensity_Q2 <- scale(p9761.a1$Intensity_Q2, center=TRUE, scale=TRUE)
> z.Intensity_Q3 <- scale(p9761.a1$Intensity_Q3, center=TRUE, scale=TRUE)
> z.Intensity_Q4 <- scale(p9761.a1$Intensity_Q4, center=TRUE, scale=TRUE)
> z.Intensity_all <- scale(p9761.a1$Intensity_all, center=TRUE, scale=TRUE)
> z.Intensity_Q2Q3 <- scale(p9761.a1$Intensity_Q2Q3, center=TRUE, scale=TRUE)
>
> # F0change_Q4_minusQ1
> z.F0change_Q4_minusQ1 <- scale(p9761.a1$F0change_Q4_minusQ1, center=TRUE,
scale=TRUE)
>
> #F0range_Max_minus_Min
> z.F0range_Max_minus_Min <- scale(p9761.a1$F0range_Max_minus_Min,
center=TRUE, scale=TRUE)
>
> new.p9761.a1 <-
cbind(p9761.a1, log.F0_Q1, log.F0_Q2, log.F0_Q3, log.F0_Q4, log.F0_ALL, log.F0_Q2Q3
, log.maxF0_Q1, log.maxF0_Q2, log.maxF0_Q3, log.maxF0_Q4, log.maxF0_ALL, log.maxF0_
Q2Q3, log.minF0_Q1, log.minF0_Q2, log.minF0_Q3, log.minF0_Q4, log.minF0_ALL, log.mi
nF0_Q2Q3, z.log.F0_Q1, z.log.F0_Q2, z.log.F0_Q3, z.log.F0_Q4, z.log.F0_ALL, z.log.F
0_Q2Q3, z.log.maxF0_Q1, z.log.maxF0_Q2, z.log.maxF0_Q3, z.log.maxF0_Q4, z.log.maxF
0_ALL, z.log.maxF0_Q2Q3, z.log.minF0_Q1, z.log.minF0_Q2, z.log.minF0_Q3, z.log.min
F0_Q4, z.log.minF0_ALL, z.log.minF0_Q2Q3, z.F1_Q1, z.F1_Q2, z.F1_Q3, z.F1_Q4, z.F1_A
LL, z.F1_Q2Q3, z.F2_Q1, z.F2_Q2, z.F2_Q3, z.F2_Q4, z.F2_ALL, z.F2_Q2Q3, z.F3_Q1, z.F3_
Q2, z.F3_Q3, z.F3_Q4, z.F3_ALL, z.F3_Q2Q3, z.Duration, z.Intensity_Q1, z.Intensity_Q
2, z.Intensity_Q3, z.Intensity_Q4, z.Intensity_all, z.Intensity_Q2Q3, z.F0change_Q
4_minusQ1, z.F0range_Max_minus_Min)
>
>
> ## combining /i/ and /a/ data
>
> comp.p9761 <- rbind(new.p9761.i, new.p9761.a1)
>
>
> ##### Speaker 5793 #####
>
> # for /i/
>
> log.F0_Q1 <- log(p5793.i$F0_Q1)
> log.F0_Q2 <- log(p5793.i$F0_Q2)
> log.F0_Q3 <- log(p5793.i$F0_Q3)
> log.F0_Q4 <- log(p5793.i$F0_Q4)
> log.F0_ALL <- log(p5793.i$F0_ALL)
> log.F0_Q2Q3 <- log(p5793.i$F0_Q2Q3)
> log.maxF0_Q1 <- log(p5793.i$maxF0_Q1)
> log.maxF0_Q2 <- log(p5793.i$maxF0_Q2)
> log.maxF0_Q3 <- log(p5793.i$maxF0_Q3)
> log.maxF0_Q4 <- log(p5793.i$maxF0_Q4)
> log.maxF0_ALL <- log(p5793.i$maxF0_ALL)
> log.maxF0_Q2Q3 <- log(p5793.i$maxF0_Q2Q3)
> log.minF0_Q1 <- log(p5793.i$minF0_Q1)
> log.minF0_Q2 <- log(p5793.i$minF0_Q2)
> log.minF0_Q3 <- log(p5793.i$minF0_Q3)
> log.minF0_Q4 <- log(p5793.i$minF0_Q4)
> log.minF0_ALL <- log(p5793.i$minF0_ALL)
> log.minF0_Q2Q3 <- log(p5793.i$minF0_Q2Q3)
>
> # now transforing the log transformed values into z-scores

```



```

> z.log.F0_Q1 <- scale(log.F0_Q1, center = TRUE, scale = TRUE)
> z.log.F0_Q2 <- scale(log.F0_Q2, center=TRUE, scale=TRUE)
> z.log.F0_Q2 <- scale(log.F0_Q2, center=TRUE, scale=TRUE)
> z.log.F0_Q3 <- scale(log.F0_Q3, center=TRUE, scale=TRUE)
> z.log.F0_Q4 <- scale(log.F0_Q4, center=TRUE, scale=TRUE)
> z.log.F0_ALL <- scale(log.F0_ALL, center=TRUE, scale=TRUE)
> z.log.F0_Q2Q3 <- scale(log.F0_Q2Q3, center=TRUE, scale=TRUE)
> z.log.maxF0_Q1 <- scale(log.maxF0_Q1, center=TRUE, scale=TRUE)
> z.log.maxF0_Q2 <- scale(log.maxF0_Q2, center=TRUE, scale=TRUE)
> z.log.maxF0_Q3 <- scale(log.maxF0_Q3, center=TRUE, scale=TRUE)
> z.log.maxF0_Q4 <- scale(log.maxF0_Q4, center=TRUE, scale=TRUE)
> z.log.maxF0_ALL <- scale(log.maxF0_ALL, center=TRUE, scale=TRUE)
> z.log.maxF0_Q2Q3 <- scale(log.maxF0_Q2Q3, center=TRUE, scale=TRUE)
> z.log.minF0_Q1 <- scale(log.minF0_Q1, center=TRUE, scale=TRUE)
> z.log.minF0_Q2 <- scale(log.minF0_Q2, center=TRUE, scale=TRUE)
> z.log.minF0_Q3 <- scale(log.minF0_Q3, center=TRUE, scale=TRUE)
> z.log.minF0_Q4 <- scale(log.minF0_Q4, center=TRUE, scale=TRUE)
> z.log.minF0_ALL <- scale(log.minF0_ALL, center=TRUE, scale=TRUE)
> z.log.minF0_Q2Q3 <- scale(log.minF0_Q2Q3, center=TRUE, scale=TRUE)
>
> # formants into z-scores
> z.F1_Q1 <- scale(p5793.i$F1_Q1, center=TRUE, scale=TRUE)
> z.F1_Q2 <- scale(p5793.i$F1_Q2, center=TRUE, scale=TRUE)
> z.F1_Q3 <- scale(p5793.i$F1_Q3, center=TRUE, scale=TRUE)
> z.F1_Q4 <- scale(p5793.i$F1_Q4, center=TRUE, scale=TRUE)
> z.F1_ALL <- scale(p5793.i$F1_ALL, center=TRUE, scale=TRUE)
> z.F1_Q2Q3 <- scale(p5793.i$F1_Q2Q3, center=TRUE, scale=TRUE)
>
> # F2
> z.F2_Q1 <- scale(p5793.i$F2_Q1, center=TRUE, scale=TRUE)
> z.F2_Q2 <- scale(p5793.i$F2_Q2, center=TRUE, scale=TRUE)
> z.F2_Q3 <- scale(p5793.i$F2_Q3, center=TRUE, scale=TRUE)
> z.F2_Q4 <- scale(p5793.i$F2_Q4, center=TRUE, scale=TRUE)
> z.F2_ALL <- scale(p5793.i$F2_ALL, center=TRUE, scale=TRUE)
> z.F2_Q2Q3 <- scale(p5793.i$F2_Q2Q3, center=TRUE, scale=TRUE)
>
> # F3
> z.F3_Q1 <- scale(p5793.i$F3_Q1, center=TRUE, scale=TRUE)
> z.F3_Q2 <- scale(p5793.i$F3_Q2, center=TRUE, scale=TRUE)
> z.F3_Q3 <- scale(p5793.i$F3_Q3, center=TRUE, scale=TRUE)
> z.F3_Q4 <- scale(p5793.i$F3_Q4, center=TRUE, scale=TRUE)
> z.F3_ALL <- scale(p5793.i$F3_ALL, center=TRUE, scale=TRUE)
> z.F3_Q2Q3 <- scale(p5793.i$F3_Q2Q3, center=TRUE, scale=TRUE)
>
> # Duration
> z.Duration <- scale(p5793.i$Duration, center=TRUE, scale=TRUE)
>
> # Intensity
> z.Intensity_Q1 <- scale(p5793.i$Intensity_Q1, center=TRUE, scale=TRUE)
> z.Intensity_Q2 <- scale(p5793.i$Intensity_Q2, center=TRUE, scale=TRUE)
> z.Intensity_Q3 <- scale(p5793.i$Intensity_Q3, center=TRUE, scale=TRUE)
> z.Intensity_Q4 <- scale(p5793.i$Intensity_Q4, center=TRUE, scale=TRUE)
> z.Intensity_all <- scale(p5793.i$Intensity_all, center=TRUE, scale=TRUE)
> z.Intensity_Q2Q3 <- scale(p5793.i$Intensity_Q2Q3, center=TRUE, scale=TRUE)
>
> # F0change_Q4_minusQ1

```

```

> z.F0change_Q4_minusQ1 <- scale(p5793.i$F0change_Q4_minusQ1, center=TRUE,
scale=TRUE)
>
> #F0range_Max_minus_Min
> z.F0range_Max_minus_Min <- scale(p5793.i$F0range_Max_minus_Min,
center=TRUE, scale=TRUE)
>
> new.p5793.i <-
cbind(p5793.i, log.F0_Q1, log.F0_Q2, log.F0_Q3, log.F0_Q4, log.F0_ALL, log.F0_Q2Q3,
log.maxF0_Q1, log.maxF0_Q2, log.maxF0_Q3, log.maxF0_Q4, log.maxF0_ALL, log.maxF0_Q
2Q3, log.minF0_Q1, log.minF0_Q2, log.minF0_Q3, log.minF0_Q4, log.minF0_ALL, log.min
F0_Q2Q3, z.log.F0_Q1, z.log.F0_Q2, z.log.F0_Q3, z.log.F0_Q4, z.log.F0_ALL, z.log.F0
_Q2Q3, z.log.maxF0_Q1, z.log.maxF0_Q2, z.log.maxF0_Q3, z.log.maxF0_Q4, z.log.maxF0
_ALL, z.log.maxF0_Q2Q3, z.log.minF0_Q1, z.log.minF0_Q2, z.log.minF0_Q3, z.log.minF
0_Q4, z.log.minF0_ALL, z.log.minF0_Q2Q3, z.F1_Q1, z.F1_Q2, z.F1_Q3, z.F1_Q4, z.F1_AL
L, z.F1_Q2Q3, z.F2_Q1, z.F2_Q2, z.F2_Q3, z.F2_Q4, z.F2_ALL, z.F2_Q2Q3, z.F3_Q1, z.F3_Q
2, z.F3_Q3, z.F3_Q4, z.F3_ALL, z.F3_Q2Q3, z.Duration, z.Intensity_Q1, z.Intensity_Q2
, z.Intensity_Q3, z.Intensity_Q4, z.Intensity_all, z.Intensity_Q2Q3, z.F0change_Q4
_minusQ1, z.F0range_Max_minus_Min)
>
>
> ## for /a/ vowel
>
> log.F0_Q1 <- log(p5793.a$F0_Q1)
> log.F0_Q2 <- log(p5793.a$F0_Q2)
> log.F0_Q3 <- log(p5793.a$F0_Q3)
> log.F0_Q4 <- log(p5793.a$F0_Q4)
> log.F0_ALL <- log(p5793.a$F0_ALL)
> log.F0_Q2Q3 <- log(p5793.a$F0_Q2Q3)
> log.maxF0_Q1 <- log(p5793.a$maxF0_Q1)
> log.maxF0_Q2 <- log(p5793.a$maxF0_Q2)
> log.maxF0_Q3 <- log(p5793.a$maxF0_Q3)
> log.maxF0_Q4 <- log(p5793.a$maxF0_Q4)
> log.maxF0_ALL <- log(p5793.a$maxF0_ALL)
> log.maxF0_Q2Q3 <- log(p5793.a$maxF0_Q2Q3)
> log.minF0_Q1 <- log(p5793.a$minF0_Q1)
> log.minF0_Q2 <- log(p5793.a$minF0_Q2)
> log.minF0_Q3 <- log(p5793.a$minF0_Q3)
> log.minF0_Q4 <- log(p5793.a$minF0_Q4)
> log.minF0_ALL <- log(p5793.a$minF0_ALL)
> log.minF0_Q2Q3 <- log(p5793.a$minF0_Q2Q3)
>
> # now transforming the log transformed values into z-scores
> z.log.F0_Q1 <- scale(log.F0_Q1, center = TRUE, scale = TRUE)
> z.log.F0_Q2 <- scale(log.F0_Q2, center=TRUE, scale=TRUE)
> z.log.F0_Q3 <- scale(log.F0_Q3, center=TRUE, scale=TRUE)
> z.log.F0_Q4 <- scale(log.F0_Q4, center=TRUE, scale=TRUE)
> z.log.F0_ALL <- scale(log.F0_ALL, center=TRUE, scale=TRUE)
> z.log.F0_Q2Q3 <- scale(log.F0_Q2Q3, center=TRUE, scale=TRUE)
> z.log.maxF0_Q1 <- scale(log.maxF0_Q1, center=TRUE, scale=TRUE)
> z.log.maxF0_Q2 <- scale(log.maxF0_Q2, center=TRUE, scale=TRUE)
> z.log.maxF0_Q3 <- scale(log.maxF0_Q3, center=TRUE, scale=TRUE)
> z.log.maxF0_Q4 <- scale(log.maxF0_Q4, center=TRUE, scale=TRUE)
> z.log.maxF0_ALL <- scale(log.maxF0_ALL, center=TRUE, scale=TRUE)
> z.log.maxF0_Q2Q3 <- scale(log.maxF0_Q2Q3, center=TRUE, scale=TRUE)
> z.log.minF0_Q1 <- scale(log.minF0_Q1, center=TRUE, scale=TRUE)

```

```

> z.log.minF0_Q2 <- scale(log.minF0_Q2, center=TRUE, scale=TRUE)
> z.log.minF0_Q3 <- scale(log.minF0_Q3, center=TRUE, scale=TRUE)
> z.log.minF0_Q4 <- scale(log.minF0_Q4, center=TRUE, scale=TRUE)
> z.log.minF0_ALL <- scale(log.minF0_ALL, center=TRUE, scale=TRUE)
> z.log.minF0_Q2Q3 <- scale(log.minF0_Q2Q3, center=TRUE, scale=TRUE)
>
> # formants into z-scores
> z.F1_Q1 <- scale(p5793.a$F1_Q1, center=TRUE, scale=TRUE)
> z.F1_Q2 <- scale(p5793.a$F1_Q2, center=TRUE, scale=TRUE)
> z.F1_Q3 <- scale(p5793.a$F1_Q3, center=TRUE, scale=TRUE)
> z.F1_Q4 <- scale(p5793.a$F1_Q4, center=TRUE, scale=TRUE)
> z.F1_ALL <- scale(p5793.a$F1_ALL, center=TRUE, scale=TRUE)
> z.F1_Q2Q3 <- scale(p5793.a$F1_Q2Q3, center=TRUE, scale=TRUE)
>
> # F2
> z.F2_Q1 <- scale(p5793.a$F2_Q1, center=TRUE, scale=TRUE)
> z.F2_Q2 <- scale(p5793.a$F2_Q2, center=TRUE, scale=TRUE)
> z.F2_Q3 <- scale(p5793.a$F2_Q3, center=TRUE, scale=TRUE)
> z.F2_Q4 <- scale(p5793.a$F2_Q4, center=TRUE, scale=TRUE)
> z.F2_ALL <- scale(p5793.a$F2_ALL, center=TRUE, scale=TRUE)
> z.F2_Q2Q3 <- scale(p5793.a$F2_Q2Q3, center=TRUE, scale=TRUE)
>
> # F3
> z.F3_Q1 <- scale(p5793.a$F3_Q1, center=TRUE, scale=TRUE)
> z.F3_Q2 <- scale(p5793.a$F3_Q2, center=TRUE, scale=TRUE)
> z.F3_Q3 <- scale(p5793.a$F3_Q3, center=TRUE, scale=TRUE)
> z.F3_Q4 <- scale(p5793.a$F3_Q4, center=TRUE, scale=TRUE)
> z.F3_ALL <- scale(p5793.a$F3_ALL, center=TRUE, scale=TRUE)
> z.F3_Q2Q3 <- scale(p5793.a$F3_Q2Q3, center=TRUE, scale=TRUE)
>
> # Duration
> z.Duration <- scale(p5793.a$Duration, center=TRUE, scale=TRUE)
>
> # Intensity
> z.Intensity_Q1 <- scale(p5793.a$Intensity_Q1, center=TRUE, scale=TRUE)
> z.Intensity_Q2 <- scale(p5793.a$Intensity_Q2, center=TRUE, scale=TRUE)
> z.Intensity_Q3 <- scale(p5793.a$Intensity_Q3, center=TRUE, scale=TRUE)
> z.Intensity_Q4 <- scale(p5793.a$Intensity_Q4, center=TRUE, scale=TRUE)
> z.Intensity_all <- scale(p5793.a$Intensity_all, center=TRUE, scale=TRUE)
> z.Intensity_Q2Q3 <- scale(p5793.a$Intensity_Q2Q3, center=TRUE, scale=TRUE)
>
> # F0change_Q4_minusQ1
> z.F0change_Q4_minusQ1 <- scale(p5793.a$F0change_Q4_minusQ1, center=TRUE,
scale=TRUE)
>
> # F0range_Max_minus_Min
> z.F0range_Max_minus_Min <- scale(p5793.a$F0range_Max_minus_Min,
center=TRUE, scale=TRUE)
>
> new.p5793.a <-
cbind(p5793.a, log.F0_Q1, log.F0_Q2, log.F0_Q3, log.F0_Q4, log.F0_ALL, log.F0_Q2Q3,
log.maxF0_Q1, log.maxF0_Q2, log.maxF0_Q3, log.maxF0_Q4, log.maxF0_ALL, log.maxF0_Q
2Q3, log.minF0_Q1, log.minF0_Q2, log.minF0_Q3, log.minF0_Q4, log.minF0_ALL, log.min
F0_Q2Q3, z.log.F0_Q1, z.log.F0_Q2, z.log.F0_Q3, z.log.F0_Q4, z.log.F0_ALL, z.log.F0
_Q2Q3, z.log.maxF0_Q1, z.log.maxF0_Q2, z.log.maxF0_Q3, z.log.maxF0_Q4, z.log.maxF0
_ALL, z.log.maxF0_Q2Q3, z.log.minF0_Q1, z.log.minF0_Q2, z.log.minF0_Q3, z.log.minF
0_Q4, z.log.minF0_ALL, z.log.minF0_Q2Q3, z.F1_Q1, z.F1_Q2, z.F1_Q3, z.F1_Q4, z.F1_AL

```

```

L, z.F1_Q2Q3, z.F2_Q1, z.F2_Q2, z.F2_Q3, z.F2_Q4, z.F2_ALL, z.F2_Q2Q3, z.F3_Q1, z.F3_Q
2, z.F3_Q3, z.F3_Q4, z.F3_ALL, z.F3_Q2Q3, z.Duration, z.Intensity_Q1, z.Intensity_Q2
, z.Intensity_Q3, z.Intensity_Q4, z.Intensity_all, z.Intensity_Q2Q3, z.F0change_Q4
_minusQ1, z.F0range_Max_minus_Min)
>
> ## combining /i/ and /a/ data
>
> comp.p5793<- rbind(new.p5793.i, new.p5793.a)
>
>
> ##### Speaker 1687 #####
>
> log.F0_Q1 <- log(p1687.i$F0_Q1)
> log.F0_Q2 <- log(p1687.i$F0_Q2)
> log.F0_Q3 <- log(p1687.i$F0_Q3)
> log.F0_Q4 <- log(p1687.i$F0_Q4)
> log.F0_ALL <- log(p1687.i$F0_ALL)
> log.F0_Q2Q3 <- log(p1687.i$F0_Q2Q3)
> log.maxF0_Q1 <- log(p1687.i$maxF0_Q1)
> log.maxF0_Q2 <- log(p1687.i$maxF0_Q2)
> log.maxF0_Q3 <- log(p1687.i$maxF0_Q3)
> log.maxF0_Q4 <- log(p1687.i$maxF0_Q4)
> log.maxF0_ALL <- log(p1687.i$maxF0_ALL)
> log.maxF0_Q2Q3 <- log(p1687.i$maxF0_Q2Q3)
> log.minF0_Q1 <- log(p1687.i$minF0_Q1)
> log.minF0_Q2 <- log(p1687.i$minF0_Q2)
> log.minF0_Q3 <- log(p1687.i$minF0_Q3)
> log.minF0_Q4 <- log(p1687.i$minF0_Q4)
> log.minF0_ALL <- log(p1687.i$minF0_ALL)
> log.minF0_Q2Q3 <- log(p1687.i$minF0_Q2Q3)
>
> # now transforming the log transformed values into z-scores
> z.log.F0_Q1 <- scale(log.F0_Q1, center = TRUE, scale = TRUE)
> z.log.F0_Q2 <- scale(log.F0_Q2, center=TRUE, scale=TRUE)
> z.log.F0_Q2 <- scale(log.F0_Q2, center=TRUE, scale=TRUE)
> z.log.F0_Q3 <- scale(log.F0_Q3, center=TRUE, scale=TRUE)
> z.log.F0_Q4 <- scale(log.F0_Q4, center=TRUE, scale=TRUE)
> z.log.F0_ALL <- scale(log.F0_ALL, center=TRUE, scale=TRUE)
> z.log.F0_Q2Q3 <- scale(log.F0_Q2Q3, center=TRUE, scale=TRUE)
> z.log.maxF0_Q1 <- scale(log.maxF0_Q1, center=TRUE, scale=TRUE)
> z.log.maxF0_Q2 <- scale(log.maxF0_Q2, center=TRUE, scale=TRUE)
> z.log.maxF0_Q3 <- scale(log.maxF0_Q3, center=TRUE, scale=TRUE)
> z.log.maxF0_Q4 <- scale(log.maxF0_Q4, center=TRUE, scale=TRUE)
> z.log.maxF0_ALL <- scale(log.maxF0_ALL, center=TRUE, scale=TRUE)
> z.log.maxF0_Q2Q3 <- scale(log.maxF0_Q2Q3, center=TRUE, scale=TRUE)
> z.log.minF0_Q1 <- scale(log.minF0_Q1, center=TRUE, scale=TRUE)
> z.log.minF0_Q2 <- scale(log.minF0_Q2, center=TRUE, scale=TRUE)
> z.log.minF0_Q3 <- scale(log.minF0_Q3, center=TRUE, scale=TRUE)
> z.log.minF0_Q4 <- scale(log.minF0_Q4, center=TRUE, scale=TRUE)
> z.log.minF0_ALL <- scale(log.minF0_ALL, center=TRUE, scale=TRUE)
> z.log.minF0_Q2Q3 <- scale(log.minF0_Q2Q3, center=TRUE, scale=TRUE)
>
> # formants into z-scores
> z.F1_Q1 <- scale(p1687.i$F1_Q1, center=TRUE, scale=TRUE)
> z.F1_Q2 <- scale(p1687.i$F1_Q2, center=TRUE, scale=TRUE)
> z.F1_Q3 <- scale(p1687.i$F1_Q3, center=TRUE, scale=TRUE)
> z.F1_Q4 <- scale(p1687.i$F1_Q4, center=TRUE, scale=TRUE)

```

```

> z.F1_ALL <- scale(p1687.i$F1_ALL, center=TRUE, scale=TRUE)
> z.F1_Q2Q3 <- scale(p1687.i$F1_Q2Q3, center=TRUE, scale=TRUE)
>
> # F2
> z.F2_Q1 <- scale(p1687.i$F2_Q1, center=TRUE, scale=TRUE)
> z.F2_Q2 <- scale(p1687.i$F2_Q2, center=TRUE, scale=TRUE)
> z.F2_Q3 <- scale(p1687.i$F2_Q3, center=TRUE, scale=TRUE)
> z.F2_Q4 <- scale(p1687.i$F2_Q4, center=TRUE, scale=TRUE)
> z.F2_ALL <- scale(p1687.i$F2_ALL, center=TRUE, scale=TRUE)
> z.F2_Q2Q3 <- scale(p1687.i$F2_Q2Q3, center=TRUE, scale=TRUE)
>
> # F3
> z.F3_Q1 <- scale(p1687.i$F3_Q1, center=TRUE, scale=TRUE)
> z.F3_Q2 <- scale(p1687.i$F3_Q2, center=TRUE, scale=TRUE)
> z.F3_Q3 <- scale(p1687.i$F3_Q3, center=TRUE, scale=TRUE)
> z.F3_Q4 <- scale(p1687.i$F3_Q4, center=TRUE, scale=TRUE)
> z.F3_ALL <- scale(p1687.i$F3_ALL, center=TRUE, scale=TRUE)
> z.F3_Q2Q3 <- scale(p1687.i$F3_Q2Q3, center=TRUE, scale=TRUE)
>
> # Duration
> z.Duration <- scale(p1687.i$Duration, center=TRUE, scale=TRUE)
>
> # Intensity
> z.Intensity_Q1 <- scale(p1687.i$Intensity_Q1, center=TRUE, scale=TRUE)
> z.Intensity_Q2 <- scale(p1687.i$Intensity_Q2, center=TRUE, scale=TRUE)
> z.Intensity_Q3 <- scale(p1687.i$Intensity_Q3, center=TRUE, scale=TRUE)
> z.Intensity_Q4 <- scale(p1687.i$Intensity_Q4, center=TRUE, scale=TRUE)
> z.Intensity_all <- scale(p1687.i$Intensity_all, center=TRUE, scale=TRUE)
> z.Intensity_Q2Q3 <- scale(p1687.i$Intensity_Q2Q3, center=TRUE, scale=TRUE)
>
> # F0change_Q4_minusQ1
> z.F0change_Q4_minusQ1 <- scale(p1687.i$F0change_Q4_minusQ1, center=TRUE,
scale=TRUE)
>
> #F0range_Max_minus_Min
> z.F0range_Max_minus_Min <- scale(p1687.i$F0range_Max_minus_Min,
center=TRUE, scale=TRUE)
>
> new.p1687.i <-
cbind(p1687.i, log.F0_Q1, log.F0_Q2, log.F0_Q3, log.F0_Q4, log.F0_ALL, log.F0_Q2Q3,
log.maxF0_Q1, log.maxF0_Q2, log.maxF0_Q3, log.maxF0_Q4, log.maxF0_ALL, log.maxF0_Q
2Q3, log.minF0_Q1, log.minF0_Q2, log.minF0_Q3, log.minF0_Q4, log.minF0_ALL, log.min
F0_Q2Q3, z.log.F0_Q1, z.log.F0_Q2, z.log.F0_Q3, z.log.F0_Q4, z.log.F0_ALL, z.log.F0
_Q2Q3, z.log.maxF0_Q1, z.log.maxF0_Q2, z.log.maxF0_Q3, z.log.maxF0_Q4, z.log.maxF0
_ALL, z.log.maxF0_Q2Q3, z.log.minF0_Q1, z.log.minF0_Q2, z.log.minF0_Q3, z.log.minF
0_Q4, z.log.minF0_ALL, z.log.minF0_Q2Q3, z.F1_Q1, z.F1_Q2, z.F1_Q3, z.F1_Q4, z.F1_AL
L, z.F1_Q2Q3, z.F2_Q1, z.F2_Q2, z.F2_Q3, z.F2_Q4, z.F2_ALL, z.F2_Q2Q3, z.F3_Q1, z.F3_Q
2, z.F3_Q3, z.F3_Q4, z.F3_ALL, z.F3_Q2Q3, z.Duration, z.Intensity_Q1, z.Intensity_Q2
, z.Intensity_Q3, z.Intensity_Q4, z.Intensity_all, z.Intensity_Q2Q3, z.F0change_Q4
_minusQ1, z.F0range_Max_minus_Min)
>
>
>
> ## for /a/ vowel
>
>
> log.F0_Q1 <- log(p1687.a1$F0_Q1)

```

```

> log.F0_Q2 <- log(p1687.a1$F0_Q2)
> log.F0_Q3 <- log(p1687.a1$F0_Q3)
> log.F0_Q4 <- log(p1687.a1$F0_Q4)
> log.F0_ALL <- log(p1687.a1$F0_ALL)
> log.F0_Q2Q3 <- log(p1687.a1$F0_Q2Q3)
> log.maxF0_Q1 <- log(p1687.a1$maxF0_Q1)
> log.maxF0_Q2 <- log(p1687.a1$maxF0_Q2)
> log.maxF0_Q3 <- log(p1687.a1$maxF0_Q3)
> log.maxF0_Q4 <- log(p1687.a1$maxF0_Q4)
> log.maxF0_ALL <- log(p1687.a1$maxF0_ALL)
> log.maxF0_Q2Q3 <- log(p1687.a1$maxF0_Q2Q3)
> log.minF0_Q1 <- log(p1687.a1$minF0_Q1)
> log.minF0_Q2 <- log(p1687.a1$minF0_Q2)
> log.minF0_Q3 <- log(p1687.a1$minF0_Q3)
> log.minF0_Q4 <- log(p1687.a1$minF0_Q4)
> log.minF0_ALL <- log(p1687.a1$minF0_ALL)
> log.minF0_Q2Q3 <- log(p1687.a1$minF0_Q2Q3)
>
> # now transforming the log transformed values into z-scores
> z.log.F0_Q1 <- scale(log.F0_Q1, center = TRUE, scale = TRUE)
> z.log.F0_Q2 <- scale(log.F0_Q2, center=TRUE, scale=TRUE)
> z.log.F0_Q3 <- scale(log.F0_Q3, center=TRUE, scale=TRUE)
> z.log.F0_Q4 <- scale(log.F0_Q4, center=TRUE, scale=TRUE)
> z.log.F0_ALL <- scale(log.F0_ALL, center=TRUE, scale=TRUE)
> z.log.F0_Q2Q3 <- scale(log.F0_Q2Q3, center=TRUE, scale=TRUE)
> z.log.maxF0_Q1 <- scale(log.maxF0_Q1, center=TRUE, scale=TRUE)
> z.log.maxF0_Q2 <- scale(log.maxF0_Q2, center=TRUE, scale=TRUE)
> z.log.maxF0_Q3 <- scale(log.maxF0_Q3, center=TRUE, scale=TRUE)
> z.log.maxF0_Q4 <- scale(log.maxF0_Q4, center=TRUE, scale=TRUE)
> z.log.maxF0_ALL <- scale(log.maxF0_ALL, center=TRUE, scale=TRUE)
> z.log.maxF0_Q2Q3 <- scale(log.maxF0_Q2Q3, center=TRUE, scale=TRUE)
> z.log.minF0_Q1 <- scale(log.minF0_Q1, center=TRUE, scale=TRUE)
> z.log.minF0_Q2 <- scale(log.minF0_Q2, center=TRUE, scale=TRUE)
> z.log.minF0_Q3 <- scale(log.minF0_Q3, center=TRUE, scale=TRUE)
> z.log.minF0_Q4 <- scale(log.minF0_Q4, center=TRUE, scale=TRUE)
> z.log.minF0_ALL <- scale(log.minF0_ALL, center=TRUE, scale=TRUE)
> z.log.minF0_Q2Q3 <- scale(log.minF0_Q2Q3, center=TRUE, scale=TRUE)
>
> # formants into z-scores
> z.F1_Q1 <- scale(p1687.a1$F1_Q1, center=TRUE, scale=TRUE)
> z.F1_Q2 <- scale(p1687.a1$F1_Q2, center=TRUE, scale=TRUE)
> z.F1_Q3 <- scale(p1687.a1$F1_Q3, center=TRUE, scale=TRUE)
> z.F1_Q4 <- scale(p1687.a1$F1_Q4, center=TRUE, scale=TRUE)
> z.F1_ALL <- scale(p1687.a1$F1_ALL, center=TRUE, scale=TRUE)
> z.F1_Q2Q3 <- scale(p1687.a1$F1_Q2Q3, center=TRUE, scale=TRUE)
>
> # F2
> z.F2_Q1 <- scale(p1687.a1$F2_Q1, center=TRUE, scale=TRUE)
> z.F2_Q2 <- scale(p1687.a1$F2_Q2, center=TRUE, scale=TRUE)
> z.F2_Q3 <- scale(p1687.a1$F2_Q3, center=TRUE, scale=TRUE)
> z.F2_Q4 <- scale(p1687.a1$F2_Q4, center=TRUE, scale=TRUE)
> z.F2_ALL <- scale(p1687.a1$F2_ALL, center=TRUE, scale=TRUE)
> z.F2_Q2Q3 <- scale(p1687.a1$F2_Q2Q3, center=TRUE, scale=TRUE)
>
> # F3
> z.F3_Q1 <- scale(p1687.a1$F3_Q1, center=TRUE, scale=TRUE)

```

```

> z.F3_Q2 <- scale(p1687.a1$F3_Q2, center=TRUE, scale=TRUE)
> z.F3_Q3 <- scale(p1687.a1$F3_Q3, center=TRUE, scale=TRUE)
> z.F3_Q4 <- scale(p1687.a1$F3_Q4, center=TRUE, scale=TRUE)
> z.F3_ALL <- scale(p1687.a1$F3_ALL, center=TRUE, scale=TRUE)
> z.F3_Q2Q3 <- scale(p1687.a1$F3_Q2Q3, center=TRUE, scale=TRUE)
>
> # Duration
> z.Duration <- scale(p1687.a1$Duration, center=TRUE, scale=TRUE)
>
> # Intensity
> z.Intensity_Q1 <- scale(p1687.a1$Intensity_Q1, center=TRUE, scale=TRUE)
> z.Intensity_Q2 <- scale(p1687.a1$Intensity_Q2, center=TRUE, scale=TRUE)
> z.Intensity_Q3 <- scale(p1687.a1$Intensity_Q3, center=TRUE, scale=TRUE)
> z.Intensity_Q4 <- scale(p1687.a1$Intensity_Q4, center=TRUE, scale=TRUE)
> z.Intensity_all <- scale(p1687.a1$Intensity_all, center=TRUE, scale=TRUE)
> z.Intensity_Q2Q3 <- scale(p1687.a1$Intensity_Q2Q3, center=TRUE, scale=TRUE)
>
> # F0change_Q4_minusQ1
> z.F0change_Q4_minusQ1 <- scale(p1687.a1$F0change_Q4_minusQ1, center=TRUE,
scale=TRUE)
>
> #F0range_Max_minus_Min
> z.F0range_Max_minus_Min <- scale(p1687.a1$F0range_Max_minus_Min,
center=TRUE, scale=TRUE)
>
> new.p1687.a1 <-
cbind(p1687.a1, log.F0_Q1, log.F0_Q2, log.F0_Q3, log.F0_Q4, log.F0_ALL, log.F0_Q2Q3
, log.maxF0_Q1, log.maxF0_Q2, log.maxF0_Q3, log.maxF0_Q4, log.maxF0_ALL, log.maxF0_
Q2Q3, log.minF0_Q1, log.minF0_Q2, log.minF0_Q3, log.minF0_Q4, log.minF0_ALL, log.mi
nF0_Q2Q3, z.log.F0_Q1, z.log.F0_Q2, z.log.F0_Q3, z.log.F0_Q4, z.log.F0_ALL, z.log.F
0_Q2Q3, z.log.maxF0_Q1, z.log.maxF0_Q2, z.log.maxF0_Q3, z.log.maxF0_Q4, z.log.min
F0_ALL, z.log.maxF0_Q2Q3, z.log.minF0_Q1, z.log.minF0_Q2, z.log.minF0_Q3, z.log.min
F0_Q4, z.log.minF0_ALL, z.log.minF0_Q2Q3, z.F1_Q1, z.F1_Q2, z.F1_Q3, z.F1_Q4, z.F1_A
LL, z.F1_Q2Q3, z.F2_Q1, z.F2_Q2, z.F2_Q3, z.F2_Q4, z.F2_ALL, z.F2_Q2Q3, z.F3_Q1, z.F3_
Q2, z.F3_Q3, z.F3_Q4, z.F3_ALL, z.F3_Q2Q3, z.Duration, z.Intensity_Q1, z.Intensity_Q
2, z.Intensity_Q3, z.Intensity_Q4, z.Intensity_all, z.Intensity_Q2Q3, z.F0change_Q
4_minusQ1, z.F0range_Max_minus_Min)
>
>
> # combining /i/ and /a/ data
>
> comp.p1687 <- rbind(new.p1687.i, new.p1687.a1)
>
>
> ##### Creating the complete dataframe with all the transformed
values #####
>
> complete.normed.data <-
rbind(comp.p6946, comp.p3791, comp.p6306, comp.7143, comp.p9301, comp.p9761, comp.p
5793, comp.p1687)

```

Appendix D – Main analysis codes

```

> pref <- subset(stress, Focus=="PreF")
> postf <- subset(stress, Focus=="PostF")
> f <- subset(stress, Focus=="Focus")
>
> ## subsetting the syllables for focus conditions
>
> # PreF
> pref.s1 <- subset(pref, Syllable==1)
> pref.s2 <- subset(pref, Syllable==2)
> pref.s3 <- subset(pref, Syllable==3)
> # Preparing the data for comparisons
> pref.s1vs2 <- rbind(pref.s1,pref.s2)
> # Re-ordering syllable 2 as the baseline category
> r.syll.fac <- factor(pref.s1vs2$Syllable)
> pref.s1vs2 <- cbind(pref.s1vs2,r.syll.fac)
>
> ## Syllable 2 v Syllable 3
>
> pref.s2vs3 <- rbind(pref.s2,pref.s3)
>
> ## Syllable 1 v Syllable 3
> pref.s1vs3 <- rbind(pref.s1,pref.s3)
>
> ##### Now running the models
> model.l1 <- model1 <- glm(r.syll.fac ~
z.log.F0_Q2Q3+z.F0change_Q4_minusQ1+ED_Q2Q3+z.Duration+z.Intensity_Q2Q3+z.F0r
ange_Max_minus_Min, data=pref.s1vs2, family="binomial")
>
> summary(model.l1)

Call:
glm(formula = r.syll.fac ~ z.log.F0_Q2Q3 + z.F0change_Q4_minusQ1 +
    ED_Q2Q3 + z.Duration + z.Intensity_Q2Q3 + z.F0range_Max_minus_Min,
    family = "binomial", data = pref.s1vs2)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.32445  -0.24533  -0.01562   0.24159   2.39893

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)      0.9643     0.6226   1.549  0.12143
z.log.F0_Q2Q3      1.8501     0.5873   3.150  0.00163 **
z.F0change_Q4_minusQ1 3.3733     0.5674   5.945 2.76e-09 ***
ED_Q2Q3           0.5743     0.4419   1.300  0.19366
z.Duration       -1.9314     0.3443  -5.609 2.03e-08 ***
z.Intensity_Q2Q3   0.0285     0.3046   0.094  0.92545
z.F0range_Max_minus_Min -0.7917     0.3856  -2.053  0.04003 *
---
Signif. codes:  0  *** 0.001 ** 0.01 * 0.05 . 0.1 1

```


(Dispersion parameter **for** binomial family taken to be 1)

Null deviance: 348.06 on 251 degrees of freedom
 Residual deviance: 114.25 on 245 degrees of freedom
 (54 observations deleted due to missingness)
 AIC: 128.25

Number of Fisher Scoring iterations: 7

```
> model.1.pred <- predict(model.1, type="response")
> S1 <- ifelse(model.1.pred > .5, 1, 2)
> pref.slvs2.1 <- pref.slvs2 %>%
drop_na(z.log.F0_Q2Q3, z.F0change_Q4_minusQ1, ED_Q2Q3, z.Duration, z.Intensity_Q2
Q3, z.F0range_Max_minus_Min)
> table(pref.slvs2.1$r.syll.fac, S1)
  S1
    2    1
1  14 121
2 105  12
>
> # chi-square test of the model
> model.1.chi <- (model.1$null.deviance - model.1$deviance)
> model.1.df <- (model.1$df.null - model.1$df.residual)
> model.1.chisq <- 1 - pchisq(model.1.chi, model.1.df)
> model.1.chisq
[1] 0
> model.1.df
[1] 6
> model.1.chisq
[1] 0
> model.1.chi
[1] 233.807
>
> ## Odds ratio
> exp(model.1$coefficients)
              (Intercept)          z.log.F0_Q2Q3      z.F0change_Q4_minusQ1
              2.6229134              6.3605581              29.1756218
              ED_Q2Q3              z.Duration              z.Intensity_Q2Q3
              1.7759629              0.1449450              1.0289150
z.F0range_Max_minus_Min
              0.4530725
>
> ## Confidence intervals
> exp(confint(model.1))
Waiting for profiling to be done...
              2.5 %              97.5 %
(Intercept)      0.79179862      9.2748262
z.log.F0_Q2Q3      2.13525727     21.7163452
z.F0change_Q4_minusQ1 10.80428499 101.5203482
ED_Q2Q3           0.77019168      4.4246572
z.Duration        0.06889731      0.2689648
z.Intensity_Q2Q3   0.56680857      1.8896579
z.F0range_Max_minus_Min 0.20753918      0.9586460
>
>
>
> ##### Now Syllable 2 v 3
```

```
> syll.fac <- factor(pref.s2vs3$Syllable)
> pref.s2vs3 <- cbind(pref.s2vs3, syll.fac)
>
> model.2 <- model1 <- glm(syll.fac ~
z.log.F0_Q2Q3+z.F0change_Q4_minusQ1+ED_Q2Q3+z.Duration+z.Intensity_Q2Q3+z.F0range_Max_minus_Min, data=pref.s2vs3, family="binomial")
> summary(model.2)
```

Call:

```
glm(formula = syll.fac ~ z.log.F0_Q2Q3 + z.F0change_Q4_minusQ1 +
    ED_Q2Q3 + z.Duration + z.Intensity_Q2Q3 + z.F0range_Max_minus_Min,
    family = "binomial", data = pref.s2vs3)
```

Deviance Residuals:

```
      Min       1Q   Median       3Q      Max
-3.0177  -0.5589   0.1326   0.4500   2.6665
```

Coefficients:

```
              Estimate Std. Error z value Pr(>|z|)
(Intercept)    -0.31640    0.34417  -0.919    0.358
z.log.F0_Q2Q3     2.97297    0.36268   8.197 2.46e-16 ***
z.F0change_Q4_minusQ1 -0.20334    0.26560  -0.766    0.444
ED_Q2Q3          0.03993    0.21899   0.182    0.855
z.Duration       0.26748    0.23937   1.117    0.264
z.Intensity_Q2Q3 -0.14763    0.19775  -0.747    0.455
z.F0range_Max_minus_Min -0.18196    0.24724  -0.736    0.462
---
```

```
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 361.39 on 262 degrees of freedom

Residual deviance: 190.38 on 256 degrees of freedom

(39 observations deleted due to missingness)

AIC: 204.38

Number of Fisher Scoring iterations: 5

```
> ## Classification table
```

```
>
```

```
> model.2.pred <- predict(model.2, type="response")
```

```
> S3 <- ifelse(model.2.pred > .5, 3, 2)
```

```
> pref.s2vs3.1 <- pref.s2vs3 %>%
```

```
drop_na(z.log.F0_Q2Q3, z.F0change_Q4_minusQ1, ED_Q2Q3, z.Duration, z.Intensity_Q2Q3, z.F0range_Max_minus_Min)
```

```
> table(pref.s2vs3.1$syll.fac, S3)
```

```
  S3
```

```
      2      3
2 100    17
3   18   128
```

```
>
```

```
> ## Odds ratio
```

```
> exp(model.2$coefficients)
```

```
      (Intercept)      z.log.F0_Q2Q3      z.F0change_Q4_minusQ1
      0.7287694      19.5499405      0.8159989
      ED_Q2Q3      z.Duration      z.Intensity_Q2Q3
      1.0407415      1.3066674      0.8627525
```

```

z.F0range_Max_minus_Min
      0.8336314
>
> ## Confidence intervals
>
> exp(confint(model.2))
Waiting for profiling to be done...
              2.5 %      97.5 %
(Intercept)      0.3685650  1.434051
z.log.F0_Q2Q3    10.1080136 42.186942
z.F0change_Q4_minusQ1 0.4770924  1.368405
ED_Q2Q3          0.6722830  1.603628
z.Duration       0.8174234  2.094214
z.Intensity_Q2Q3 0.5826747  1.270433
z.F0range_Max_minus_Min 0.5091144  1.354737
>
> ## Chi-sq test
>
> model.2.chi <- (model.2$null.deviance - model.2$deviance)
> model.2.chi
[1] 171.0073
> model.2.df <- (model.2$df.null - model.2$df.residual)
> model.2.df
[1] 6
> model.2.chisq <- 1-pchisq(model.2.chi, model.2.df)
> model.2.chisq
[1] 0
>
>
> ### Syllable 1 vs 3
> syll.fac <- factor(pref.slvs3$Syllable)
> pref.slvs3 <- cbind(pref.slvs3, syll.fac)
>
> model.3 <- glm(syll.fac ~
z.log.F0_Q2Q3+z.F0change_Q4_minusQ1+ED_Q2Q3+z.Duration+z.Intensity_Q2Q3+z.F0r
ange_Max_minus_Min, data=pref.slvs3, family="binomial")
> summary(model.3)

Call:
glm(formula = syll.fac ~ z.log.F0_Q2Q3 + z.F0change_Q4_minusQ1 +
    ED_Q2Q3 + z.Duration + z.Intensity_Q2Q3 + z.F0range_Max_minus_Min,
    family = "binomial", data = pref.slvs3)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.27534  -0.19665   0.00571   0.08510   2.87385

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)      0.10243    0.71806   0.143 0.886570
z.log.F0_Q2Q3     3.14386    0.57964   5.424 5.83e-08 ***
z.F0change_Q4_minusQ1 2.15198    0.56422   3.814 0.000137 ***
ED_Q2Q3          0.79851    0.58879   1.356 0.175037
z.Duration       -0.76642    0.32855  -2.333 0.019663 *
z.Intensity_Q2Q3  0.08550    0.38759   0.221 0.825418
z.F0range_Max_minus_Min 0.05101    0.49629   0.103 0.918132
---

```

```

Signif. codes:  0  ***  0.001  **  0.01  *  0.05  .  0.1  1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 389.118  on 280  degrees of freedom
Residual deviance:  73.813  on 274  degrees of freedom
    (33 observations deleted due to missingness)
AIC: 87.813

Number of Fisher Scoring iterations: 8

>
> ## Classification table
>
> model.3.pred <- predict(model.3, type="response")
> S3 <- ifelse(model.3.pred > .5, 3, 1)
> pref.slvs3.1 <- pref.slvs3 %>%
drop_na(z.log.F0_Q2Q3, z.F0change_Q4_minusQ1, ED_Q2Q3, z.Duration, z.Intensity_Q2
Q3, z.F0range_Max_minus_Min)
> table(pref.slvs3.1$syll.fac, S3)
      S3
      1   3
1 130   5
3   9 137
>
>
> ## Chisq test
> model.3.chi <- (model.3$null.deviance - model.3$deviance)
> model.3.chi
[1] 315.3048
> model.3.df <- (model.3$df.null - model.3$df.residual)
> model.3.df
[1] 6
> model.3.chisq <- 1-pchisq(model.3.chi, model.3.df)
> model.3.chisq
[1] 0
>
> ## Odds ratio
> exp(model.3$coefficients)
              (Intercept)          z.log.F0_Q2Q3      z.F0change_Q4_minusQ1
              1.1078574             23.1931085             8.6019115
              ED_Q2Q3             z.Duration             z.Intensity_Q2Q3
              2.2222350             0.4646725             1.0892568
z.F0range_Max_minus_Min
              1.0523355
>
> ## Confidence intervals
> exp(confint(model.3))
Waiting for profiling to be done...
              2.5 %          97.5 %
(Intercept)    0.2686934    4.6035721
z.log.F0_Q2Q3   8.5003997   85.4737642
z.F0change_Q4_minusQ1 3.2908060 29.4315150
ED_Q2Q3         0.7565700    7.4887401
z.Duration      0.2328463    0.8566892
z.Intensity_Q2Q3 0.5062543    2.3655117
z.F0range_Max_minus_Min 0.3983080    2.8255672

```

```

>
>
> ##### Focus Condition #####
>
> f.s1 <- subset(f, Syllable==1)
> f.s2 <- subset(f, Syllable==2)
> f.s3 <- subset(f, Syllable==3)
>
> ## Preparing data for syllable comparison
>
> f.s1vs2 <- rbind(f.s1, f.s2)
> f.s2vs3 <- rbind(f.s2, f.s3)
> f.s1vs3 <- rbind(f.s1, f.s3)
>
> ## Syllable 1 vs 2
>
> # Releveling Syllables
> r.syll.fac <- factor(f.s1vs2$Syllable)
> f.s1vs2 <- cbind(f.s1vs2, r.syll.fac)
>
> ## Now running the models
>
> # S1 v S2
>
> model.4 <- glm(r.syll.fac ~
z.log.F0_Q2Q3+z.F0change_Q4_minusQ1+ED_Q2Q3+z.Duration+z.Intensity_Q2Q3+z.F0r
ange_Max_minus_Min, data=f.s1vs2, family="binomial")
> summary(model.4)

```

Call:

```

glm(formula = r.syll.fac ~ z.log.F0_Q2Q3 + z.F0change_Q4_minusQ1 +
    ED_Q2Q3 + z.Duration + z.Intensity_Q2Q3 + z.F0range_Max_minus_Min,
    family = "binomial", data = f.s1vs2)

```

Deviance Residuals:

Min	1Q	Median	3Q	Max
-3.2580	-0.4368	-0.0136	0.4493	2.4118

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	2.3266	0.4537	5.128	2.93e-07 ***
z.log.F0_Q2Q3	1.9966	0.4445	4.492	7.06e-06 ***
z.F0change_Q4_minusQ1	1.3958	0.2996	4.659	3.18e-06 ***
ED_Q2Q3	-0.3290	0.2353	-1.398	0.162
z.Duration	-1.3756	0.2563	-5.366	8.04e-08 ***
z.Intensity_Q2Q3	-0.1629	0.2386	-0.683	0.495
z.F0range_Max_minus_Min	-0.3291	0.2543	-1.294	0.196

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 356.27 on 256 degrees of freedom

Residual deviance: 166.56 on 250 degrees of freedom

(44 observations deleted due to missingness)

AIC: 180.56

Number of Fisher Scoring iterations: 6

```

>
> ## Classification table
> model.4.pred <- predict(model.4, type="response")
> S1 <- ifelse(model.4.pred > .5, 1, 2)
> f.s1vs2.1 <- f.s1vs2 %>%
drop_na(z.log.F0_Q2Q3, z.F0change_Q4_minusQ1, ED_Q2Q3, z.Duration, z.Intensity_Q2
Q3, z.F0range_Max_minus_Min)
> table(f.s1vs2.1$r.syll.fac, S1)
      S1
      2   1
1  14 115
2 111  17
>
> ## Chisq test
>
> model.4.chi <- (model.4$null.deviance - model.4$deviance)
> model.4.chi
[1] 189.7151
> model.4.df <- (model.4$df.null - model.4$df.residual)
> model.4.df
[1] 6
> model.4.chisq <- 1-pchisq(model.4.chi, model.4.df)
> model.4.chisq
[1] 0
>
> ## Odds ratio
> exp(model.4$coefficients)
              (Intercept)          z.log.F0_Q2Q3      z.F0change_Q4_minusQ1
              10.2432735              7.3637110              4.0380564
              ED_Q2Q3              z.Duration              z.Intensity_Q2Q3
              0.7196410              0.2526921              0.8496844
z.F0range_Max_minus_Min
              0.7195380
> ## Confidence intervals
> exp(confint(model.4))
Waiting for profiling to be done...
              2.5 %          97.5 %
(Intercept)      4.4033102 26.5182205
z.log.F0_Q2Q3      3.2383704 18.6696454
z.F0change_Q4_minusQ1 2.3421421 7.5605142
ED_Q2Q3           0.4348541 1.1531499
z.Duration         0.1474850 0.4048797
z.Intensity_Q2Q3    0.5280545 1.3556190
z.F0range_Max_minus_Min 0.4401420 1.1855566
>
>
>
> ## Syllable 2 vs 3
>
> syll.fac <- factor(f.s2vs3$Syllable)
> f.s2vs3 <- cbind(f.s2vs3, syll.fac)
>
> model.5 <- glm(syll.fac ~
z.log.F0_Q2Q3+z.F0change_Q4_minusQ1+ED_Q2Q3+z.Duration+z.Intensity_Q2Q3+z.F0r
ange_Max_minus_Min, data=f.s2vs3, family="binomial")

```

```

> summary(model.5)

Call:
glm(formula = syll.fac ~ z.log.F0_Q2Q3 + z.F0change_Q4_minusQ1 +
    ED_Q2Q3 + z.Duration + z.Intensity_Q2Q3 + z.F0range_Max_minus_Min,
    family = "binomial", data = f.s2vs3)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.70983  -0.59321   0.09691   0.53834   2.65037

Coefficients:
                Estimate Std. Error z value Pr(>|z|)
(Intercept)      -0.9079     0.3340  -2.718  0.00657 **
z.log.F0_Q2Q3       2.8913     0.3560   8.121 4.62e-16 ***
z.F0change_Q4_minusQ1 -0.1805     0.2752  -0.656  0.51197
ED_Q2Q3           0.1050     0.2081   0.505  0.61390
z.Duration         0.2127     0.2177   0.977  0.32852
z.Intensity_Q2Q3   -0.2150     0.2041  -1.053  0.29219
z.F0range_Max_minus_Min -0.5702     0.2376  -2.400  0.01640 *
---
Signif. codes:  0  ***  0.001  **  0.01  *  0.05  .  0.1  1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 381.17  on 275  degrees of freedom
Residual deviance: 215.29  on 269  degrees of freedom
(23 observations deleted due to missingness)
AIC: 229.29

Number of Fisher Scoring iterations: 6

>
> ## Classification table
> model.5.pred <- predict(model.5, type="response")
> S3 <- ifelse(model.5.pred > .5, 3, 2)
> f.s2vs3.1 <- f.s2vs3 %>%
drop_na(z.log.F0_Q2Q3,z.F0change_Q4_minusQ1,ED_Q2Q3,z.Duration,z.Intensity_Q2
Q3,z.F0range_Max_minus_Min)
> table(f.s2vs3.1$syll.fac, S3)
      S3
      2   3
2 106  22
3   29 119

>
> ## Chisq
> model.5.chi <- (model.5$null.deviance - model.5$deviance)
> model.5.chi
[1] 165.8802
> model.5.df <- (model.5$df.null - model.5$df.residual)
> model.5.df
[1] 6
> model.5.chisq <- 1 - pchisq(model.5.chi, model.5.df)
> model.5.chisq
[1] 0
>
> ## Odds ratio

```

```

> exp(model.5$coefficients)
              (Intercept)          z.log.F0_Q2Q3      z.F0change_Q4_minusQ1
              0.4033661             18.0167115             0.8348906
              ED_Q2Q3              z.Duration          z.Intensity_Q2Q3
              1.1107144             1.2370381             0.8065634
z.F0range_Max_minus_Min
              0.5653867
>
> ## Confidence interval
>
> exp(confint(model.5))
Waiting for profiling to be done...
              2.5 %          97.5 %
(Intercept)          0.2072035    0.7771149
z.log.F0_Q2Q3          9.4542383   38.4175715
z.F0change_Q4_minusQ1  0.4840344    1.4331371
ED_Q2Q3              0.7093674    1.6377076
z.Duration            0.8134797    1.9184096
z.Intensity_Q2Q3      0.5375241    1.2025215
z.F0range_Max_minus_Min 0.3473609    0.8838400
>
>
> ##### Syllable 1 v 3
>
> syll.fac <- factor(f.slvs3$Syllable)
> f.slvs3 <- cbind(f.slvs3, syll.fac)
>
> model.6 <- glm(syll.fac ~
z.log.F0_Q2Q3+z.F0change_Q4_minusQ1+ED_Q2Q3+z.Duration+z.Intensity_Q2Q3+z.F0range_Max_minus_Min, data=f.slvs3, family="binomial")
> summary(model.6)

Call:
glm(formula = syll.fac ~ z.log.F0_Q2Q3 + z.F0change_Q4_minusQ1 +
    ED_Q2Q3 + z.Duration + z.Intensity_Q2Q3 + z.F0range_Max_minus_Min,
    family = "binomial", data = f.slvs3)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-3.06083  -0.14410   0.00396   0.06058   2.52864

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)          1.2278     0.6467   1.898  0.05763 .
z.log.F0_Q2Q3          4.6749     0.8906   5.249 1.53e-07 ***
z.F0change_Q4_minusQ1  1.1159     0.4805   2.322  0.02022 *
ED_Q2Q3              -0.3035     0.4023  -0.754  0.45070
z.Duration            -0.1285     0.3497  -0.367  0.71335
z.Intensity_Q2Q3      -0.3503     0.3286  -1.066  0.28632
z.F0range_Max_minus_Min -1.3147     0.5070  -2.593  0.00951 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 382.699  on 276  degrees of freedom
Residual deviance:  70.555  on 270  degrees of freedom

```



```

(31 observations deleted due to missingness)
AIC: 84.555

Number of Fisher Scoring iterations: 8

>
>
>
> ## Classification table ##
>
> model.6.pred <- predict(model.6, type = "response")
> S3 <- ifelse(model.6.pred > .5, 3, 1)
> f.slv3.1 <- f.slv3 %>%
drop_na(z.log.F0_Q2Q3, z.F0change_Q4_minusQ1, ED_Q2Q3, z.Duration, z.Intensity_Q2
Q3, z.F0range_Max_minus_Min)
> table(f.slv3.1$syll.fac, S3)
      S3
      1   3
1 124   5
3   7 141
>
> ## Chisq test
> model.6.chi <- (model.6$null.deviance - model.6$deviance)
> model.6.chi
[1] 312.1447
> model.6.df <- (model.6$df.null - model.6$df.residual)
> model.6.df
[1] 6
> model.6.chisq <- 1 - pchisq(model.6.chi, model.6.df)
> model.6.chisq
[1] 0
>
>
> ## Odds ratio
> exp(model.6$coefficients)
              (Intercept)          z.log.F0_Q2Q3      z.F0change_Q4_minusQ1
              3.4135758          107.2198195          3.0521891
              ED_Q2Q3           z.Duration           z.Intensity_Q2Q3
              0.7382547           0.8794284           0.7044597
z.F0range_Max_minus_Min
              0.2685601
>
> ## Confidence intervals
>
> exp(confint(model.6))
Waiting for profiling to be done...
              2.5 %          97.5 %
(Intercept)      1.0373070    13.716840
z.log.F0_Q2Q3    24.8290196   861.864578
z.F0change_Q4_minusQ1 1.2651349    8.380563
ED_Q2Q3          0.3269756    1.675896
z.Duration       0.4476293    1.784846
z.Intensity_Q2Q3 0.3567408    1.312354
z.F0range_Max_minus_Min 0.0905597    0.681234
>
>
> ##### Post Focus Condition #####

```

```

>
> postf <- subset(stress, Focus=="PostF")
> syll.fac <- factor(postf$Syllable)
> postf <- cbind(postf, syll.fac)
>
> ## Subsetting the syllables
>
> postf.s1 <- subset(postf, Syllable==1)
> postf.s2 <- subset(postf, Syllable==2)
> postf.s3 <- subset(postf, Syllable==3)
>
> ## Preparing the data for comparisons
>
> postf.s1vs2 <- rbind(postf.s1,postf.s2)
> postf.s2vs3 <- rbind(postf.s2,postf.s3)
> postf.s1vs3 <- rbind(postf.s1,postf.s3)
>
> ## Releveling Syllables in Syllable 1 vs 2 comparison
>
> r.syll.fac <- relevel(postf.s1vs2$syll.fac, "2")
>
> postf.s1vs2 <- cbind(postf.s1vs2,r.syll.fac)
>
>
> ## Model 7
>
> model.7 <- glm(r.syll.fac ~
z.log.F0_Q2Q3+z.F0change_Q4_minusQ1+ED_Q2Q3+z.Duration+z.Intensity_Q2Q3+z.F0r
ange_Max_minus_Min, data=postf.s1vs2, family="binomial")
> summary(model.7)

```

Call:

```

glm(formula = r.syll.fac ~ z.log.F0_Q2Q3 + z.F0change_Q4_minusQ1 +
    ED_Q2Q3 + z.Duration + z.Intensity_Q2Q3 + z.F0range_Max_minus_Min,
    family = "binomial", data = postf.s1vs2)

```

Deviance Residuals:

Min	1Q	Median	3Q	Max
-2.53981	-0.31463	0.01288	0.32693	2.69480

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)	
(Intercept)	-1.46938	0.53796	-2.731	0.00631	**
z.log.F0_Q2Q3	-1.10303	0.46749	-2.360	0.01830	*
z.F0change_Q4_minusQ1	-2.55782	0.45233	-5.655	1.56e-08	***
ED_Q2Q3	0.04196	0.32948	0.127	0.89865	
z.Duration	1.52249	0.31584	4.820	1.43e-06	***
z.Intensity_Q2Q3	0.34960	0.27386	1.277	0.20176	
z.F0range_Max_minus_Min	0.24743	0.37034	0.668	0.50406	

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 360.42 on 259 degrees of freedom
Residual deviance: 135.32 on 253 degrees of freedom
(52 observations deleted due to missingness)

AIC: 149.32

Number of Fisher Scoring iterations: 6

```

>
>
>
> ## Classification table
>
> model.7.pred <- predict(model.7, type="response")
> S1 <- ifelse(model.7.pred > .5, 1, 2)
> postf.s1vs2.1 <- postf.s1vs2 %>%
drop_na(z.log.F0_Q2Q3, z.F0change_Q4_minusQ1, ED_Q2Q3, z.Duration, z.Intensity_Q2
Q3, z.F0range_Max_minus_Min)
> table(postf.s1vs2.1$r.syll.fac, S1)
  S1
    1  2
2  13 116
1 115  16
3   0   0
>
> ## Chisq test
>
> model.7.chi <- (model.7$null.deviance - model.7$deviance)
> model.7.chi <-
+
+ > model.7.chi
Error: unexpected '>' in:
"
>"
>
> model.7.df <- (model.7$df.null - model.7$df.residual)
> model.7.df
[1] 6
> model.7.chisq <- 1 - pchisq(model.7.chi, model.7.df)
> model.7.chisq
[1] 0
>
> ## Odds ratio
>
> exp(model.7$coefficients)
      (Intercept)      z.log.F0_Q2Q3      z.F0change_Q4_minusQ1
      0.23006896      0.33186292      0.07747317
      ED_Q2Q3      z.Duration      z.Intensity_Q2Q3
      1.04285627      4.58362918      1.41850432
z.F0range_Max_minus_Min
      1.28073200
>
> ## Confidence intervals
>
> exp(confint(model.7))
Waiting for profiling to be done...
      2.5 %      97.5 %
(Intercept)      0.07617047 0.6452595
z.log.F0_Q2Q3      0.12507451 0.8048755
z.F0change_Q4_minusQ1      0.02816124 0.1683817
ED_Q2Q3      0.51667637 1.9369719

```

```

z.Duration                2.55114383  8.8716588
z.Intensity_Q2Q3          0.82957030  2.4449443
z.F0range_Max_minus_Min  0.60416740  2.5911103
>
> model.7.chi
[1] 225.1005
>
>
> #### Syllable 2 vs 3
>
> ## Model 8
>
> model.8 <- glm(syll.fac ~
z.log.F0_Q2Q3+z.F0change_Q4_minusQ1+ED_Q2Q3+z.Duration+z.Intensity_Q2Q3+z.F0r
ange_Max_minus_Min, data=postf.s2vs3, family="binomial")
> summary(model.8)

Call:
glm(formula = syll.fac ~ z.log.F0_Q2Q3 + z.F0change_Q4_minusQ1 +
    ED_Q2Q3 + z.Duration + z.Intensity_Q2Q3 + z.F0range_Max_minus_Min,
    family = "binomial", data = postf.s2vs3)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.4223 -0.5944  0.1235  0.5047  2.5703

Coefficients:
                Estimate Std. Error z value Pr(>|z|)
(Intercept)      -1.2628     0.3757  -3.361 0.000777 ***
z.log.F0_Q2Q3       2.9739     0.3572   8.326 < 2e-16 ***
z.F0change_Q4_minusQ1 -0.7838     0.2563  -3.059 0.002223 **
ED_Q2Q3            0.1878     0.2134   0.880 0.378878
z.Duration         -0.3843     0.2429  -1.582 0.113635
z.Intensity_Q2Q3    -0.2789     0.2153  -1.295 0.195224
z.F0range_Max_minus_Min -0.2742     0.2444  -1.122 0.261821
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 376.35  on 271  degrees of freedom
Residual deviance: 208.21  on 265  degrees of freedom
(37 observations deleted due to missingness)
AIC: 222.21

Number of Fisher Scoring iterations: 5

>
>
> ## Classification table
>
> model.8.pred <- predict(model.8, type="response")
> S3 <- ifelse(model.8.pred > .5, 3, 2)
> postf.s2vs3.1 <- postf.s2vs3 %>%
drop_na(z.log.F0_Q2Q3,z.F0change_Q4_minusQ1,ED_Q2Q3,z.Duration,z.Intensity_Q2
Q3,z.F0range_Max_minus_Min)
> table(postf.s2vs3.1$syll.fac, S3)

```

```

      S3
      2   3
1     0   0
2 111  18
3   23 120
>
> ## Chisq test
>
> model.8.chi <- (model.8$null.deviance - model.8$deviance)
> model.8.chi
[1] 168.1442
> model.8.df <- (model.8$df.null - model.8$df.residual)
> model.8.df
[1] 6
> model.8.chisq <- 1 - pchisq(model.8.chi, model.8.df)
> model.8.chisq
[1] 0
>
> exp(model.8$coefficients)
              (Intercept)          z.log.F0_Q2Q3      z.F0change_Q4_minusQ1
              0.2828694          19.5678738          0.4566518
              ED_Q2Q3          z.Duration          z.Intensity_Q2Q3
              1.2066074          0.6809142          0.7566006
z.F0range_Max_minus_Min
              0.7601470
>
>
> ## Confidence intervals
>
> exp(confint(model.8))
Waiting for profiling to be done...
              2.5 %          97.5 %
(Intercept)          0.1330513    0.5853124
z.log.F0_Q2Q3        10.1947914   41.6276898
z.F0change_Q4_minusQ1 0.2667420    0.7366226
ED_Q2Q3              0.7862607    1.8307176
z.Duration            0.4209019    1.0968829
z.Intensity_Q2Q3      0.4923836    1.1504360
z.F0range_Max_minus_Min 0.4710519    1.2342126
>
>
> ## Syllable 1 vs 3
>
> ## Model 9
>
> model.9 <- glm(syll.fac ~
z.log.F0_Q2Q3+z.F0change_Q4_minusQ1+ED_Q2Q3+z.Duration+z.Intensity_Q2Q3+z.F0r
ange_Max_minus_Min, data=postf.s1vs3, family="binomial")
> summary(model.9)

Call:
glm(formula = syll.fac ~ z.log.F0_Q2Q3 + z.F0change_Q4_minusQ1 +
  ED_Q2Q3 + z.Duration + z.Intensity_Q2Q3 + z.F0range_Max_minus_Min,
  family = "binomial", data = postfix.s1vs3)

Deviance Residuals:
    Min       1Q   Median       3Q      Max

```

-2.1539 -0.1473 0.0273 0.1779 3.9068

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-0.1708	0.5084	-0.336	0.73694
z.log.F0_Q2Q3	2.8201	0.5506	5.122	3.03e-07 ***
z.F0change_Q4_minusQ1	1.4192	0.5139	2.762	0.00575 **
ED_Q2Q3	0.2817	0.2762	1.020	0.30779
z.Duration	-0.9565	0.4036	-2.370	0.01779 *
z.Intensity_Q2Q3	-0.4976	0.3910	-1.273	0.20311
z.F0range_Max_minus_Min	-0.7229	0.5001	-1.446	0.14830

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 379.319 on 273 degrees of freedom

Residual deviance: 80.876 on 267 degrees of freedom

(39 observations deleted due to missingness)

AIC: 94.876

Number of Fisher Scoring iterations: 7

```
>
> ## Classification table
>
> model.9.pred <- predict(model.9, type="response")
> S3 <- ifelse(model.9.pred > .5, 3, 1)
> postf.slv3.1 <- postf.slv3 %>%
drop_na(z.log.F0_Q2Q3, z.F0change_Q4_minusQ1, ED_Q2Q3, z.Duration, z.Intensity_Q2
Q3, z.F0range_Max_minus_Min)
> table(postf.slv3.1$syll.fac, S3)
  S3
    1  3
1 124  7
2   0  0
3   6 137
>
> ## Chisq test
>
> model.9.chi <- (model.9$null.deviance - model.9$deviance)
> model.9.chi
[1] 298.4429
> model.9.df <- (model.9$df.null - model.9$df.residual)
> model.9.df
[1] 6
> model.9.chisq <- 1 - pchisq(model.9.chi, model.9.df)
> model.9.chisq
[1] 0
>
> ## Odds ratio
> exp(model.9$coefficients)
      (Intercept)      z.log.F0_Q2Q3      z.F0change_Q4_minusQ1
      0.8430057      16.7784035      4.1337117
      ED_Q2Q3      z.Duration      z.Intensity_Q2Q3
      1.3253691      0.3842365      0.6079807
z.F0range_Max_minus_Min
```

```

0.4853321
>
> ## Confidence intervals
>
> exp(confint(model.9))
Waiting for profiling to be done...
              2.5 %      97.5 %
(Intercept)    0.3035576  2.3268006
z.log.F0_Q2Q3   6.4123637 57.3694433
z.F0change_Q4_minusQ1 1.6483129 12.8090106
ED_Q2Q3         0.8080669  2.5297740
z.Duration      0.1650016  0.8097355
z.Intensity_Q2Q3 0.2723357  1.2794081
z.F0range_Max_minus_Min 0.1799302  1.3234136
>
>
>
> ##### Across focus comparisons
#####
>
> ##### Syllable 1 #####
>
> #### Pre Focus (pf) vs Focus (f) ####
>
> s1.pfvf <- rbind(pref.s1,f.s1)
> foc.fac <- factor(s1.pfvf$Focus)
> foc.fac <- relevel(foc.fac, "PreF")
> s1.pfvf <- cbind(s1.pfvf,foc.fac)
>
> model.10 <- glm(foc.fac ~ z.log.F0_Q2Q3 + z.F0change_Q4_minusQ1 + ED_Q2Q3 +
z.Duration + z.Intensity_Q2Q3 + z.F0range_Max_minus_Min, data=s1.pfvf,
family="binomial")
> summary(model.10)

Call:
glm(formula = foc.fac ~ z.log.F0_Q2Q3 + z.F0change_Q4_minusQ1 +
    ED_Q2Q3 + z.Duration + z.Intensity_Q2Q3 + z.F0range_Max_minus_Min,
    family = "binomial", data = s1.pfvf)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.1282  -1.0540  -0.6553   1.0852   1.7249

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)   -0.808478   0.400526  -2.019  0.043535 *
z.log.F0_Q2Q3   0.005713   0.269900   0.021  0.983113
z.F0change_Q4_minusQ1 0.546352   0.252852   2.161  0.030714 *
ED_Q2Q3         0.612813   0.249479   2.456  0.014035 *
z.Duration      0.549791   0.162279   3.388  0.000704 ***
z.Intensity_Q2Q3 0.070274   0.150644   0.466  0.640866
z.F0range_Max_minus_Min 0.218333   0.193137   1.130  0.258286
---
Signif. codes:  0  ***  0.001  **  0.01  *  0.05  .  0.1  1

(Dispersion parameter for binomial family taken to be 1)

```

```

Null deviance: 365.85 on 263 degrees of freedom
Residual deviance: 336.31 on 257 degrees of freedom
(50 observations deleted due to missingness)
AIC: 350.31

```

```
Number of Fisher Scoring iterations: 4
```

```

>
>
>
> ## classification table
>
> model.10.pred <- predict(model.10, type="response")
> Focus <- ifelse(model.10.pred > .5, 1, 0)
> s1.pfvf.1 <- s1.pfvf %>%
drop_na(z.log.F0_Q2Q3, z.F0change_Q4_minusQ1, ED_Q2Q3, z.Duration, z.Intensity_Q2
Q3, z.F0range_Max_minus_Min)
> table(s1.pfvf.1$foc.fac, Focus)
      Focus
      0    1
PreF   89 46
Focus  52 77
>
> ## chisq test
>
> model.10.chi <- (model.10$null.deviance - model.10$deviance)
> model.10.df <- (model.10$df.null - model.10$df.residual)
> model.10.chisq <- 1-pchisq(model.10.chi, model.10.df)
>
> model.10.chi
[1] 29.53753
> model.10.chisq
[1] 4.81188e-05
> model.10.df
[1] 6
>
> ##### Odds ratio #####
> exp(model.10$coefficients)
      (Intercept)          z.log.F0_Q2Q3      z.F0change_Q4_minusQ1
      0.4455357          1.0057291          1.7269414
      ED_Q2Q3          z.Duration          z.Intensity_Q2Q3
      1.8456162          1.7328904          1.0728019
z.F0range_Max_minus_Min
      1.2440008
> ##### CI #####
> exp(confint(model.10))
Waiting for profiling to be done...
              2.5 %      97.5 %
(Intercept)    0.1999385 0.9677385
z.log.F0_Q2Q3    0.5883161 1.7032471
z.F0change_Q4_minusQ1 1.0648470 2.8835316
ED_Q2Q3         1.1380360 3.0377390
z.Duration      1.2693391 2.4036679
z.Intensity_Q2Q3 0.7988649 1.4447868
z.F0range_Max_minus_Min 0.8550438 1.8276083
>
>

```



```

> ##### PreF vs Post F (pof) #####
>
> postf.s1 <- subset(postf, Syllable==1)
> postf.s2 <- subset(postf, Syllable==2)
> postf.s3 <- subset(postf, Syllable==3)
>
> ##### PreF vs Post F (pof) #####
>
> s1.pfvpof <- rbind(pref.s1,postf.s1)
> foc.fac <- factor(s1.pfvpof$Focus)
> foc.fac <- relevel(foc.fac, "PreF")
> s1.pfvpof <- cbind(s1.pfvpof, foc.fac)
>
> model.11 <- glm(foc.fac ~ z.log.F0_Q2Q3 + z.F0change_Q4_minusQ1 + ED_Q2Q3 +
z.Duration + z.Intensity_Q2Q3 + z.F0range_Max_minus_Min, data=s1.pfvpof,
family="binomial")
> summary(model.11)

```

Call:

```

glm(formula = foc.fac ~ z.log.F0_Q2Q3 + z.F0change_Q4_minusQ1 +
    ED_Q2Q3 + z.Duration + z.Intensity_Q2Q3 + z.F0range_Max_minus_Min,
    family = "binomial", data = s1.pfvpof)

```

Deviance Residuals:

Min	1Q	Median	3Q	Max
-1.9549	-1.0751	-0.5408	1.0956	1.8937

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-0.23776	0.39081	-0.608	0.5429
z.log.F0_Q2Q3	0.64836	0.27452	2.362	0.0182 *
z.F0change_Q4_minusQ1	-0.58084	0.30681	-1.893	0.0583 .
ED_Q2Q3	0.18100	0.22351	0.810	0.4181
z.Duration	-0.19759	0.16522	-1.196	0.2317
z.Intensity_Q2Q3	0.33416	0.15649	2.135	0.0327 *
z.F0range_Max_minus_Min	-0.01441	0.22145	-0.065	0.9481

Signif. codes: 0 *** 0.001 ** 0.01 * 0.05 . 0.1 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 368.69 on 265 degrees of freedom

Residual deviance: 338.60 on 259 degrees of freedom

(51 observations deleted due to missingness)

AIC: 352.6

Number of Fisher Scoring iterations: 4

```

> ## classification table
> # 1 is pof, 0 is pf
>
> model.11.pred <- predict(model.11, type="response")
> PostF <- ifelse(model.11.pred > .5, 1, 0)
> s1.pfvpof.1 <- s1.pfvpof %>%
drop_na(z.log.F0_Q2Q3,z.F0change_Q4_minusQ1,ED_Q2Q3,z.Duration,z.Intensity_Q2
Q3,z.F0range_Max_minus_Min)
> table(s1.pfvpof.1$foc.fac,PostF)

```

```

      PostF
        0  1
PreF    90 45
PostF   50 81
>
> ## chisq test
>
> model.11.chi <- (model.11$null.deviance - model.11$deviance)
> model.11.df <- (model.11$df.null - model.11$df.residual)
> model.11.chisq <- 1-pchisq(model.11.chi, model.11.df)
> model.11.chi
[1] 30.09499
> model.11.df
[1] 6
> model.11.chisq
[1] 3.770719e-05
>
> ##### Odds ratio #####
> exp(model.11$coefficients)
              (Intercept)          z.log.F0_Q2Q3      z.F0change_Q4_minusQ1
              0.7883955             1.9124065             0.5594300
              ED_Q2Q3              z.Duration          z.Intensity_Q2Q3
              1.1984095             0.8207096             1.3967643
z.F0range_Max_minus_Min
              0.9856932
> ##### CI #####
> exp(confint(model.11))
Waiting for profiling to be done...
              2.5 %      97.5 %
(Intercept)      0.3638033 1.697540
z.log.F0_Q2Q3     1.1305319 3.331291
z.F0change_Q4_minusQ1 0.3007171 1.008761
ED_Q2Q3          0.7710896 1.886424
z.Duration       0.5911265 1.132368
z.Intensity_Q2Q3 1.0315607 1.909087
z.F0range_Max_minus_Min 0.6356006 1.519635
>
> ##### PostF vs Focus #####
>
> s1.pofvf <- rbind(postf.s1, f.s1)
> foc.fac <- factor(s1.pofvf$Focus)
> foc.fac <- relevel(foc.fac, "PostF")
> s1.pofvf <- cbind(s1.pofvf, foc.fac)
>
> ## model.12
>
> model.12 <- glm(foc.fac ~ z.log.F0_Q2Q3 + z.F0change_Q4_minusQ1 + ED_Q2Q3 +
z.Duration+z.Intensity_Q2Q3 + z.F0range_Max_minus_Min, data=s1.pofvf,
family="binomial")
>
> ## classification table
>
> model.12.pred <- predict(model.12, type="response")
> Focus <- ifelse(model.12.pred > .5, 1, 0)
> s1.pofvf.1 <- s1.pofvf %>%
drop_na(z.log.F0_Q2Q3, z.F0change_Q4_minusQ1, ED_Q2Q3, z.Duration, z.Intensity_Q2
Q3, z.F0range_Max_minus_Min)

```

```

> table(s1.pofvf.1$foc.fac, Focus)
      Focus
      0  1
PostF 93 38
Focus 33 96
>
> ## chisq test
>
> model.12.chi <- (model.12$null.deviance - model.12$deviance)
> model.12.df <- (model.12$df.null - model.12$df.residual)
> model.12.chisq <- 1-pchisq(model.12.chi, model.12.df)
> model.12.chi
[1] 74.40203
> model.12.df
[1] 6
> model.12.chisq
[1] 5.095924e-14
>
> ##### Odds ratio #####
> exp(model.12$coefficients)
      (Intercept)      z.log.F0_Q2Q3      z.F0change_Q4_minusQ1
      0.5489257      0.5056133      2.8557681
      ED_Q2Q3      z.Duration      z.Intensity_Q2Q3
      1.4368279      2.2051028      0.6907462
z.F0range_Max_minus_Min
      1.1551037
> ##### CI #####
> exp(confint(model.12))
Waiting for profiling to be done...
      2.5 %      97.5 %
(Intercept)      0.2326860 1.2694523
z.log.F0_Q2Q3      0.2677779 0.9130176
z.F0change_Q4_minusQ1 1.6518462 5.1597914
ED_Q2Q3      0.9224097 2.3102224
z.Duration      1.5435160 3.2329992
z.Intensity_Q2Q3 0.4926158 0.9578632
z.F0range_Max_minus_Min 0.7536913 1.7894767
> summary(model.12)

Call:
glm(formula = foc.fac ~ z.log.F0_Q2Q3 + z.F0change_Q4_minusQ1 +
     ED_Q2Q3 + z.Duration + z.Intensity_Q2Q3 + z.F0range_Max_minus_Min,
     family = "binomial", data = s1.pofvf)

Deviance Residuals:
      Min       1Q   Median       3Q      Max
-2.2704  -0.9001  -0.2442   0.9199   2.3596

Coefficients:
      Estimate Std. Error z value Pr(>|z|)
(Intercept)    -0.5998     0.4302  -1.394 0.163288
z.log.F0_Q2Q3   -0.6820     0.3114  -2.190 0.028528 *
z.F0change_Q4_minusQ1 1.0493     0.2886   3.636 0.000277 ***
ED_Q2Q3         0.3624     0.2315   1.565 0.117486
z.Duration      0.7908     0.1879   4.208 2.58e-05 ***
z.Intensity_Q2Q3 -0.3700     0.1690  -2.190 0.028543 *
z.F0range_Max_minus_Min 0.1442     0.2196   0.656 0.511520

```

```

---
Signif. codes:  0  ***  0.001  **  0.01  *  0.05  .  0.1  1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 360.42  on 259  degrees of freedom
Residual deviance: 286.02  on 253  degrees of freedom
    (53 observations deleted due to missingness)
AIC: 300.02

Number of Fisher Scoring iterations: 4

>
> ##### Syllable 2 #####
>
> #### PreF vs Focus ####
>
> s2.pfvf <- rbind(pref.s2,f.s2)
> foc.fac <- factor(s2.pfvf$Focus)
> foc.fac <- relevel(foc.fac, "PreF")
> s2.pfvf <- cbind(s2.pfvf,foc.fac)
>
> ## Model 13
> model.13 <- glm(foc.fac ~ z.log.F0_Q2Q3 + z.F0change_Q4_minusQ1 + ED_Q2Q3 +
+ z.Duration+z.Intensity_Q2Q3 + z.F0range_Max_minus_Min, data=s2.pfvf,
+ family="binomial")
> summary(model.13)

Call:
glm(formula = foc.fac ~ z.log.F0_Q2Q3 + z.F0change_Q4_minusQ1 +
    ED_Q2Q3 + z.Duration + z.Intensity_Q2Q3 + z.F0range_Max_minus_Min,
    family = "binomial", data = s2.pfvf)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.1269  -1.0292   0.5285   1.0380   1.8717

Coefficients:
                Estimate Std. Error z value Pr(>|z|)
(Intercept)         0.5412     0.2784   1.944  0.0519 .
z.log.F0_Q2Q3         0.4164     0.2733   1.524  0.1276
z.F0change_Q4_minusQ1 -0.4405     0.2305  -1.911  0.0560 .
ED_Q2Q3              0.1267     0.1777   0.713  0.4759
z.Duration           0.8044     0.1940   4.147 3.37e-05 ***
z.Intensity_Q2Q3      0.4244     0.1769   2.399  0.0164 *
z.F0range_Max_minus_Min 0.1256     0.1826   0.688  0.4913
---
Signif. codes:  0  ***  0.001  **  0.01  *  0.05  .  0.1  1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 339.15  on 244  degrees of freedom
Residual deviance: 303.71  on 238  degrees of freedom
    (48 observations deleted due to missingness)
AIC: 317.71

Number of Fisher Scoring iterations: 4

```

```

>
>
> ## classifcation table
>
> model.13.pred <- predict(model.13, type="response")
> Focus <- ifelse(model.13.pred > .5, 1, 0)
> s2.pfvf.1 <- s2.pfvf %>%
drop_na(z.log.F0_Q2Q3, z.F0change_Q4_minusQ1, ED_Q2Q3, z.Duration, z.Intensity_Q2
Q3, z.F0range_Max_minus_Min)
> table(s2.pfvf.1$foc.fac, Focus)
      Focus
      0    1
PreF   72  45
Focus  40  88
>
> ## chisq test
>
> model.13.chi <- (model.13$null.deviance - model.13$deviance)
> model.13.df <- (model.13$df.null - model.13$df.residual)
> model.13.chisq <- 1-pchisq(model.13.chi, model.13.df)
>
> model.13.chi
[1] 35.44302
> model.13.df
[1] 6
> model.13.chisq
[1] 3.536184e-06
>
> ##### Odds ratio #####
> exp(model.13$coefficients)
      (Intercept)      z.log.F0_Q2Q3      z.F0change_Q4_minusQ1
      1.7181105      1.5165420      0.6437295
      ED_Q2Q3      z.Duration      z.Intensity_Q2Q3
      1.1350621      2.2352493      1.5286674
z.F0range_Max_minus_Min
      1.1338703
> ##### CI #####
> exp(confint(model.13))
Waiting for profiling to be done...
      2.5 %      97.5 %
(Intercept)      1.0043737 3.006470
z.log.F0_Q2Q3      0.8939064 2.623096
z.F0change_Q4_minusQ1 0.4058845 1.006030
ED_Q2Q3      0.7945111 1.606596
z.Duration      1.5462987 3.316008
z.Intensity_Q2Q3 1.0854653 2.177603
z.F0range_Max_minus_Min 0.7973774 1.638145
>
>
> ##### PreF vs PostF #####
>
> s2.pfvpof <- rbind(pref.s2, postf.s2)
> foc.fac <- factor(s2.pfvpof$Focus)
> foc.fac <- relevel(foc.fac, "PreF")
> s2.pfvpof <- cbind(s2.pfvpof, foc.fac)
>

```

```
> ## Model 14
>
> model.14 <- glm(foc.fac ~ z.log.F0_Q2Q3 + z.F0change_Q4_minusQ1 + ED_Q2Q3 +
z.Duration+z.Intensity_Q2Q3 + z.F0range_Max_minus_Min, data=s2.pfvpof,
family="binomial")
> summary(model.14)
```

Call:

```
glm(formula = foc.fac ~ z.log.F0_Q2Q3 + z.F0change_Q4_minusQ1 +
ED_Q2Q3 + z.Duration + z.Intensity_Q2Q3 + z.F0range_Max_minus_Min,
family = "binomial", data = s2.pfvpof)
```

Deviance Residuals:

Min	1Q	Median	3Q	Max
-1.9454	-1.1462	0.7614	1.0959	1.7534

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	0.78020	0.30636	2.547	0.0109 *
z.log.F0_Q2Q3	0.86508	0.28836	3.000	0.0027 **
z.F0change_Q4_minusQ1	-0.09483	0.20294	-0.467	0.6403
ED_Q2Q3	-0.24081	0.19011	-1.267	0.2053
z.Duration	0.30883	0.18466	1.672	0.0944 .
z.Intensity_Q2Q3	-0.12332	0.16496	-0.748	0.4547
z.F0range_Max_minus_Min	0.07761	0.18619	0.417	0.6768

```
---
Signif. codes:  0  ***  0.001  **  0.01  *  0.05  .  0.1  1
```

(Dispersion parameter for binomial family taken to be 1)

```
Null deviance: 340.44 on 245 degrees of freedom
Residual deviance: 323.82 on 239 degrees of freedom
(55 observations deleted due to missingness)
AIC: 337.82
```

Number of Fisher Scoring iterations: 4

```
>
>
>
> ## classification table
>
> model.14.pred <- predict(model.14, type="response")
> PostF <- ifelse(model.14.pred > .5, 1, 0)
> s2.pfvpof.1 <- s2.pfvpof %>%
drop_na(z.log.F0_Q2Q3,z.F0change_Q4_minusQ1,ED_Q2Q3,z.Duration,z.Intensity_Q2
Q3,z.F0range_Max_minus_Min)
> table(s2.pfvpof.1$foc.fac,PostF)
      PostF
      0    1
PreF   62  55
PostF  45  84
>
> ## chisq test
>
> model.14.chi <- (model.14$null.deviance - model.14$deviance)
> model.14.df <- (model.14$df.null - model.14$df.residual)
```

```

> model.14.chisq <- 1-pchisq(model.14.chi, model.14.df)
> model.14.chi
[1] 16.62098
> model.14.chisq
[1] 0.01078192
>
> ## odds ratio
>
> exp(model.14$coefficients)
              (Intercept)          z.log.F0_Q2Q3      z.F0change_Q4_minusQ1
              2.1819023              2.3751911              0.9095290
              ED_Q2Q3              z.Duration              z.Intensity_Q2Q3
              0.7859892              1.3618295              0.8839810
z.F0range_Max_minus_Min
              1.0807009
> ##### CI #####
> exp(confint(model.14))
Waiting for profiling to be done...
              2.5 %      97.5 %
(Intercept)          1.2092887  4.033427
z.log.F0_Q2Q3          1.3737420  4.271787
z.F0change_Q4_minusQ1  0.6083137  1.353527
ED_Q2Q3                0.5380823  1.137137
z.Duration             0.9526202  1.970269
z.Intensity_Q2Q3       0.6373807  1.219804
z.F0range_Max_minus_Min 0.7510306  1.568151
>
>
> ##### PostF vs Focus #####
>
> ## Model 15
> s2.pofvf <- rbind(postf.s2,f.s2)
> foc.fac <- factor(s2.pofvf$Focus)
> foc.fac <- relevel(foc.fac, "PostF")
> s2.pofvf <- cbind(s2.pofvf,foc.fac)
>
> ## Model 15
> model.15 <- glm(foc.fac ~ z.log.F0_Q2Q3 + z.F0change_Q4_minusQ1 + ED_Q2Q3 +
z.Duration+z.Intensity_Q2Q3 + z.F0range_Max_minus_Min, data=s2.pofvf,
family="binomial")
> summary(model.15)

Call:
glm(formula = foc.fac ~ z.log.F0_Q2Q3 + z.F0change_Q4_minusQ1 +
      ED_Q2Q3 + z.Duration + z.Intensity_Q2Q3 + z.F0range_Max_minus_Min,
      family = "binomial", data = s2.pofvf)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.6935  -1.1038  -0.5697   1.1329   1.5838

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)   -0.08459    0.26203   -0.323   0.7468
z.log.F0_Q2Q3 -0.40225    0.26823  -1.500   0.1337
z.F0change_Q4_minusQ1 -0.22272    0.18759  -1.187   0.2351
ED_Q2Q3        0.17162    0.17009   1.009   0.3130

```

```

z.Duration                0.40171    0.18025    2.229    0.0258 *
z.Intensity_Q2Q3          0.37883    0.17168    2.207    0.0273 *
z.F0range_Max_minus_Min  0.04853    0.15519    0.313    0.7545
---
Signif. codes:  0  ***  0.001  **  0.01  *  0.05  .  0.1    1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 356.27  on 256  degrees of freedom
Residual deviance: 340.93  on 250  degrees of freedom
(43 observations deleted due to missingness)
AIC: 354.93

Number of Fisher Scoring iterations: 4

>
>
>
> ## classification table
>
> model.15.pred <- predict(model.15, type="response")
> Focus <- ifelse(model.15.pred > .5, 1, 0)
> s2.pofvf.1 <- s2.pofvf %>%
drop_na(z.log.F0_Q2Q3,z.F0change_Q4_minusQ1,ED_Q2Q3,z.Duration,z.Intensity_Q2
Q3,z.F0range_Max_minus_Min)
> table(s2.pofvf.1$foc.fac,Focus)
      Focus
      0    1
PostF 77 52
Focus 52 76
>
> ## chisq
>
> model.15.chi <- (model.15$null.deviance - model.15$deviance)
> model.15.df <- (model.15$df.null - model.15$df.residual)
> model.15.chisq <- 1-pchisq(model.15.chi, model.15.df)
> model.15.chi
[1] 15.34202
> model.15.chisq
[1] 0.01775701
>
> exp(model.15$coefficients)
      (Intercept)          z.log.F0_Q2Q3      z.F0change_Q4_minusQ1
      0.9188915          0.6688148          0.8003419
      ED_Q2Q3          z.Duration          z.Intensity_Q2Q3
      1.1872297          1.4943821          1.4605705
z.F0range_Max_minus_Min
      1.0497238
>
> ##### CI #####
> exp(confint(model.15))
Waiting for profiling to be done...
      2.5 %    97.5 %
(Intercept)    0.5473606 1.539760
z.log.F0_Q2Q3    0.3917546 1.126143
z.F0change_Q4_minusQ1 0.5508752 1.153154
ED_Q2Q3          0.8482931 1.675489

```



```

z.Duration                1.0551857 2.144953
z.Intensity_Q2Q3          1.0479880 2.059579
z.F0range_Max_minus_Min  0.7748359 1.430918
>
>
>
> ##### Syllable 3 #####
> ##### PreF vs Focus #####
>
> s3.pfvf <- rbind(pref.s3, f.s3)
> foc.fac <- factor(s3.pfvf$Focus)
> foc.fac <- relevel(foc.fac, "PreF")
>
> s3.pfvf <- cbind(s3.pfvf, foc.fac)
>
> ## Model.16
> model.16 <- glm(foc.fac ~ z.log.F0_Q2Q3 + z.F0change_Q4_minusQ1 + ED_Q2Q3 +
z.Duration+z.Intensity_Q2Q3 + z.F0range_Max_minus_Min, data=s3.pfvf,
family="binomial")
> summary(model.16)

Call:
glm(formula = foc.fac ~ z.log.F0_Q2Q3 + z.F0change_Q4_minusQ1 +
    ED_Q2Q3 + z.Duration + z.Intensity_Q2Q3 + z.F0range_Max_minus_Min,
    family = "binomial", data = s3.pfvf)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.1847  -1.0748   0.4137   1.0982   1.7198

Coefficients:
                Estimate Std. Error z value Pr(>|z|)
(Intercept)         0.03478    0.29884   0.116   0.9074
z.log.F0_Q2Q3        0.21321    0.18109   1.177   0.2391
z.F0change_Q4_minusQ1 0.08418    0.19066   0.442   0.6588
ED_Q2Q3             -0.16862    0.16954  -0.995   0.3200
z.Duration           0.67278    0.14788   4.550 5.38e-06 ***
z.Intensity_Q2Q3      0.15908    0.13472   1.181   0.2377
z.F0range_Max_minus_Min -0.30590    0.17036  -1.796   0.0726 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 407.56  on 293  degrees of freedom
Residual deviance: 377.74  on 287  degrees of freedom
(14 observations deleted due to missingness)
AIC: 391.74

Number of Fisher Scoring iterations: 4

>
>
>
> ## classification table
>

```

```

> model.16.pred <- predict(model.16, type="response")
> Focus <- ifelse(model.16.pred > .5, 1, 0)
> s3.pfvf.1 <- s3.pfvf %>%
drop_na(z.log.F0_Q2Q3, z.F0change_Q4_minusQ1, ED_Q2Q3, z.Duration, z.Intensity_Q2
Q3, z.F0range_Max_minus_Min)
> table(s3.pfvf.1$foc.fac, Focus)
      Focus
      0    1
PreF   94  52
Focus  57  91
>
> ## chisq
>
> model.16.chi <- (model.16$null.deviance - model.16$deviance)
> model.16.df <- (model.16$df.null - model.16$df.residual)
> model.16.chisq <- 1-pchisq(model.16.chi, model.16.df)
> model.16.chi
[1] 29.81913
> model.16.chisq
[1] 4.254587e-05
>
>
> ##### Odds ratio #####
> exp(model.16$coefficients)
              (Intercept)          z.log.F0_Q2Q3          z.F0change_Q4_minusQ1
              1.0353890              1.2376439              1.0878252
              ED_Q2Q3              z.Duration              z.Intensity_Q2Q3
              0.8448319              1.9596716              1.1724285
z.F0range_Max_minus_Min
              0.7364603
> ##### CI #####
> exp(confint(model.16))
Waiting for profiling to be done...
              2.5 %    97.5 %
(Intercept)      0.5768464 1.872253
z.log.F0_Q2Q3    0.8687944 1.771306
z.F0change_Q4_minusQ1 0.7532920 1.602859
ED_Q2Q3          0.5958168 1.168541
z.Duration       1.4822225 2.650418
z.Intensity_Q2Q3 0.9014515 1.531217
z.F0range_Max_minus_Min 0.5205453 1.020809
>
>
> ##### PreF vs PostF #####
> s3.pfvpof <- rbind(pref.s3, postf.s3)
> foc.fac <- factor(s3.pfvpof$Focus)
> foc.fac <- relevel(foc.fac, "PreF")
> s3.pfvpof <- cbind(s3.pfvpof, foc.fac)
>
>
> model.17 <- glm(foc.fac ~ z.log.F0_Q2Q3 + z.F0change_Q4_minusQ1 + ED_Q2Q3 +
z.Duration+z.Intensity_Q2Q3 + z.F0range_Max_minus_Min, data=s3.pfvpof,
family="binomial")
> summary(model.17)

Call:
glm(formula = foc.fac ~ z.log.F0_Q2Q3 + z.F0change_Q4_minusQ1 +

```

```

ED_Q2Q3 + z.Duration + z.Intensity_Q2Q3 + z.F0range_Max_minus_Min,
family = "binomial", data = s3.pfvpof)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.4935  -1.1361  -0.7747   1.1320   1.7249

Coefficients:
                Estimate Std. Error z value Pr(>|z|)
(Intercept)      -0.39752    0.30219  -1.315   0.1884
z.log.F0_Q2Q3      0.35219    0.19107   1.843   0.0653 .
z.F0change_Q4_minusQ1 -0.35005    0.17803  -1.966   0.0493 *
ED_Q2Q3           0.09176    0.14635   0.627   0.5307
z.Duration        -0.03487    0.15222  -0.229   0.8188
z.Intensity_Q2Q3    0.12619    0.13603   0.928   0.3536
z.F0range_Max_minus_Min -0.23785    0.17194  -1.383   0.1666
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 400.61  on 288  degrees of freedom
Residual deviance: 388.89  on 282  degrees of freedom
(21 observations deleted due to missingness)
AIC: 402.89

Number of Fisher Scoring iterations: 4

>
>
>
> ## classification table
>
> model.17.pred <- predict(model.17, type="response")
> PostF <- ifelse(model.17.pred > .5, 1, 0)
> s3.pfvpof.1 <- s3.pfvpof %>%
drop_na(z.log.F0_Q2Q3,z.F0change_Q4_minusQ1,ED_Q2Q3,z.Duration,z.Intensity_Q2
Q3,z.F0range_Max_minus_Min)
> table(s3.pfvpof.1$foc.fac,PostF)
      PostF
        0  1
PreF   85 61
PostF  60 83
>
> ## chisq
>
> model.17.chi <- (model.17$null.deviance - model.17$deviance)
> model.17.df <- (model.17$df.null - model.17$df.residual)
> model.17.chisq <- 1-pchisq(model.17.chi, model.17.df)
> model.17.chi
[1] 11.7195
> model.17.chisq
[1] 0.06852707
>
> ##### Odds ratio #####
> exp(model.17$coefficients)
      (Intercept)      z.log.F0_Q2Q3      z.F0change_Q4_minusQ1

```

```

                0.6719858                1.4221741                0.7046533
                ED_Q2Q3                z.Duration                z.Intensity_Q2Q3
                1.0960972                0.9657276                1.1344989
z.F0range_Max_minus_Min
                0.7883248
> ##### CI #####
> exp(confint(model.17))
Waiting for profiling to be done...
                2.5 %      97.5 %
(Intercept)      0.3684486  1.2110936
z.log.F0_Q2Q3    0.9810882  2.0798122
z.F0change_Q4_minusQ1 0.4927058  0.9995714
ED_Q2Q3          0.8229082  1.4709939
z.Duration       0.7144482  1.3015021
z.Intensity_Q2Q3 0.8696211  1.4846278
z.F0range_Max_minus_Min 0.5596169  1.1052821
>
>
> ##### PostF vs Focus #####
>
> s3.pofvf <- rbind(postf.s3, f.s3)
> foc.fac <- factor(s3.pofvf$Focus)
> foc.fac <- relevel(foc.fac, "PostF")
> s3.pofvf <- cbind(s3.pofvf, foc.fac)
>
> model.18 <- glm(foc.fac ~ z.log.F0_Q2Q3 + z.F0change_Q4_minusQ1 + ED_Q2Q3 +
z.Duration+z.Intensity_Q2Q3 + z.F0range_Max_minus_Min, data=s3.pofvf,
family="binomial")
> summary(model.18)

Call:
glm(formula = foc.fac ~ z.log.F0_Q2Q3 + z.F0change_Q4_minusQ1 +
    ED_Q2Q3 + z.Duration + z.Intensity_Q2Q3 + z.F0range_Max_minus_Min,
    family = "binomial", data = s3.pofvf)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.9312  -1.0248   0.4006   1.0370   2.3064

Coefficients:
                Estimate Std. Error z value Pr(>|z|)
(Intercept)      0.63909   0.32467   1.968   0.0490 *
z.log.F0_Q2Q3    -0.22996   0.19462  -1.182   0.2374
z.F0change_Q4_minusQ1 0.55724   0.20358   2.737   0.0062 **
ED_Q2Q3          -0.37146   0.17401  -2.135   0.0328 *
z.Duration       0.90096   0.16601   5.427 5.72e-08 ***
z.Intensity_Q2Q3  0.04264   0.14994   0.284   0.7761
z.F0range_Max_minus_Min -0.19411   0.17918  -1.083   0.2787
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 403.33 on 290 degrees of freedom
Residual deviance: 355.10 on 284 degrees of freedom
(17 observations deleted due to missingness)

```

AIC: 369.1

Number of Fisher Scoring iterations: 4

```

>
>
> ## classification table
>
> model.18.pred <- predict(model.18, type="response")
> Focus <- ifelse(model.18.pred > .5, 1, 0)
> s3.pofvf.1 <- s3.pofvf %>%
drop_na(z.log.F0_Q2Q3, z.F0change_Q4_minusQ1, ED_Q2Q3, z.Duration, z.Intensity_Q2
Q3, z.F0range_Max_minus_Min)
> table(s3.pofvf.1$foc.fac, Focus)
      Focus
      0    1
PostF  93  50
Focus  47 101
>
> ## chisq
>
> model.18.chi <- (model.18$null.deviance - model.18$deviance)
> model.18.df <- (model.18$df.null - model.18$df.residual)
> model.18.chisq <- 1-pchisq(model.18.chi, model.18.df)
> model.18.chi
[1] 48.22192
> model.18.chisq
[1] 1.066909e-08
>
> ##### Odds ratio #####
> exp(model.18$coefficients)
              (Intercept)          z.log.F0_Q2Q3      z.F0change_Q4_minusQ1
              1.8947587              0.7945627              1.7458489
              ED_Q2Q3              z.Duration              z.Intensity_Q2Q3
              0.6897279              2.4619607              1.0435621
z.F0range_Max_minus_Min
              0.8235696
> ##### CI #####
> exp(confint(model.18))
Waiting for profiling to be done...
              2.5 %      97.5 %
(Intercept)      1.0131872  3.6390374
z.log.F0_Q2Q3      0.5401244  1.1614176
z.F0change_Q4_minusQ1  1.1664218  2.6219769
ED_Q2Q3           0.4804877  0.9571288
z.Duration        1.8027614  3.4614705
z.Intensity_Q2Q3   0.7777772  1.4029681
z.F0range_Max_minus_Min 0.5782312  1.1762068
>
>
>
> ##### Post Hoc Tests #####
>
> ### Post 1 ###
> post.1 <- glm(r.syll.fac ~ z.log.F0_Q2Q3, data=pref.slvs2,
family="binomial")

```

```

> summary(post.1)

Call:
glm(formula = r.syll.fac ~ z.log.F0_Q2Q3, family = "binomial",
    data = pref.slvs2)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.3714  -0.9755  -0.5840   1.0442   2.2009

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)    0.9750     0.2212   4.408 1.04e-05 ***
z.log.F0_Q2Q3    1.7468     0.2850   6.128 8.88e-10 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 383.19  on 276  degrees of freedom
Residual deviance: 332.76  on 275  degrees of freedom
(29 observations deleted due to missingness)
AIC: 336.76

Number of Fisher Scoring iterations: 4

>
>
> ## Classification table
> post.1.pred <- predict(post.1, type="response")
> S1 <- ifelse(post.1.pred > .5, 1, 2)
> pref.slvs2.1 <- pref.slvs2 %>% drop_na(z.log.F0_Q2Q3)
> table(pref.slvs2.1$r.syll.fac, S1)
   S1
     1  2
1  36 110
2  82  49

>
> post.1.chi <- (post.1$null.deviance - post.1$deviance)
> post.1.df <- (post.1$df.null - post.1$df.residual)
> post.1.chi
[1] 50.4337
> post.1.df
[1] 1
> post.1.chisq <- 1-pchisq(post.1.chi, post.1.df)
> post.1.chisq
[1] 1.23257e-12
>
>
> ## Odds ratio
>
> exp(post.1$coefficients)
(Intercept) z.log.F0_Q2Q3
    2.651080    5.736387

>
> ## Confidence intervals
>

```

```

> exp(confint(post.1))
Waiting for profiling to be done...
              2.5 %      97.5 %
(Intercept)   1.744065   4.159001
z.log.F0_Q2Q3 3.363129 10.305348
>
>
> #### Post 2 ####
>
> post.2 <- glm(r.syll.fac ~ z.F0change_Q4_minusQ1, data=pref.slvs2,
family="binomial")
> summary(post.2)

Call:
glm(formula = r.syll.fac ~ z.F0change_Q4_minusQ1, family = "binomial",
    data = pref.slvs2)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.7547  -0.6249  -0.1724   0.7254   2.3135

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)    0.6692     0.1941   3.447 0.000566 ***
z.F0change_Q4_minusQ1 2.7802     0.3471   8.009 1.16e-15 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 348.06  on 251  degrees of freedom
Residual deviance: 213.00  on 250  degrees of freedom
(54 observations deleted due to missingness)
AIC: 217

Number of Fisher Scoring iterations: 5

>
>
> ## Classification table
>
> post.2.pred <- predict(post.2, type="response")
> S1 <- ifelse(post.2.pred > .5, 1, 2)
> pref.slvs2.1 <- pref.slvs2 %>% drop_na(z.F0change_Q4_minusQ1)
> table(pref.slvs2.1$r.syll.fac, S1)
      S1
      1  2
1    24 111
2    99  18
>
> ## Chisq test
> post.2.chi <- (post.2$null.deviance - post.2$deviance)
> post.2.df <- (post.2$df.null - post.2$df.residual)
> post.2.chisq <- 1-pchisq(post.2.chi, post.2.df)
> post.2.chi
[1] 135.0555
> post.2.df

```

```

[1] 1
> post.2.chisq
[1] 0
>
> ## odds ratio
>
> exp(post.2$coefficients)
      (Intercept)  z.F0change_Q4_minusQ1
      1.952671      16.121794
>
> ## confidence intervals
> exp(confint(post.2))
Waiting for profiling to be done...
      2.5 %      97.5 %
(Intercept)      1.351241  2.900226
z.F0change_Q4_minusQ1 8.557438 33.537122
>
> ##### Post hoc 3 #####
>
> post.3 <- glm(r.syll.fac ~ z.Duration, data=pref.slvs2, family="binomial")
> summary(post.3)

Call:
glm(formula = r.syll.fac ~ z.Duration, family = "binomial", data =
pref.slvs2)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.2952  -0.8025  -0.2912   0.8155   2.3870

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  -0.1160     0.1387  -0.836    0.403
z.Duration    -1.5574     0.1879  -8.287 <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 423.74  on 305  degrees of freedom
Residual deviance: 314.77  on 304  degrees of freedom
AIC: 318.77

Number of Fisher Scoring iterations: 4

>
>
>
> ## classification table
>
> post.3.pred <- predict(post.3, type="response")
> S1 <- ifelse(post.3.pred > .5, 1, 2)
> pref.slvs2.1 <- pref.slvs2 %>% drop_na(z.Duration)
> table(pref.slvs2.1$r.syll.fac, S1)
      S1
      1  2
1  38 121

```



```

2 110 37
>
> ## chisq test
>
> post.3.chi <- (post.3$null.deviance - post.3$deviance)
> post.3.df <- (post.3$df.null - post.3$df.residual)
> post.3.chisq <- 1-pchisq(post.3.chi, post.3.df)
> post.3.chi
[1] 108.9608
>
> post.3.chisq
[1] 0
>
> ## Odds ratio
> exp(post.3$coefficients)
(Intercept)    z.Duration
  0.8905086    0.2106866
>
> ## CI
> exp(confint(post.3))
Waiting for profiling to be done...
              2.5 %      97.5 %
(Intercept)  0.6769960  1.1678861
z.Duration   0.1428395  0.2989873
>
>
>
> ##### Post 4 #####
> post.4 <- glm(r.syll.fac ~ z.F0range_Max_minus_Min, data=pref.slvs2,
family="binomial")
> summary(post.4)

Call:
glm(formula = r.syll.fac ~ z.F0range_Max_minus_Min, family = "binomial",
    data = pref.slvs2)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.7196  -1.0247  -0.4135   0.9626   2.4727

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)   -0.2801    0.1385  -2.023   0.0431 *
z.F0range_Max_minus_Min -1.0365    0.1699  -6.100 1.06e-09 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 383.19  on 276  degrees of freedom
Residual deviance: 334.52  on 275  degrees of freedom
(29 observations deleted due to missingness)
AIC: 338.52

Number of Fisher Scoring iterations: 4
>

```

```

>
> ## classification table
>
> post.4.pred <- predict(post.4, type="response")
> S1 <- ifelse(post.4.pred > .5, 1, 2)
> pref.s1vs2.1 <- pref.s1vs2 %>% drop_na(z.log.F0range_Max_minus_Min)
Error in `chr_as_locations()` :
! Can't subset columns past the end.
x Column `z.log.F0range_Max_minus_Min` doesn't exist.
Run `rlang::last_error()` to see where the error occurred.
> table(pref.s1vs2.1$r.syll.fac, S1)
Error in table(pref.s1vs2.1$r.syll.fac, S1) :
  all arguments must have the same length
>
> ## chisq
>
> post.4.chi <- (post.4$null.deviance - post.4$deviance)
> post.4.df <- (post.4$df.null - post.4$df.residual)
> post.4.chisq <- 1-pchisq(post.4.chi, post.4.df)
> post.4.chi
[1] 48.66624
> post.4.chisq
[1] 3.034462e-12
>
> ## odds ratio
> exp(post.4$coefficients)
      (Intercept) z.F0range_Max_minus_Min
      0.7556962      0.3546939
>
> ## confidence intervals
> exp(confint(post.4))
Waiting for profiling to be done...
      2.5 %      97.5 %
(Intercept)      0.5729046 0.9874328
z.F0range_Max_minus_Min 0.2500838 0.4877497
> ## classification table
>
> post.4.pred <- predict(post.4, type="response")
> S1 <- ifelse(post.4.pred > .5, 1, 2)
> pref.s1vs2.1 <- pref.s1vs2 %>% drop_na(z.F0range_Max_minus_Min)
> table(pref.s1vs2.1$r.syll.fac, S1)
      S1
      1  2
1 54 92
2 98 33
>
>
> ##### S2 vs S3 #####
> ##### Post 5 #####
> post.5 <- glm(syll.fac ~ z.log.F0_Q2Q3, data=pref.s2vs3, family="binomial")
> summary(post.5)

Call:
glm(formula = syll.fac ~ z.log.F0_Q2Q3, family = "binomial",
    data = pref.s2vs3)

Deviance Residuals:

```

```

      Min       1Q   Median       3Q      Max
-3.3309 -0.5581  0.1101  0.4747  2.7492

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)   -0.4928     0.1821  -2.707   0.0068 **
z.log.F0_Q2Q3  2.8253     0.3158   8.946  <2e-16 ***
---
Signif. codes:  0 *** 0.001 ** 0.01 * 0.05 . 0.1 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 389.52  on 281  degrees of freedom
Residual deviance: 207.10  on 280  degrees of freedom
(20 observations deleted due to missingness)
AIC: 211.1

Number of Fisher Scoring iterations: 5

>
>
> post.5.pred <- predict(post.5, type="response")
> S3 <- ifelse(post.5.pred > .5, 3, 2)
> pref.s2vs3.1 <- pref.s2vs3 %>% drop_na(z.log.F0_Q2Q3)
> table(pref.s2vs3.1$syll.fac, S3)
      S3
      2   3
2  112  19
3   20 131
>
> ## chisq
>
> post.5.chi <- (post.5$null.deviance - post.5$deviance)
> post.5.df <- (post.5$df.null - post.5$df.residual)
> post.5.chisq <- 1-pchisq(post.5.chi, post.5.df)
> post.5.chi
[1] 182.4179
> post.5.chisq
[1] 0
>
> ## odds ratio
>
> exp(post.5$coefficients)
(Intercept) z.log.F0_Q2Q3
  0.6108923  16.8658531
>
> ## confidence intervals
>
> exp(confint(post.5))
Waiting for profiling to be done...
              2.5 %      97.5 %
(Intercept)  0.4229997  0.8662049
z.log.F0_Q2Q3 9.4873541 32.9058732
>
>
> ##### S1 vs S3 #####
>

```

```
> ##### Post 6 #####
> post.6 <- glm(syll.fac ~ z.log.F0_Q2Q3, data=pref.slvs3, family="binomial")
> summary(post.6)
```

Call:

```
glm(formula = syll.fac ~ z.log.F0_Q2Q3, family = "binomial",
     data = pref.slvs3)
```

Deviance Residuals:

Min	1Q	Median	3Q	Max
-2.86049	-0.31260	0.01327	0.20572	2.84544

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	0.2811	0.2387	1.178	0.239
z.log.F0_Q2Q3	3.7331	0.4334	8.614	<2e-16 ***

Signif.	codes:	0	***	0.001	**	0.01	*	0.05	.	0.1	1
---------	--------	---	-----	-------	----	------	---	------	---	-----	---

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 411.65 on 296 degrees of freedom
 Residual deviance: 129.97 on 295 degrees of freedom
 (17 observations deleted due to missingness)
 AIC: 133.97

Number of Fisher Scoring iterations: 7

```
>
>
> ## classification table
> post.6.pred <- predict(post.6, type="response")
> S3 <- ifelse(post.6.pred > .5, 3, 1)
> pref.slvs3.1 <- pref.slvs3 %>% drop_na(z.log.F0_Q2Q3)
> table(pref.slvs3.1$syll.fac, S3)
      S3
      1   3
1 135  11
3  15 136
>
> ## chisq test
>
> post.6.chi <- (post.6$null.deviance - post.6$deviance)
> post.6.df <- (post.6$df.null - post.6$df.residual)
> post.6.chisq <- 1-pchisq(post.6.chi, post.6.df)
> post.6.chi
[1] 281.678
> post.6.chisq
[1] 0
>
> ## Odds ratio
>
> exp(post.6$coefficients)
      (Intercept)  z.log.F0_Q2Q3
      1.324563    41.810343
>
> ## confidence intervals
```

```

>
> exp(confint(post.6))
Waiting for profiling to be done...
              2.5 %      97.5 %
(Intercept)    0.8384245    2.154769
z.log.F0_Q2Q3 19.4552156 107.866756
>
>
> ##### Post 7 #####
> post.7 <- glm(syll.fac ~ z.F0change_Q4_minusQ1, data=pref.slvs3,
family="binomial")
> summary(post.7)

Call:
glm(formula = syll.fac ~ z.F0change_Q4_minusQ1, family = "binomial",
    data = pref.slvs3)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.6837  -0.5393   0.0726   0.5096   3.7606

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)    0.5056     0.1841   2.746  0.00604 **
z.F0change_Q4_minusQ1 2.7493     0.3212   8.560 < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 389.12  on 280  degrees of freedom
Residual deviance: 207.77  on 279  degrees of freedom
(33 observations deleted due to missingness)
AIC: 211.77

Number of Fisher Scoring iterations: 6

>
>
>
> ## classification table
> post.7.pred <- predict(post.7, type="response")
> S3 <- ifelse(post.7.pred > .5, 3, 1)
> pref.slvs3.1 <- pref.slvs3 %>% drop_na(z.F0change_Q4_minusQ1)
> table(pref.slvs3.1$syll.fac, S3)
      S3
      1  3
1 117  18
3  22 124
>
> ## chisq test
> post.7.chi <- (post.7$null.deviance - post.7$deviance)
> post.7.df <- (post.7$df.null - post.7$df.residual)
> post.7.chisq <- 1-pchisq(post.7.chi, post.7.df)
> post.7.chi
[1] 181.3442
> post.7.chisq

```

```

[1] 0
>
> ## odds ratio
> exp(post.7$coefficients)
      (Intercept) z.F0change_Q4_minusQ1
      1.657953      15.631440
>
> ## confidence intervals (CI)
> exp(confint(post.7))
Waiting for profiling to be done...
      (Intercept)      2.5 %      97.5 %
      1.165914      2.407307
z.F0change_Q4_minusQ1 8.735205 30.933957
>
>
> ##### Post 8 #####
>
> post.8 <- glm(syll.fac ~ z.Duration, data=pref.slvs3, family="binomial")
> summary(post.8)

Call:
glm(formula = syll.fac ~ z.Duration, family = "binomial", data = pref.slvs3)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.1611  -0.8690  -0.2310   0.8935   3.0555

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) -0.001632   0.130948  -0.012    0.99
z.Duration   -1.300941   0.165479  -7.862 3.79e-15 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 435.25  on 313  degrees of freedom
Residual deviance: 345.85  on 312  degrees of freedom
AIC: 349.85

Number of Fisher Scoring iterations: 4

>
>
>
> ## classification table
>
> post.8.pred <- predict(post.8, type="response")
> S3 <- ifelse(post.8.pred > .5, 3, 1)
> pref.slvs3.1 <- pref.slvs3 %>% drop_na(z.Duration)
> table(pref.slvs3.1$syll.fac, S3)
      S3
      1  3
1 117  42
3   34 121
>
> ## chisq test

```

```

>
> post.8.chi <- (post.8$null.deviance - post.8$deviance)
> post.8.df <- (post.8$df.null - post.8$df.residual)
> post.8.chisq <- 1-pchisq(post.8.chi, post.8.df)
>
> post.8.chi
[1] 89.39162
> post.8.chisq
[1] 0
> post.8.df
[1] 1
>
> ## odds ratio
>
> exp(post.8$coefficients)
(Intercept)    z.Duration
    0.9983691    0.2722755
>
> ## CI
>
> exp(confint(post.8))
Waiting for profiling to be done...
              2.5 %      97.5 %
(Intercept)  0.7718717  1.2910579
z.Duration   0.1937538  0.3712371
>
>
> ##### Focus Condition #####
> ## S1 vs S2
>
>
>
>
> post.9 <- glm(r.syll.fac ~ z.log.F0_Q2Q3, data=f.s1vs2, family="binomial")
> summary(post.9)

Call:
glm(formula = r.syll.fac ~ z.log.F0_Q2Q3, family = "binomial",
    data = f.s1vs2)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.4321  -0.8103  -0.1318   0.8452   2.3670

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)    1.4870     0.2482   5.992 2.08e-09 ***
z.log.F0_Q2Q3  2.5881     0.3328   7.777 7.40e-15 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 395.01  on 284  degrees of freedom
Residual deviance: 291.25  on 283  degrees of freedom
(16 observations deleted due to missingness)
AIC: 295.25

```

Number of Fisher Scoring iterations: 5

```

>
> ## classification table
>
> post.9.pred <- predict(post.9, type="response")
> S1 <- ifelse(post.9.pred > .5, 1, 2)
> f.s1vs2.1 <- f.s1vs2 %>% drop_na(z.log.F0_Q2Q3)
> table(f.s1vs2.1$syll.fac, S1)
Error in table(f.s1vs2.1$syll.fac, S1) :
  all arguments must have the same length
>
> ## chisq test
>
> post.9.chi <- (post.9$null.deviance - post.9$deviance)
> post.9.df <- (post.9$df.null - post.9$df.residual)
> post.9.chisq <- 1-pchisq(post.9.chi, post.9.df)
> post.9.chi
[1] 103.7568
> post.9.chisq
[1] 0
>
> ## odds ratio
>
> exp(post.9$coefficients)
  (Intercept) z.log.F0_Q2Q3
      4.423613      13.303981
>
> ##### CI #####
> exp(confint(post.9))
Waiting for profiling to be done...
              2.5 %      97.5 %
(Intercept)  2.786961  7.394972
z.log.F0_Q2Q3 7.194843 26.610767
> ## classification table
>
>
> post.9.pred <- predict(post.9, type="response")
> S1 <- ifelse(post.9.pred > .5, 1, 2)
> f.s1vs2.1 <- f.s1vs2 %>% drop_na(z.log.F0_Q2Q3)
> table(f.s1vs2.1$r.syll.fac, S1)
  S1
    1  2
1  35 110
2  97  43
>
>
> ##### Post 10 #####
> post.10 <- glm(r.syll.fac ~ z.F0change_Q4_minusQ1, data=f.s1vs2,
family="binomial")
> summary(post.10)

Call:
glm(formula = r.syll.fac ~ z.F0change_Q4_minusQ1, family = "binomial",
    data = f.s1vs2)

```



```

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.3906 -0.8423 -0.2000  0.8975  2.1879

Coefficients:
                Estimate Std. Error z value Pr(>|z|)
(Intercept)      0.2653     0.1523   1.741   0.0816 .
z.F0change_Q4_minusQ1  1.6172     0.2217   7.294   3e-13 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 356.27  on 256  degrees of freedom
Residual deviance: 274.15  on 255  degrees of freedom
(44 observations deleted due to missingness)
AIC: 278.15

Number of Fisher Scoring iterations: 4

>
> ## Classification table
> post.10.pred <- predict(post.10, type="response")
> S1 <- ifelse(post.10.pred > .5, 1, 2)
> f.s1vs2.1 <- f.s1vs2 %>% drop_na(z.F0change_Q4_minusQ1)
> table(f.s1vs2.1$r.syll.fac, S1)
   S1
   1  2
1 32 97
2 97 31

>
> ## chisq test
>
> post.10.chi <- (post.10$null.deviance - post.10$deviance)
> post.10.df <- (post.10$df.null - post.10$df.residual)
> post.10.chisq <- 1-pchisq(post.10.chi, post.10.df)
> post.10.chi
[1] 82.11891
>
> post.10.chisq
[1] 0
>
> ## odds ratio
>
> exp(post.10$coefficients)
      (Intercept) z.F0change_Q4_minusQ1
      1.303783      5.039198

>
> ##### CI #####
> exp(confint(post.10))
Waiting for profiling to be done...
              2.5 %    97.5 %
(Intercept)  0.9709229 1.766989
z.F0change_Q4_minusQ1 3.3399197 7.988227
>
>
> ##### Post 11 #####

```

```

> post.11 <- glm(r.syll.fac ~ z.Duration, data=f.s1vs2, family="binomial")
> summary(post.11)

Call:
glm(formula = r.syll.fac ~ z.Duration, family = "binomial", data = f.s1vs2)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.6302  -0.8444  -0.2951   0.7818   2.6834

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)   0.5772     0.1574   3.667 0.000245 ***
z.Duration   -1.5370     0.1874  -8.203 2.34e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 417.01  on 300  degrees of freedom
Residual deviance: 310.50  on 299  degrees of freedom
AIC: 314.5

Number of Fisher Scoring iterations: 4

>
>
> ## classification table
>
> post.11.pred <- predict(post.11, type="response")
> S1 <- ifelse(post.11.pred > .5, 1, 2)
> f.s1vs2.1 <- f.s1vs2 %>% drop_na(z.Duration)
> table(f.s1vs2.1$syll.fac, S1)
Error in table(f.s1vs2.1$syll.fac, S1) :
  all arguments must have the same length
>
> ## chisq test
>
> post.11.chi <- (post.11$null.deviance - post.11$deviance)
> post.11.df <- (post.11$df.null - post.11$df.residual)
> post.11.chisq <- 1-pchisq(post.11.chi, post.11.df)
> post.11.chi
[1] 106.5057
> post.11.chisq
[1] 0
>
> ##### Odds ratio #####
> exp(post.11$coefficients)
(Intercept)  z.Duration
  1.7810812   0.2150237
> ##### CI #####
> exp(confint(post.11))
Waiting for profiling to be done...
              2.5 %      97.5 %
(Intercept)  1.3182145 2.4469806
z.Duration   0.1459113 0.3047359
>

```

```

> table(f.s1vs2.1$r.syll.fac, S1)
      S1
      1  2
1  36 119
2 111  35
>
>
> ##### S2 vs S3 #####
>
> ##### Post 12 #####
> post.12 <- glm(syll.fac ~ z.log.F0_Q2Q3, data=f.s2vs3, family="binomial")
> summary(post.12)

Call:
glm(formula = syll.fac ~ z.log.F0_Q2Q3, family = "binomial",
    data = f.s2vs3)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.47336  -0.61019   0.09169   0.55862   2.74192

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  -0.8330     0.1859  -4.48 7.46e-06 ***
z.log.F0_Q2Q3  2.5121     0.2791   9.00 < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 403.00  on 290  degrees of freedom
Residual deviance: 233.34  on 289  degrees of freedom
(8 observations deleted due to missingness)
AIC: 237.34

Number of Fisher Scoring iterations: 5

>
>
>
> ## classification table
> post.12.pred <- predict(post.12, type="response")
> S3 <- ifelse(post.12.pred > .5, 3, 2)
> f.s2vs3.1 <- f.s2vs3 %>% drop_na(z.log.F0_Q2Q3)
> table(f.s2vs3.1$r.syll.fac, S3)
      S3
      2  3
2 112  28
3  27 124
>
> ## chisq test
>
> post.12.chi <- (post.12$null.deviance - post.12$deviance)
> post.12.df <- (post.12$df.null - post.12$df.residual)
> post.12.chisq <- 1-pchisq(post.12.chi, post.12.df)
> post.12.chi
[1] 169.6563

```

```

> post.12.chisq
[1] 0
>
> ## Odds ratio
>
> exp(post.12$coefficients)
      (Intercept)  z.log.F0_Q2Q3
      0.4347608    12.3312965
>
> ## CI
>
> exp(confint(post.12))
Waiting for profiling to be done...
              2.5 %    97.5 %
(Intercept)  0.2974171  0.618075
z.log.F0_Q2Q3 7.3929547 22.175563
>
>
>
> ##### Post 13 #####
>
> post.13 <- glm(syll.fac ~ z.F0range_Max_minus_Min, data=f.s2vs3,
family="binomial")
> summary(post.13)

Call:
glm(formula = syll.fac ~ z.F0range_Max_minus_Min, family = "binomial",
    data = f.s2vs3)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.6788  -1.1746   0.9718   1.1577   1.2520

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)    0.09985    0.11907   0.839   0.402
z.F0range_Max_minus_Min 0.19476    0.12360   1.576   0.115

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 403.00  on 290  degrees of freedom
Residual deviance: 400.41  on 289  degrees of freedom
(8 observations deleted due to missingness)
AIC: 404.41

Number of Fisher Scoring iterations: 4

>
>
>
> ## classification table
>
> post.13.pred <- predict(post.13, type="response")
> S3 <- ifelse(post.13.pred > .5, 3, 2)
> f.s2vs3.1 <- f.s2vs3 %>% drop_na(z.log.F0range_Max_minus_Min)
> table(f.s2vs3.1$syll.fac, S3)

```

```

      S3
      2  3
2 72 68
3 55 96
>
> ## chisq test
>
> post.13.chi <- (post.13$null.deviance - post.13$deviance)
> post.13.df <- (post.13$df.null - post.13$df.residual)
> post.13.chisq <- 1-pchisq(post.13.chi, post.13.df)
>
> post.13.chi
[1] 2.582516
> post.13.chisq
[1] 0.1080498
>
> ##### Odds ratio #####
> exp(post.13$coefficients)
      (Intercept) z.F0range_Max_minus_Min
      1.105004      1.215019
> ##### CI #####
> exp(confint(post.13))
Waiting for profiling to be done...
      2.5 %    97.5 %
(Intercept)      0.8754316 1.396973
z.F0range_Max_minus_Min 0.9587769 1.561541
>
> ## classification table
>
> post.13.pred <- predict(post.13, type="response")
> S3 <- ifelse(post.13.pred > .5, 3, 2)
> f.s2vs3.1 <- f.s2vs3 %>% drop_na(z.F0range_Max_minus_Min)
> table(f.s2vs3.1$syll.fac, S3)
      S3
      2  3
2 72 68
3 55 96
>
>
> ##### Post 14 #####
>
> post.14 <- glm(syll.fac ~ z.log.F0_Q2Q3, data=f.s1vs3, family="binomial")
> summary(post.14)

Call:
glm(formula = syll.fac ~ z.log.F0_Q2Q3, family = "binomial",
    data = f.s1vs3)

Deviance Residuals:
      Min       1Q   Median       3Q      Max
-2.34314  -0.23891   0.00304   0.13247   2.93213

Coefficients:
      Estimate Std. Error z value Pr(>|z|)
(Intercept)    0.4394    0.2730   1.609   0.108
z.log.F0_Q2Q3  4.0890    0.5170   7.910 2.58e-15 ***
---

```

```

Signif. codes:  0  ***  0.001  **  0.01  *  0.05  .  0.1  1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 410.22  on 295  degrees of freedom
Residual deviance: 108.68  on 294  degrees of freedom
    (12 observations deleted due to missingness)
AIC: 112.68

Number of Fisher Scoring iterations: 7

>
>
> ## classification table
>
> post.14.pred <- predict(post.14, type="response")
> S3 <- ifelse(post.14.pred > .5, 3, 1)
> f.slvs3.1 <- f.slvs3 %>% drop_na(z.log.F0_Q2Q3)
> table(f.slvs3.1$syll.fac, S3)
   S3
     1   3
1 136   9
3  12 139
>
> ## chisq
>
> post.14.chi <- (post.14$null.deviance - post.14$deviance)
> post.14.df <- (post.14$df.null - post.14$df.residual)
> post.14.chisq <- 1-pchisq(post.14.chi, post.14.df)
>
> post.14.chi
[1] 301.5462
> post.14.chisq
[1] 0
>
>
> ##### Odds ratio #####
> exp(post.14$coefficients)
    (Intercept)  z.log.F0_Q2Q3
      1.551774      59.680479
> ##### CI #####
> exp(confint(post.14))
Waiting for profiling to be done...
              2.5 %      97.5 %
(Intercept)  0.9275686  2.734675
z.log.F0_Q2Q3 24.3181342 188.250258
>
>
> ##### Post 15 #####
>
> post.15 <- glm(syll.fac ~ z.F0change_Q4_minusQ1, data=f.slvs3,
family="binomial")
>
> summary(post.15)

Call:
glm(formula = syll.fac ~ z.F0change_Q4_minusQ1, family = "binomial",

```

```

data = f.s1vs3)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.6405 -0.6735  0.2104  0.6983  2.1559

Coefficients:
                Estimate Std. Error z value Pr(>|z|)
(Intercept)      0.1650     0.1587   1.040    0.298
z.F0change_Q4_minusQ1 2.1004     0.2489   8.438 <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 382.70 on 276 degrees of freedom
Residual deviance: 245.58 on 275 degrees of freedom
(31 observations deleted due to missingness)
AIC: 249.58

Number of Fisher Scoring iterations: 5

>
>
>
> ## classification table
>
> post.15.pred <- predict(post.15, type="response")
> S3 <- ifelse(post.15.pred > .5, 3, 1)
> f.s1vs3.1 <- f.s1vs3 %>% drop_na(z.F0change_Q4_minusQ1)
> table(f.s1vs3.1$syll.fac,S3)
  S3
    1  3
1 101 28
3  24 124
>
> ## chisq
>
> post.15.chi <- (post.15$null.deviance - post.15$deviance)
> post.15.df <- (post.15$df.null - post.15$df.residual)
> post.15.chisq <- 1-pchisq(post.15.chi, post.15.df)
> post.15.chi
[1] 137.1203
> post.15.chisq
[1] 0
>
> ## odds ratio
> exp(post.15$coefficients)
      (Intercept) z.F0change_Q4_minusQ1
      1.179424      8.169035
> ##### CI #####
> exp(confint(post.15))
Waiting for profiling to be done...
              2.5 %      97.5 %
(Intercept)  0.8647495  1.614381
z.F0change_Q4_minusQ1 5.1699547 13.763841
>

```

```

> ##### Post 16 #####
>
>
>
> post.16 <- glm(syll.fac ~ z.F0range_Max_minus_Min, data=f.s1vs3,
family="binomial")
> summary(post.16)

Call:
glm(formula = syll.fac ~ z.F0range_Max_minus_Min, family = "binomial",
    data = f.s1vs3)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.359  -1.190   1.026   1.130   1.672

Coefficients:
                Estimate Std. Error z value Pr(>|z|)
(Intercept)      0.06233    0.11752   0.530   0.5959
z.F0range_Max_minus_Min -0.24943    0.12159  -2.051   0.0402 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 410.22  on 295  degrees of freedom
Residual deviance: 405.87  on 294  degrees of freedom
(12 observations deleted due to missingness)
AIC: 409.87

Number of Fisher Scoring iterations: 4

>
>
>
> ## classification table
>
> post.16.pred <- predict(post.16, type="response")
> S3 <- ifelse(post.16.pred > .5, 3, 1)
> f.s1vs3.1 <- f.s1vs3 %>% drop_na(z.F0range_Max_minus_Min)
> table(f.s1vs3.1$syll.fac,S3)
      S3
      1  3
1    65 80
3    47 104
>
> ## chisq test
>
> post.16.chi <- (post.16$null.deviance - post.16$deviance)
> post.16.df <- (post.16$df.null - post.16$df.residual)
> post.16.chisq <- 1-pchisq(post.16.chi, post.16.df)
> post.16.chi
[1] 4.348235
> post.16.chisq
[1] 0.03704732
>
>

```



```

> ##### Odds ratio #####
> exp(post.16$coefficients)
              (Intercept) z.F0range_Max_minus_Min
              1.0643136              0.7792453
> ##### CI #####
> exp(confint(post.16))
Waiting for profiling to be done...
              2.5 %    97.5 %
(Intercept)      0.8454814 1.340931
z.F0range_Max_minus_Min 0.6105341 0.985280
>
>
> ##### Post Focal #####
>
> ##### Syllable 1 vs 2 #####
>
> ##### Post 17 #####
> post.17 <- glm(syll.fac ~ z.log.F0_Q2Q3, data=postf.slvs2,
family="binomial")
> summary(post.17)

Call:
glm(formula = syll.fac ~ z.log.F0_Q2Q3, family = "binomial",
    data = postf.slvs2)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.3955  -1.0080  -0.3358   1.0880   2.0826

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)    0.5964     0.1694   3.52 0.000432 ***
z.log.F0_Q2Q3  1.5217     0.2619   5.81 6.23e-09 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 395.06  on 284  degrees of freedom
Residual deviance: 350.44  on 283  degrees of freedom
(27 observations deleted due to missingness)
AIC: 354.44

Number of Fisher Scoring iterations: 3

>
>
>
> ## classification table
>
> post.17.pred <- predict(post.17, type="response")
> S1 <- ifelse(post.17.pred > .5, 1, 2)
> postf.slvs2.1 <- postf.slvs2 %>% drop_na(z.log.F0_Q2Q3)
> table(postf.slvs2.1$syll.fac,S1)
  S1
    1    2
1  36 108

```

```

      2  93  48
      3   0   0
>
> ## chisq
>
> post.17.chi <- (post.17$null.deviance - post.17$deviance)
> post.17.df <- (post.17$df.null - post.17$df.residual)
> post.17.chisq <- 1-pchisq(post.17.chi, post.17.df)
>
> post.17.chi
[1] 44.62341
> post.17.chisq
[1] 2.38819e-11
>
> ##### Odds ratio #####
> exp(post.17$coefficients)
      (Intercept)      z.log.F0_Q2Q3
      1.815630      4.579828
> ##### CI #####
> exp(confint(post.17))
Waiting for profiling to be done...
              2.5 %      97.5 %
(Intercept)   1.315390  2.560706
z.log.F0_Q2Q3  2.806566  7.856629
>
> ##### Post 18 #####
>
> post.18 <- glm(syll.fac ~ z.F0change_Q4_minusQ1, data=postf.slvs2,
family="binomial")
> summary(post.18)

Call:
glm(formula = syll.fac ~ z.F0change_Q4_minusQ1, family = "binomial",
    data = postf.slvs2)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.80832  -0.58681  -0.02637   0.51630   2.75161

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)    1.1116     0.2354   4.723 2.33e-06 ***
z.F0change_Q4_minusQ1  2.6510     0.3238   8.187 2.69e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 360.42  on 259  degrees of freedom
Residual deviance: 186.30  on 258  degrees of freedom
(52 observations deleted due to missingness)
AIC: 190.3

Number of Fisher Scoring iterations: 6

>
>

```

```

> ## classification table
>
> post.18.pred <- predict(post.18, type="response")
> S1 <- ifelse(post.18.pred > .5, 1, 2)
> postf.slvs2.1 <- postf.slvs2 %>% drop_na(z.F0change_Q4_minusQ1)
> table(postf.slvs2.1$syll.fac,S1)
      S1
      1  2
1    16 115
2   106  23
3     0   0
>
> ## chisq
> post.18.chi <- (post.18$null.deviance - post.18$deviance)
> post.18.df <- (post.18$df.null - post.18$df.residual)
> post.18.chisq <- 1-pchisq(post.18.chi, post.18.df)
> post.18.chi
[1] 174.1168
> post.18.chisq
[1] 0
>
> ##### Odds ratio #####
> exp(post.18$coefficients)
      (Intercept)  z.F0change_Q4_minusQ1
      3.039239      14.168580
> ##### CI #####
> exp(confint(post.18))
Waiting for profiling to be done...
      (Intercept)      2.5 %      97.5 %
      1.963871      4.965645
z.F0change_Q4_minusQ1 7.896054 28.256394
>
>
> ##### Post 19 #####
>
> post.19 <- glm(syll.fac ~ z.Duration, data=postf.slvs2, family="binomial")
> summary(post.19)

Call:
glm(formula = syll.fac ~ z.Duration, family = "binomial", data = postf.slvs2)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.3513  -0.9319  -0.2470   0.9006   2.4589

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) -0.003544   0.129187  -0.027   0.978
z.Duration  -1.402472   0.188311  -7.448 9.5e-14 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 432.47  on 311  degrees of freedom
Residual deviance: 352.45  on 310  degrees of freedom
AIC: 356.45

```

Number of Fisher Scoring iterations: 4

```

>
>
> ## classification table
>
> post.19.pred <- predict(post.19, type="response")
> S1 <- ifelse(post.19.pred > .5, 1, 2)
> postf.s1vs2.1 <- postf.s1vs2 %>% drop_na(z.Duration)
> table(postf.s1vs2.1$syll.fac, S1)
  S1
    1  2
1  39 119
2 114  40
3   0   0
>
> ## chisq
> post.19.chi <- (post.19$null.deviance - post.19$deviance)
> post.19.df <- (post.19$df.null - post.19$df.residual)
> post.19.chisq <- 1-pchisq(post.19.chi, post.19.df)
> post.19.chi
[1] 80.02356
> post.19.chisq
[1] 0
>
> ##### Odds ratio #####
> exp(post.19$coefficients)
(Intercept)  z.Duration
  0.9964626   0.2459881
> ##### CI #####
> exp(confint(post.19))
Waiting for profiling to be done...
              2.5 %      97.5 %
(Intercept) 0.7731020 1.2841096
z.Duration  0.1669689 0.3498927
>
> ##### Syllable 2 vs 3 #####
> ##### Post 20 #####
>
> post.20 <- glm(syll.fac ~ z.log.F0_Q2Q3, data=postf.s2vs3,
family="binomial")
> summary(post.20)

```

Call:

```

glm(formula = syll.fac ~ z.log.F0_Q2Q3, family = "binomial",
    data = postf.s2vs3)

```

Deviance Residuals:

Min	1Q	Median	3Q	Max
-2.5827	-0.6184	0.1135	0.6242	2.5386

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-0.9318	0.1902	-4.899	9.65e-07 ***
z.log.F0_Q2Q3	2.3578	0.2599	9.070	< 2e-16 ***

```

Signif. codes:  0  ***  0.001  **  0.01  *  0.05  .  0.1  1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 397.78  on 286  degrees of freedom
Residual deviance: 242.44  on 285  degrees of freedom
(22 observations deleted due to missingness)
AIC: 246.44

Number of Fisher Scoring iterations: 5

>
>
>
> ## classification table
>
> post.20.pred <- predict(post.20, type="response")
> S1 <- ifelse(post.20.pred > .5, 3, 2)
> postf.s2vs3.1 <- postf.s2vs3 %>% drop_na(z.log.F0_Q2Q3)
> table(postf.s2vs3.1$syll.fac, S1)
  S1
    2   3
1   0   0
2 117  24
3   24 122
>
> ## chisq
> post.20.chi <- (post.20$null.deviance - post.20$deviance)
> post.20.df <- (post.20$df.null - post.20$df.residual)
> post.20.chisq <- 1-pchisq(post.20.chi, post.20.df)
>
> post.20.chi
[1] 155.3396
> post.20.chisq
[1] 0
>
> ##### Odds ratio #####
> exp(post.20$coefficients)
(Intercept) z.log.F0_Q2Q3
  0.3938376   10.5675245
> ##### CI #####
> exp(confint(post.20))
Waiting for profiling to be done...
              2.5 %    97.5 %
(Intercept)  0.2667039  0.5637002
z.log.F0_Q2Q3 6.5409045 18.1831229
>
>
> ## Post 21
>
> post.21 <- glm(syll.fac ~ z.F0change_Q4_minusQ1, data=postf.s2vs3,
family="binomial")
> summary(post.21)

Call:
glm(formula = syll.fac ~ z.F0change_Q4_minusQ1, family = "binomial",
    data = postf.s2vs3)

```

```

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.225  -1.222   1.133   1.134   1.137

Coefficients:
                Estimate Std. Error z value Pr(>|z|)
(Intercept)      0.104255   0.135464    0.77   0.442
z.F0change_Q4_minusQ1 -0.003208   0.157529   -0.02   0.984

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 376.35  on 271  degrees of freedom
Residual deviance: 376.35  on 270  degrees of freedom
(37 observations deleted due to missingness)
AIC: 380.35

Number of Fisher Scoring iterations: 3

>
>
>
> ## classification table
>
> post.21.pred <- predict(post.21, type="response")
> S3 <- ifelse(post.21.pred > .5, 3, 2)
> postf.s2vs3.1 <- postf.s2vs3 %>% drop_na(z.F0change_Q4_minusQ1)
> table(postf.s2vs3.1$syll.fac,S3)
  S3
    3
  1  0
  2 129
  3 143
>
> ## chisq
>
> post.21.chi <- (post.21$null.deviance - post.21$deviance)
> post.21.df <- (post.21$df.null - post.21$df.residual)
> post.21.chisq <- 1-pchisq(post.21.chi, post.21.df)
>
> ##### Odds ratio #####
> exp(post.21$coefficients)
      (Intercept) z.F0change_Q4_minusQ1
      1.1098835      0.9967967
> ##### CI #####
> exp(confint(post.21))
Waiting for profiling to be done...
                2.5 %    97.5 %
(Intercept)      0.8512031 1.449196
z.F0change_Q4_minusQ1 0.7308523 1.359401
> post.21.chi
[1] 0.0004148248
> post.21.chisq
[1] 0.9837504
>
>
> ##### Syllable 1 vs 3 #####

```

```

>
> ##### Post 22 #####
>
> post.22 <- glm(syll.fac ~ z.log.F0_Q2Q3, data=postf.sivs3,
family="binomial")
> summary(post.22)

Call:
glm(formula = syll.fac ~ z.log.F0_Q2Q3, family = "binomial",
    data = postf.sivs3)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.97045  -0.38501   0.01473   0.29947   2.62743

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)   -0.3229     0.2105  -1.534    0.125
z.log.F0_Q2Q3  3.2454     0.3527   9.201 <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 402.01  on 289  degrees of freedom
Residual deviance: 153.78  on 288  degrees of freedom
(23 observations deleted due to missingness)
AIC: 157.78

Number of Fisher Scoring iterations: 6

>
>
> ## classification table
>
> post.22.pred <- predict(post.22, type="response")
> S3 <- ifelse(post.22.pred > .5, 3, 1)
> postf.sivs3.1 <- postf.sivs3 %>% drop_na(z.log.F0_Q2Q3)
> table(postf.sivs3.1$syll.fac, S3)
      S3
      1  3
1 133 11
2   0  0
3  18 128
>
> ## chisq
>
> post.22.chi <- (post.22$null.deviance - post.22$deviance)
> post.22.df <- (post.22$df.null - post.22$df.residual)
> post.22.chisq <- 1-pchisq(post.22.chi, post.22.df)
> post.22.chi
[1] 248.2332
> post.22.chisq
[1] 0
>
> ##### Odds ratio #####
> exp(post.22$coefficients)

```

```

      (Intercept)  z.log.F0_Q2Q3
              0.7240255      25.6714803
> ##### CI #####
> exp(confint(post.22))
Waiting for profiling to be done...
              2.5 %      97.5 %
(Intercept)      0.4759744  1.093249
z.log.F0_Q2Q3 13.6250132 54.811120
>
>
> ##### Post 23 #####
> post.23 <- glm(syll.fac ~ z.F0change_Q4_minusQ1, data=postf.slvs3,
family="binomial")
> summary(post.23)

Call:
glm(formula = syll.fac ~ z.F0change_Q4_minusQ1, family = "binomial",
    data = postf.slvs3)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-3.0621  -0.4458   0.0605   0.4755   4.1507

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)      1.2774     0.2417   5.286 1.25e-07 ***
z.F0change_Q4_minusQ1  3.2067     0.3867   8.293 < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 379.32  on 273  degrees of freedom
Residual deviance: 173.70  on 272  degrees of freedom
(39 observations deleted due to missingness)
AIC: 177.7

Number of Fisher Scoring iterations: 6

>
>
>
> ## classification table
> post.23.pred <- predict(post.23, type="response")
> S3 <- ifelse(post.23.pred > .5, 3, 1)
> postf.slvs3.1 <- postf.slvs3 %>% drop_na(z.F0change_Q4_minusQ1)
> table(postf.slvs3.1$syll.fac, S3)
      S3
      1   3
1 115  16
2   0   0
3  14 129
>
> ## chisq
>
> post.23.chi <- (post.23$null.deviance - post.23$deviance)
> post.23.df <- (post.23$df.null - post.23$df.residual)

```



```

> post.23.chisq <- 1-pchisq(post.23.chi, post.23.df)
> post.23.chi
[1] 205.6188
> post.23.chisq
[1] 0
>
>
> ##### Odds ratio #####
> exp(post.23$coefficients)
      (Intercept)  z.F0change_Q4_minusQ1
      3.587259      24.698062
> ##### CI #####
> exp(confint(post.23))
Waiting for profiling to be done...
      2.5 %    97.5 %
(Intercept)      2.293807  5.94572
z.F0change_Q4_minusQ1 12.333998 56.55250
>
>
> ##### Post 24 #####
>
> post.24 <- glm(syll.fac ~ z.Duration, data=postf.slvs3, family="binomial")
> summary(post.24)

Call:
glm(formula = syll.fac ~ z.Duration, family = "binomial", data = postfix.slvs3)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.4091  -0.8611  -0.1695   0.8484   3.0073

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  -0.1325     0.1354  -0.979   0.328
z.Duration    -1.5452     0.1919  -8.052 8.15e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 433.88  on 312  degrees of freedom
Residual deviance: 332.34  on 311  degrees of freedom
AIC: 336.34

Number of Fisher Scoring iterations: 4

>
>
>
> ## classification table
>
> post.24.pred <- predict(post.24, type="response")
> S3 <- ifelse(post.24.pred > .5, 3, 1)
> postfix.slvs3.1 <- postfix.slvs3 %>% drop_na(z.Duration)
> table(postfix.slvs3.1$syll.fac,S3)
  S3
  1   3

```

```

1 122 36
2 0 0
3 36 119
>
> ## chisq
> post.24.chi <- (post.24$null.deviance - post.24$deviance)
> post.24.df <- (post.24$df.null - post.24$df.residual)
> post.24.chisq <- 1-pchisq(post.24.chi, post.24.df)
>
> post.24.chi
[1] 101.5407
> post.24.chisq
[1] 0
>
> ##### Odds ratio #####
> exp(post.24$coefficients)
(Intercept)    z.Duration
  0.8759380    0.2132684
> ##### CI #####
> exp(confint(post.24))
Waiting for profiling to be done...
              2.5 %      97.5 %
(Intercept)  0.6700177  1.1404242
z.Duration   0.1434301  0.3049105
>
> ##### POST HOC TESTS FOR ACROSS FOCAL CONDITION
MODELS #####
>
> ##### Syllable 1 #####
>
> ##### Post 25 #####
> post.25 <- glm(foc.fac ~ z.F0change_Q4_minusQ1, data=s1.pfvf,
family="binomial")
> summary(post.25)

Call:
glm(formula = foc.fac ~ z.F0change_Q4_minusQ1, family = "binomial",
    data = s1.pfvf)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.4538  -1.1429  -0.9411   1.1867   1.4940

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)    0.2221    0.1764   1.259   0.2080
z.F0change_Q4_minusQ1 0.3653    0.1709   2.138   0.0325 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 365.85  on 263  degrees of freedom
Residual deviance: 361.13  on 262  degrees of freedom
(50 observations deleted due to missingness)
AIC: 365.13

```

```

Number of Fisher Scoring iterations: 4

>
>
> ## classification table
>
> post.25.pred <- predict(post.25, type="response")
> Focus <- ifelse(post.25.pred > .5, 1, 0)
> s1.pfvf.1 <- s1.pfvf %>% drop_na(z.F0change_Q4_minusQ1)
> table(s1.pfvf.1$foc.fac, Focus)
      Focus
      0    1
PreF   88  47
Focus  68  61
>
> ## chisq
>
> post.25.chi <- (post.25$null.deviance - post.25$deviance)
> post.25.df <- (post.25$df.null - post.25$df.residual)
> post.25.chisq <- 1-pchisq(post.25.chi, post.25.df)
> post.25.chi
[1] 4.716362
> post.25.chisq
[1] 0.02987689
>
> ##### Odds ratio #####
> exp(post.25$coefficients)
      (Intercept) z.F0change_Q4_minusQ1
      1.248641      1.440934
> ##### CI #####
> exp(confint(post.25))
Waiting for profiling to be done...
      2.5 %    97.5 %
(Intercept)    0.8865189 1.774137
z.F0change_Q4_minusQ1 1.0358989 2.029508
>
>
> ##### Post 26 #####
>
> post.26 <- glm(foc.fac ~ ED_Q2Q3, data=s1.pfvf, family="binomial")
> summary(post.26)

Call:
glm(formula = foc.fac ~ ED_Q2Q3, family = "binomial", data = s1.pfvf)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.202  -1.144  -1.019   1.175   1.350

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  -0.4383     0.2477  -1.770   0.0768 .
ED_Q2Q3       0.3694     0.1985   1.861   0.0627 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

```

```

Null deviance: 435.25 on 313 degrees of freedom
Residual deviance: 431.38 on 312 degrees of freedom
AIC: 435.38

```

```

Number of Fisher Scoring iterations: 4

```

```

>
>
> ## classification table
> post.26.pred <- predict(post.26, type="response")
> Focus <- ifelse(post.26.pred > .5, 1, 0)
> s1.pfvf.1 <- s1.pfvf %>% drop_na(ED_Q2Q3)
> table(s1.pfvf.1$foc.fac, Focus)
      Focus
      0    1
PreF   99  60
Focus  77  78
>
> ## chisq
>
> post.26.chi <- (post.26$null.deviance - post.26$deviance)
> post.26.df <- (post.26$df.null - post.26$df.residual)
> post.26.chisq <- 1-pchisq(post.26.chi, post.26.df)
> post.26.chi
[1] 3.864034
> post.26.chisq
[1] 0.0493316
>
> ##### Odds ratio #####
> exp(post.26$coefficients)
(Intercept)      ED_Q2Q3
  0.6451606    1.4468102
> ##### CI #####
> exp(confint(post.26))
Waiting for profiling to be done...
              2.5 %    97.5 %
(Intercept) 0.3913369 1.031446
ED_Q2Q3      1.0010414 2.170864
>
>
>
>
> ##### Post 27 #####
>
> post.27 <- glm(foc.fac ~ z.Duration, data=s1.pfvf, family="binomial")
> summary(post.27)

Call:
glm(formula = foc.fac ~ z.Duration, family = "binomial", data = s1.pfvf)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.7370  -1.1311  -0.7134   1.1347   1.8425

Coefficients:
            Estimate Std. Error z value Pr(>|z|)

```

```

(Intercept)  -0.4542      0.1570  -2.893  0.00382 **
z.Duration    0.5615      0.1371   4.096 4.19e-05 ***
---
Signif. codes:  0  ***  0.001  **  0.01  *  0.05  .  0.1  1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 435.25  on 313  degrees of freedom
Residual deviance: 416.96  on 312  degrees of freedom
AIC: 420.96

Number of Fisher Scoring iterations: 4

>
>
> ## classification table
> post.27.pred <- predict(post.27, type="response")
> Focus <- ifelse(post.27.pred > .5, 1, 0)
> s1.pfvf.1 <- s1.pfvf %>% drop_na(z.Duration)
> table(s1.pfvf.1$foc.fac, Focus)
      Focus
      0    1
PreF   97  62
Focus  62  93
>
> ## chisq
>
> post.27.chi <- (post.27$null.deviance - post.27$deviance)
> post.27.df <- (post.27$df.null - post.27$df.residual)
> post.27.chisq <- 1-pchisq(post.27.chi, post.27.df)
> post.27.chi
[1] 18.2856
> post.27.chisq
[1] 1.901392e-05
>
> ##### Odds ratio #####
> exp(post.27$coefficients)
(Intercept)  z.Duration
  0.6349746   1.7532720
> ##### CI #####
> exp(confint(post.27))
Waiting for profiling to be done...
              2.5 %    97.5 %
(Intercept)  0.4637431 0.8594458
z.Duration   1.3484255 2.3109703
>
> ##### PreF vs PostF #####
>
> post.28 <- glm(foc.fac ~ z.log.F0_Q2Q3, data=s1.pfvpof, family="binomial")
> summary(post.28)

Call:
glm(formula = foc.fac ~ z.log.F0_Q2Q3, family = "binomial", data = s1.pfvpof)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.8365  -1.1209  -0.7367   1.1569   1.7823

```

```

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)    0.6140     0.2181   2.816 0.004865 **
z.log.F0_Q2Q3  0.8537     0.2461   3.469 0.000522 ***
---
Signif. codes:  0 *** 0.001 ** 0.01 * 0.05 . 0.1 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 402.01 on 289 degrees of freedom
Residual deviance: 388.74 on 288 degrees of freedom
(27 observations deleted due to missingness)
AIC: 392.74

Number of Fisher Scoring iterations: 4

>
>
>
> ## classification table
>
> post.28.pred <- predict(post.28, type="response")
> PostF <- ifelse(post.28.pred > .5, 1, 0)
> s1.pfvpof.1 <- s1.pfvpof %>% drop_na(z.log.F0_Q2Q3)
> table(s1.pfvpof.1$foc.fac, PostF)
      PostF
      0    1
PreF  93  53
PostF  66  78
>
> ## chisq
>
> post.28.chi <- (post.28$null.deviance - post.28$deviance)
> post.28.df <- (post.28$df.null - post.28$df.residual)
> post.28.chisq <- 1-pchisq(post.28.chi, post.28.df)
> post.28.chi
[1] 13.27276
> post.28.chisq
[1] 0.0002692903
>
> ##### Odds ratio #####
> exp(post.28$coefficients)
(Intercept) z.log.F0_Q2Q3
      1.847890      2.348386
> ##### CI #####
> exp(confint(post.28))
Waiting for profiling to be done...
              2.5 %    97.5 %
(Intercept)  1.217508 2.870091
z.log.F0_Q2Q3 1.470415 3.871337
>
> ##### Post 29 #####
>
> post.29 <- glm(foc.fac ~ z.Intensity_Q2Q3, data=s1.pfvpof,
family="binomial")
> summary(post.29)

```

```
Call:
glm(formula = foc.fac ~ z.Intensity_Q2Q3, family = "binomial",
    data = s1.pfvpof)
```

```
Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.3737  -1.1652  -0.9917   1.1700   1.4331
```

```
Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)    0.01592    0.11375   0.140   0.889
z.Intensity_Q2Q3 0.16774    0.11660   1.439   0.150
```

```
(Dispersion parameter for binomial family taken to be 1)
```

```
Null deviance: 439.45 on 316 degrees of freedom
Residual deviance: 437.36 on 315 degrees of freedom
AIC: 441.36
```

```
Number of Fisher Scoring iterations: 3
```

```
>
>
>
> ## classification table
>
> post.29.pred <- predict(post.29, type="response")
> PostF <- ifelse(post.29.pred > .5, 1, 0)
> s1.pfvpof.1 <- s1.pfvpof %>% drop_na(z.Intensity_Q2Q3)
> table(s1.pfvpof.1$foc.fac, PostF)
      PostF
      0    1
PreF   90  69
PostF  71  87
>
> ## chisq
> post.29.chi <- (post.29$null.deviance - post.29$deviance)
> post.29.df <- (post.29$df.null - post.29$df.residual)
> post.29.chisq <- 1-pchisq(post.29.chi, post.29.df)
> post.29.chi
[1] 2.090776
> post.29.chisq
[1] 0.1481908
>
> ##### Odds ratio #####
> exp(post.29$coefficients)
      (Intercept) z.Intensity_Q2Q3
      1.016046    1.182631
> ##### CI #####
> exp(confint(post.29))
Waiting for profiling to be done...
      2.5 %    97.5 %
(Intercept)  0.8129939 1.270428
z.Intensity_Q2Q3 0.9423273 1.490409
>
> ##### PostF vs Focus #####
```

```

>
> ##### Post 30 #####
> post.30 <- glm(foc.fac ~ z.log.F0_Q2Q3, data=s1.pofvf, family="binomial")
> summary(post.30)

Call:
glm(formula = foc.fac ~ z.log.F0_Q2Q3, family = "binomial", data = s1.pofvf)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.9659  -1.1270   0.5017   1.0868   1.8497

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  -0.8819     0.2342  -3.766 0.000166 ***
z.log.F0_Q2Q3 -1.1495     0.2580  -4.455 8.4e-06 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 400.64  on 288  degrees of freedom
Residual deviance: 377.08  on 287  degrees of freedom
(24 observations deleted due to missingness)
AIC: 381.08

Number of Fisher Scoring iterations: 4

>
>
> ## classification table
>
> post.30.pred <- predict(post.30, type="response")
> Focus <- ifelse(post.30.pred > .5, 1, 0)
> s1.pofvf.1 <- s1.pofvf %>% drop_na(z.log.F0_Q2Q3)
> table(s1.pofvf.1$foc.fac, Focus)
      Focus
      0    1
PostF 85 59
Focus 50 95

>
> ## chisq
> post.30.chi <- (post.30$null.deviance - post.30$deviance)
> post.30.df <- (post.30$df.null - post.30$df.residual)
> post.30.chisq <- 1-pchisq(post.30.chi, post.30.df)
> post.30.chi
[1] 23.55949
> post.30.chisq
[1] 1.211108e-06
>
> ##### Odds ratio #####
> exp(post.30$coefficients)
      (Intercept) z.log.F0_Q2Q3
      0.414006    0.316788
> ##### CI #####
> exp(confint(post.30))
Waiting for profiling to be done...

```



```

                2.5 %      97.5 %
(Intercept)    0.2573549 0.6461420
z.log.F0_Q2Q3  0.1867451 0.5150669
>
> ##### Post 31 #####
> post.31 <- glm(foc.fac ~ z.F0change_Q4_minusQ1, data=s1.pofvf,
family="binomial")
> summary(post.31)

Call:
glm(formula = foc.fac ~ z.F0change_Q4_minusQ1, family = "binomial",
    data = s1.pofvf)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.9458  -1.1187  -0.4436   1.0975   1.8410

Coefficients:
                Estimate Std. Error z value Pr(>|z|)
(Intercept)      0.7903      0.2101   3.762 0.000168 ***
z.F0change_Q4_minusQ1  0.8857      0.1801   4.916 8.82e-07 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 360.42  on 259  degrees of freedom
Residual deviance: 330.86  on 258  degrees of freedom
(53 observations deleted due to missingness)
AIC: 334.86

Number of Fisher Scoring iterations: 4

>
>
>
> ## classification table
>
> post.31.pred <- predict(post.31, type="response")
> Focus <- ifelse(post.31.pred > .5, 1, 0)
> s1.pofvf.1 <- s1.pofvf %>% drop_na(z.F0change_Q4_minusQ1)
> table(s1.pofvf.1$foc.fac, Focus)
      Focus
      0    1
PostF 85 46
Focus 47 82
>
> ## chisq
> post.31.chi <- (post.31$null.deviance - post.31$deviance)
> post.31.df <- (post.31$df.null - post.31$df.residual)
> post.31.chisq <- 1-pchisq(post.31.chi, post.31.df)
> post.31.chi
[1] 29.56407
> post.31.chisq
[1] 5.409857e-08
>
> exp(post.31$coefficients)

```

```

      (Intercept)  z.F0change_Q4_minusQ1
      2.204111      2.424597
> ##### CI #####
> exp(confint(post.31))
Waiting for profiling to be done...
      2.5 %    97.5 %
(Intercept)      1.478342 3.376503
z.F0change_Q4_minusQ1 1.728554 3.511014
>
>
> ##### Post 32 #####
> post.32 <- glm(foc.fac ~ z.Duration, data=s1.pofvf, family="binomial")
>
> summary(post.31)

Call:
glm(formula = foc.fac ~ z.F0change_Q4_minusQ1, family = "binomial",
    data = s1.pofvf)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.9458  -1.1187  -0.4436   1.0975   1.8410

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)      0.7903     0.2101   3.762 0.000168 ***
z.F0change_Q4_minusQ1 0.8857     0.1801   4.916 8.82e-07 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 360.42  on 259  degrees of freedom
Residual deviance: 330.86  on 258  degrees of freedom
(53 observations deleted due to missingness)
AIC: 334.86

Number of Fisher Scoring iterations: 4

>
>
> ## classification table
>
> post.32.pred <- predict(post.32, type="response")
> Focus <- ifelse(post.32.pred > .5, 1, 0)
> s1.pofvf.1 <- s1.pofvf %>% drop_na(z.Duration)
> table(s1.pofvf.1$foc.fac, Focus)
      Focus
      0    1
PostF 108  50
Focus  58  97
> ## chisq
> post.32.chi <- (post.32$null.deviance - post.32$deviance)
> post.32.df <- (post.32$df.null - post.32$df.residual)
> post.32.chisq <- 1-pchisq(post.32.chi, post.32.df)
> post.32.chi
[1] 27.60724

```

```

> post.32.chisq
[1] 1.486213e-07
>
> ##### Odds ratio #####
> exp(post.32$coefficients)
(Intercept)    z.Duration
    0.5877007    2.0423440
> ##### CI #####
> exp(confint(post.32))
Waiting for profiling to be done...
              2.5 %    97.5 %
(Intercept)  0.4282008  0.796138
z.Duration   1.5492552  2.740273
>
>
> ##### Post 33 #####
> post.33 <- glm(foc.fac ~ z.Intensity_Q2Q3, data=s1.pofvf,
family="binomial")
>
> summary(post.31)

Call:
glm(formula = foc.fac ~ z.F0change_Q4_minusQ1, family = "binomial",
    data = s1.pofvf)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.9458  -1.1187  -0.4436   1.0975   1.8410

Coefficients:
                Estimate Std. Error z value Pr(>|z|)
(Intercept)         0.7903     0.2101   3.762 0.000168 ***
z.F0change_Q4_minusQ1 0.8857     0.1801   4.916 8.82e-07 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 360.42  on 259  degrees of freedom
Residual deviance: 330.86  on 258  degrees of freedom
(53 observations deleted due to missingness)
AIC: 334.86

Number of Fisher Scoring iterations: 4

>
>
> ## classification table
>
> post.33.pred <- predict(post.33, type="response")
> Focus <- ifelse(post.33.pred > .5, 1, 0)
> s1.pofvf.1 <- s1.pofvf %>% drop_na(z.Intensity_Q2Q3)
> table(s1.pofvf.1$foc.fac, Focus)
      Focus
      0    1
PostF 99 59
Focus 79 76

```

```

> ## chisq
> post.33.chi <- (post.33$null.deviance - post.33$deviance)
> post.33.df <- (post.33$df.null - post.33$df.residual)
> post.33.chisq <- 1-pchisq(post.33.chi, post.33.df)
> post.33.chi
[1] 1.062821
> post.33.chisq
[1] 0.3025726
>
> ##### Odds ratio #####
> exp(post.33$coefficients)
      (Intercept)  z.Intensity_Q2Q3
      0.9682930    0.8901952
> ##### CI #####
> exp(confint(post.33))
Waiting for profiling to be done...
              2.5 %   97.5 %
(Intercept)    0.7740925 1.210627
z.Intensity_Q2Q3 0.7115457 1.110286
>
>
> ##### Syllable 2 #####
> ##### PreF vs Focus #####
> ##### Post 34 #####
> post.34 <- glm(foc.fac ~ z.Duration, data=s2.pfvf, family="binomial")
> summary(post.34)

Call:
glm(formula = foc.fac ~ z.Duration, family = "binomial", data = s2.pfvf)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.7948  -1.0972  -0.5513   1.1324   1.7177

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)    0.2271     0.1334   1.702   0.0887 .
z.Duration     0.6762     0.1593   4.246 2.18e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 406.18  on 292  degrees of freedom
Residual deviance: 385.91  on 291  degrees of freedom
AIC: 389.91

Number of Fisher Scoring iterations: 4

>
>
>
> ## classification table
> post.34.pred <- predict(post.34, type="response")
> Focus <- ifelse(post.34.pred > .5, 1, 0)
> s2.pfvf.1 <- s2.pfvf %>% drop_na(z.Duration)
> table(s2.pfvf.1$foc.fac, Focus)

```

```

      Focus
      0  1
PreF   99 48
Focus  67 79
>
> ## chisq
> post.34.chi <- (post.34$null.deviance - post.34$deviance)
> post.34.df <- (post.34$df.null - post.34$df.residual)
> post.34.chisq <- 1-pchisq(post.34.chi, post.34.df)
> post.34.chi
[1] 20.27517
> post.34.chisq
[1] 6.706518e-06
>
> ##### Odds ratio #####
> exp(post.34$coefficients)
(Intercept)   z.Duration
    1.254950    1.966461
> ##### CI #####
> exp(confint(post.34))
Waiting for profiling to be done...
      2.5 %   97.5 %
(Intercept) 0.9690016 1.636385
z.Duration   1.4523072 2.716376
>
> ##### Post 35 #####
> post.35 <- glm(foc.fac ~ z.Intensity_Q2Q3, data=s2.pfvf, family="binomial")
> summary(post.35)

Call:
glm(formula = foc.fac ~ z.Intensity_Q2Q3, family = "binomial",
    data = s2.pfvf)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.7245  -1.1099  -0.6576   1.1348   1.9030

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)    0.08511    0.12257   0.694   0.487
z.Intensity_Q2Q3 0.54311    0.13576   4.000 6.32e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 406.18  on 292  degrees of freedom
Residual deviance: 388.62  on 291  degrees of freedom
AIC: 392.62

Number of Fisher Scoring iterations: 4

>
>
>
> ## classification table
>

```

```

> post.35.pred <- predict(post.35, type="response")
> Focus <- ifelse(post.35.pred > .5, 1, 0)
> s2.pfvf.1 <- s2.pfvf %>% drop_na(z.Intensity_Q2Q3)
> table(s2.pfvf.1$foc.fac, Focus)
      Focus
      0    1
PreF   92  55
Focus  62  84
>
> ## chisq
> post.35.chi <- (post.35$null.deviance - post.35$deviance)
> post.35.df <- (post.35$df.null - post.35$df.residual)
> post.35.chisq <- 1-pchisq(post.35.chi, post.35.df)
> post.35.chi
[1] 17.55966
> post.35.chisq
[1] 2.784327e-05
>
> ##### Odds ratio #####
> exp(post.35$coefficients)
      (Intercept)      z.Intensity_Q2Q3
      1.088832      1.721357
> ##### CI #####
> exp(confint(post.35))
Waiting for profiling to be done...
      2.5 %    97.5 %
(Intercept)    0.8570234 1.386637
z.Intensity_Q2Q3 1.3279568 2.264600
>
>
> ##### PreF vs PostF #####
>
> ##### Post 36 #####
> post.36 <- glm(foc.fac ~ z.log.F0_Q2Q3, data=s2.pfvpopf, family="binomial")
> summary(post.36)

Call:
glm(formula = foc.fac ~ z.log.F0_Q2Q3, family = "binomial", data = s2.pfvpopf)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.8667  -1.1660   0.8184   1.1455   1.5422

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)   0.2394    0.1375   1.741  0.08167 .
z.log.F0_Q2Q3  0.6133    0.2180   2.813  0.00491 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 376.70  on 271  degrees of freedom
Residual deviance: 368.24  on 270  degrees of freedom
(29 observations deleted due to missingness)
AIC: 372.24

```

```

Number of Fisher Scoring iterations: 4

>
>
>
> ## classification table
> post.36.pred <- predict(post.36, type="response")
> PostF <- ifelse(post.36.pred > .5, 1, 0)
> s2.pfvf.1 <- s2.pfvf %>% drop_na(z.log.F0_Q2Q3)
> table(s2.pfvf.1$foc.fac, PostF)
      PostF
      0    1
PreF   66  65
PostF  48  93
>
> ## chisq
> post.36.chi <- (post.36$null.deviance - post.36$deviance)
> post.36.df <- (post.36$df.null - post.36$df.residual)
> post.36.chisq <- 1-pchisq(post.36.chi, post.36.df)
> post.36.chi
[1] 8.459777
> post.36.chisq
[1] 0.003630864
>
> ##### Odds ratio #####
> exp(post.36$coefficients)
      (Intercept) z.log.F0_Q2Q3
      1.270467      1.846494
> ##### CI #####
> exp(confint(post.36))
Waiting for profiling to be done...
              2.5 %    97.5 %
(Intercept)  0.9731337 1.670178
z.log.F0_Q2Q3 1.2169829 2.870489
>
> ##### PostF vs Focus #####
>
> ##### Post 37 #####
> post.37 <- glm(foc.fac ~ z.Duration, data=s2.pfvf, family="binomial")
> summary(post.37)

Call:
glm(formula = foc.fac ~ z.Duration, family = "binomial", data = s2.pfvf)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.6222  -1.1156  -0.8885   1.1836   1.5688

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  0.06268    0.12413   0.505   0.6136
z.Duration   0.44430    0.15599   2.848   0.0044 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

```

```

Null deviance: 415.67 on 299 degrees of freedom
Residual deviance: 407.11 on 298 degrees of freedom
AIC: 411.11

```

```

Number of Fisher Scoring iterations: 4

```

```

>
>
>
> ## classification table
>
> post.37.pred <- predict(post.37, type="response")
> Focus <- ifelse(post.37.pred > .5, 1, 0)
> s2.pofvf.1 <- s2.pofvf %>% drop_na(z.Duration)
> table(s2.pofvf.1$foc.fac, Focus)
      Focus
      0    1
PostF 102  52
Focus  79  67
>
> ## chisq
> post.37.chi <- (post.37$null.deviance - post.37$deviance)
> post.37.df <- (post.37$df.null - post.37$df.residual)
> post.37.chisq <- 1-pchisq(post.37.chi, post.37.df)
> post.37.chi
[1] 8.561737
> post.37.chisq
[1] 0.003433017
>
> ##### Odds ratio #####
> exp(post.37$coefficients)
(Intercept)   z.Duration
   1.064687    1.559401
> ##### CI #####
> exp(confint(post.37))
Waiting for profiling to be done...
              2.5 %    97.5 %
(Intercept) 0.8356086 1.360399
z.Duration   1.1555753 2.134246
>
>
> ##### Post 38 #####
>
> post.38 <- glm(foc.fac ~ z.Intensity_Q2Q3, data=s2.pofvf,
family="binomial")
> summary(post.38)

Call:
glm(formula = foc.fac ~ z.Intensity_Q2Q3, family = "binomial",
    data = s2.pofvf)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.5197  -1.1457  -0.8958   1.1794   1.6417

Coefficients:
              Estimate Std. Error z value Pr(>|z|)

```



```

(Intercept)      -0.02717      0.11722  -0.232    0.8167
z.Intensity_Q2Q3  0.32241      0.12706   2.537    0.0112 *
---
Signif. codes:  0  ***  0.001  **  0.01  *  0.05  .  0.1    1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 415.67  on 299  degrees of freedom
Residual deviance: 408.98  on 298  degrees of freedom
AIC: 412.98

Number of Fisher Scoring iterations: 4

>
>
>
> ## classification table
>
> post.38.pred <- predict(post.38, type="response")
> Focus <- ifelse(post.38.pred > .5, 1, 0)
> s2.pofvf.1 <- s2.pofvf %>% drop_na(z.Intensity_Q2Q3)
> table(s2.pofvf.1$foc.fac, Focus)
      Focus
      0    1
PostF 96 58
Focus 78 68
>
> ## chisq
> post.38.chi <- (post.38$null.deviance - post.38$deviance)
> post.38.df <- (post.38$df.null - post.38$df.residual)
> post.38.chisq <- 1-pchisq(post.38.chi, post.38.df)
> post.38.chi
[1] 6.696319
> post.38.chisq
[1] 0.009661214
>
> ##### Odds ratio #####
> exp(post.38$coefficients)
      (Intercept) z.Intensity_Q2Q3
      0.9731946    1.3804551
> ##### CI #####
> exp(confint(post.38))
Waiting for profiling to be done...
      2.5 %    97.5 %
(Intercept)  0.7732965 1.224998
z.Intensity_Q2Q3 1.0804019 1.780817
>
>
> ##### Syllable 3 #####
> ##### PreF vs Focus #####
> ##### Post 39 #####
> post.39 <- glm(foc.fac ~ z.Duration, data=s3.pfvf, family="binomial")
> summary(post.39)

Call:
glm(formula = foc.fac ~ z.Duration, family = "binomial", data = s3.pfvf)

```

```

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.1876  -1.0961  -0.6869   1.1495   1.6918

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)   0.1256     0.1233   1.018   0.309
z.Duration    0.6066     0.1370   4.427 9.55e-06 ***
---
Signif. codes:  0  ***  0.001  **  0.01  *  0.05  .  0.1  1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 426.97  on 307  degrees of freedom
Residual deviance: 404.41  on 306  degrees of freedom
AIC: 408.41

Number of Fisher Scoring iterations: 4

>
>
> ## classification table
> post.39.pred <- predict(post.39, type="response")
> Focus <- ifelse(post.39.pred > .5, 1, 0)
> s3.pfvf.1 <- s3.pfvf %>% drop_na(z.Duration)
> table(s3.pfvf.1$foc.fac, Focus)
      Focus
      0    1
PreF 101  54
Focus  67  86
>
> ## chisq
> post.39.chi <- (post.39$null.deviance - post.39$deviance)
> post.39.df <- (post.39$df.null - post.39$df.residual)
> post.39.chisq <- 1-pchisq(post.39.chi, post.39.df)
> post.39.chi
[1] 22.55112
> post.39.chisq
[1] 2.046248e-06
>
> ##### Odds ratio #####
> exp(post.39$coefficients)
(Intercept)  z.Duration
    1.133777    1.834132
> ##### CI #####
> exp(confint(post.39))
Waiting for profiling to be done...
              2.5 %    97.5 %
(Intercept) 0.8919253 1.447419
z.Duration   1.4146248 2.424104
>
>
> ##### PreF vs PostF #####
> ##### Post 40 #####
>
> post.40 <- glm(foc.fac ~ z.F0change_Q4_minusQ1, data=s3.pfvpof,
family="binomial")

```

```

> summary(post.40)

Call:
glm(formula = foc.fac ~ z.F0change_Q4_minusQ1, family = "binomial",
    data = s3.pfvf)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.6478  -1.1591  -0.9215   1.1634   1.4876

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)      0.1378     0.1414   0.974   0.3300
z.F0change_Q4_minusQ1 -0.3347     0.1625  -2.059   0.0395 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 400.61  on 288  degrees of freedom
Residual deviance: 396.20  on 287  degrees of freedom
(21 observations deleted due to missingness)
AIC: 400.2

Number of Fisher Scoring iterations: 4

>
>
>
> ## classification table
>
> post.40.pred <- predict(post.40, type="response")
> Focus <- ifelse(post.40.pred > .5, 1, 0)
> s3.pfvf.1 <- s3.pfvf %>% drop_na(z.F0change_Q4_minusQ1)
> table(s3.pfvf.1$foc.fac, Focus)
Error in table(s3.pfvf.1$foc.fac, Focus) :
  all arguments must have the same length
>
> ## chisq
> post.40.chi <- (post.40$null.deviance - post.40$deviance)
> post.40.df <- (post.40$df.null - post.40$df.residual)
> post.40.chisq <- 1-pchisq(post.40.chi, post.40.df)
> post.40.chisq
[1] 0.03585949
> post.40.chi
[1] 4.403774
>
> ##### Odds ratio #####
> exp(post.40$coefficients)
              (Intercept) z.F0change_Q4_minusQ1
              1.1477229      0.7155428
> ##### CI #####
> exp(confint(post.40))
Waiting for profiling to be done...
              2.5 %      97.5 %
(Intercept)      0.8714809 1.5191647
z.F0change_Q4_minusQ1 0.5160721 0.9784098

```

```

> ## classification table
>
> post.40.pred <- predict(post.40, type="response")
> Focus <- ifelse(post.40.pred > .5, 1, 0)
> s3.pfvf.1 <- s3.pfvf %>% drop_na(z.F0change_Q4_minusQ1)
> table(s3.pfvf.1$foc.fac, Focus)
      Focus
      0    1
PreF   80  66
PostF  66  77
>
> ##### PostF vs Focus #####
>
> ##### Post 41 #####
> post.41 <- glm(foc.fac ~ z.F0change_Q4_minusQ1, data=s3.pfvf,
family="binomial")
> summary(post.41)

Call:
glm(formula = foc.fac ~ z.F0change_Q4_minusQ1, family = "binomial",
    data = s3.pfvf)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.5885  -1.1561   0.7698   1.1498   1.4815

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)    -0.1876    0.1441  -1.302  0.19306
z.F0change_Q4_minusQ1  0.4434    0.1653   2.683  0.00729 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 403.33  on 290  degrees of freedom
Residual deviance: 395.59  on 289  degrees of freedom
(17 observations deleted due to missingness)
AIC: 399.59

Number of Fisher Scoring iterations: 4

>
>
> ## classification table
>
> post.41.pred <- predict(post.41, type="response")
> Focus <- ifelse(post.41.pred > .5, 1, 0)
> s3.pfvf.1 <- s3.pfvf %>% drop_na(z.F0change_Q4_minusQ1)
> table(s3.pfvf.1$foc.fac, Focus)
      Focus
      0    1
PostF  77  66
Focus  58  90
>
> ## chisq
>

```

```

> post.41.chi <- (post.41$null.deviance - post.41$deviance)
> post.41.df <- (post.41$df.null - post.41$df.residual)
> post.41.chisq <- 1-pchisq(post.41.chi, post.41.df)
> post.41.chisq
[1] 0.005400789
> post.41.chi
[1] 7.740097
>
> ##### Odds ratio #####
> exp(post.41$coefficients)
      (Intercept)  z.F0change_Q4_minusQ1
      0.8289811      1.5580243
> ##### CI #####
> exp(confint(post.41))
Waiting for profiling to be done...
              2.5 %    97.5 %
(Intercept)    0.6229078 1.097092
z.F0change_Q4_minusQ1 1.1368962 2.177549
>
>
> ##### Post 42 #####
>
> post.42 <- glm(foc.fac ~ ED_Q2Q3, data=s3.pofvf, family="binomial")
> summary(post.42)

Call:
glm(formula = foc.fac ~ ED_Q2Q3, family = "binomial", data = s3.pofvf)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.279  -1.178  -0.794   1.164   1.650

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)    0.2563     0.2018   1.270   0.204
ED_Q2Q3       -0.2230     0.1391  -1.603   0.109

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 426.97  on 307  degrees of freedom
Residual deviance: 424.25  on 306  degrees of freedom
AIC: 428.25

Number of Fisher Scoring iterations: 4

>
>
>
> ## classification table
>
> post.42.pred <- predict(post.42, type="response")
> Focus <- ifelse(post.42.pred > .5, 1, 0)
> s3.pofvf.1 <- s3.pofvf %>% drop_na(ED_Q2Q3)
> table(s3.pofvf.1$foc.fac, Focus)
      Focus
      0    1
PostF 76 79

```

```

Focus 60 93
>
> ## chisq
>
> post.42.chi <- (post.42$null.deviance - post.42$deviance)
> post.42.df <- (post.42$df.null - post.42$df.residual)
> post.42.chisq <- 1-pchisq(post.42.chi, post.42.df)
>
> post.42.chi
[1] 2.712682
> post.42.chisq
[1] 0.0995535
>
>
> ##### Odds ratio #####
> exp(post.42$coefficients)
(Intercept)      ED_Q2Q3
  1.2921478    0.8000938
> ##### CI #####
> exp(confint(post.42))
Waiting for profiling to be done...
              2.5 %   97.5 %
(Intercept) 0.8741836 1.934603
ED_Q2Q3      0.6007952 1.042400
>
>
> ##### Post 43 #####
>
> post.43 <- glm(foc.fac ~ z.Duration, data=s3.pofvf, family="binomial")
> summary(post.43)

Call:
glm(formula = foc.fac ~ z.Duration, family = "binomial", data = s3.pofvf)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.2457 -1.0597 -0.5614  1.1229  1.8265

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)   0.2068     0.1295   1.597    0.11
z.Duration    0.7873     0.1514   5.200 2e-07 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 426.97  on 307  degrees of freedom
Residual deviance: 393.72  on 306  degrees of freedom
AIC: 397.72

Number of Fisher Scoring iterations: 4

>
>
>
> ## classification table

```

```

>
> post.43.pred <- predict(post.43, type="response")
> Focus <- ifelse(post.43.pred > .5, 1, 0)
> s3.pofvf.1 <- s3.pofvf %>% drop_na(z.Duration)
> table(s3.pofvf.1$foc.fac, Focus)
      Focus
      0    1
PostF 109  46
Focus  62  91
>
> ## chisq
>
> post.43.chi <- (post.43$null.deviance - post.43$deviance)
> post.43.df <- (post.43$df.null - post.43$df.residual)
> post.43.chisq <- 1-pchisq(post.43.chi, post.43.df)
>
> post.43.chi
[1] 33.24639
> post.43.chisq
[1] 8.119048e-09
>
>
> ##### Odds ratio #####
> exp(post.43$coefficients)
(Intercept)   z.Duration
    1.229736    2.197484
> ##### CI #####
> exp(confint(post.43))
Waiting for profiling to be done...
              2.5 %    97.5 %
(Intercept) 0.9570938 1.591573
z.Duration   1.6526165 2.996508
>
>

```

Appendix E – *k^hnallo* word analysis codes

```

> ##### Testing predictors Individually
#####
>
> ## Focus ##
>
> ## Model 1 - F0
>
> model.1 <- glm(syll.fac ~ z.log.F0_Q2Q3, data=k.f, family="binomial")
> summary(model.1)

Call:
glm(formula = syll.fac ~ z.log.F0_Q2Q3, family = "binomial",
    data = k.f)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.1118  -0.6149  -0.4724   0.6463   4.9345

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)    0.1793     0.3536   0.507 0.612001
z.log.F0_Q2Q3  2.3994     0.6211   3.863 0.000112 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 77.347  on 55  degrees of freedom
Residual deviance: 52.894  on 54  degrees of freedom
(3 observations deleted due to missingness)
AIC: 56.894

Number of Fisher Scoring iterations: 5

>
> ## classification tables
>
> model.1.pred <- predict(model.1, type="response")
> S2 <- ifelse(model.1.pred > .5, 2, 1)
> k.f.1 <- k.f %>% drop_na(z.log.F0_Q2Q3)
> table(k.f.1$Syllable, S2)
  S2
    1  2
1 30  0
2  1 25

>
>
> ## chisq
>
> model.1.chi <- (model.1$null.deviance - model.1$deviance)
> model.1.df <- (model.1$df.null - model.1$df.residual)

```



```

> model.1.chisq <- 1-pchisq(model.1.chi, model.1.df)
> model.1.chi
[1] 24.45235
> model.1.chisq
[1] 7.617062e-07
> model.1.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.1$coefficients)
      (Intercept)  z.log.F0_Q2Q3
      1.196429      11.016876
> ##### CI #####
> exp(confint(model.1))
Waiting for profiling to be done...
              2.5 %      97.5 %
(Intercept)  0.6067206  2.487665
z.log.F0_Q2Q3 3.6889814 43.703812
>
>
> ## Model 2 - F0 range
>
> model.2 <- glm(syll.fac ~ z.F0range_Max_minus_Min, data=k.f,
family="binomial")
> summary(model.2)

Call:
glm(formula = syll.fac ~ z.F0range_Max_minus_Min, family = "binomial",
    data = k.f)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.5329  -0.5106  -0.2845   0.2971   2.6794

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)    -0.3005     0.4173  -0.720  0.471426
z.F0range_Max_minus_Min  3.0059     0.8038   3.739  0.000184 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 77.347  on 55  degrees of freedom
Residual deviance: 37.547  on 54  degrees of freedom
(3 observations deleted due to missingness)
AIC: 41.547

Number of Fisher Scoring iterations: 6

>
> ## classification tables
>
> model.2.pred <- predict(model.2, type="response")
> S2 <- ifelse(model.2.pred > .5, 2, 1)

```

```

> k.f.1 <- k.f %>% drop_na(z.F0range_Max_minus_Min)
> table(k.f.1$Syllable,S2)
      S2
      1  2
1 27  3
2  6 20
>
>
> ## chisq
>
> model.2.chi <- (model.2$null.deviance - model.2$deviance)
> model.2.df <- (model.2$df.null - model.2$df.residual)
> model.2.chisq <- 1-pchisq(model.2.chi, model.2.df)
> model.2.chi
[1] 39.7997
> model.2.chisq
[1] 2.813885e-10
> model.2.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.2$coefficients)
      (Intercept) z.F0range_Max_minus_Min
      0.7404234      20.2035623
> ##### CI #####
> exp(confint(model.2))
Waiting for profiling to be done...
      2.5 %      97.5 %
(Intercept)      0.3201872      1.71516
z.F0range_Max_minus_Min 5.4248575 139.21724
>
>
>
> ## Model 3 - F0 change
>
> model.3 <- glm(syll.fac ~ z.F0change_Q4_minusQ1, data=k.f,
family="binomial")
> summary(model.3)

Call:
glm(formula = syll.fac ~ z.F0change_Q4_minusQ1, family = "binomial",
    data = k.f)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.35955  -0.32631  -0.05347   0.05098   2.42860

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)   -0.007469   0.640314  -0.012   0.99069
z.F0change_Q4_minusQ1  5.449481   1.720419   3.168   0.00154 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

```

```

Null deviance: 76.082 on 54 degrees of freedom
Residual deviance: 20.518 on 53 degrees of freedom
(4 observations deleted due to missingness)
AIC: 24.518

```

```

Number of Fisher Scoring iterations: 8

```

```

>
> ## classification tables
>
> model.3.pred <- predict(model.3, type="response")
> S2 <- ifelse(model.3.pred > .5, 2, 1)
> k.f.1 <- k.f %>% drop_na(z.F0change_Q4_minusQ1)
> table(k.f.1$Syllable, S2)
  S2
    1  2
1 28  1
2  3 23
>
>
> ## chisq
>
> model.3.chi <- (model.3$null.deviance - model.3$deviance)
> model.3.df <- (model.3$df.null - model.3$df.residual)
> model.3.chisq <- 1-pchisq(model.3.chi, model.3.df)
> model.3.chi
[1] 55.5644
> model.3.chisq
[1] 9.048318e-14
> model.3.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.3$coefficients)
      (Intercept)  z.F0change_Q4_minusQ1
      0.9925593      232.6373934
> ##### CI #####
> exp(confint(model.3))
Waiting for profiling to be done...
      2.5 %      97.5 %
(Intercept)      0.2972066      4.277485
z.F0change_Q4_minusQ1 18.4483879 23219.841159
Warning messages:
1: glm.fit: fitted probabilities numerically 0 or 1 occurred
2: glm.fit: fitted probabilities numerically 0 or 1 occurred
3: glm.fit: fitted probabilities numerically 0 or 1 occurred
4: glm.fit: fitted probabilities numerically 0 or 1 occurred
5: glm.fit: fitted probabilities numerically 0 or 1 occurred
6: glm.fit: fitted probabilities numerically 0 or 1 occurred
7: glm.fit: fitted probabilities numerically 0 or 1 occurred
8: glm.fit: fitted probabilities numerically 0 or 1 occurred
9: glm.fit: fitted probabilities numerically 0 or 1 occurred
10: glm.fit: fitted probabilities numerically 0 or 1 occurred
>

```

```

> ## Model 4 - ED_Q2Q3
>
> model.4 <- glm(syll.fac ~ ED_Q2Q3, data=k.f, family="binomial")
> summary(model.1)

Call:
glm(formula = syll.fac ~ ED_Q2Q3, family = "binomial", data = k.f)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.3877  -1.1458  -0.8671   1.1975   1.4005

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  -1.1857     0.9908  -1.197   0.231
ED_Q2Q3         1.0044     0.8340   1.204   0.228

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 81.774  on 58  degrees of freedom
Residual deviance: 80.255  on 57  degrees of freedom
AIC: 84.255

Number of Fisher Scoring iterations: 4

>
> ## classification tables
>
> model.4.pred <- predict(model.4, type="response")
> S2 <- ifelse(model.4.pred > .5, 2, 1)
> k.f.1 <- k.f %>% drop_na(ED_Q2Q3)
> table(k.f.1$Syllable, S2)
  S2
    1  2
1 20 10
2 17 12
>
>
> ## chisq
>
> model.4.chi <- (model.4$null.deviance - model.4$deviance)
> model.4.df <- (model.4$df.null - model.4$df.residual)
> model.4.chisq <- 1-pchisq(model.4.chi, model.4.df)
> model.4.chi
[1] 1.519632
> model.4.chisq
[1] 0.2176752
> model.4.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.4$coefficients)
(Intercept)      ED_Q2Q3
  0.305519    2.730207
> ##### CI #####

```

```

> exp(confint(model.4))
Waiting for profiling to be done...
              2.5 %      97.5 %
(Intercept) 0.03912668 2.024091
ED_Q2Q3      0.55861760 15.593136
>
>
> ## Model 5 - Duration
>
> model.5 <- glm(syll.fac ~ z.Duration, data=k.f, family="binomial")
>
> summary(model.5)

Call:
glm(formula = syll.fac ~ z.Duration, family = "binomial", data = k.f)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.5528  -1.0971  -0.7146   1.0871   1.9081

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept) -0.007222   0.270156  -0.027   0.9787
z.Duration   -0.580413   0.298276  -1.946   0.0517 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 81.774  on 58  degrees of freedom
Residual deviance: 77.509  on 57  degrees of freedom
AIC: 81.509

Number of Fisher Scoring iterations: 4

> model.5.pred <- predict(model.5, type="response")
> S2 <- ifelse(model.5.pred > .5, 2, 1)
> k.f.1 <- k.f %>% drop_na(z.Duration)
> table(k.f.1$Syllable, S2)
      S2
      1  2
1 19 11
2 11 18
>
>
> ## chisq
>
> model.5.chi <- (model.5$null.deviance - model.5$deviance)
> model.5.df <- (model.5$df.null - model.5$df.residual)
> model.5.chisq <- 1-pchisq(model.5.chi, model.5.df)
> model.5.chi
[1] 4.265255
> model.5.chisq
[1] 0.0388994
> model.5.df

```

```

[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.5$coefficients)
(Intercept)  z.Duration
  0.9928041   0.5596672
> ##### CI #####
> exp(confint(model.5))
Waiting for profiling to be done...
              2.5 %      97.5 %
(Intercept)  0.5829406 1.6932548
z.Duration   0.2962991 0.9719744
>
>
> ## Model 6 - Intensity_Q2Q3
>
> model.6 <- glm(syll.fac ~ z.Intensity_Q2Q3, data=k.f, family="binomial")
> summary(model.6)

Call:
glm(formula = syll.fac ~ z.Intensity_Q2Q3, family = "binomial",
    data = k.f)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.207  -1.161  -1.113   1.197   1.220

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)   -0.04972    0.27062  -0.184   0.854
z.Intensity_Q2Q3 -0.08034    0.37203  -0.216   0.829

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 81.774  on 58  degrees of freedom
Residual deviance: 81.728  on 57  degrees of freedom
AIC: 85.728

Number of Fisher Scoring iterations: 3

>
> ## classification tables
>
> model.6.pred <- predict(model.6, type="response")
> S2 <- ifelse(model.6.pred > .5, 2, 1)
> k.f.1 <- k.f %>% drop_na(z.Intensity_Q2Q3)
> table(k.f.1$Syllable, S2)
  S2
    1  2
1 21  9
2 24  5
>
>
> ## chisq
>

```

```

> model.6.chi <- (model.6$null.deviance - model.6$deviance)
> model.6.df <- (model.6$df.null - model.6$df.residual)
> model.6.chisq <- 1-pchisq(model.6.chi, model.6.df)
> model.6.chi
[1] 0.04669766
> model.6.chisq
[1] 0.8289126
> model.6.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.6$coefficients)
      (Intercept)  z.Intensity_Q2Q3
      0.9515003      0.9228009
> ##### CI #####
> exp(confint(model.6))
Waiting for profiling to be done...
              2.5 %    97.5 %
(Intercept)    0.5569102 1.620210
z.Intensity_Q2Q3 0.4358598 1.931205

>
>
>
>
> ##### PostF #####
>
> ## Model 1 - F0
>
> model.7 <- glm(syll.fac ~ z.log.F0_Q2Q3, data=k.pof, family="binomial")
> summary(model.7)

Call:
glm(formula = syll.fac ~ z.log.F0_Q2Q3, family = "binomial",
    data = k.pof)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.3393  -0.9049  -0.7443   0.9372   4.3129

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)    0.2192     0.3143   0.698  0.48546
z.log.F0_Q2Q3  1.4275     0.5531   2.581  0.00986 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 73.455  on 52  degrees of freedom
Residual deviance: 64.378  on 51  degrees of freedom
(1 observation deleted due to missingness)
AIC: 68.378

Number of Fisher Scoring iterations: 5

```

```

>
> ## classification tables
>
> model.7.pred <- predict(model.7, type="response")
> S2 <- ifelse(model.7.pred > .5, 2, 1)
> k.pof.1 <- k.pof %>% drop_na(z.log.F0_Q2Q3)
> table(k.pof.1$Syllable, S2)
      S2
      1  2
1 25  2
2  5 21
>
>
> ## chisq
>
> model.7.chi <- (model.7$null.deviance - model.7$deviance)
> model.7.df <- (model.7$df.null - model.7$df.residual)
> model.7.chisq <- 1-pchisq(model.7.chi, model.7.df)
> model.7.chi
[1] 9.076325
> model.7.chisq
[1] 0.002589399
> model.7.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.7$coefficients)
      (Intercept)      z.log.F0_Q2Q3
      1.245100      4.168214
> ##### CI #####
> exp(confint(model.7))
Waiting for profiling to be done...
              2.5 %    97.5 %
(Intercept)  0.6810521  2.37039
z.log.F0_Q2Q3 1.5202825 13.46201
>
>
> ## Model 8 - F0 range
>
>
> model.8 <- glm(syll.fac ~ z.F0range_Max_minus_Min, data=k.pof,
family="binomial")
> summary(model.8)

Call:
glm(formula = syll.fac ~ z.F0range_Max_minus_Min, family = "binomial",
    data = k.pof)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.8236  -0.6263  -0.3310   0.4667   1.9898

Coefficients:
                Estimate Std. Error z value Pr(>|z|)

```



```

(Intercept)          0.03619      0.40533      0.089 0.928846
z.F0range_Max_minus_Min 2.79508      0.73975      3.778 0.000158 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 73.455 on 52 degrees of freedom
Residual deviance: 42.074 on 51 degrees of freedom
(1 observation deleted due to missingness)
AIC: 46.074

Number of Fisher Scoring iterations: 5

>
> ## classification tables
>
> model.8.pred <- predict(model.8, type="response")
> S2 <- ifelse(model.8.pred > .5, 2, 1)
> k.pof.1 <- k.pof %>% drop_na(z.F0range_Max_minus_Min)
> table(k.f.1$Syllable, S2)
Error in table(k.f.1$Syllable, S2) :
  all arguments must have the same length
>
>
> ## chisq
>
> model.8.chi <- (model.8$null.deviance - model.8$deviance)
> model.8.df <- (model.8$df.null - model.8$df.residual)
> model.8.chisq <- 1-pchisq(model.8.chi, model.8.df)
> model.8.chi
[1] 31.38075
> model.8.chisq
[1] 2.120726e-08
> model.8.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.8$coefficients)
      (Intercept) z.F0range_Max_minus_Min
      1.036857      16.363989
> ##### CI #####
> exp(confint(model.8))
Waiting for profiling to be done...
              2.5 %      97.5 %
(Intercept)    0.4748104  2.435099
z.F0range_Max_minus_Min 4.7486237 90.080274
>
> ## classification tables
>
> model.8.pred <- predict(model.8, type="response")
> S2 <- ifelse(model.8.pred > .5, 2, 1)
> k.pof.1 <- k.pof %>% drop_na(z.F0range_Max_minus_Min)
> table(k.pof.1$Syllable, S2)
  S2

```

```

      1  2
1 22  5
2  6 20
>
>
> ## Model 9 - F0 change
>
> model.9 <- glm(syll.fac ~ z.F0change_Q4_minusQ1, data=k.pof,
family="binomial")
> summary(model.9)

Call:
glm(formula = syll.fac ~ z.F0change_Q4_minusQ1, family = "binomial",
    data = k.pof)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.8070  -0.2599  -0.1296   0.1945   1.8076

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)    -1.4114     0.6893  -2.048 0.040583 *
z.F0change_Q4_minusQ1  4.4662     1.3133   3.401 0.000672 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 62.985  on 45  degrees of freedom
Residual deviance: 19.485  on 44  degrees of freedom
(8 observations deleted due to missingness)
AIC: 23.485

Number of Fisher Scoring iterations: 6

>
> ## classification tables
>
> model.9.pred <- predict(model.9, type="response")
> S2 <- ifelse(model.9.pred > .5, 2, 1)
> k.pof.1 <- k.pof %>% drop_na(z.F0change_Q4_minusQ1)
> table(k.pof.1$Syllable, S2)
      S2
      1  2
1 23  3
2  2 18
>
>
> ## chisq
>
> model.9.chi <- (model.9$null.deviance - model.9$deviance)
> model.9.df <- (model.9$df.null - model.9$df.residual)
> model.9.chisq <- 1-pchisq(model.9.chi, model.9.df)
> model.9.chi
[1] 43.49949
> model.9.chisq
[1] 4.240708e-11

```

```

> model.9.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.9$coefficients)
      (Intercept)  z.F0change_Q4_minusQ1
      0.2437921      87.0213831
> ##### CI #####
> exp(confint(model.9))
Waiting for profiling to be done...
      2.5 %      97.5 %
(Intercept)      0.04459591      0.7877767
z.F0change_Q4_minusQ1 11.82273292 2799.7689912
>
>
> ## Model 10 - ED_Q2Q3
>
> model.10 <- glm(syll.fac ~ ED_Q2Q3, data=k.pof, family="binomial")
> summary(model.10)

Call:
glm(formula = syll.fac ~ ED_Q2Q3, family = "binomial", data = k.pof)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.5904  -1.1120  -0.2579   1.1941   1.5237

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  -1.1445     0.7972  -1.436   0.151
ED_Q2Q3       0.9984     0.6659   1.499   0.134

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 74.860  on 53  degrees of freedom
Residual deviance: 72.107  on 52  degrees of freedom
AIC: 76.107

Number of Fisher Scoring iterations: 3

>
> ## classification tables
>
> model.10.pred <- predict(model.10, type="response")
> S2 <- ifelse(model.10.pred > .5, 2, 1)
> k.pof.1 <- k.pof %>% drop_na(ED_Q2Q3)
> table(k.pof.1$Syllable, S2)
  S2
    1  2
1 20  7
2 14 13
>
>
> ## chisq
>

```

```

> model.10.chi <- (model.10$null.deviance - model.10$deviance)
> model.10.df <- (model.10$df.null - model.10$df.residual)
> model.10.chisq <- 1-pchisq(model.10.chi, model.10.df)
> model.10.chi
[1] 2.753316
> model.10.chisq
[1] 0.09705297
> model.10.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.10$coefficients)
(Intercept)      ED_Q2Q3
  0.3183928    2.7139874
> ##### CI #####
> exp(confint(model.10))
Waiting for profiling to be done...
              2.5 %      97.5 %
(Intercept) 0.0572148  1.352247
ED_Q2Q3      0.8472279 11.968868
>
>
>
> ## Model 11 - Duration
>
> model.11 <- glm(syll.fac ~ z.Duration, data=k.pof, family="binomial")
> summary(model.6)

Call:
glm(formula = syll.fac ~ z.Intensity_Q2Q3, family = "binomial",
    data = k.f)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.207  -1.161  -1.113   1.197   1.220

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)   -0.04972    0.27062  -0.184   0.854
z.Intensity_Q2Q3 -0.08034    0.37203  -0.216   0.829

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 81.774  on 58  degrees of freedom
Residual deviance: 81.728  on 57  degrees of freedom
AIC: 85.728

Number of Fisher Scoring iterations: 3

>
> ## classification tables
>
> model.11.pred <- predict(model.11, type="response")
> S2 <- ifelse(model.11.pred > .5, 2, 1)
> k.pof.1 <- k.pof %>% drop_na(z.Duration)

```

```

> table(k.pof.1$Syllable,S2)
      S2
      1  2
1 14 13
2 14 13
>
>
> ## chisq
>
> model.11.chi <- (model.11$null.deviance - model.11$deviance)
> model.11.df <- (model.11$df.null - model.11$df.residual)
> model.11.chisq <- 1-pchisq(model.11.chi, model.11.df)
> model.11.chi
[1] 0.1173931
> model.11.chisq
[1] 0.7318793
> model.11.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.11$coefficients)
(Intercept)   z.Duration
  1.0040527   0.9084143
> ##### CI #####
> exp(confint(model.11))
Waiting for profiling to be done...
              2.5 %    97.5 %
(Intercept) 0.5865967 1.719626
z.Duration   0.5179771 1.577919
>
>
> ## Model 12 - Intensity_Q2Q3
>
> model.12 <- glm(syll.fac ~ z.Intensity_Q2Q3, data=k.pof, family="binomial")
> summary(model.12)

Call:
glm(formula = syll.fac ~ z.Intensity_Q2Q3, family = "binomial",
    data = k.pof)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.33588 -1.17839 -0.01504  1.12500  1.45480

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  -0.05573    0.28034  -0.199   0.842
z.Intensity_Q2Q3 -0.36659    0.35112  -1.044   0.296

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 74.860  on 53  degrees of freedom
Residual deviance: 73.744  on 52  degrees of freedom
AIC: 77.744

```

Number of Fisher Scoring iterations: 4

```
>
> ## classification tables
>
> model.12.pred <- predict(model.12, type="response")
> S2 <- ifelse(model.12.pred > .5, 2, 1)
> k.pof.1 <- k.pof %>% drop_na(z.Intensity_Q2Q3)
> table(k.pof.1$Syllable,S2)
  S2
    1  2
1 13 14
2 10 17
>
>
> ## chisq
>
> model.12.chi <- (model.12$null.deviance - model.12$deviance)
> model.12.df <- (model.12$df.null - model.12$df.residual)
> model.12.chisq <- 1-pchisq(model.12.chi, model.12.df)
> model.12.chi
[1] 1.115585
> model.12.chisq
[1] 0.2908712
> model.12.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.12$coefficients)
      (Intercept)  z.Intensity_Q2Q3
      0.9457905      0.6930940
> ##### CI #####
> exp(confint(model.12))
Waiting for profiling to be done...
              2.5 %    97.5 %
(Intercept)    0.5413841 1.637939
z.Intensity_Q2Q3 0.3384723 1.364940
>
>
> ##### PreF #####
>
> ## Model 13 - F0
>
> model.13 <- glm(syll.fac ~ z.log.F0_Q2Q3, data=k.pf.s1vs2,
family="binomial")
> summary(model.13)
```

Call:

```
glm(formula = syll.fac ~ z.log.F0_Q2Q3, family = "binomial",
    data = k.pf.s1vs2)
```

Deviance Residuals:

Min	1Q	Median	3Q	Max
-1.1088	-1.0571	-0.9994	1.3015	1.3981

```

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)   -0.3911     0.3555  -1.100   0.271
z.log.F0_Q2Q3 -0.2595     0.7878  -0.329   0.742

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 68.029 on 49 degrees of freedom
Residual deviance: 67.920 on 48 degrees of freedom
(8 observations deleted due to missingness)
AIC: 71.92

Number of Fisher Scoring iterations: 4

>
> ## classification tables
>
> model.13.pred <- predict(model.13, type="response")
> S2 <- ifelse(model.13.pred > .5, 2, 1)
> k.pf.s1vs2.1 <- k.pf.s1vs2 %>% drop_na(z.log.F0_Q2Q3)
> table(k.pf.s1vs2.1$Syllable, S2)
  S2
    1
1 29
2 21
>
>
> ## chisq
>
> model.13.chi <- (model.13$null.deviance - model.13$deviance)
> model.13.df <- (model.13$df.null - model.13$df.residual)
> model.13.chisq <- 1-pchisq(model.13.chi, model.13.df)
> model.13.chi
[1] 0.1090821
> model.13.chisq
[1] 0.7411915
> model.13.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.13$coefficients)
  (Intercept) z.log.F0_Q2Q3
    0.6762923    0.7714585
> ##### CI #####
> exp(confint(model.13))
Waiting for profiling to be done...
              2.5 %    97.5 %
(Intercept)   0.3260111 1.342959
z.log.F0_Q2Q3 0.1558051 3.607652
>
>
> ## Model 14 - F0 range
>
> model.14 <- glm(syll.fac ~ z.F0range_Max_minus_Min, data=k.pf.s1vs2,
family="binomial")

```

```

> summary(model.14)

Call:
glm(formula = syll.fac ~ z.F0range_Max_minus_Min, family = "binomial",
    data = k.pf.s1vs2)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.5971  -0.8819  -0.3587   0.8922   2.0280

Coefficients:
                Estimate Std. Error z value Pr(>|z|)
(Intercept)      -1.4478     0.5694  -2.543  0.01100 *
z.F0range_Max_minus_Min -2.3824     0.7962  -2.992  0.00277 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 71.393  on 51  degrees of freedom
Residual deviance: 57.288  on 50  degrees of freedom
(6 observations deleted due to missingness)
AIC: 61.288

Number of Fisher Scoring iterations: 5

>
> ## classification tables
>
> model.14.pred <- predict(model.14, type="response")
> S2 <- ifelse(model.14.pred > .5, 2, 1)
> k.pf.s1vs2.1 <- k.pf.s1vs2 %>% drop_na(z.F0range_Max_minus_Min)
> table(k.pf.s1vs2.1$Syllable, S2)
  S2
    1  2
1 19 10
2  7 16
>
>
> ## chisq
>
> model.14.chi <- (model.14$null.deviance - model.14$deviance)
> model.14.df <- (model.14$df.null - model.14$df.residual)
> model.14.chisq <- 1-pchisq(model.14.chi, model.14.df)
> model.14.chi
[1] 14.10569
> model.14.chisq
[1] 0.0001728204
> model.14.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.14$coefficients)
      (Intercept) z.F0range_Max_minus_Min
      0.23507980      0.09232586

```



```

> ##### CI #####
> exp(confint(model.14))
Waiting for profiling to be done...
              2.5 %      97.5 %
(Intercept)      0.06449068 0.6286457
z.F0range_Max_minus_Min 0.01557399 0.3694731
>
>
> ## Model 15 - F0 change
>
> model.15 <- glm(syll.fac ~ z.F0change_Q4_minusQ1, data=k.pf.slvs2,
family="binomial")
> summary(model.15)

Call:
glm(formula = syll.fac ~ z.F0change_Q4_minusQ1, family = "binomial",
    data = k.pf.slvs2)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.1745  -0.8584  -0.7647   1.4807   1.6635

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)    -1.1833     0.4805  -2.463   0.0138 *
z.F0change_Q4_minusQ1 -0.5052     0.5993  -0.843   0.3993
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 46.401  on 38  degrees of freedom
Residual deviance: 45.654  on 37  degrees of freedom
(19 observations deleted due to missingness)
AIC: 49.654

Number of Fisher Scoring iterations: 4

>
> ## classification tables
>
> model.15.pred <- predict(model.15, type="response")
> S2 <- ifelse(model.15.pred > .5, 2, 1)
> k.pf.slvs2.1 <- k.pf.slvs2 %>% drop_na(z.F0change_Q4_minusQ1)
> table(k.pf.slvs2.1$Syllable, S2)
      S2
      1
1 28
2 11
>
>
> ## chisq
>
> model.15.chi <- (model.15$null.deviance - model.15$deviance)
> model.15.df <- (model.15$df.null - model.15$df.residual)
> model.15.chisq <- 1-pchisq(model.15.chi, model.15.df)
> model.15.chi

```

```

[1] 0.7464135
> model.15.chisq
[1] 0.3876141
> model.15.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.15$coefficients)
      (Intercept)  z.F0change_Q4_minusQ1
      0.3062682      0.6033970
> ##### CI #####
> exp(confint(model.15))
Waiting for profiling to be done...
      2.5 %      97.5 %
(Intercept)      0.1058003 0.7285916
z.F0change_Q4_minusQ1 0.1620008 1.8735625
>
>
> ## Model 16 - ED_Q2Q3
>
> model.16 <- glm(syll.fac ~ ED_Q2Q3, data=k.pf.s1vs2, family="binomial")
> summary(model.16)

Call:
glm(formula = syll.fac ~ ED_Q2Q3, family = "binomial", data = k.pf.s1vs2)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.85789  -1.03333  -0.04209   1.10171   1.54072

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)   -2.556      1.110  -2.303   0.0213 *
ED_Q2Q3        1.642      0.695   2.363   0.0181 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 80.405  on 57  degrees of freedom
Residual deviance: 73.851  on 56  degrees of freedom
AIC: 77.851

Number of Fisher Scoring iterations: 4

>
> ## classification tables
>
> model.16.pred <- predict(model.16, type="response")
> S2 <- ifelse(model.16.pred > .5, 2, 1)
> k.pf.s1vs2.1 <- k.pf.s1vs2 %>% drop_na(ED_Q2Q3)
> table(k.pf.s1vs2.1$Syllable, S2)
      S2
      1  2
1 19 10

```

```

2 11 18
>
>
> ## chisq
>
> model.16.chi <- (model.16$null.deviance - model.16$deviance)
> model.16.df <- (model.16$df.null - model.16$df.residual)
> model.16.chisq <- 1-pchisq(model.16.chi, model.16.df)
> model.16.chi
[1] 6.554094
> model.16.chisq
[1] 0.01046431
> model.16.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.16$coefficients)
(Intercept)      ED_Q2Q3
  0.07760411   5.16599289
> ##### CI #####
> exp(confint(model.16))
Waiting for profiling to be done...
              2.5 %      97.5 %
(Intercept)  0.007332266  0.6041747
ED_Q2Q3      1.443320537 22.9130556
>
>
> ## Model 17 - Duration
>
> model.17 <- glm(syll.fac ~ z.Duration, data=k.pf.slvs2, family="binomial")
> summary(model.6)

Call:
glm(formula = syll.fac ~ z.Intensity_Q2Q3, family = "binomial",
    data = k.f)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.207  -1.161  -1.113   1.197   1.220

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)  -0.04972    0.27062  -0.184   0.854
z.Intensity_Q2Q3 -0.08034    0.37203  -0.216   0.829

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 81.774  on 58  degrees of freedom
Residual deviance: 81.728  on 57  degrees of freedom
AIC: 85.728

Number of Fisher Scoring iterations: 3

>
> ## classification tables

```

```

>
> model.17.pred <- predict(model.17, type="response")
> S2 <- ifelse(model.17.pred > .5, 2, 1)
> k.pf.slvs2.1 <- k.pf.slvs2 %>% drop_na(z.Duration)
> table(k.pf.slvs2.1$Syllable, S2)
  S2
    1  2
1 17 12
2  8 21
>
>
> ## chisq
>
> model.17.chi <- (model.17$null.deviance - model.17$deviance)
> model.17.df <- (model.17$df.null - model.17$df.residual)
> model.17.chisq <- 1-pchisq(model.17.chi, model.17.df)
> model.17.chi
[1] 7.321827
> model.17.chisq
[1] 0.006812211
> model.17.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.17$coefficients)
(Intercept)  z.Duration
  1.0728115   0.4715521
> ##### CI #####
> exp(confint(model.17))
Waiting for profiling to be done...
              2.5 %      97.5 %
(Intercept)  0.6185806 1.8762421
z.Duration   0.2481517 0.8212897
>
> summary(model.17)

Call:
glm(formula = syll.fac ~ z.Duration, family = "binomial", data = k.pf.slvs2)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.76858  -1.02331   0.01151   0.99937   2.27058

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)   0.07028    0.28077   0.250   0.8023
z.Duration   -0.75173    0.30217  -2.488   0.0129 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 80.405  on 57  degrees of freedom
Residual deviance: 73.083  on 56  degrees of freedom
AIC: 77.083

```

```

Number of Fisher Scoring iterations: 4

>
> ## Model 18 - Intensity_Q2Q3
>
> model.18 <- glm(syll.fac ~ z.Intensity_Q2Q3, data=k.pf.s1vs2,
family="binomial")
Warning messages:
1: glm.fit: algorithm did not converge
2: glm.fit: fitted probabilities numerically 0 or 1 occurred
> summary(model.18)

Call:
glm(formula = syll.fac ~ z.Intensity_Q2Q3, family = "binomial",
    data = k.pf.s1vs2)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-5.328e-04 -2.000e-08  0.000e+00  2.000e-08  6.088e-04

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)    -834.7     57250.5  -0.015   0.988
z.Intensity_Q2Q3 -2083.6    142561.3  -0.015   0.988

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 8.0405e+01  on 57  degrees of freedom
Residual deviance: 6.5451e-07  on 56  degrees of freedom
AIC: 4

Number of Fisher Scoring iterations: 25

>
> ## classification tables
>
> model.18.pred <- predict(model.18, type="response")
> S2 <- ifelse(model.18.pred > .5, 2, 1)
> k.pf.s1vs2.1 <- k.pf.s1vs2 %>% drop_na(z.Intensity_Q2Q3)
> table(k.pf.s1vs2.1$Syllable, S2)
      S2
      1  2
1 29  0
2  0 29

>
>
> ## chisq
>
> model.18.chi <- (model.18$null.deviance - model.18$deviance)
> model.18.df <- (model.18$df.null - model.18$df.residual)
> model.18.chisq <- 1-pchisq(model.18.chi, model.18.df)
> model.18.chi
[1] 80.40507
> model.18.chisq
[1] 0
> model.18.df

```

```

[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.18$coefficients)
      (Intercept)  z.Intensity_Q2Q3
              0              0
> ##### CI #####
> exp(confint(model.18))
Waiting for profiling to be done...
              2.5 % 97.5 %
(Intercept)          0      Inf
z.Intensity_Q2Q3      0      0
Warning messages:
1: glm.fit: fitted probabilities numerically 0 or 1 occurred
2: glm.fit: fitted probabilities numerically 0 or 1 occurred
3: glm.fit: fitted probabilities numerically 0 or 1 occurred
4: glm.fit: fitted probabilities numerically 0 or 1 occurred
5: glm.fit: fitted probabilities numerically 0 or 1 occurred
6: glm.fit: fitted probabilities numerically 0 or 1 occurred
>
>
> ## S2 v S3
>
> ## S2 v S3 ##
>
> ## Model 19 - F0
>
> model.19 <- glm(syll.fac ~ z.log.F0_Q2Q3, data=k.pf.s2vs3,
family="binomial")
Warning messages:
1: glm.fit: algorithm did not converge
2: glm.fit: fitted probabilities numerically 0 or 1 occurred
> summary(model.19)

Call:
glm(formula = syll.fac ~ z.log.F0_Q2Q3, family = "binomial",
    data = k.pf.s2vs3)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-6.591e-05 -2.100e-08  2.100e-08  2.100e-08  7.166e-05

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)   -113.2     51854.2  -0.002    0.998
z.log.F0_Q2Q3    212.0     94335.9   0.002    0.998

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 6.8029e+01  on 49  degrees of freedom
Residual deviance: 9.4794e-09  on 48  degrees of freedom
(9 observations deleted due to missingness)
AIC: 4

Number of Fisher Scoring iterations: 25

```

```

>
> ## classification tables
>
> model.19.pred <- predict(model.19, type="response")
> S2 <- ifelse(model.19.pred > .5, 2, 1)
> k.pf.s2vs3.1 <- k.pf.s2vs3 %>% drop_na(z.log.F0_Q2Q3)
> table(k.pf.s2vs3.1$Syllable, S2)
      S2
      1  2
2 21  0
3  0 29
>
>
> ## chisq
>
> model.19.chi <- (model.19$null.deviance - model.19$deviance)
> model.19.df <- (model.19$df.null - model.19$df.residual)
> model.19.chisq <- 1-pchisq(model.19.chi, model.19.df)
> model.19.chi
[1] 68.0292
> model.19.chisq
[1] 1.110223e-16
> model.19.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.19$coefficients)
      (Intercept)  z.log.F0_Q2Q3
6.632316e-50  1.127084e+92
> ##### CI #####
> exp(confint(model.19))
Waiting for profiling to be done...
      2.5 % 97.5 %
(Intercept)      0      Inf
z.log.F0_Q2Q3    Inf      Inf
Warning messages:
1: glm.fit: fitted probabilities numerically 0 or 1 occurred
2: glm.fit: fitted probabilities numerically 0 or 1 occurred
3: glm.fit: fitted probabilities numerically 0 or 1 occurred
4: glm.fit: fitted probabilities numerically 0 or 1 occurred
5: glm.fit: fitted probabilities numerically 0 or 1 occurred
6: glm.fit: fitted probabilities numerically 0 or 1 occurred
7: glm.fit: fitted probabilities numerically 0 or 1 occurred
8: glm.fit: fitted probabilities numerically 0 or 1 occurred
9: glm.fit: fitted probabilities numerically 0 or 1 occurred
10: glm.fit: fitted probabilities numerically 0 or 1 occurred
>
>
> ## Model 20 - F0 range
>
> model.20 <- glm(syll.fac ~ z.F0range_Max_minus_Min, data=k.pf.s2vs3,
family="binomial")
> summary(model.20)

```

```

Call:
glm(formula = syll.fac ~ z.F0range_Max_minus_Min, family = "binomial",
    data = k.pf.s2vs3)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.2669  -0.7066   0.1275   0.7210   1.7834

Coefficients:
                Estimate Std. Error z value Pr(>|z|)
(Intercept)         1.8184     0.6315   2.880 0.003981 **
z.F0range_Max_minus_Min 3.3903     0.9802   3.459 0.000543 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 71.393  on 51  degrees of freedom
Residual deviance: 49.650  on 50  degrees of freedom
(7 observations deleted due to missingness)
AIC: 53.65

Number of Fisher Scoring iterations: 5

>
> ## classification tables
>
> model.20.pred <- predict(model.20, type="response")
> S2 <- ifelse(model.20.pred > .5, 2, 1)
> k.pf.s2vs3.1 <- k.pf.s2vs3 %>% drop_na(z.F0range_Max_minus_Min)
> table(k.pf.s2vs3.1$Syllable, S2)
  S2
    1  2
2 18  5
3  7 22
>
>
> ## chisq
>
> model.20.chi <- (model.20$null.deviance - model.20$deviance)
> model.20.df <- (model.20$df.null - model.20$df.residual)
> model.20.chisq <- 1-pchisq(model.20.chi, model.20.df)
> model.20.chi
[1] 21.74346
> model.20.chisq
[1] 3.116512e-06
> model.20.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.20$coefficients)
              (Intercept) z.F0range_Max_minus_Min
              6.162275      29.673547
> ##### CI #####
> exp(confint(model.20))

```


Waiting **for** profiling to be done...

```

                2.5 %    97.5 %
(Intercept)      2.070704  25.6390
z.F0range_Max_minus_Min 5.451691 264.8413
>
>
> ## Model 21 - F0 change
>
> model.21 <- glm(syll.fac ~ z.F0change_Q4_minusQ1, data=k.pf.s2vs3,
family="binomial")
> summary(model.21)

```

Call:

```
glm(formula = syll.fac ~ z.F0change_Q4_minusQ1, family = "binomial",
    data = k.pf.s2vs3)
```

Deviance Residuals:

```

      Min       1Q   Median       3Q      Max
-1.6892  -1.4443   0.7016   0.8485   1.0971

```

Coefficients:

```

                Estimate Std. Error z value Pr(>|z|)
(Intercept)      1.2668     0.4752   2.666  0.00768 **
z.F0change_Q4_minusQ1  0.6563     0.5913   1.110  0.26700
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

(Dispersion parameter **for** binomial family taken to be 1)

```

Null deviance: 47.054 on 39 degrees of freedom
Residual deviance: 45.625 on 38 degrees of freedom
(19 observations deleted due to missingness)
AIC: 49.625

```

Number of Fisher Scoring iterations: 4

```

>
> ## classification tables
>
> model.21.pred <- predict(model.21, type="response")
> S2 <- ifelse(model.21.pred > .5, 2, 1)
> k.pf.s2vs3.1 <- k.pf.s2vs3 %>% drop_na(z.F0change_Q4_minusQ1)
> table(k.pf.s2vs3.1$Syllable, S2)
      S2
      2
2  11
3  29
>
>
> ## chisq
>
> model.21.chi <- (model.21$null.deviance - model.21$deviance)
> model.21.df <- (model.21$df.null - model.21$df.residual)
> model.21.chisq <- 1-pchisq(model.21.chi, model.21.df)
> model.21.chi
[1] 1.428226
> model.21.chisq

```

```

[1] 0.2320542
> model.21.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.21$coefficients)
      (Intercept) z.F0change_Q4_minusQ1
      3.549639      1.927631
> ##### CI #####
> exp(confint(model.21))
Waiting for profiling to be done...
              2.5 %      97.5 %
(Intercept)      1.5425873 10.414782
z.F0change_Q4_minusQ1 0.6837941  7.144206
>
>
> ## Model 22 - ED_Q2Q3
>
> model.22 <- glm(syll.fac ~ ED_Q2Q3, data=k.pf.s2vs3, family="binomial")
> summary(model.22)

Call:
glm(formula = syll.fac ~ ED_Q2Q3, family = "binomial", data = k.pf.s2vs3)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.4802  -1.1465   0.6331   1.1105   1.5767

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)    1.9826     1.0476   1.892   0.0584 .
ED_Q2Q3        -1.2261     0.6344  -1.933   0.0533 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 81.774  on 58  degrees of freedom
Residual deviance: 77.554  on 57  degrees of freedom
AIC: 81.554

Number of Fisher Scoring iterations: 4

>
> ## classification tables
>
> model.22.pred <- predict(model.22, type="response")
> S2 <- ifelse(model.22.pred > .5, 2, 1)
> k.pf.s2vs3.1 <- k.pf.s2vs3 %>% drop_na(ED_Q2Q3)
> table(k.pf.s2vs3.1$Syllable, S2)
  S2
    1  2
2 17 12
3 13 17
>

```

```

>
> ## chisq
>
> model.22.chi <- (model.22$null.deviance - model.22$deviance)
> model.22.df <- (model.22$df.null - model.22$df.residual)
> model.22.chisq <- 1-pchisq(model.22.chi, model.22.df)
> model.22.chi
[1] 4.220771
> model.22.chisq
[1] 0.03993202
> model.22.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.22$coefficients)
(Intercept)      ED_Q2Q3
  7.2614213    0.2934381
> ##### CI #####
> exp(confint(model.22))
Waiting for profiling to be done...
              2.5 %      97.5 %
(Intercept) 1.04911332 68.0895371
ED_Q2Q3      0.07561382 0.9473216
>
>
> ## Model 23 - Duration
>
> model.23 <- glm(syll.fac ~ z.Duration, data=k.pf.s2vs3, family="binomial")
> summary(model.23)

Call:
glm(formula = syll.fac ~ z.Duration, family = "binomial", data = k.pf.s2vs3)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.277  -1.197   1.074   1.153   1.436

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) -0.02101    0.27733  -0.076    0.940
z.Duration  -0.16780    0.27905  -0.601    0.548

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 81.774  on 58  degrees of freedom
Residual deviance: 81.404  on 57  degrees of freedom
AIC: 85.404

Number of Fisher Scoring iterations: 4

>
> ## classification tables
>
> model.23.pred <- predict(model.23, type="response")
> S2 <- ifelse(model.23.pred > .5, 2, 1)

```

```

> k.pf.s2vs3.1 <- k.pf.s2vs3 %>% drop_na(z.Duration)
> table(k.pf.s2vs3.1$Syllable, S2)
  S2
    1  2
  2 11 18
  3  6 24
>
>
> ## chisq
>
> model.23.chi <- (model.23$null.deviance - model.23$deviance)
> model.23.df <- (model.23$df.null - model.23$df.residual)
> model.23.chisq <- 1-pchisq(model.23.chi, model.23.df)
> model.23.chi
[1] 0.3706276
> model.23.chisq
[1] 0.5426624
> model.23.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.23$coefficients)
(Intercept)  z.Duration
  0.9792125   0.8455230
> ##### CI #####
> exp(confint(model.23))
Waiting for profiling to be done...
              2.5 %    97.5 %
(Intercept)  0.5621008 1.685634
z.Duration   0.4657469 1.454054
>
>
> ## Model 24 - Intensity_Q2Q3
>
> model.24 <- glm(syll.fac ~ z.Intensity_Q2Q3, data=k.pf.s2vs3,
family="binomial")
Warning message:
glm.fit: fitted probabilities numerically 0 or 1 occurred
> summary(model.24)

Call:
glm(formula = syll.fac ~ z.Intensity_Q2Q3, family = "binomial",
    data = k.pf.s2vs3)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.93914  -0.01512   0.00000   0.00110   2.20999

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)      4.223      3.026   1.396   0.1628
z.Intensity_Q2Q3  11.795      6.466   1.824   0.0681 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

(Dispersion parameter **for** binomial family taken to be 1)

Null deviance: 81.7744 on 58 degrees of freedom
 Residual deviance: 8.7299 on 57 degrees of freedom
 AIC: 12.73

Number of Fisher Scoring iterations: 10

```
>
> ## classification tables
>
> model.24.pred <- predict(model.24, type="response")
> S2 <- ifelse(model.24.pred > .5, 2, 1)
> k.pf.s2vs3.1 <- k.pf.s2vs3 %>% drop_na(z.Intensity_Q2Q3)
> table(k.pf.s2vs3.1$Syllable, S2)
  S2
    1  2
2 29  0
3  1 29
>
>
> ## chisq
>
> model.24.chi <- (model.24$null.deviance - model.24$deviance)
> model.24.df <- (model.24$df.null - model.24$df.residual)
> model.24.chisq <- 1-pchisq(model.24.chi, model.24.df)
> model.24.chi
[1] 73.04455
> model.24.chisq
[1] 0
> model.24.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.24$coefficients)
      (Intercept)  z.Intensity_Q2Q3
      68.20763    132601.83728
> ##### CI #####
> exp(confint(model.24))
Waiting for profiling to be done...
              2.5 %      97.5 %
(Intercept)  1.895951 6.108689e+05
z.Intensity_Q2Q3 97.740936 1.218555e+14
There were 18 warnings (use warnings() to see them)
>
>
>
> ## S1 v S3 ##
>
> ## Model 25 - F0
>
> model.25 <- glm(syll.fac ~ z.log.F0_Q2Q3, data=k.pf.s1vs3,
family="binomial")
> summary(model.25)
```

```

Call:
glm(formula = syll.fac ~ z.log.F0_Q2Q3, family = "binomial",
    data = k.pf.slvs3)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.27490  -0.02860  -0.00056   0.08893   0.95291

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)   -5.587      2.884  -1.937  0.0527 .
z.log.F0_Q2Q3   9.785      4.055   2.413  0.0158 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 80.4051 on 57 degrees of freedom
Residual deviance:  8.0146 on 56 degrees of freedom
(1 observation deleted due to missingness)
AIC: 12.015

Number of Fisher Scoring iterations: 9

>
> ## classification tables
>
> model.25.pred <- predict(model.25, type="response")
> S2 <- ifelse(model.25.pred > .5, 2, 1)
> k.pf.slvs3.1 <- k.pf.slvs3 %>% drop_na(z.log.F0_Q2Q3)
> table(k.pf.slvs3.1$Syllable, S2)
      S2
      1  2
1 28  1
3  0 29
>
>
> ## chisq
>
> model.25.chi <- (model.25$null.deviance - model.25$deviance)
> model.25.df <- (model.25$df.null - model.25$df.residual)
> model.25.chisq <- 1-pchisq(model.25.chi, model.25.df)
> model.25.chi
[1] 72.39048
> model.25.chisq
[1] 0
> model.25.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.25$coefficients)
      (Intercept) z.log.F0_Q2Q3
3.746768e-03 1.776953e+04
> ##### CI #####
> exp(confint(model.25))

```

```

Waiting for profiling to be done...
                2.5 %          97.5 %
(Intercept)    1.176761e-07 1.158873e-01
z.log.F0_Q2Q3  1.218588e+02 4.746142e+10
There were 14 warnings (use warnings() to see them)
>
>
> ## Model 26 - F0 range
>
> model.26 <- glm(syll.fac ~ z.F0range_Max_minus_Min, data=k.pf.slvs3,
family="binomial")
> summary(model.26)

Call:
glm(formula = syll.fac ~ z.F0range_Max_minus_Min, family = "binomial",
    data = k.pf.slvs3)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.41147  -1.16520  -0.04483   1.18179   1.24208

Coefficients:
                Estimate Std. Error z value Pr(>|z|)
(Intercept)         0.01585    0.26536    0.06   0.952
z.F0range_Max_minus_Min 0.17762    0.37017    0.48   0.631

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 80.405  on 57  degrees of freedom
Residual deviance: 80.171  on 56  degrees of freedom
(1 observation deleted due to missingness)
AIC: 84.171

Number of Fisher Scoring iterations: 3

>
> ## classification tables
>
> model.26.pred <- predict(model.26, type="response")
> S2 <- ifelse(model.26.pred > .5, 2, 1)
> k.pf.slvs3.1 <- k.pf.slvs3 %>% drop_na(z.F0range_Max_minus_Min)
> table(k.pf.slvs3.1$Syllable, S2)
      S2
      1  2
1 19 10
3 16 13
>
>
> ## chisq
>
> model.26.chi <- (model.26$null.deviance - model.26$deviance)
> model.26.df <- (model.26$df.null - model.26$df.residual)
> model.26.chisq <- 1-pchisq(model.26.chi, model.26.df)
> model.26.chi
[1] 0.233643
> model.26.chisq
[1] 0.6288356

```

```

> model.26.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.26$coefficients)
              (Intercept) z.F0range_Max_minus_Min
              1.015979              1.194375
> ##### CI #####
> exp(confint(model.26))
Waiting for profiling to be done...
              2.5 %    97.5 %
(Intercept)      0.6028616 1.716949
z.F0range_Max_minus_Min 0.5782233 2.598098
>
>
> ## Model 27 - F0 change
>
> model.27 <- glm(syll.fac ~ z.F0change_Q4_minusQ1, data=k.pf.slvs3,
family="binomial")
> summary(model.27)

Call:
glm(formula = syll.fac ~ z.F0change_Q4_minusQ1, family = "binomial",
    data = k.pf.slvs3)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.2954  -1.1806   0.9767   1.1616   1.2575

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)      0.09458    0.29161   0.324    0.746
z.F0change_Q4_minusQ1 0.17154    0.34545   0.497    0.619

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 79.001  on 56  degrees of freedom
Residual deviance: 78.752  on 55  degrees of freedom
(2 observations deleted due to missingness)
AIC: 82.752

Number of Fisher Scoring iterations: 3

>
> ## classification tables
>
> model.27.pred <- predict(model.27, type="response")
> S2 <- ifelse(model.27.pred > .5, 2, 1)
> k.pf.slvs3.1 <- k.pf.slvs3 %>% drop_na(z.F0change_Q4_minusQ1)
> table(k.pf.slvs3.1$Syllable, S2)
  S2
    1  2
1 12 16
3 11 18
>

```



```

>
> ## chisq
>
> model.27.chi <- (model.27$null.deviance - model.27$deviance)
> model.27.df <- (model.27$df.null - model.27$df.residual)
> model.27.chisq <- 1-pchisq(model.27.chi, model.27.df)
> model.27.chi
[1] 0.2490376
> model.27.chisq
[1] 0.6177536
> model.27.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.27$coefficients)
      (Intercept)  z.F0change_Q4_minusQ1
      1.099193      1.187127
> ##### CI #####
> exp(confint(model.27))
Waiting for profiling to be done...
              2.5 %    97.5 %
(Intercept)    0.6209772 1.970774
z.F0change_Q4_minusQ1 0.6038130 2.411512
>
>
> ## Model 28 - ED_Q2Q3
>
> model.28 <- glm(syll.fac ~ ED_Q2Q3, data=k.pf.slvs3, family="binomial")
> summary(model.28)

Call:
glm(formula = syll.fac ~ ED_Q2Q3, family = "binomial", data = k.pf.slvs3)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.289  -1.181   1.081   1.159   1.260

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  -0.2759     0.8414  -0.328   0.743
ED_Q2Q3       0.2150     0.5553   0.387   0.699

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 81.774  on 58  degrees of freedom
Residual deviance: 81.624  on 57  degrees of freedom
AIC: 85.624

Number of Fisher Scoring iterations: 3

>
> ## classification tables
>
> model.28.pred <- predict(model.28, type="response")
> S2 <- ifelse(model.28.pred > .5, 2, 1)

```

```

> k.pf.slvs3.1 <- k.pf.slvs3 %>% drop_na(ED_Q2Q3)
> table(k.pf.slvs3.1$Syllable, S2)
      S2
      1  2
1 13 16
3  9 21
>
>
> ## chisq
>
> model.28.chi <- (model.28$null.deviance - model.28$deviance)
> model.28.df <- (model.28$df.null - model.28$df.residual)
> model.28.chisq <- 1-pchisq(model.28.chi, model.28.df)
> model.28.chi
[1] 0.150405
> model.28.chisq
[1] 0.6981486
> model.28.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.28$coefficients)
(Intercept)      ED_Q2Q3
  0.7588985    1.2398432
> ##### CI #####
> exp(confint(model.28))
Waiting for profiling to be done...
              2.5 %    97.5 %
(Intercept) 0.1399080 3.981598
ED_Q2Q3      0.4161072 3.788893
>
>
> ## Model 29 - Duration
>
> model.29 <- glm(syll.fac ~ z.Duration, data=k.pf.slvs3, family="binomial")
> summary(model.29)

Call:
glm(formula = syll.fac ~ z.Duration, family = "binomial", data = k.pf.slvs3)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.0845  -0.8930   0.5120   0.9433   2.8795

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  0.008012   0.294833   0.027  0.97832
z.Duration  -1.220474   0.394327  -3.095  0.00197 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 81.774  on 58  degrees of freedom
Residual deviance: 68.219  on 57  degrees of freedom

```

AIC: 72.219

Number of Fisher Scoring iterations: 4

```
>
> ## classification tables
>
> model.29.pred <- predict(model.29, type="response")
> S2 <- ifelse(model.29.pred > .5, 2, 1)
> k.pf.slvs3.1 <- k.pf.slvs3 %>% drop_na(z.Duration)
> table(k.pf.slvs3.1$Syllable, S2)
      S2
      1  2
1 18 11
3  4 26
>
>
> ## chisq
>
> model.29.chi <- (model.29$null.deviance - model.29$deviance)
> model.29.df <- (model.29$df.null - model.29$df.residual)
> model.29.chisq <- 1-pchisq(model.29.chi, model.29.df)
> model.29.chi
[1] 13.55552
> model.29.chisq
[1] 0.0002316087
> model.29.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.29$coefficients)
(Intercept)   z.Duration
  1.0080447    0.2950903
> ##### CI #####
> exp(confint(model.29))
Waiting for profiling to be done...
              2.5 %      97.5 %
(Intercept) 0.5594247 1.7995839
z.Duration   0.1236763 0.5931314
>
>
> ## Model 30 - Intensity_Q2Q3
>
> model.30 <- glm(syll.fac ~ z.Intensity_Q2Q3, data=k.pf.slvs3,
family="binomial")
> summary(model.30)
```

Call:

```
glm(formula = syll.fac ~ z.Intensity_Q2Q3, family = "binomial",
    data = k.pf.slvs3)
```

Deviance Residuals:

Min	1Q	Median	3Q	Max
-1.273	-1.181	1.075	1.160	1.282

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	0.1655	0.4072	0.407	0.684
z.Intensity_Q2Q3	-0.1454	0.3453	-0.421	0.674

(Dispersion parameter **for binomial family** taken to be 1)

Null deviance: 81.774 on 58 degrees of freedom
 Residual deviance: 81.596 on 57 degrees of freedom
 AIC: 85.596

Number of Fisher Scoring iterations: 3

```
>
> ## classification tables
>
> model.30.pred <- predict(model.30, type="response")
> S2 <- ifelse(model.30.pred > .5, 2, 1)
> k.pf.slvs3.1 <- k.pf.slvs3 %>% drop_na(z.Intensity_Q2Q3)
> table(k.pf.slvs3.1$Syllable, S2)
  S2
    1  2
1 14 15
3  9 21
>
>
> ## chisq
>
> model.30.chi <- (model.30$null.deviance - model.30$deviance)
> model.30.df <- (model.30$df.null - model.30$df.residual)
> model.30.chisq <- 1-pchisq(model.30.chi, model.30.df)
> model.30.chi
[1] 0.1780249
> model.30.chisq
[1] 0.6730761
> model.30.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.30$coefficients)
      (Intercept) z.Intensity_Q2Q3
      1.1800236      0.8646441
> ##### CI #####
> exp(confint(model.30))
Waiting for profiling to be done...
      2.5 %      97.5 %
(Intercept)  0.5305152  2.669911
z.Intensity_Q2Q3 0.4320632 1.703760
>
>
>
> ##### Across focus comparisons
#####
>
> ## Syllable 1
```

```

>
> ## Focus v Pre F ##
>
> ## Model 31 - F0
>
>
>
>
> s1.fvpf <- rbind(k.f.s1, k.pf.s1)
> foc.fac <- factor(s1.fvpf$Focus)
> s1.fvpf <- cbind(s1.fvpf, foc.fac)
>
> model.31 <- glm(foc.fac ~ z.log.F0_Q2Q3, data=s1.fvpf, family="binomial")
> summary(model.31)

```

Call:

```
glm(formula = foc.fac ~ z.log.F0_Q2Q3, family = "binomial", data = s1.fvpf)
```

Deviance Residuals:

Min	1Q	Median	3Q	Max
-1.7106	-0.8003	-0.3618	0.7873	1.8501

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)	
(Intercept)	1.7142	0.6014	2.85	0.004365	**
z.log.F0_Q2Q3	3.6781	1.0303	3.57	0.000357	***

 Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 81.774 on 58 degrees of freedom
 Residual deviance: 62.860 on 57 degrees of freedom
 AIC: 66.86

Number of Fisher Scoring iterations: 4

```

> ## classification tables
>
>
>
> model.31.pred <- predict(model.31, type="response")
> PreF <- ifelse(model.31.pred > .5, 0, 1)
> s1.fvpf.1 <- s1.fvpf %>% drop_na(z.log.F0_Q2Q3)
> table(s1.fvpf.1$Focus, PreF)
      PreF
Focus    0  1
  7      23
 20      9

>
> ## chisq
>
> model.31.chi <- (model.31$null.deviance - model.31$deviance)
> model.31.df <- (model.31$df.null - model.31$df.residual)
> model.31.chisq <- 1-pchisq(model.31.chi, model.31.df)
> model.31.chi

```

```

[1] 18.91479
> model.31.chisq
[1] 1.36689e-05
> model.31.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.31$coefficients)
      (Intercept)  z.log.F0_Q2Q3
      5.552359      39.571296
> ##### CI #####
> exp(confint(model.31))
Waiting for profiling to be done...
              2.5 %      97.5 %
(Intercept)  1.916195  20.95063
z.log.F0_Q2Q3 6.351452 377.86423
>
>
> ## Model 32 - F0 range
>
> model.32 <- glm(foc.fac ~ z.F0range_Max_minus_Min, data=s1.fvpf,
family="binomial")
> summary(model.32)

Call:
glm(formula = foc.fac ~ z.F0range_Max_minus_Min, family = "binomial",
    data = s1.fvpf)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.5502  -1.0491  -0.8547   1.1302   1.5444

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)    0.3951    0.3526   1.121  0.2625
z.F0range_Max_minus_Min  1.2193    0.5800   2.102  0.0355 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 81.774  on 58  degrees of freedom
Residual deviance: 76.010  on 57  degrees of freedom
AIC: 80.01

Number of Fisher Scoring iterations: 4

>
> ## classification tables
>
> model.32.pred <- predict(model.32, type="response")
> PreF <- ifelse(model.32.pred > .5, 1, 0)
> s1.fvpf.1 <- s1.fvpf %>% drop_na(z.F0range_Max_minus_Min)
> table(s1.fvpf.1$Focus, PreF)
      PreF

```

```

      0  1
Focus 21  9
PreF  12 17
>
>
> ## chisq
>
> model.32.chi <- (model.32$null.deviance - model.32$deviance)
> model.32.df <- (model.32$df.null - model.32$df.residual)
> model.32.chisq <- 1-pchisq(model.32.chi, model.32.df)
> model.32.chi
[1] 5.764381
> model.32.chisq
[1] 0.01635424
> model.32.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.32$coefficients)
      (Intercept)  z.F0range_Max_minus_Min
      1.484511      3.384975
> ##### CI #####
> exp(confint(model.32))
Waiting for profiling to be done...
      2.5 %      97.5 %
(Intercept)      0.7709449  3.114746
z.F0range_Max_minus_Min 1.2200206 11.648656
>
>
>
> ## Model 33 - F0 change
>
> model.33 <- glm(foc.fac ~ z.F0change_Q4_minusQ1, data=s1.fvpf,
family="binomial")
> summary(model.33)

Call:
glm(formula = foc.fac ~ z.F0change_Q4_minusQ1, family = "binomial",
    data = s1.fvpf)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.3162  -1.1474  -0.9311   1.1843   1.6992

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)      0.2720     0.3650   0.745   0.456
z.F0change_Q4_minusQ1  0.6211     0.4981   1.247   0.212

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 79.001  on 56  degrees of freedom
Residual deviance: 77.341  on 55  degrees of freedom
(2 observations deleted due to missingness)
AIC: 81.341

```

Number of Fisher Scoring iterations: 4

```
>
> ## classification tables
>
> model.33.pred <- predict(model.33, type="response")
> S2 <- ifelse(model.33.pred > .5, 1, 0)
> s1.fvpf.1 <- s1.fvpf %>% drop_na(z.F0change_Q4_minusQ1)
> table(s1.fvpf.1$Focus, S2)
      S2
Focus  0  1
PreF   18 11
      16 12
>
>
> ## chisq
>
> model.33.chi <- (model.33$null.deviance - model.33$deviance)
> model.33.df <- (model.33$df.null - model.33$df.residual)
> model.33.chisq <- 1-pchisq(model.33.chi, model.33.df)
> model.33.chi
[1] 1.659929
> model.33.chisq
[1] 0.1976129
> model.33.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.33$coefficients)
      (Intercept) z.F0change_Q4_minusQ1
      1.312598      1.860941
> ##### CI #####
> exp(confint(model.33))
Waiting for profiling to be done...
      2.5 %    97.5 %
(Intercept)    0.6517263 2.791872
z.F0change_Q4_minusQ1 0.7292588 5.372312
> table(s1.fvpf.1$Focus, PreF)
Error in table(s1.fvpf.1$Focus, PreF) :
  all arguments must have the same length
>
> ## Model 34 - ED_Q2Q3
>
> model.34 <- glm(foc.fac ~ ED_Q2Q3, data=s1.fvpf, family="binomial")
> summary(model.34)
```

Call:

```
glm(formula = foc.fac ~ ED_Q2Q3, family = "binomial", data = s1.fvpf)
```

Deviance Residuals:

Min	1Q	Median	3Q	Max
-1.6457	-1.0196	-0.4548	1.0537	1.8786

Coefficients:


```

              Estimate Std. Error z value Pr(>|z|)
(Intercept)  -3.2540      1.1795  -2.759  0.00580 **
ED_Q2Q3       2.5954      0.9361   2.773  0.00556 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 81.774  on 58  degrees of freedom
Residual deviance: 70.992  on 57  degrees of freedom
AIC: 74.992

Number of Fisher Scoring iterations: 4

>
> ## classification tables
>
> model.34.pred <- predict(model.34, type="response")
> PreF <- ifelse(model.34.pred > .5, 1, 0)
> s1.fvpf.1 <- s1.fvpf %>% drop_na(ED_Q2Q3)
> > table(s1.fvpf.1$Focus, PreF)
      PreF
      0   1
Focus 22   8
PreF  13  16
>
>
> ## chisq
>
> model.34.chi <- (model.34$null.deviance - model.34$deviance)
> model.34.df <- (model.34$df.null - model.34$df.residual)
> model.34.chisq <- 1-pchisq(model.34.chi, model.34.df)
> model.34.chi
[1] 10.78237
> model.34.chisq
[1] 0.001024713
> model.34.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.34$coefficients)
(Intercept)      ED_Q2Q3
 0.03861892 13.40179650
> ##### CI #####
> exp(confint(model.34))
Waiting for profiling to be done...
              2.5 %          97.5 %
(Intercept) 0.002904084  0.3148012
ED_Q2Q3      2.594513173 106.9153347
> mean(model.34$coefficients)
[1] -0.3293121
> mean(model.34)
[1] NA
Warning message:
In mean.default(model.34) :

```

```

    argument is not numeric or logical: returning NA
>
>
> ## Model 35 - Duration
>
> model.35 <- glm(foc.fac ~ z.Duration, data=s1.fvpf, family="binomial")
> summary(model.35)

Call:
glm(formula = foc.fac ~ z.Duration, family = "binomial", data = s1.fvpf)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.317  -1.157  -1.005   1.174   1.378

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  -0.1145     0.2869  -0.399   0.690
z.Duration     0.2069     0.3019   0.685   0.493

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 81.774  on 58  degrees of freedom
Residual deviance: 81.300  on 57  degrees of freedom
AIC: 85.3

Number of Fisher Scoring iterations: 3

>
> ## classification tables
>
> model.35.pred <- predict(model.35, type="response")
> PreF <- ifelse(model.35.pred > .5, 1, 0)
> s1.fvpf.1 <- s1.fvpf %>% drop_na(z.Duration)
> table(s1.fvpf.1$Focus, PreF)
      PreF
      0  1
Focus 19 11
PreF   14 15

>
>
> ## chisq
>
> model.35.chi <- (model.35$null.deviance - model.35$deviance)
> model.35.df <- (model.35$df.null - model.35$df.residual)
> model.35.chisq <- 1-pchisq(model.35.chi, model.35.df)
> model.35.chi
[1] 0.4744959
> model.35.chisq
[1] 0.4909261
> model.35.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.35$coefficients)

```

```

(Intercept)  z.Duration
  0.8917729   1.2298849
> ##### CI #####
> exp(confint(model.35))
Waiting for profiling to be done...
              2.5 %    97.5 %
(Intercept)  0.5024855 1.562861
z.Duration   0.6828206 2.266061
>
>
> ## Model 36 - Intensity_Q2Q3
>
> model.36 <- glm(foc.fac ~ z.Intensity_Q2Q3, data=s1.fvpf,
family="binomial")
> summary(model.36)

Call:
glm(formula = foc.fac ~ z.Intensity_Q2Q3, family = "binomial",
    data = s1.fvpf)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.9965  -0.7875  -0.2154   0.6611   1.8655

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)   -0.7543     0.3738  -2.018  0.043575 *
z.Intensity_Q2Q3  2.0170     0.5192   3.885  0.000102 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 81.774  on 58  degrees of freedom
Residual deviance: 55.003  on 57  degrees of freedom
AIC: 59.003

Number of Fisher Scoring iterations: 5

>
> ## classification tables
>
> model.36.pred <- predict(model.36, type="response")
> PreF <- ifelse(model.36.pred > .5, 1, 0)
> s1.fvpf.1 <- s1.fvpf %>% drop_na(z.Intensity_Q2Q3)
> table(s1.fvpf.1$Focus, PreF)
      PreF
      0    1
Focus 24    6
PreF   8   21
>
>
> ## chisq
>
> model.36.chi <- (model.36$null.deviance - model.36$deviance)
> model.36.df <- (model.36$df.null - model.36$df.residual)
> model.36.chisq <- 1-pchisq(model.36.chi, model.36.df)

```

```

> model.36.chi
[1] 26.77115
> model.36.chisq
[1] 2.290314e-07
> model.36.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.36$coefficients)
      (Intercept)  z.Intensity_Q2Q3
      0.470331      7.515973
> ##### CI #####
> exp(confint(model.36))
Waiting for profiling to be done...
              2.5 %      97.5 %
(Intercept)    0.2127918  0.9394119
z.Intensity_Q2Q3 3.0684064 24.3337802
>
>
> ##### F v PoF #####
>
> s1.fvpof <- rbind(k.f.s1, k.pof.s1)
> foc.fac <- factor(s1.fvpof$Focus)
> s1.fvpof <- cbind(s1.fvpof, foc.fac)
>
>
> ## Model 37 - F0
>
> model.37 <- glm(foc.fac ~ z.log.F0_Q2Q3, data=s1.fvpof, family="binomial")
> summary(model.37)

Call:
glm(formula = foc.fac ~ z.log.F0_Q2Q3, family = "binomial", data = s1.fvpof)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.310  -1.097  -1.013   1.213   1.343

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)    0.4245     0.6772   0.627   0.531
z.log.F0_Q2Q3  0.8459     0.9935   0.851   0.395

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 78.861  on 56  degrees of freedom
Residual deviance: 78.124  on 55  degrees of freedom
AIC: 82.124

Number of Fisher Scoring iterations: 4

>
> ## classification tables
>
> model.37.pred <- predict(model.37, type="response")

```

```

> PostF <- ifelse(model.37.pred > .5, 0, 1)
> s1.fvpof.1 <- s1.fvpof %>% drop_na(z.log.F0_Q2Q3)
> table(s1.fvpof.1$Focus, PostF)
      PostF
      0    1
Focus  8 22
PostF 10 17
>
>
> ## chisq
>
> model.37.chi <- (model.37$null.deviance - model.37$deviance)
> model.37.df <- (model.37$df.null - model.37$df.residual)
> model.37.chisq <- 1-pchisq(model.37.chi, model.37.df)
> model.37.chi
[1] 0.7369938
> model.37.chisq
[1] 0.3906256
> model.37.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.37$coefficients)
      (Intercept) z.log.F0_Q2Q3
      1.528834      2.330007
> ##### CI #####
> exp(confint(model.37))
Waiting for profiling to be done...
              2.5 %      97.5 %
(Intercept)  0.4083077  6.124379
z.log.F0_Q2Q3 0.3385960 17.706837
>
>
> ## Model 38 - F0 range
>
> model.38 <- glm(foc.fac ~ z.F0range_Max_minus_Min, data=s1.fvpof,
family="binomial")
> summary(model.38)

Call:
glm(formula = foc.fac ~ z.F0range_Max_minus_Min, family = "binomial",
    data = s1.fvpof)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.201  -1.127  -1.096   1.225   1.267

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)   -0.01398    0.43653  -0.032   0.974
z.F0range_Max_minus_Min  0.18695    0.70967   0.263   0.792

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 78.861 on 56 degrees of freedom

```

Residual deviance: 78.791 on 55 degrees of freedom
AIC: 82.791

Number of Fisher Scoring iterations: 3

```
>
> ## classification tables
>
> model.38.pred <- predict(model.38, type="response")
> PostF <- ifelse(model.38.pred > .5, 1, 0)
> s1.fvpof.1 <- s1.fvpof %>% drop_na(z.F0range_Max_minus_Min)
> table(s1.fvpof.1$Focus, PostF)
      PostF
      0    1
Focus 26   4
PostF 24   3
>
>
> ## chisq
>
> model.38.chi <- (model.38$null.deviance - model.38$deviance)
> model.38.df <- (model.38$df.null - model.38$df.residual)
> model.38.chisq <- 1-pchisq(model.38.chi, model.38.df)
> model.38.chi
[1] 0.069448
> model.38.chisq
[1] 0.7921422
> model.38.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.38$coefficients)
      (Intercept) z.F0range_Max_minus_Min
      0.9861155      1.2055668
> ##### CI #####
> exp(confint(model.38))
Waiting for profiling to be done...
      2.5 %    97.5 %
(Intercept)    0.4124988 2.363448
z.F0range_Max_minus_Min 0.2954941 4.985753
>
>
> ## Model 39 - F0 change
>
> model.39 <- glm(foc.fac ~ z.F0change_Q4_minusQ1, data=s1.fvpof,
family="binomial")
> summary(model.39)

Call:
glm(formula = foc.fac ~ z.F0change_Q4_minusQ1, family = "binomial",
    data = s1.fvpof)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.4945  -1.1079  -0.7465   1.1936   1.4912
```

```

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)      0.6067      0.4865   1.247   0.2123
z.F0change_Q4_minusQ1  1.4511      0.8010   1.812   0.0701 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 76.082  on 54  degrees of freedom
Residual deviance: 72.272  on 53  degrees of freedom
(2 observations deleted due to missingness)
AIC: 76.272

Number of Fisher Scoring iterations: 4

>
> ## classification tables
>
> model.39.pred <- predict(model.39, type="response")
> PostF <- ifelse(model.39.pred > .5, 1, 0)
> s1.fvpof.1 <- s1.fvpof %>% drop_na(z.F0change_Q4_minusQ1)
> table(s1.fvpof.1$Focus, PostF)
      PostF
      0    1
Focus 18 11
PostF 15 11
>
>
> ## chisq
>
> model.39.chi <- (model.39$null.deviance - model.39$deviance)
> model.39.df <- (model.39$df.null - model.39$df.residual)
> model.39.chisq <- 1-pchisq(model.39.chi, model.39.df)
> model.39.chi
[1] 3.810659
> model.39.chisq
[1] 0.0509274
> model.39.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.39$coefficients)
      (Intercept) z.F0change_Q4_minusQ1
      1.834382      4.267650
> ##### CI #####
> exp(confint(model.39))
Waiting for profiling to be done...
              2.5 %    97.5 %
(Intercept)      0.7448489  5.20066
z.F0change_Q4_minusQ1 0.9945202 24.66849
>
>
> ## Model 40 - ED_Q2Q3

```

```

>
> model.40 <- glm(foc.fac ~ ED_Q2Q3, data=s1.fvpof, family="binomial")
> summary(model.40)

Call:
glm(formula = foc.fac ~ ED_Q2Q3, family = "binomial", data = s1.fvpof)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.292  -1.128  -1.046   1.202   1.467

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)   0.4850     1.0569   0.459   0.646
ED_Q2Q3      -0.5496     0.9537  -0.576   0.564

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 78.861  on 56  degrees of freedom
Residual deviance: 78.524  on 55  degrees of freedom
AIC: 82.524

Number of Fisher Scoring iterations: 4

>
> ## classification tables
>
> model.40.pred <- predict(model.40, type="response")
> PostF <- ifelse(model.40.pred > .5, 1, 0)
> s1.fvpof.1 <- s1.fvpof %>% drop_na(ED_Q2Q3)
> table(s1.fvpof.1$Focus, PostF)
      PostF
      0    1
Focus 25    5
PostF 21    6

>
>
> ## chisq
>
> model.40.chi <- (model.40$null.deviance - model.40$deviance)
> model.40.df <- (model.40$df.null - model.40$df.residual)
> model.40.chisq <- 1-pchisq(model.40.chi, model.40.df)
> model.40.chi
[1] 0.3372498
> model.40.chisq
[1] 0.561421
> model.40.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.40$coefficients)
(Intercept)      ED_Q2Q3
  1.6241199   0.5771888
> ##### CI #####
> exp(confint(model.40))

```



```

Waiting for profiling to be done...
              2.5 %      97.5 %
(Intercept) 0.20607763 14.224341
ED_Q2Q3     0.08019353  3.692456
>
>
> ## Model 41 - Duration
>
> model.41 <- glm(foc.fac ~ z.Duration, data=s1.fvpof, family="binomial")
> summary(model.41)

Call:
glm(formula = foc.fac ~ z.Duration, family = "binomial", data = s1.fvpof)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.3338  -1.1231  -0.9507   1.1922   1.4039

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept) -0.04987     0.27359  -0.182    0.855
z.Duration  -0.27793     0.29942  -0.928    0.353

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 78.861  on 56  degrees of freedom
Residual deviance: 77.981  on 55  degrees of freedom
AIC: 81.981

Number of Fisher Scoring iterations: 4

>
> ## classification tables
>
> model.41.pred <- predict(model.41, type="response")
> PostF <- ifelse(model.41.pred > .5, 1, 0)
> s1.fvpof.1 <- s1.fvpof %>% drop_na(z.Duration)
> table(s1.fvpof.1$Focus, PostF)
      PostF
      0    1
Focus 22    8
PostF 15   12
>
>
> ## chisq
>
> model.41.chi <- (model.41$null.deviance - model.41$deviance)
> model.41.df <- (model.41$df.null - model.41$df.residual)
> model.41.chisq <- 1-pchisq(model.41.chi, model.41.df)
> model.41.chi
[1] 0.8795231
> model.41.chisq
[1] 0.3483323
> model.41.df
[1] 1
>
>

```

```

> ## ORs
> ##### Odds ratio #####
> exp(model.41$coefficients)
(Intercept)   z.Duration
  0.9513540    0.7573497
> ##### CI #####
> exp(confint(model.41))
Waiting for profiling to be done...
              2.5 %    97.5 %
(Intercept)  0.5550942 1.634356
z.Duration   0.4105969 1.351185
>
>
> ## Model 42 - Intensity_Q2Q3
>
> model.42 <- glm(foc.fac ~ z.Intensity_Q2Q3, data=s1.fvpof,
family="binomial")
> summary(model.42)

Call:
glm(formula = foc.fac ~ z.Intensity_Q2Q3, family = "binomial",
    data = s1.fvpof)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.3065  -1.1405  -0.9799   1.2252   1.3541

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)    -0.0743    0.2696  -0.276   0.783
z.Intensity_Q2Q3  0.2891    0.3835   0.754   0.451

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 78.861  on 56  degrees of freedom
Residual deviance: 78.286  on 55  degrees of freedom
AIC: 82.286

Number of Fisher Scoring iterations: 4

>
> ## classification tables
>
> model.42.pred <- predict(model.42, type="response")
> PostF <- ifelse(model.42.pred > .5, 1, 0)
> s1.fvpof.1 <- s1.fvpof %>% drop_na(z.Intensity_Q2Q3)
> table(s1.fvpof.1$Focus, PostF)
      PostF
      0    1
Focus 21    9
PostF 16   11
>
>
> ## chisq
>
> model.42.chi <- (model.42$null.deviance - model.42$deviance)
> model.42.df <- (model.42$df.null - model.42$df.residual)

```

```

> model.42.chisq <- 1-pchisq(model.42.chi, model.42.df)
> model.42.chi
[1] 0.5745977
> model.42.chisq
[1] 0.4484377
> model.42.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.42$coefficients)
      (Intercept)  z.Intensity_Q2Q3
      0.9283946      1.3352479
> ##### CI #####
> exp(confint(model.42))
Waiting for profiling to be done...
              2.5 %    97.5 %
(Intercept)    0.5452908 1.579582
z.Intensity_Q2Q3 0.6326575 2.898291
>
>
> ##### Syllable 2 #####
>
> s2.fvpf <- rbind(k.f.s2, k.pf.s2)
> foc.fac <- factor(s2.fvpf$Focus)
> s2.fvpf <- cbind(s2.fvpf, foc.fac)
>
> ## F v PF ##
>
> ## Model 43 - F0
>
> model.43 <- glm(foc.fac ~ z.log.F0_Q2Q3, data=s2.fvpf, family="binomial")
> summary(model.43)

```

Call:

```
glm(formula = foc.fac ~ z.log.F0_Q2Q3, family = "binomial", data = s2.fvpf)
```

Deviance Residuals:

Min	1Q	Median	3Q	Max
-3.7096	-0.9533	-0.6042	1.0102	1.4709

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-0.0734	0.3229	-0.227	0.8202
z.log.F0_Q2Q3	-1.3504	0.6250	-2.161	0.0307 *

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 64.623 on 46 degrees of freedom
 Residual deviance: 57.714 on 45 degrees of freedom
 (11 observations deleted due to missingness)
 AIC: 61.714

Number of Fisher Scoring iterations: 5

```

>
> ## classification tables
>
> model.43.pred <- predict(model.43, type="response")
> PreF <- ifelse(model.43.pred > .5, 0, 1)
> s2.fvpf.1 <- s2.fvpf %>% drop_na(z.log.F0_Q2Q3)
> table(s2.fvpf.1$Focus, PreF)
      PreF
Focus    0  1
  2 24
PreF 15  6
>
>
> ## chisq
>
> model.43.chi <- (model.43$null.deviance - model.43$deviance)
> model.43.df <- (model.43$df.null - model.43$df.residual)
> model.43.chisq <- 1-pchisq(model.43.chi, model.43.df)
> model.43.chi
[1] 6.909163
> model.43.chisq
[1] 0.008575511
> model.43.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.43$coefficients)
(Intercept) z.log.F0_Q2Q3
  0.9292253   0.2591317
> ##### CI #####
> exp(confint(model.43))
Waiting for profiling to be done...
              2.5 %   97.5 %
(Intercept)  0.49310626 1.771645
z.log.F0_Q2Q3 0.06765806 0.762909
>
>
> ## Model 44 - F0 range
>
> model.44 <- glm(foc.fac ~ z.F0range_Max_minus_Min, data=s2.fvpf,
family="binomial")
> summary(model.44)

Call:
glm(formula = foc.fac ~ z.F0range_Max_minus_Min, family = "binomial",
    data = s2.fvpf)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.52864  -0.19166  -0.00079   0.39060   1.73400

Coefficients:
(Intercept)              Estimate Std. Error z value Pr(>|z|)
      -0.5716              0.5900  -0.969 0.332645

```

```

z.F0range_Max_minus_Min  -3.4353      0.9996  -3.437 0.000589 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 67.745 on 48 degrees of freedom
Residual deviance: 26.550 on 47 degrees of freedom
(9 observations deleted due to missingness)
AIC: 30.55

Number of Fisher Scoring iterations: 7

>
> ## classification tables
>
> model.44.pred <- predict(model.44, type="response")
> PreF <- ifelse(model.44.pred > .5, 1, 0)
> s2.fvpf.1 <- s2.fvpf %>% drop_na(z.F0range_Max_minus_Min)
> table(s2.fvpf.1$Focus, PreF)
      PreF
      0  1
Focus 23  3
PreF   2 21
>
>
> ## chisq
>
> model.44.chi <- (model.44$null.deviance - model.44$deviance)
> model.44.df <- (model.44$df.null - model.44$df.residual)
> model.44.chisq <- 1-pchisq(model.44.chi, model.44.df)
> model.44.chi
[1] 41.19439
> model.44.chisq
[1] 1.378174e-10
> model.44.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.44$coefficients)
      (Intercept) z.F0range_Max_minus_Min
      0.56463929      0.03221514
> ##### CI #####
> exp(confint(model.44))
Waiting for profiling to be done...
      2.5 %      97.5 %
(Intercept)      0.145701153 1.6153362
z.F0range_Max_minus_Min 0.002724646 0.1545919
Warning messages:
1: glm.fit: fitted probabilities numerically 0 or 1 occurred
2: glm.fit: fitted probabilities numerically 0 or 1 occurred
3: glm.fit: fitted probabilities numerically 0 or 1 occurred
>
>
> ## Model 45 - F0 change

```

```

>
> model.45 <- glm(foc.fac ~ z.F0change_Q4_minusQ1, data=s2.fvpf,
family="binomial")
> summary(model.45)

Call:
glm(formula = foc.fac ~ z.F0change_Q4_minusQ1, family = "binomial",
    data = s2.fvpf)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.99671  -0.07684  -0.01273   0.17148   1.29670

Coefficients:
                Estimate Std. Error z value Pr(>|z|)
(Intercept)      -1.320      1.105  -1.194   0.2325
z.F0change_Q4_minusQ1 -5.976      2.782  -2.148   0.0317 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 45.033  on 36  degrees of freedom
Residual deviance: 12.486  on 35  degrees of freedom
(21 observations deleted due to missingness)
AIC: 16.486

Number of Fisher Scoring iterations: 9

>
> ## classification tables
>
> model.45.pred <- predict(model.45, type="response")
> PreF <- ifelse(model.45.pred > .5, 1, 0)
> s2.fvpf.1 <- s2.fvpf %>% drop_na(z.F0change_Q4_minusQ1)
> table(s2.fvpf.1$Focus, PreF)
      PreF
Focus 0  1
PreF  1 10

>
>
> ## chisq
>
> model.45.chi <- (model.45$null.deviance - model.45$deviance)
> model.45.df <- (model.45$df.null - model.45$df.residual)
> model.45.chisq <- 1-pchisq(model.45.chi, model.45.df)
> model.45.chi
[1] 32.54673
> model.45.chisq
[1] 1.16361e-08
> model.45.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####

```

```

> exp(model.45$coefficients)
      (Intercept) z.F0change_Q4_minusQ1
      0.267158847      0.002538486
> ##### CI #####
> exp(confint(model.45))
Waiting for profiling to be done...
      2.5 %      97.5 %
(Intercept)      1.379864e-02 1.42017091
z.F0change_Q4_minusQ1 3.586789e-07 0.08170906
There were 16 warnings (use warnings() to see them)
>
>
> ## Model 46 - ED_Q2Q3
>
> model.46 <- glm(foc.fac ~ ED_Q2Q3, data=s2.fvpf, family="binomial")
> summary(model.46)

Call:
glm(formula = foc.fac ~ ED_Q2Q3, family = "binomial", data = s2.fvpf)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.2671  -0.7356  -0.1009   0.8606   1.7590

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)  -4.9532      1.3986  -3.541 0.000398 ***
ED_Q2Q3       3.4537       0.9623   3.589 0.000332 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 80.405  on 57  degrees of freedom
Residual deviance: 59.437  on 56  degrees of freedom
AIC: 63.437

Number of Fisher Scoring iterations: 4

>
> ## classification tables
>
> model.46.pred <- predict(model.46, type="response")
> PreF <- ifelse(model.46.pred > .5, 1, 0)
> s2.fvpf.1 <- s2.fvpf %>% drop_na(ED_Q2Q3)
> table(s2.fvpf.1$Focus, PreF)
      PreF
      0  1
Focus 23  6
PreF   9 20
>
>
> ## chisq
>
> model.46.chi <- (model.46$null.deviance - model.46$deviance)
> model.46.df <- (model.46$df.null - model.46$df.residual)
> model.46.chisq <- 1-pchisq(model.46.chi, model.46.df)

```

```

> model.46.chi
[1] 20.96851
> model.46.chisq
[1] 4.668947e-06
> model.46.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.46$coefficients)
      (Intercept)      ED_Q2Q3
      0.007060888  31.616783525
> ##### CI #####
> exp(confint(model.46))
Waiting for profiling to be done...
              2.5 %      97.5 %
(Intercept) 0.0003153665  0.08207969
ED_Q2Q3      5.9188964704 270.59170306
>
>
> ## Model 47 - Duration
>
> model.47 <- glm(foc.fac ~ z.Duration, data=s2.fvpf, family="binomial")
> summary(model.47)

Call:
glm(formula = foc.fac ~ z.Duration, family = "binomial", data = s2.fvpf)

Deviance Residuals:
      Min       1Q   Median       3Q      Max
-1.20759  -1.17821   0.01337   1.17350   1.23361

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept) -0.008205   0.268780  -0.031   0.976
z.Duration   -0.035987   0.249868  -0.144   0.885

(Dispersion parameter for binomial family taken to be 1)

      Null deviance: 80.405  on 57  degrees of freedom
Residual deviance: 80.384  on 56  degrees of freedom
AIC: 84.384

Number of Fisher Scoring iterations: 3

>
> ## classification tables
>
> model.47.pred <- predict(model.47, type="response")
> PreF <- ifelse(model.47.pred > .5, 1, 0)
> s2.fvpf.1 <- s2.fvpf %>% drop_na(z.Duration)
> table(s2.fvpf.1$Focus, PreF)
      PreF
      0  1
Focus 14 15
PreF   13 16

```



```

>
>
> ## chisq
>
> model.47.chi <- (model.47$null.deviance - model.47$deviance)
> model.47.df <- (model.47$df.null - model.47$df.residual)
> model.47.chisq <- 1-pchisq(model.47.chi, model.47.df)
> model.47.chi
[1] 0.02076104
> model.47.chisq
[1] 0.8854318
> model.47.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.47$coefficients)
(Intercept)    z.Duration
    0.9918285    0.9646524
> ##### CI #####
> exp(confint(model.47))
Waiting for profiling to be done...
              2.5 %    97.5 %
(Intercept) 0.5831623 1.684524
z.Duration   0.5819261 1.587817
>
>
> ## Model 48 - Intensity_Q2Q3
>
> model.48 <- glm(foc.fac ~ z.Intensity_Q2Q3, data=s2.fvpf,
family="binomial")
> summary(model.48)

Call:
glm(formula = foc.fac ~ z.Intensity_Q2Q3, family = "binomial",
    data = s2.fvpf)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.6755  -0.6898  -0.0972   0.8160   1.3846

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)    -1.2866     0.4586  -2.806 0.005020 **
z.Intensity_Q2Q3 -1.9892     0.5428  -3.665 0.000248 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 80.405  on 57  degrees of freedom
Residual deviance: 57.966  on 56  degrees of freedom
AIC: 61.966

Number of Fisher Scoring iterations: 5

```

```

>
> ## classification tables
>
> model.48.pred <- predict(model.48, type="response")
> PreF <- ifelse(model.48.pred > .5, 1, 0)
> s2.fvpf.1 <- s2.fvpf %>% drop_na(z.Intensity_Q2Q3)
> table(s2.fvpf.1$Focus, PreF)
      PreF
      0  1
Focus 24  5
PreF   7 22
>
>
> ## chisq
>
> model.48.chi <- (model.48$null.deviance - model.48$deviance)
> model.48.df <- (model.48$df.null - model.48$df.residual)
> model.48.chisq <- 1-pchisq(model.48.chi, model.48.df)
> model.48.chi
[1] 22.43865
> model.48.chisq
[1] 2.169635e-06
> model.48.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.48$coefficients)
      (Intercept)  z.Intensity_Q2Q3
      0.2762059      0.1367992
> ##### CI #####
> exp(confint(model.48))
Waiting for profiling to be done...
              2.5 %      97.5 %
(Intercept)    0.10214080 0.6331685
z.Intensity_Q2Q3 0.04005416 0.3498666
>
>
> ## Focus v PostF ##
>
>
> s2.fvpof <- cbind(s2.fvpof, foc.fac)
>
> ## Model 49 - F0
>
> model.49 <- glm(foc.fac ~ z.log.F0_Q2Q3, data=s2.fvpof, family="binomial")
> summary(model.49)

Call:
glm(formula = foc.fac ~ z.log.F0_Q2Q3, family = "binomial", data = s2.fvpof)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.5570  -1.1616  -0.1746   1.1784   1.2390

Coefficients:

```

```

              Estimate Std. Error z value Pr(>|z|)
(Intercept)    0.03495    0.28499   0.123   0.902
z.log.F0_Q2Q3 -0.16003    0.23855  -0.671   0.502

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 72.087 on 51 degrees of freedom
Residual deviance: 71.587 on 50 degrees of freedom
(4 observations deleted due to missingness)
AIC: 75.587

Number of Fisher Scoring iterations: 4

>
> ## classification tables
>
> model.49.pred <- predict(model.49, type="response")
> PostF <- ifelse(model.49.pred > .5, 0, 1)
> s2.fvpof.1 <- s2.fvpof %>% drop_na(z.log.F0_Q2Q3)
> table(s2.fvpof.1$Focus, PostF)
      PostF
      0    1
Focus  7 19
PostF 12 14
>
>
> ## chisq
>
> model.49.chi <- (model.49$null.deviance - model.49$deviance)
> model.49.df <- (model.49$df.null - model.49$df.residual)
> model.49.chisq <- 1-pchisq(model.49.chi, model.49.df)
> model.49.chi
[1] 0.5007149
> model.49.chisq
[1] 0.4791861
> model.49.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.49$coefficients)
(Intercept) z.log.F0_Q2Q3
      1.0355697      0.8521212
> ##### CI #####
> exp(confint(model.49))
Waiting for profiling to be done...
              2.5 %    97.5 %
(Intercept)    0.5929426 1.834803
z.log.F0_Q2Q3 0.4548231 1.321820
>
>
> ## Model 50 - F0 range
>
> model.50 <- glm(foc.fac ~ z.F0range_Max_minus_Min, data=s2.fvpof,
family="binomial")
> summary(model.50)

```

```

Call:
glm(formula = foc.fac ~ z.F0range_Max_minus_Min, family = "binomial",
    data = s2.fvpof)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.5464  -1.1580   0.1438   1.1365   1.3910

Coefficients:
                Estimate Std. Error z value Pr(>|z|)
(Intercept)         0.3879     0.3728   1.040   0.298
z.F0range_Max_minus_Min -0.4125     0.2656  -1.553   0.120

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 72.087  on 51  degrees of freedom
Residual deviance: 69.387  on 50  degrees of freedom
(4 observations deleted due to missingness)
AIC: 73.387

Number of Fisher Scoring iterations: 4

>
> ## classification tables
>
> model.50.pred <- predict(model.50, type="response")
> PostF <- ifelse(model.50.pred > .5, 1, 0)
> s2.fvpof.1 <- s2.fvpof %>% drop_na(z.F0range_Max_minus_Min)
> table(s2.fvpof.1$Focus, PostF)
      PostF
      0    1
Focus 15 11
PostF 11 15
>
>
> ## chisq
>
> model.50.chi <- (model.50$null.deviance - model.50$deviance)
> model.50.df <- (model.50$df.null - model.50$df.residual)
> model.50.chisq <- 1-pchisq(model.50.chi, model.50.df)
> model.50.chi
[1] 2.700539
> model.50.chisq
[1] 0.1003143
> model.50.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.50$coefficients)
      (Intercept) z.F0range_Max_minus_Min
      1.4739407      0.6619961
> ##### CI #####
> exp(confint(model.50))
Waiting for profiling to be done...

```

```

              2.5 %    97.5 %
(Intercept)      0.7194022 3.157500
z.F0range_Max_minus_Min 0.3722587 1.079124
>
>
> ## Model 51 - F0 change
>
> model.51 <- glm(foc.fac ~ z.F0change_Q4_minusQ1, data=s2.fvpof,
family="binomial")
> summary(model.51)

Call:
glm(formula = foc.fac ~ z.F0change_Q4_minusQ1, family = "binomial",
    data = s2.fvpof)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.211  -1.087  -0.942   1.283   1.375

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)    -0.02966    0.48848  -0.061   0.952
z.F0change_Q4_minusQ1 -0.20303    0.34150  -0.595   0.552

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 62.985  on 45  degrees of freedom
Residual deviance: 62.623  on 44  degrees of freedom
(10 observations deleted due to missingness)
AIC: 66.623

Number of Fisher Scoring iterations: 4

>
> ## classification tables
>
> model.51.pred <- predict(model.51, type="response")
> PostF <- ifelse(model.51.pred > .5, 1, 0)
> s2.fvpof.1 <- s2.fvpof %>% drop_na(z.F0change_Q4_minusQ1)
> table(s2.fvpof.1$Focus, PostF)
      PostF
      0    1
Focus 23    3
PostF 20    0
>
>
> ## chisq
>
> model.51.chi <- (model.51$null.deviance - model.51$deviance)
> model.51.df <- (model.51$df.null - model.51$df.residual)
> model.51.chisq <- 1-pchisq(model.51.chi, model.51.df)
> model.51.chi
[1] 0.3617485
> model.51.chisq
[1] 0.5475368
> model.51.df
[1] 1

```

```

>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.51$coefficients)
      (Intercept)  z.F0change_Q4_minusQ1
      0.9707749      0.8162569
> ##### CI #####
> exp(confint(model.51))
Waiting for profiling to be done...
      2.5 %      97.5 %
(Intercept)      0.3691522 2.579582
z.F0change_Q4_minusQ1 0.3984260 1.575439
>
>
> ## Model 52 - ED_Q2Q3
>
> model.52 <- glm(foc.fac ~ ED_Q2Q3, data=s2.fvpof, family="binomial")
> summary(model.52)

Call:
glm(formula = foc.fac ~ ED_Q2Q3, family = "binomial", data = s2.fvpof)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.256  -1.134  -1.085   1.219   1.313

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  -0.4120     0.6983  -0.590   0.555
ED_Q2Q3       0.2756     0.5225   0.527   0.598

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 77.561  on 55  degrees of freedom
Residual deviance: 77.278  on 54  degrees of freedom
AIC: 81.278

Number of Fisher Scoring iterations: 3

>
> ## classification tables
>
> model.52.pred <- predict(model.52, type="response")
> PostF <- ifelse(model.52.pred > .5, 1, 0)
> s2.fvpof.1 <- s2.fvpof %>% drop_na(ED_Q2Q3)
> table(s2.fvpof.1$Focus, PostF)
      PostF
        0  1
Focus 23  6
PostF 21  6
>
>
> ## chisq
>
> model.52.chi <- (model.52$null.deviance - model.52$deviance)
> model.52.df <- (model.52$df.null - model.52$df.residual)

```

```

> model.52.chisq <- 1-pchisq(model.52.chi, model.52.df)
> model.52.chi
[1] 0.2829924
> model.52.chisq
[1] 0.5947466
> model.52.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.52$coefficients)
(Intercept)      ED_Q2Q3
  0.6623303    1.3172864
> ##### CI #####
> exp(confint(model.52))
Waiting for profiling to be done...
              2.5 %    97.5 %
(Intercept) 0.1571086 2.586952
ED_Q2Q3      0.4728678 3.963073
>
>
> ## Model 53 - Duration
>
> model.53 <- glm(foc.fac ~ z.Duration, data=s2.fvpof, family="binomial")
> summary(model.53)

```

Call:

```
glm(formula = foc.fac ~ z.Duration, family = "binomial", data = s2.fvpof)
```

Deviance Residuals:

Min	1Q	Median	3Q	Max
-1.3969	-1.1329	-0.9872	1.1941	1.3423

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-0.05053	0.27020	-0.187	0.852
z.Duration	0.19612	0.26417	0.742	0.458

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 77.561 on 55 degrees of freedom
 Residual deviance: 77.002 on 54 degrees of freedom
 AIC: 81.002

Number of Fisher Scoring iterations: 4

```

>
> ## classification tables
>
> model.53.pred <- predict(model.53, type="response")
> PostF <- ifelse(model.53.pred > .5, 1, 0)
> s2.fvpof.1 <- s2.fvpof %>% drop_na(z.Duration)
> table(s2.fvpof.1$Focus, PostF)
      PostF
        0  1
Focus 22  7

```

```

PostF 15 12
>
>
> ## chisq
>
> model.53.chi <- (model.53$null.deviance - model.53$deviance)
> model.53.df <- (model.53$df.null - model.53$df.residual)
> model.53.chisq <- 1-pchisq(model.53.chi, model.53.df)
> model.53.chi
[1] 0.5588679
> model.53.chisq
[1] 0.4547168
> model.53.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.53$coefficients)
(Intercept)    z.Duration
  0.9507221    1.2166739
> ##### CI #####
> exp(confint(model.53))
Waiting for profiling to be done...
              2.5 %   97.5 %
(Intercept) 0.5578855 1.619628
z.Duration   0.7278972 2.084581
>
>
> ## Model 54 - Intensity_Q2Q3
>
> model.54 <- glm(foc.fac ~ z.Intensity_Q2Q3, data=s2.fvpof,
family="binomial")
> summary(model.54)

Call:
glm(formula = foc.fac ~ z.Intensity_Q2Q3, family = "binomial",
    data = s2.fvpof)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.219  -1.140  -1.120   1.198   1.268

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)  -0.08985    0.27982  -0.321   0.748
z.Intensity_Q2Q3 -0.07654    0.34012  -0.225   0.822

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 77.561  on 55  degrees of freedom
Residual deviance: 77.510  on 54  degrees of freedom
AIC: 81.51

Number of Fisher Scoring iterations: 3
>

```



```

> ## classification tables
>
> model.54.pred <- predict(model.54, type="response")
> PostF <- ifelse(model.54.pred > .5, 1, 0)
> s2.fvpof.1 <- s2.fvpof %>% drop_na(z.Intensity_Q2Q3)
> table(s2.fvpof.1$Focus, PostF)
      PostF
      0    1
Focus 26    3
PostF 25    2
>
>
> ## chisq
>
> model.54.chi <- (model.54$null.deviance - model.54$deviance)
> model.54.df <- (model.54$df.null - model.54$df.residual)
> model.54.chisq <- 1-pchisq(model.54.chi, model.54.df)
> model.54.chi
[1] 0.05070313
> model.54.chisq
[1] 0.8218443
> model.54.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.54$coefficients)
      (Intercept) z.Intensity_Q2Q3
      0.9140665      0.9263165
> ##### CI #####
> exp(confint(model.54))
Waiting for profiling to be done...
              2.5 %    97.5 %
(Intercept)    0.5244058 1.583470
z.Intensity_Q2Q3 0.4674685 1.817622
>
>
> ##### F (S2) v PF (S3) #####
> s3.fvpf <- rbind(k.f.s2, k.pf.s3)
> foc.fac <- factor(s3.fvpf$Factor)
> s3.fvpf <- cbind(s3.fvpf, foc.fac)
Error in data.frame(..., check.names = FALSE) :
  arguments imply differing number of rows: 59, 0
> foc.fac <- factor(s3.fvpf$Focus)
> s3.fvpf <- cbind(s3.fvpf, foc.fac)
>
>
> ##### Focus (S2) v PreF (S3) #####
>
> ## Focus v PostF ##
>
> ## Model 55 - F0
>
> model.55 <- glm(foc.fac ~ z.log.F0_Q2Q3, data=s3.fvpf, family="binomial")
> summary(model.55)

```

```

Call:
glm(formula = foc.fac ~ z.log.F0_Q2Q3, family = "binomial", data = s3.fvpf)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.07984  -0.40122   0.02631   0.71503   1.68302

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)    -4.229      1.306   -3.239 0.001198 **
z.log.F0_Q2Q3    4.925      1.403    3.510 0.000447 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 76.082  on 54  degrees of freedom
Residual deviance: 42.586  on 53  degrees of freedom
(4 observations deleted due to missingness)
AIC: 46.586

Number of Fisher Scoring iterations: 7

>
> ## classification tables
>
> model.55.pred <- predict(model.55, type="response")
> PreF <- ifelse(model.55.pred > .5, 0, 1)
> s3.fvpf.1 <- s3.fvpf %>% drop_na(z.log.F0_Q2Q3)
> table(s3.fvpf.1$Focus, PreF)
      PreF
      0   1
Focus  7 19
PreF   25  4
>
>
> ## chisq
>
> model.55.chi <- (model.55$null.deviance - model.55$deviance)
> model.55.df <- (model.55$df.null - model.55$df.residual)
> model.55.chisq <- 1-pchisq(model.55.chi, model.55.df)
> model.55.chi
[1] 33.49647
> model.55.chisq
[1] 7.139334e-09
> model.55.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.55$coefficients)
      (Intercept) z.log.F0_Q2Q3
      0.01456519 137.68179910
> ##### CI #####
> exp(confint(model.55))
Waiting for profiling to be done...

```

```

                2.5 %          97.5 %
(Intercept)    6.485091e-04    0.1223251
z.log.F0_Q2Q3  1.388706e+01 3829.4861883
There were 14 warnings (use warnings() to see them)
>
>
> ## Model 56 - F0 range
>
> model.56 <- glm(foc.fac ~ z.F0range_Max_minus_Min, data=s3.fvpf,
family="binomial")
> summary(model.56)

Call:
glm(formula = foc.fac ~ z.F0range_Max_minus_Min, family = "binomial",
    data = s3.fvpf)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.1588  -0.8460   0.5352   0.8218   2.1406

Coefficients:
                Estimate Std. Error z value Pr(>|z|)
(Intercept)          0.7106     0.3504   2.028  0.04254 *
z.F0range_Max_minus_Min -1.3985     0.4374  -3.197  0.00139 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 76.082  on 54  degrees of freedom
Residual deviance: 57.821  on 53  degrees of freedom
(4 observations deleted due to missingness)
AIC: 61.821

Number of Fisher Scoring iterations: 5

>
> ## classification tables
>
> model.56.pred <- predict(model.56, type="response")
> PreF <- ifelse(model.56.pred > .5, 1, 0)
> s3.fvpf.1 <- s3.fvpf %>% drop_na(z.F0range_Max_minus_Min)
> table(s3.fvpf.1$Focus, PreF)
      PreF
      0   1
Focus 19   7
PreF   5  24

>
>
> ## chisq
>
> model.56.chi <- (model.56$null.deviance - model.56$deviance)
> model.56.df <- (model.56$df.null - model.56$df.residual)
> model.56.chisq <- 1-pchisq(model.56.chi, model.56.df)
> model.56.chi
[1] 18.26172
> model.56.chisq

```

```

[1] 1.925377e-05
> model.56.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.56$coefficients)
              (Intercept) z.F0range_Max_minus_Min
              2.0352948              0.2469548
> ##### CI #####
> exp(confint(model.56))
Waiting for profiling to be done...
              2.5 %      97.5 %
(Intercept)      1.0566368  4.2464449
z.F0range_Max_minus_Min 0.0937016  0.5225594
>
>
> ## Model 57 - F0 change
>
> model.57 <- glm(foc.fac ~ z.F0change_Q4_minusQ1, data=s3.fvpf,
family="binomial")
> summary(model.57)

Call:
glm(formula = foc.fac ~ z.F0change_Q4_minusQ1, family = "binomial",
    data = s3.fvpf)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.9669  -0.6338   0.2358   0.6920   2.6755

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)      0.7871     0.3943   1.996 0.045887 *
z.F0change_Q4_minusQ1 -1.8703     0.5106  -3.663 0.000249 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 76.082  on 54  degrees of freedom
Residual deviance: 48.089  on 53  degrees of freedom
(4 observations deleted due to missingness)
AIC: 52.089

Number of Fisher Scoring iterations: 5

>
> ## classification tables
>
> model.57.pred <- predict(model.57, type="response")
> PreF <- ifelse(model.57.pred > .5, 1, 0)
> s3.fvpf.1 <- s3.fvpf %>% drop_na(z.F0change_Q4_minusQ1)
> table(s3.fvpf.1$Focus, PreF)
      PreF
      0  1

```

```

Focus 20 6
PreF 5 24
>
>
> ## chisq
>
> model.57.chi <- (model.57$null.deviance - model.57$deviance)
> model.57.df <- (model.57$df.null - model.57$df.residual)
> model.57.chisq <- 1-pchisq(model.57.chi, model.57.df)
> model.57.chi
[1] 27.99342
> model.57.chisq
[1] 1.217287e-07
> model.57.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.57$coefficients)
      (Intercept) z.F0change_Q4_minusQ1
      2.1971001      0.1540729
> ##### CI #####
> exp(confint(model.57))
Waiting for profiling to be done...
      2.5 %      97.5 %
(Intercept)      1.06310717 5.1295183
z.F0change_Q4_minusQ1 0.04803466 0.3649741
>
>
> ## Model 58 - ED_Q2Q3
>
> model.58 <- glm(foc.fac ~ ED_Q2Q3, data=s3.fvpf, family="binomial")
> summary(model.58)

Call:
glm(formula = foc.fac ~ ED_Q2Q3, family = "binomial", data = s3.fvpf)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.6894 -1.0558  0.6576  1.0752  1.7311

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  -1.7738      0.8843  -2.006  0.0449 *
ED_Q2Q3       1.3578      0.6339   2.142  0.0322 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 81.774  on 58  degrees of freedom
Residual deviance: 76.672  on 57  degrees of freedom
AIC: 80.672

Number of Fisher Scoring iterations: 4

```

```

>
> ## classification tables
>
> model.58.pred <- predict(model.58, type="response")
> PreF <- ifelse(model.58.pred > .5, 1, 0)
> s3.fvpf.1 <- s3.fvpf %>% drop_na(ED_Q2Q3)
> table(s3.fvpf.1$Focus, PreF)
      PreF
      0   1
Focus 20   9
PreF  10  20
>
>
> ## chisq
>
> model.58.chi <- (model.58$null.deviance - model.58$deviance)
> model.58.df <- (model.58$df.null - model.58$df.residual)
> model.58.chisq <- 1-pchisq(model.58.chi, model.58.df)
> model.58.chi
[1] 5.102585
> model.58.chisq
[1] 0.02389022
> model.58.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.58$coefficients)
(Intercept)      ED_Q2Q3
  0.1696828    3.8877441
> ##### CI #####
> exp(confint(model.58))
Waiting for profiling to be done...
              2.5 %      97.5 %
(Intercept) 0.02665195 0.8919298
ED_Q2Q3      1.18968575 14.7388119
>
>
> ## Model 59 - Duration
>
> model.59 <- glm(foc.fac ~ z.Duration, data=s3.fvpf, family="binomial")
> summary(model.59)

Call:
glm(formula = foc.fac ~ z.Duration, family = "binomial", data = s3.fvpf)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.368  -1.184   1.048   1.149   1.512

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) -0.03214    0.27644  -0.116   0.907
z.Duration  -0.21442    0.28218  -0.760   0.447

(Dispersion parameter for binomial family taken to be 1)

```

```

Null deviance: 81.774 on 58 degrees of freedom
Residual deviance: 81.178 on 57 degrees of freedom
AIC: 85.178

```

```

Number of Fisher Scoring iterations: 4

```

```

>
> ## classification tables
>
> model.59.pred <- predict(model.59, type="response")
> PreF <- ifelse(model.59.pred > .5, 1, 0)
> s3.fvpf.1 <- s3.fvpf %>% drop_na(z.Duration)
> table(s3.fvpf.1$Focus, PreF)
      PreF
      0  1
Focus 14 15
PreF   7 23
>
>
> ## chisq
>
> model.59.chi <- (model.59$null.deviance - model.59$deviance)
> model.59.df <- (model.59$df.null - model.59$df.residual)
> model.59.chisq <- 1-pchisq(model.59.chi, model.59.df)
> model.59.chi
[1] 0.5967131
> model.59.chisq
[1] 0.4398349
> model.59.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.59$coefficients)
(Intercept)  z.Duration
  0.9683714   0.8070123
> ##### CI #####
> exp(confint(model.59))
Waiting for profiling to be done...
              2.5 %   97.5 %
(Intercept)  0.5570886 1.662907
z.Duration   0.4428708 1.388147
>
>
> ## Model 60 - Intensity_Q2Q3
>
> model.60 <- glm(foc.fac ~ z.Intensity_Q2Q3, data=s3.fvpf,
family="binomial")
> summary(model.60)

Call:
glm(formula = foc.fac ~ z.Intensity_Q2Q3, family = "binomial",
    data = s3.fvpf)

```

```

Deviance Residuals:

```

```

      Min       1Q       Median       3Q      Max
-1.57841  -0.77952   0.03779   0.61553   2.29806

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)   -0.9394     0.4327  -2.171 0.029936 *
z.Intensity_Q2Q3  2.9197     0.8281   3.526 0.000422 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 81.774  on 58  degrees of freedom
Residual deviance: 51.888  on 57  degrees of freedom
AIC: 55.888

Number of Fisher Scoring iterations: 6

>
> ## classification tables
>
> model.60.pred <- predict(model.60, type="response")
> PreF <- ifelse(model.60.pred > .5, 1, 0)
> s3.fvpf.1 <- s3.fvpf %>% drop_na(z.Intensity_Q2Q3)
> table(s3.fvpf.1$Focus, PreF)
      PreF
      0  1
Focus 23  6
PreF   8 22
>
>
> ## chisq
>
> model.60.chi <- (model.60$null.deviance - model.60$deviance)
> model.60.df <- (model.60$df.null - model.60$df.residual)
> model.60.chisq <- 1-pchisq(model.60.chi, model.60.df)
> model.60.chi
[1] 29.88615
> model.60.chisq
[1] 4.581737e-08
> model.60.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.60$coefficients)
      (Intercept) z.Intensity_Q2Q3
      0.3908706   18.5352229
> ##### CI #####
> exp(confint(model.60))
Waiting for profiling to be done...
      2.5 %      97.5 %
(Intercept)  0.1529816  0.8554769
z.Intensity_Q2Q3 4.6963515 127.2593002
>
>

```



```

>
>
> ##### Knalo (PF) v Target (F)
#####
>
> ## Syllable 1 ##
>
> ## Model 61 - F0
> s1.kva <- rbind(k.pf.s1, a.f.s1)
> knalo.fac <- factor(s1.kva$KnaloWord)
> s1.kva <- cbind(s1.kva, knalo.fac)
>
> model.61 <- glm(knalo.fac ~ z.log.F0_Q2Q3, data=s1.kva, family="binomial")
> summary(model.61)

```

Call:

```
glm(formula = knalo.fac ~ z.log.F0_Q2Q3, family = "binomial",
    data = s1.kva)
```

Deviance Residuals:

Min	1Q	Median	3Q	Max
-1.9463	-0.8067	-0.4728	0.8820	1.7386

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)	
(Intercept)	1.2653	0.4893	2.586	0.00971	**
z.log.F0_Q2Q3	2.8811	0.8006	3.599	0.00032	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 86.939 on 62 degrees of freedom
 Residual deviance: 67.915 on 61 degrees of freedom
 AIC: 71.915

Number of Fisher Scoring iterations: 4

```

>
> ## classification tables
>
> model.61.pred <- predict(model.61, type="response")
> Knalo <- ifelse(model.61.pred > .5, 0, 1)
> s1.kva.1 <- s1.kva %>% drop_na(z.log.F0_Q2Q3)
> table(s1.kva.1$KnaloWord, Knalo)
      Knalo
      0    1
0    8 26
1   18 11
>
>
> ## chisq
>
> model.61.chi <- (model.61$null.deviance - model.61$deviance)
> model.61.df <- (model.61$df.null - model.61$df.residual)
> model.61.chisq <- 1-pchisq(model.61.chi, model.61.df)
> model.61.chi

```

```

[1] 19.02401
> model.61.chisq
[1] 1.29084e-05
> model.61.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.61$coefficients)
      (Intercept)  z.log.F0_Q2Q3
      3.544054      17.834585
> ##### CI #####
> exp(confint(model.61))
Waiting for profiling to be done...
              2.5 %      97.5 %
(Intercept)   1.45753  10.17435
z.log.F0_Q2Q3  4.27845 102.20266
>
>
> ## Model 62 - F0 range
>
>
>
> model.62 <- glm(knalo.fac ~ z.F0range_Max_minus_Min, data=s1.kva,
family="binomial")
> summary(model.62)

Call:
glm(formula = knalo.fac ~ z.F0range_Max_minus_Min, family = "binomial",
    data = s1.kva)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.3278  -1.1044  -0.7938   1.1783   1.8612

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)    -0.1464    0.2578  -0.568   0.570
z.F0range_Max_minus_Min -0.4757    0.3161  -1.505   0.132

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 86.939  on 62  degrees of freedom
Residual deviance: 84.443  on 61  degrees of freedom
AIC: 88.443

Number of Fisher Scoring iterations: 4

>
> ## classification tables
>
> model.62.pred <- predict(model.62, type="response")
> Knalo <- ifelse(model.62.pred > .5, 1, 0)
> s1.kva.1 <- s1.kva %>% drop_na(z.F0range_Max_minus_Min)
> table(s1.kva.1$KnaloWord, Knalo)
      Knalo

```

```

      0  1
0 22 12
1 16 13
>
>
> ## chisq
>
> model.62.chi <- (model.62$null.deviance - model.62$deviance)
> model.62.df <- (model.62$df.null - model.62$df.residual)
> model.62.chisq <- 1-pchisq(model.62.chi, model.62.df)
> model.62.chi
[1] 2.49613
> model.62.chisq
[1] 0.1141264
> model.62.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.62$coefficients)
      (Intercept)  z.F0range_Max_minus_Min
      0.8638522      0.6214299
> ##### CI #####
> exp(confint(model.62))
Waiting for profiling to be done...
      2.5 %    97.5 %
(Intercept)      0.5180472 1.431483
z.F0range_Max_minus_Min 0.3166492 1.116163
>
>
>
> ## Model 63 - F0 change
>
> model.63 <- glm(knalo.fac ~ z.F0change_Q4_minusQ1, data=s1.kva,
family="binomial")
> summary(model.63)

Call:
glm(formula = knalo.fac ~ z.F0change_Q4_minusQ1, family = "binomial",
    data = s1.kva)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.4173  -1.1003  -0.8766   1.2409   1.6773

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)      0.06884   0.32590   0.211   0.833
z.F0change_Q4_minusQ1  0.51295   0.39305   1.305   0.192

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 85.369  on 61  degrees of freedom
Residual deviance: 83.587  on 60  degrees of freedom
(1 observation deleted due to missingness)

```

AIC: 87.587

Number of Fisher Scoring iterations: 4

```
>
> ## classification tables
>
> model.63.pred <- predict(model.63, type="response")
> knalo <- ifelse(model.63.pred > .5, 1, 0)
> s1.kva.1 <- s1.kva %>% drop_na(z.F0change_Q4_minusQ1)
> table(s1.kva.1$KnaloWord, knalo)
      knalo
      0    1
0 28    6
1 20    8
>
>
> ## chisq
>
> model.63.chi <- (model.63$null.deviance - model.63$deviance)
> model.63.df <- (model.63$df.null - model.63$df.residual)
> model.63.chisq <- 1-pchisq(model.63.chi, model.63.df)
> model.63.chi
[1] 1.781293
> model.63.chisq
[1] 0.1819906
> model.63.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.63$coefficients)
      (Intercept) z.F0change_Q4_minusQ1
      1.071261      1.670218
> ##### CI #####
> exp(confint(model.63))
Waiting for profiling to be done...
              2.5 %    97.5 %
(Intercept)    0.5672494 2.066937
z.F0change_Q4_minusQ1 0.7894978 3.777174
>
>
>
> ## Model 64 - ED_Q2Q3
>
> model.64 <- glm(knalo.fac ~ ED_Q2Q3, data=s1.kva, family="binomial")
> summary(model.64)
```

Call:

```
glm(formula = knalo.fac ~ ED_Q2Q3, family = "binomial", data = s1.kva)
```

Deviance Residuals:

Min	1Q	Median	3Q	Max
-2.0045	-1.1019	-0.7144	1.1595	1.5850

Coefficients:

```

              Estimate Std. Error z value Pr(>|z|)
(Intercept)  -1.7442      0.7345  -2.375   0.0176 *
ED_Q2Q3       1.2737      0.5498   2.316   0.0205 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 86.939  on 62  degrees of freedom
Residual deviance: 80.677  on 61  degrees of freedom
AIC: 84.677

Number of Fisher Scoring iterations: 4

>
> ## classification tables
>
> model.64.pred <- predict(model.64, type="response")
> knalo <- ifelse(model.64.pred > .5, 1, 0)
> s1.kva.1 <- s1.kva %>% drop_na(ED_Q2Q3)
> table(s1.kva.1$KnaloWord, knalo)
      knalo
      0    1
0 24 10
1 15 14
>
>
> ## chisq
>
> model.64.chi <- (model.64$null.deviance - model.64$deviance)
> model.64.df <- (model.64$df.null - model.64$df.residual)
> model.64.chisq <- 1-pchisq(model.64.chi, model.64.df)
> model.64.chi
[1] 6.262638
> model.64.chisq
[1] 0.01233105
> model.64.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.64$coefficients)
(Intercept)      ED_Q2Q3
  0.1747839    3.5740102
> ##### CI #####
> exp(confint(model.64))
Waiting for profiling to be done...
              2.5 %      97.5 %
(Intercept)  0.03659928  0.6789334
ED_Q2Q3      1.30160031 11.5857839
>
>
> ## Model 65 - Duration
>
> model.65 <- glm(knalo.fac ~ z.Duration, data=s1.kva, family="binomial")
> summary(model.65)

```

```

Call:
glm(formula = knalo.fac ~ z.Duration, family = "binomial", data = s1.kva)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.6008  -1.0919  -0.8257   1.1979   1.4616

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)   0.1404     0.3160   0.444   0.657
z.Duration   -0.4399     0.2697  -1.631   0.103

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 86.939  on 62  degrees of freedom
Residual deviance: 84.121  on 61  degrees of freedom
AIC: 88.121

Number of Fisher Scoring iterations: 4

>
> ## classification tables
>
> model.65.pred <- predict(model.65, type="response")
> knalo <- ifelse(model.65.pred > .5, 1, 0)
> s1.kva.1 <- s1.kva %>% drop_na(z.Duration)
> table(s1.kva.1$KnaloWord, knalo)
      knalo
      0    1
0 25    9
1 17   12
>
>
> ## chisq
>
> model.65.chi <- (model.65$null.deviance - model.65$deviance)
> model.65.df <- (model.65$df.null - model.65$df.residual)
> model.65.chisq <- 1-pchisq(model.65.chi, model.65.df)
> model.65.chi
[1] 2.817832
> model.65.chisq
[1] 0.09322224
> model.65.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.65$coefficients)
(Intercept)  z.Duration
  1.1507326   0.6440979
> ##### CI #####
> exp(confint(model.65))
Waiting for profiling to be done...
              2.5 %    97.5 %
(Intercept)  0.6242692 2.184538

```

```

z.Duration  0.3683657 1.074932
>
>
> ## Model 66 - Intensity_Q2Q3
>
> model.66 <- glm(knalo.fac ~ z.Intensity_Q2Q3, data=s1.kva,
family="binomial")
> summary(model.66)

Call:
glm(formula = knalo.fac ~ z.Intensity_Q2Q3, family = "binomial",
    data = s1.kva)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.7430  -1.0119  -0.5246   0.9441   1.7409

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)   -0.8110     0.3529  -2.298  0.02155 *
z.Intensity_Q2Q3  1.1607     0.3640   3.189  0.00143 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 86.939  on 62  degrees of freedom
Residual deviance: 74.051  on 61  degrees of freedom
AIC: 78.051

Number of Fisher Scoring iterations: 4

>
> ## classification tables
>
> model.66.pred <- predict(model.66, type="response")
> knalo <- ifelse(model.66.pred > .5, 1, 0)
> s1.kva.1 <- s1.kva %>% drop_na(z.Intensity_Q2Q3)
> table(s1.kva.1$KnaloWord, knalo)
      knalo
      0    1
0 28    6
1 11   18
>
>
> ## chisq
>
> model.66.chi <- (model.66$null.deviance - model.66$deviance)
> model.66.df <- (model.66$df.null - model.66$df.residual)
> model.66.chisq <- 1-pchisq(model.66.chi, model.66.df)
> model.66.chi
[1] 12.88786
> model.66.chisq
[1] 0.0003307206
> model.66.df
[1] 1
>

```

```

>
> ## ORs
> ##### Odds ratio #####
> exp(model.66$coefficients)
      (Intercept)  z.Intensity_Q2Q3
      0.4444171      3.1922713
> ##### CI #####
> exp(confint(model.66))
Waiting for profiling to be done...
              2.5 %      97.5 %
(Intercept)    0.2109723  0.8546324
z.Intensity_Q2Q3 1.6453288  6.9728562
>
>
> ##### Syllable 2 #####
> s2.kva <- rbind(k.pf.s2, a.f.s2)
> knalo.fac <- factor(s2.kva$KnaloWord)
> s2.kva <- cbind(s2.kva, knalo.fac)
>
> ## Model 67 - F0
>
> model.67 <- glm(knalo.fac ~ z.log.F0_Q2Q3, data=s2.kva, family="binomial")
> summary(model.67)

Call:
glm(formula = knalo.fac ~ z.log.F0_Q2Q3, family = "binomial",
    data = s2.kva)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.2563  -1.0778  -0.9388   1.2634   1.3996

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)  -0.05911    0.37019  -0.160   0.873
z.log.F0_Q2Q3  0.57858    0.69656   0.831   0.406

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 65.790  on 47  degrees of freedom
Residual deviance: 65.082  on 46  degrees of freedom
(8 observations deleted due to missingness)
AIC: 69.082

Number of Fisher Scoring iterations: 4

>
> ## classification tables
>
> model.67.pred <- predict(model.67, type="response")
> Knalo <- ifelse(model.67.pred > .5, 1, 0)
> s2.kva.1 <- s2.kva %>% drop_na(z.log.F0_Q2Q3)
> table(s2.kva.1$KnaloWord, Knalo)
      Knalo
      0    1
0 23    4
1 17    4

```



```

>
>
> ## chisq
>
> model.67.chi <- (model.67$null.deviance - model.67$deviance)
> model.67.df <- (model.67$df.null - model.67$df.residual)
> model.67.chisq <- 1-pchisq(model.67.chi, model.67.df)
> model.67.chi
[1] 0.707889
> model.67.chisq
[1] 0.4001455
> model.67.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.67$coefficients)
  (Intercept) z.log.F0_Q2Q3
      0.9426038      1.7835021
> ##### CI #####
> exp(confint(model.67))
Waiting for profiling to be done...
              2.5 %    97.5 %
(Intercept)  0.4527118 1.971098
z.log.F0_Q2Q3 0.4668276 7.513872
>
>
> ## Model 68 - F0 range
>
> model.68 <- glm(knalo.fac ~ z.F0range_Max_minus_Min, data=s2.kva,
family="binomial")
> summary(model.68)

Call:
glm(formula = knalo.fac ~ z.F0range_Max_minus_Min, family = "binomial",
    data = s2.kva)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.3721  -1.1540  -0.6557   1.0955   1.7340

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)   -0.9921     0.5772  -1.719   0.0857 .
z.F0range_Max_minus_Min -1.3116     0.7488  -1.752   0.0798 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 68.994  on 49  degrees of freedom
Residual deviance: 65.427  on 48  degrees of freedom
(6 observations deleted due to missingness)
AIC: 69.427

Number of Fisher Scoring iterations: 4

```

```

>
> ## classification tables
>
> model.68.pred <- predict(model.68, type="response")
> Knalo <- ifelse(model.68.pred > .5, 1, 0)
> s2.kva.1 <- s2.kva %>% drop_na(z.F0range_Max_minus_Min)
> table(s2.kva.1$KnaloWord, Knalo)
      Knalo
      0    1
0  17  10
1  10  13
>
>
> ## chisq
>
> model.68.chi <- (model.68$null.deviance - model.68$deviance)
> model.68.df <- (model.68$df.null - model.68$df.residual)
> model.68.chisq <- 1-pchisq(model.68.chi, model.68.df)
> model.68.chi
[1] 3.567242
> model.68.chisq
[1] 0.05893012
> model.68.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.68$coefficients)
      (Intercept)  z.F0range_Max_minus_Min
      0.3708107      0.2693779
> ##### CI #####
> exp(confint(model.68))
Waiting for profiling to be done...
      2.5 %    97.5 %
(Intercept)    0.10210135 1.044289
z.F0range_Max_minus_Min 0.05202718 1.047771
>
>
> ## Model 69 - F0 change
>
> model.69 <- glm(knalo.fac ~ z.F0change_Q4_minusQ1, data=s2.kva,
family="binomial")
> summary(model.69)

Call:
glm(formula = knalo.fac ~ z.F0change_Q4_minusQ1, family = "binomial",
    data = s2.kva)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.1610  -0.3582  -0.1255   0.2141   1.7734

Coefficients:
(Intercept)          Estimate Std. Error z value Pr(>|z|)
      -2.4919          0.9046  -2.755  0.00588 **

```

```

z.F0change_Q4_minusQ1  -6.5955      2.2805  -2.892  0.00383 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 45.728  on 37  degrees of freedom
Residual deviance: 20.695  on 36  degrees of freedom
(18 observations deleted due to missingness)
AIC: 24.695

Number of Fisher Scoring iterations: 6

>
> ## classification tables
>
> model.69.pred <- predict(model.69, type="response")
> knalo <- ifelse(model.69.pred > .5, 1, 0)
> s2.kva.1 <- s2.kva %>% drop_na(z.F0change_Q4_minusQ1)
> table(s2.kva.1$KnaloWord, knalo)
      knalo
      0    1
0 26    1
1   3    8
>
>
> ## chisq
>
> model.69.chi <- (model.69$null.deviance - model.69$deviance)
> model.69.df <- (model.69$df.null - model.69$df.residual)
> model.69.chisq <- 1-pchisq(model.69.chi, model.69.df)
> model.69.chi
[1] 25.03281
> model.69.chisq
[1] 5.636305e-07
> model.69.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.69$coefficients)
      (Intercept) z.F0change_Q4_minusQ1
      0.082752007      0.001366524
> ##### CI #####
> exp(confint(model.69))
Waiting for profiling to be done...
              2.5 %          97.5 %
(Intercept)      8.723003e-03 0.34530768
z.F0change_Q4_minusQ1 3.142861e-06 0.04312664
>
>
> ## Model 70 - ED_Q2Q3
>
> model.70 <- glm(knalo.fac ~ ED_Q2Q3, data=s2.kva, family="binomial")
> summary(model.70)

```

```

Call:
glm(formula = knalo.fac ~ ED_Q2Q3, family = "binomial", data = s2.kva)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.134  -1.137   1.009   1.132   1.218

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)  -0.4498     0.6144  -0.732   0.464
ED_Q2Q3       0.3365     0.3660   0.919   0.358

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 77.561  on 55  degrees of freedom
Residual deviance: 76.445  on 54  degrees of freedom
AIC: 80.445

Number of Fisher Scoring iterations: 3

>
> ## classification tables
>
> model.70.pred <- predict(model.70, type="response")
> knalo <- ifelse(model.70.pred > .5, 1, 0)
> s2.kva.1 <- s2.kva %>% drop_na(ED_Q2Q3)
> table(s2.kva.1$KnaloWord, knalo)
      knalo
      0    1
0  16  11
1   4  25
>
>
> ## chisq
>
> model.70.chi <- (model.70$null.deviance - model.70$deviance)
> model.70.df <- (model.70$df.null - model.70$df.residual)
> model.70.chisq <- 1-pchisq(model.70.chi, model.70.df)
> model.70.chi
[1] 1.116213
> model.70.chisq
[1] 0.2907354
> model.70.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.70$coefficients)
(Intercept)      ED_Q2Q3
  0.6377505   1.400668
> ##### CI #####
> exp(confint(model.70))
Waiting for profiling to be done...
              2.5 %    97.5 %
(Intercept)  0.1546309  1.857498
ED_Q2Q3      0.7748623  3.429422

```

```

>
>
> ## Model 71 - Duration
>
> model.71 <- glm(knalo.fac ~ z.Duration, data=s2.kva, family="binomial")
> summary(model.71)

```

Call:

```
glm(formula = knalo.fac ~ z.Duration, family = "binomial", data = s2.kva)
```

Deviance Residuals:

Min	1Q	Median	3Q	Max
-1.3744	-1.1691	0.8526	1.0641	1.9522

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	0.04482	0.27556	0.163	0.871
z.Duration	-0.52356	0.32095	-1.631	0.103

(Dispersion parameter **for** binomial family taken to be 1)

Null deviance: 77.561 on 55 degrees of freedom
 Residual deviance: 74.567 on 54 degrees of freedom
 AIC: 78.567

Number of Fisher Scoring iterations: 4

```

>
> ## classification tables
>
> model.71.pred <- predict(model.71, type="response")
> knalo <- ifelse(model.71.pred > .5, 1, 0)
> s2.kva.1 <- s2.kva %>% drop_na(z.Duration)
> table(s2.kva.1$KnaloWord, knalo)
      knalo
      0    1
0 13 14
1   8 21
>
>
> ## chisq
>
> model.71.chi <- (model.71$null.deviance - model.71$deviance)
> model.71.df <- (model.71$df.null - model.71$df.residual)
> model.71.chisq <- 1-pchisq(model.71.chi, model.71.df)
> model.71.chi
[1] 2.994156
> model.71.chisq
[1] 0.08356546
> model.71.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.71$coefficients)
(Intercept)  z.Duration

```

```

      1.0458374    0.5924087
> ##### CI #####
> exp(confint(model.71))
Waiting for profiling to be done...
              2.5 %    97.5 %
(Intercept)  0.6065923 1.800533
z.Duration   0.2977109 1.068719
>
>
> ## Model 72 - Intensity_Q2Q3
>
> model.72 <- glm(knalo.fac ~ z.Intensity_Q2Q3, data=s2.kva,
family="binomial")
> summary(model.72)

Call:
glm(formula = knalo.fac ~ z.Intensity_Q2Q3, family = "binomial",
    data = s2.kva)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.8311  -0.8739   0.3655   0.9527   1.3566

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)    -1.0641     0.4554  -2.337  0.01945 *
z.Intensity_Q2Q3 -1.5982     0.5031  -3.176  0.00149 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 77.561  on 55  degrees of freedom
Residual deviance: 61.710  on 54  degrees of freedom
AIC: 65.71

Number of Fisher Scoring iterations: 4

>
> ## classification tables
>
> model.72.pred <- predict(model.72, type="response")
> knalo <- ifelse(model.72.pred > .5, 1, 0)
> s2.kva.1 <- s2.kva %>% drop_na(z.Intensity_Q2Q3)
> table(s2.kva.1$KnaloWord, knalo)
      knalo
      0    1
0  21    6
1   7   22
>
>
> ## chisq
>
> model.72.chi <- (model.72$null.deviance - model.72$deviance)
> model.72.df <- (model.72$df.null - model.72$df.residual)
> model.72.chisq <- 1-pchisq(model.72.chi, model.72.df)
> model.72.chi

```

```

[1] 15.851
> model.72.chisq
[1] 6.853043e-05
> model.72.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.72$coefficients)
      (Intercept)  z.Intensity_Q2Q3
      0.3450248      0.2022618
> ##### CI #####
> exp(confint(model.72))
Waiting for profiling to be done...
              2.5 %      97.5 %
(Intercept)    0.13060198 0.7940467
z.Intensity_Q2Q3 0.06500094 0.4830923
>
>
> ##### Syllable 3 #####
>
> s3.kva <- rbind(k.pf.s3, a.f.s3)
> knalo.fac <- factor(s3.kva$KnaloWord)
> s3.kva <- cbind(s3.kva, knalo.fac)
>
> ## Model 73 - F0
>
> model.73 <- glm(knalo.fac ~ z.log.F0_Q2Q3, data=s3.kva, family="binomial")
> summary(model.73)

Call:
glm(formula = knalo.fac ~ z.log.F0_Q2Q3, family = "binomial",
    data = s3.kva)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.473  -1.160   1.008   1.174   1.233

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)   -0.3016     0.4876  -0.618   0.536
z.log.F0_Q2Q3  0.2734     0.3328   0.822   0.411

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 79.001  on 56  degrees of freedom
Residual deviance: 78.310  on 55  degrees of freedom
(1 observation deleted due to missingness)
AIC: 82.31

Number of Fisher Scoring iterations: 4

>
> ## classification tables
>
> model.73.pred <- predict(model.73, type="response")

```

```

> Knalo <- ifelse(model.73.pred > .5, 1, 0)
> s3.kva.1 <- s3.kva %>% drop_na(z.log.F0_Q2Q3)
> table(s3.kva.1$KnaloWord, Knalo)
      Knalo
      0    1
0 15 13
1 14 15
>
>
> ## chisq
>
> model.73.chi <- (model.73$null.deviance - model.73$deviance)
> model.73.df <- (model.73$df.null - model.73$df.residual)
> model.73.chisq <- 1-pchisq(model.73.chi, model.73.df)
> model.73.chi
[1] 0.6908317
> model.73.chisq
[1] 0.4058816
> model.73.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.73$coefficients)
      (Intercept) z.log.F0_Q2Q3
      0.7396542    1.3144637
> ##### CI #####
> exp(confint(model.73))
Waiting for profiling to be done...
              2.5 %    97.5 %
(Intercept)  0.2747356 1.910936
z.log.F0_Q2Q3 0.6914293 2.616069
>
>
> ## Model 74 - F0 range
>
> model.74 <- glm(knalo.fac ~ z.F0range_Max_minus_Min, data=s3.kva,
family="binomial")
> summary(model.74)

Call:
glm(formula = knalo.fac ~ z.F0range_Max_minus_Min, family = "binomial",
    data = s3.kva)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.386   -1.225    1.024    1.126    1.435

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)      0.07295   0.26955   0.271   0.787
z.F0range_Max_minus_Min -0.31910   0.26601  -1.200   0.230

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 79.001  on 56  degrees of freedom

```


Residual deviance: 77.406 on 55 degrees of freedom
 (1 observation deleted due to missingness)
 AIC: 81.406

Number of Fisher Scoring iterations: 4

```
>
> ## classification tables
>
> model.74.pred <- predict(model.74, type="response")
> Knalo <- ifelse(model.74.pred > .5, 1, 0)
> s3.kva.1 <- s3.kva %>% drop_na(z.F0range_Max_minus_Min)
> table(s3.kva.1$KnaloWord, Knalo)
      Knalo
      0    1
0 10 18
1   5 24
>
>
> ## chisq
>
> model.74.chi <- (model.74$null.deviance - model.74$deviance)
> model.74.df <- (model.74$df.null - model.74$df.residual)
> model.74.chisq <- 1-pchisq(model.74.chi, model.74.df)
> model.74.chi
[1] 1.59565
> model.74.chisq
[1] 0.2065207
> model.74.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.74$coefficients)
      (Intercept) z.F0range_Max_minus_Min
      1.0756774      0.7268003
> ##### CI #####
> exp(confint(model.74))
Waiting for profiling to be done...
      2.5 %    97.5 %
(Intercept)    0.6338784 1.835235
z.F0range_Max_minus_Min 0.4029572 1.184498
>
>
> ## Model 75 - F0 change
>
> model.75 <- glm(knalo.fac ~ z.F0change_Q4_minusQ1, data=s3.kva,
family="binomial")
> summary(model.75)

Call:
glm(formula = knalo.fac ~ z.F0change_Q4_minusQ1, family = "binomial",
    data = s3.kva)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
```

```

-1.7577 -0.7194 0.2170 0.7163 2.7890

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)      0.5890     0.3652   1.613 0.106769
z.F0change_Q4_minusQ1 -1.9219     0.5312  -3.618 0.000297 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 79.001 on 56 degrees of freedom
Residual deviance: 52.593 on 55 degrees of freedom
(1 observation deleted due to missingness)
AIC: 56.593

Number of Fisher Scoring iterations: 5

>
> ## classification tables
>
> model.75.pred <- predict(model.75, type="response")
> knalo <- ifelse(model.75.pred > .5, 1, 0)
> s3.kva.1 <- s3.kva %>% drop_na(z.F0change_Q4_minusQ1)
> table(s3.kva.1$KnaloWord, knalo)
      knalo
      0  1
0 21  7
1  5 24
>
>
> ## chisq
>
> model.75.chi <- (model.75$null.deviance - model.75$deviance)
> model.75.df <- (model.75$df.null - model.75$df.residual)
> model.75.chisq <- 1-pchisq(model.75.chi, model.75.df)
> model.75.chi
[1] 26.4084
> model.75.chisq
[1] 2.763366e-07
> model.75.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.75$coefficients)
      (Intercept) z.F0change_Q4_minusQ1
      1.8022408      0.1463285
> ##### CI #####
> exp(confint(model.75))
Waiting for profiling to be done...
              2.5 %      97.5 %
(Intercept)      0.90998025 3.8939327
z.F0change_Q4_minusQ1 0.04360059 0.3604738
>
>

```

```

> ## Model 78 - ED_Q2Q3
>
> model.78 <- glm(knalo.fac ~ ED_Q2Q3, data=s3.kva, family="binomial")
> summary(model.78)

Call:
glm(formula = knalo.fac ~ ED_Q2Q3, family = "binomial", data = s3.kva)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.0356  -0.8855   0.2467   0.7879   2.1332

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  -3.3024     0.9620  -3.433 0.000598 ***
ED_Q2Q3        2.9182     0.7974   3.660 0.000253 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 80.336  on 57  degrees of freedom
Residual deviance: 58.974  on 56  degrees of freedom
AIC: 62.974

Number of Fisher Scoring iterations: 4

>
> ## classification tables
>
> model.78.pred <- predict(model.78, type="response")
> knalo <- ifelse(model.78.pred > .5, 1, 0)
> s3.kva.1 <- s3.kva %>% drop_na(ED_Q2Q3)
> table(s3.kva.1$KnaloWord, knalo)
      knalo
      0    1
0 24    4
1  7   23
>
>
> ## chisq
>
> model.78.chi <- (model.78$null.deviance - model.78$deviance)
> model.78.df <- (model.78$df.null - model.78$df.residual)
> model.78.chisq <- 1-pchisq(model.78.chi, model.78.df)
> model.78.chi
[1] 21.3617
> model.78.chisq
[1] 3.802931e-06
> model.78.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.78$coefficients)
(Intercept)      ED_Q2Q3

```

```

0.03679627 18.50785193
> ##### CI #####
> exp(confint(model.78))
Waiting for profiling to be done...
              2.5 %      97.5 %
(Intercept) 0.004343906 0.2007815
ED_Q2Q3     4.604612362 111.0744581
>
>
> ## Model 79 - Duration
>
> model.79 <- glm(knalo.fac ~ z.Duration, data=s3.kva, family="binomial")
> summary(model.79)

Call:
glm(formula = knalo.fac ~ z.Duration, family = "binomial", data = s3.kva)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.6144  -1.1518   0.9162   1.1040   1.9394

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept) -0.05187     0.28310  -0.183   0.855
z.Duration   -0.49062     0.34572  -1.419   0.156

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 80.336  on 57  degrees of freedom
Residual deviance: 78.065  on 56  degrees of freedom
AIC: 82.065

Number of Fisher Scoring iterations: 4

>
> ## classification tables
>
> model.79.pred <- predict(model.79, type="response")
> knalo <- ifelse(model.79.pred > .5, 1, 0)
> s3.kva.1 <- s3.kva %>% drop_na(z.Duration)
> table(s3.kva.1$KnaloWord, knalo)
      knalo
      0    1
0 16 12
1  5 25
>
>
> ## chisq
>
> model.79.chi <- (model.79$null.deviance - model.79$deviance)
> model.79.df <- (model.79$df.null - model.79$df.residual)
> model.79.chisq <- 1-pchisq(model.79.chi, model.79.df)
> model.79.chi
[1] 2.271484
> model.79.chisq
[1] 0.1317736
> model.79.df

```

```

[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.79$coefficients)
(Intercept)    z.Duration
    0.9494485    0.6122483
> ##### CI #####
> exp(confint(model.79))
Waiting for profiling to be done...
              2.5 %    97.5 %
(Intercept)  0.5368438  1.645562
z.Duration   0.2885823  1.151044
>
>
> ## Model 80 - Intensity_Q2Q3
>
> model.80 <- glm(knalo.fac ~ z.Intensity_Q2Q3, data=s3.kva,
family="binomial")
> summary(model.80)

Call:
glm(formula = knalo.fac ~ z.Intensity_Q2Q3, family = "binomial",
    data = s3.kva)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.8194  -1.1096   0.7564   1.0994   1.4501

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)    -0.2998     0.3386  -0.885   0.376
z.Intensity_Q2Q3  0.5769     0.3195   1.805   0.071 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 80.336  on 57  degrees of freedom
Residual deviance: 76.705  on 56  degrees of freedom
AIC: 80.705

Number of Fisher Scoring iterations: 4

>
> ## classification tables
>
> model.80.pred <- predict(model.80, type="response")
> knalo <- ifelse(model.80.pred > .5, 1, 0)
> s3.kva.1 <- s3.kva %>% drop_na(z.Intensity_Q2Q3)
> table(s3.kva.1$KnaloWord, knalo)
      knalo
      0    1
0 16 12
1 11 19
>

```

```

>
> ## chisq
>
> model.80.chi <- (model.80$null.deviance - model.80$deviance)
> model.80.df <- (model.80$df.null - model.80$df.residual)
> model.80.chisq <- 1-pchisq(model.80.chi, model.80.df)
> model.80.chi
[1] 3.630789
> model.80.chisq
[1] 0.05671991
> model.80.df
[1] 1
>
>
> ## ORs
> ##### Odds ratio #####
> exp(model.80$coefficients)
      (Intercept)  z.Intensity_Q2Q3
      0.7409443      1.7804855
> ##### CI #####
> exp(confint(model.80))
Waiting for profiling to be done...
              2.5 %    97.5 %
(Intercept)    0.3695583 1.415855
z.Intensity_Q2Q3 0.9842506 3.514226
>

```

Appendix F – Mean & sd for reversion in original units

Mean and standard deviation (sd) of speaker 1687 used for reversion of transformed measurements back into original units.

Mean and sd for the main analysis:

	Mean	sd
F0	229.9313	24.56441
Duration	88.963	15.44157
Intensity	65.43466	2.335231
F0 change	1.955319	9.784909
F0_Q1	229.8718	21.1496
F0_Q4	231.8271	26.69275
F0 range	11.49281	8.083143
minF0	225.4974	21.84562
maxF0	236.9902	25.21988

Mean and sd for the *k^hnallo* word analysis:

K^hnallo word:

	Mean	sd
F0	232.5642	25.75476
Duration		
Intensity	61.5849	2.098483
F0 change		
F0_Q1	230.5844	24.3947
F0_Q4	234.1457	26.29512
F0 range	8.434115	6.718649
minF0	228.0271	23.3286
maxF0	236.4612	26.06343

The /a/ data:

	Mean	sd
F0	229.9313	24.56441
Duration	88.963	15.44157
Intensity	65.43466	2.335231
F0 change	1.955319	9.784909
F0_Q1	230.5844	24.3947
F0_Q4	234.1457	26.29512
F0 range	8.434115	6.718649
minF0	228.0271	23.3286
maxF0	236.4612	26.06343

Appendix G – List of target words used in the study

Garó	IPA	Gloss
abini	[a.bi.ni]	"sister-Gen"
adani	[a.da.ni]	"brother-Gen"
aroba	[a.ro.ba]	"also"
ba'angna	[baʔ.aŋ.na]	"to carry while on the way"
ba'bana	[baʔ.ba.na]	"to carry on the way"
badena	[ba.de.na]	"to surpass"
badina	[ba.di.na]	"to overtake"
badingna	[ba.dəŋ-na]	"to sell"
banoba	[ba.no.ba]	"somewhere"
basena	[ba.se.na]	"to sort out"
bibani	[bi.ba.ni]	"smell-Gen"
bidani	[bi.da.ni]	"knowledge-Gen"
bijani	[bi.ɖza.ni]	"bee-Gen"
bikani	[bi.k ^h a.ni]	"liver-Gen"
bimako	[bi.ma.k ^h o]	"female (of an animal)-Acc"
bimako	[bi.ma.k ^h o]	"female (of an animal)-Acc"
bipangni	[bi.paŋ.ni]	"plant-Acc"
bisini	[bi.si.ni]	"poison-Gen"
bobani	[bo.ba.ni]	"mute-Gen"
chaba'a	[ts ^h a.baʔ.a]	"eat on the way"
choba'a	[ts ^h o.baʔ.a]	"row on the way"
dabina	[da.bi.na]	"to demand"
dabina	[da.bi.na]	"to demand"
damani	[da.ma.ni]	"drum-Gen"
damani	[da.ma.ni]	"drum-Gen"
ga'angna	[gaʔ.aŋ.na]	"to step while on the way"
ga'bana	[gaʔ.ba.na]	"to step on the way"
ga'bana	[gaʔ.ba.na]	"to step on the way"
gadona	[ga.do.na]	"to climb up"
genasi	[ge.na.si]	"kidney beans"
gisini	[gi.si.ni]	"dried-Gen"
goba'a	[go.baʔ.a]	"shoot on the way"
kaba'a	[k ^h a.baʔ.a]	"tie on the way"
keba'a	[k ^h e.baʔ.a]	"gore on the way"

komina	[k ^h o.mi.na]	"to be less"
ma'bakna	[maʔ.bak.na]	"to stick"
magani	[ma.ga.ni]	"mark-Gen"
ma'kapa	[maʔ.k ^h ap.pa]	"stick strong"
mamingba	[ma.məŋ.ba]	"nothing"
maniko	[ma.ni.k ^h o]	"aunt-Acc"
manina	[ma.ni.na]	"to celebrate"
misini	[mi.si.ni]	"millet-Gen"
moba'a	[mo.baʔ.a]	"herd on the way"
naba'a	[na.baʔ.a]	"rise on the way"
nabana	[na.ba.na]	"to start rising"
nadona	[na.do.na]	"to come up"
na'tikko	[naʔ.t ^h ək.k ^h o]	"shrimp-Acc"
na'tokko	[naʔ.t ^h ok.k ^h o]	"fish-Acc"
na'tokming	[naʔ.t ^h ok.məŋ]	"fish-Asso"
nibana	[ni.ba.na]	"to see and come"
roba'a	[ro.baʔ.a]	"hang out on the way"
saba'a	[sa.baʔ.a]	"get sick on the way"
sabisi	[sa.bi.si]	"sickness"
sabisi	[sa.bi.si]	"sickness"
sadani	[sa.da.ni]	"tobacco-Gen"
sanaba	[sa.na.ba]	"for someone"
sanaba	[sa.na.ba]	"for someone"
soba'a	[so.baʔ.a]	"stink on the way"
togina	[t ^h o.gi.na]	"to lie"