1-8-2014 12:00 AM

A Bayesian Model of Stress Assignment in Reading

Olessia Jouravlev
The University of Western Ontario

Supervisor
Stephen J. Lupker
The University of Western Ontario

Graduate Program in Psychology
A thesis submitted in partial fulfillment of the requirements for the degree in Doctor of Philosophy

A BAYESIAN MODEL OF STRESS ASSIGNMENT IN READING

(Thesis format: Monograph)

by

Olessia Jouravlev

Graduate Program in Psychology

A thesis submitted in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy

The School of Graduate and Postdoctoral Studies
The University of Western Ontario
London, Ontario, Canada

Abstract

The goal of the present thesis was to introduce a Bayesian model of stress assignment in reading. According to this model, readers compute probabilities of stress patterns by assessing prior beliefs about the likelihoods of stress patterns in a language and combining that information with non-lexical evidence for stress patterns provided by the word. The choice of a response is thought of as a random walk-type process which takes the system from a starting point to a response boundary. The calculated Bayesian probabilities determine the drift rate towards each boundary such that the probability of an error and the response latency are related to the posterior probabilities of the stress patterns.

The Bayesian model of stress assignment was implemented for Russian disyllabic words. In Study 1, the distribution of stress patterns in a corpus of Russian disyllabic words (reflecting prior beliefs about the likelihoods of stress patterns) was analyzed. Further, non-lexical sources of evidence for stress in Russian were investigated. In Study 2, the effect of spelling-to-stress consistency of word endings on naming performance was examined. Study 3 was a binary logistic regression analysis of a set of predictors of stress patterns (length, log frequency, grammatical category, word onset complexity, word coda complexity, and spelling-to-stress consistency of six orthographic components) in a corpus of disyllabic words. In Study 4, a generalized linear mixed effects model with the same variables as predictors of stress assignment performance was applied to word naming data. Based on the combination of the results, it was concluded that there are three sources of evidence for stress in Russian: the orthography of the first syllable, of the second syllable, and of the ending of the second syllable.

The model was tested in two simulations. In Study 5, the predictions of the model were compared with stress assignment performance of speakers of Russian naming words. In Study 6, the model was tested on its ability to simulate stress assignment performance of readers naming nonwords. The model managed to predict not only the most frequent stress pattern that readers assigned, but also the relative ratio of trochaic versus iambic responses given by the participants.

Keywords: stress assignment, lexical stress, computational model, Bayesian probabilities, Russian, polysyllabic words, corpus analysis, stress cues, simulations, word recognition

Co-Authorship Statement

The data presented in this dissertation were obtained in collaboration with Dr. Stephen J. Lupker. The written material in this dissertation is my own work. However, Dr. Stephen J. Lupker provided assistance in revision of the content.

Acknowledgements

I would like to thank many people who have helped me through the completion of this thesis. First of all, I am extremely grateful to have had Dr. Stephen J. Lupker as my supervisor. He has been a source of incredible support and encouragement throughout my graduate career. I thank my supervisor for extremely valuable discussions on my thesis and other projects that we collaborate on, for pleasant chats on airplanes when visiting conferences, for inspiring e-mails, and for inserting some of the correct articles into this work.

I have also been lucky to have some of the best people on my advisory committee. Dr. Debra Jared has provided not just her insight on this work, but also important advice and concrete help in my professional development. I also wish to thank Dr. Marc Joanisse for his suggestion to go big and to work on a computational model of stress assignment in this thesis. My words of gratitude also go to the wonderful members of my examination committee: Dr. Ken McRae, Dr. Victor Kupperman, and Dr. Jeff Tennant. Their insightful and thought-provoking questions and comments undoubtedly improved the quality of this thesis and gave me some ideas about a number of potential research projects that I hope to run in future.

This work was not completed in a vacuum. I received a lot of useful feedback from other faculty members and graduate students of the Psychology Department of the University of Western Ontario: Dr. Albert Katz, Dr. Paul Minda, Dr. Lisa Archibald, Dr. Patrick Brown, Dr. Alan Paivio, Dr. Robert Gardner, Dr. Paul Tremblay, Jason Perry, Eric Stinchcombe, Mark McPhedran, Sarah Miles, Ruby Nadler, Rachel Rabi, Andrea Bowes, James Boylan, Daniel Trinh, Eriko Ando, Kazunaga Matsuki, Jeff Malins, Laura

Westmaas-Sweet, Emily Nichols, Jimmie Zhang and many others. Working with each of these people has been a gift that went much further than just completing work that needed to be done.

I want to extend my love and gratitude to my husband Igor for believing in my potentials and pushing me forward every single day. His love, support, and encouragement mean more than words can express. I also wish to thank the inventors of Skype. The fact that I could see members of my beloved family and my dear friends, who are back in Russia, and share with them some of my troubles or achievements, is what made me work harder. I want to thank my friends and family for keeping in touch with me, for cheering for me, and for providing support.

One of my life mottos is that happiness is a journey not a destination. These four years were an enjoyable journey thanks to many wonderful people who I met in Canada. Although I feel a bit sad finally reaching this destination, I understand that it is only a beginning of another, more exciting journey that is ahead. I hope that many of you will still be a part of my life when I embark on this new journey.

Table of Contents

List of Tables

List of Figures

List of Appendices

Bayesian Model of Stress Assignment in Reading

Chapter 1 – General Introduction

Lexical stress, defined as the relation between prominent and weak syllables in a word realized via changes in frequency, duration, and intensity, has been shown to perform many functions in oral and written communication. For example, stress aids in the process of speech segmentation (Cutler & Norris, 1988; Norris, McQueen, & Cutler, 1995), regulates attentional processes in speech perception (Mens & Povel, 1986; Pitt & Samuel, 1990), and facilitates lexical access in spoken word recognition (Cutler & Clifton, 1984; van Donselaar, Koster, & Cutler, 2005). It has also been reported that a reader's sensitivity to lexical stress information predicts reading abilities (Kuhn & Stahl, 2003; Whalley & Hansen, 2006) and that activation of lexical stress information is a vital step in word processing in overt as well as in silent reading (Ashby & Clifton, 2005; Breen & Clifton, 2011).

Due to the apparent importance of prosodic (especially stress) information in reading, questions concerning the mechanisms of stress assignment in written word comprehension clearly need additional investigation. To this point, however, the majority of theoretical and computational constructs developed in the area of reading research have centred on the mechanisms involved in the processing of single-syllable words that, due to their structure, do not require prosodic processing by a reader. Only recently the field has seen a shift toward the study of polysyllabic words, making it obvious that a full-fledged model of word reading should provide an explanation of not only the mechanisms of grapheme-to-phoneme mapping, but also of the principles of lexical stress assignment.

In modeling the process of grapheme-to-phoneme mapping, there are two general computational approaches: the dual-route view implemented in the Dual Route Cascaded (DRC) model of reading (Coltheart, Rastle, Perry, Langdon, & Ziegler, 2001) and the single-route, connectionist view implemented in the Parallel Distributed Processing (PDP) model of reading (Harm & Seidenberg, 2004). Although neither model explicitly models the stress assignment process, there are ways within each model to expand the architecture to allow it to, potentially, explain how lexical stress is assigned (Arciuli, Monaghan, & Ševa, 2010; Perry, Ziegler, & Zorzi, 2010; Rastle & Coltheart, 2000; Ševa, Monaghan, & Arciuli, 2009). However, as will be shown below, the performance of these models in terms of stress assignment is not very good, especially when one compares the models' output on nonwords with behavioral data; that is, in assigning stress to nonwords these models are consistent with participants' behavior for only about 65% of the stimuli.

In this thesis, an alternative, previously not considered, approach to the modeling of the process of lexical stress assignment in reading is proposed. Specifically, it is suggested that stress assignment in reading can be thought of as a Bayesian decision-making process that involves updating the probability estimates of hypothetical outcomes (i.e., stress patterns) by considering evidence, specifically, non-lexical cues to stress, that provide various levels of support for each of the possible stress patterns. This Bayesian model of stress assignment is intended to be a universal model that can be applied to any language of the world that is characterized by the presence of lexical stress. Further, the proposed model can, potentially, explain the process of stress assignment in reading polysyllabic words of any length. However, the present thesis is only concerned with evaluating a Bayesian model of stress assignment for disyllabic Russian words.

In Russian, the process of stress assignment appears to be complicated because stress is not explicitly marked in the orthography and it does not conform to any clear implicit rules. Although there are a number of morphemes that provide readers with stress position information (e.g., the suffix "*изм*" is always stressed as in *фашИзм* ([fashizm]), *афорИзм* ([afarizm]); throughout the thesis stressed vowels in examples are capitalized), the majority of Russian words have stress-ambiguous morphemes (for a review see, Coats, 1976; Lagerberg, 1999). Therefore, even morphology has limited usefulness in terms of helping readers accurately assign stress. Finally, Russian readers cannot rely on information about the frequency of stress patterns in the language because the percentage of disyllabic words with stress on first syllable (i.e., a trochaic stress pattern) appears to be virtually the same as the percentage of words with stress on second syllable (i.e., an iambic stress pattern).

Due to the complexity of the stress assignment process for Russian speakers, a widely accepted view has been that a Russian word's stress is assigned only following the retrieval of accurate stress information from the word's lexical representation (Gouskova, 2010; Lukyanchenko, Idsardi, & Jiang, 2011). Although it is quite possible that, in making stress assignment decisions, Russian readers demonstrate greater reliance on lexical processing than readers of a language with a more predictable prosodic system, it seems unlikely that, in Russian, lexical retrieval is the only means of stress assignment used by readers. Indeed, the main goal of the present research, the development of a Bayesian model of stress assignment, is based on the assumption that native readers of Russian do use non-lexical information to assign stress. If that assumption is incorrect, then, the Bayesian model of stress assignment, a model that is essentially non-lexical, will not be able to simulate stress assignment performance in Russian.

The selection of Russian provides a number of additional benefits. First of all, it expands the range of languages in which the modeling of the process of stress assignment in reading has been attempted. In fact, all existing models have been created to explain stress assignment in English. Doing so limits the generalizability of those models. Secondly, English is likely not the best choice of a language for investigating this issue. It has been noted that around 80% of disyllabic English words have trochaic stress, which likely creates a strong bias toward this stress pattern in native speakers of English (Arciuli & Cupples, 2004; 2006; Kelly, Morris, & Verrekia, 1998). Therefore, in English it becomes difficult to disentangle the effect of the bias toward a trochaic stress pattern from other non-lexical factors that readers may utilize. By employing Russian, a language with no apparent stress bias, one should be able to overcome this limitation.

In the present thesis, material is presented in the following order. In *Chapter 2*, an overview of three computational models of stress assignment is provided. According to the model by Rastle and Coltheart (2000), word stress can be assigned lexically or non-lexically, following stress assignment rules. The second model (Seva et al., 2009) involves a connectionist network that considers orthographic cues in assigning stress. Finally, according to the Connectionist Dual Process (CDP++) model of reading (Perry et al., 2010), stress can be processed via a lexical route or a non-lexical route that is conceived of as a connectionist network. The models were tested on their ability to predict stress patterns in English disyllabic words and nonwords. While the performance of the models on words was decent, none of the models provided an especially good fit to the nonword data. These results suggested that further attempts to model stress assignment process are needed.

In *Chapter 3*, the general framework of a Bayesian model of stress assignment in reading that can compute the posterior probabilities of stress patterns for any letter string is described. In calculating the posterior probabilities, the model considers two types of information: prior probabilities of the stress patterns and the likelihood of a particular stress pattern given certain types of non-lexical evidence. The prior probabilities refer to the frequency with which various stress patterns occur in a specific language. The likelihood of stress patterns given certain non-lexical evidence refers to the probability of stress patterns when different potential stress cues present in the orthographic input are considered. The Bayesian model of stress assignment can be applied to any language that utilizes lexical prosody, although prior probabilities and sources of evidence for stress would be language-specific.

Chapter 4 is a review of the prior research looking for the potential sources of evidence for stress in a number of languages. First of all, studies that investigated the impact of the frequency of stress patterns in the language (i.e., stress regularity) on native speakers' performance are described. Thus, the validity of the statement that the information about overall prior probabilities of stress patterns is considered in the process of stress assignment is assessed. Then, research that investigated other potential sources of evidence for stress patterns is described. Among some of the proposed cues to stress are graphemic complexity of the onset of a word, graphemic complexity of the coda of a word, grammatical category, consistency with which the ending of a word maps onto a stress pattern, and, finally, consistency with which the beginning of a word maps onto a stress pattern.

In *Chapter 5*, the factors underlying the implementation of the Bayesian model of stress assignment for Russian disyllables are laid out. First, to assess prior probabilities of iambic and trochaic stress patterns in Russian, an analysis of a corpus of Russian disyllabic words was conducted. This analysis showed that 55% of disyllabic Russian words have iambic stress, while 45% of disyllabic words have trochaic stress. Then, a factorial study and two regression analyses were conducted to distinguish the sources of evidence for stress patterns in Russian. In the factorial study, the naming performance of speakers of Russian on words that differed in stress patterns (iambic vs. trochaic), grammatical categories (adjective vs. noun vs. verb), and consistency with which word endings can predict stress patterns (consistent vs. inconsistent) was observed. The analysis demonstrated a reliance of speakers of Russian on the consistency with which the orthography of word ending maps onto the stress pattern of a word.

Next, a binary logistic regression analysis using a corpus of Russian disyllabic words was run with a goal of assessing what cues exist in the language that predict stress patterns. Then, in a generalized linear mixed effects model, the same predictor cues were used to assess the stress assignment performance of speakers of Russian on a set of 500 disyllabic words. Out of eleven potential predictors considered (Log Frequency, Length, Onset Complexity, Ending Complexity, Grammatical Category, Consistency of the First Syllable, Consistency of the Beginning of the First Syllable, Consistency of the Ending of the First Syllable, Consistency of the Second Syllable, Consistency of the Beginning of the Second Syllable, Consistency of the Ending of the Second Syllable), the spelling-to-stress consistency measures of three orthographic components (the First Syllable, the Second Syllable, and the Ending of the Second Syllable) were the most important predictors of stress assignment in Russian. Thus, it was concluded that the orthography of the first syllable, the orthography of the second syllable, and the orthography of the ending of the second syllable are the most likely sources of evidence for readers to use when assigning stress patterns in Russian disyllabic words.

In *Chapter 6*, two simulations were run to test the predictive power of the Bayesian model of stress assignment in Russian. The predictions of the model concerning stress assignment performance were compared to behavioral data. The posterior probabilities of iambic and trochaic stress patterns that the model computed were reflective of the performance of native speakers of Russian on a set of Russian disyllabic words. That is, participants were more likely to make stress assignment errors if, according to the model's computation, the posterior probability of the actual stress pattern that a word has was comparatively low. On the other hand, if the posterior probability of the actual stress pattern of a word was high, participants were less likely to assign an incorrect stress pattern to this word. Further, the model was successful in predicting stress assignment performance on a set of nonwords.

Chapter 7 is a summary of the research reported in this thesis. The general conclusion is that the Bayesian model of lexical stress assignment derived here, which is based on the idea that in making lexical stress decisions readers integrate non-lexical sources of evidence for lexical stress to update prior beliefs about stress patterns, is a viable computational model of stress assignment.

Chapter 2 – Models of Stress Assignment

2.1. Introduction

One of the greatest limitations of the majority of the models of visual word recognition is that, for the sake of simplicity, they were created to deal with monosyllabic words only. The models of monosyllabic reading cannot be readily applied to polysyllabic words as they lack, in their architecture, mechanisms that would enable them to deal with syllabification and stress assignment. This limitation has been acknowledged by a number of researchers who have created models of polysyllabic word reading (Ans, Carbonnel, & Valdois, 1998; Kello, 2006; Perry et al., 2010; Rastle & Coltheart, 2000), or models of stress assignment (Black & Byng, 1986; Seva et al., 2009). The three most cited models that provide some insight into the mechanisms by which lexical stress is assigned are the dual-route model by Rastle and Coltheart (2000), the connectionist model by Seva et al. (2009), and the CDP++ model by Perry et al. (2010). These three models are discussed in this Chapter in detail, but, prior to that, a brief overview of other attempts to explain how stress is assigned in polysyllabic words is provided.

One of the first models of stress assignment was proposed by Black and Byng (1986). This model advances the idea that in the process of assigning stress, readers use the knowledge of the frequency of stress patterns in the language. More specifically, a reader identifies the number of syllables in a word and assigns the most frequent stress type for words of that syllabic length. Then, the assembled phonological representation guides a lexical search. If the phonological candidate matches a memory representation, the word is pronounced. If the matching of the candidate and lexical representation fails, the entire cycle is repeated assigning the second most frequent stress type.

The model by Black and Byng (1986) has several drawbacks. First of all, the frequency of stress patterns in the language has not been consistently demonstrated to affect readers' performance (Gutierrez-Palma & Palma-Reyes, 2008; Rastle & Coltheart, 2000). In fact, it has been shown that readers more often rely on non-lexical orthographic cues to stress rather than rules of the type proposed by Black and Byng (Burani & Arduino, 2004; Sulpizio, Job, & Burani, 2012). Secondly, while this model might have some success in simulating stress assignment in languages with a dominate stress pattern (e.g., in English or Italian), it would be unable to do so in languages that do not possess a stress pattern that dominates (e.g., in Russian). Finally, the suggestion of a mandatory check of a candidate against memory representations seems to be questionable because it presupposes an obligatory access of the lexicon when reading words. If lexical access is an obligatory step in the process of word recognition, it is unclear why readers would not retrieve stress pattern information directly from memory rather than applying some non-lexical rules and, then, follow that process with checks of lexical memory.

A quite different theoretical approach was taken by Ans et al. (1998), who proposed a connectionist multiple-trace memory model (MTM) of polysyllabic word reading. The MTM contains a network of connections between two orthographic input layers, an episodic memory layer, and a phonological output layer. The weights of connections between layers are adjusted via back-propagation as the model is exposed to lexical representations and naming errors made by the model are discovered. A lexical item presented to the MTM is processed in a global mode and in an analytical mode. In the global mode, all letters of the word are processed in parallel. In the analytical mode, a word is decomposed into syllables and each syllable is processed one-by-one by the model. Hence, there are two orthographic input layers (traces): whole-word orthographic representations and syllable orthographic representations. The phonological output is based on the processing of both representations (multiple traces).

The MTM has been implemented and successfully tested in French word and nonword naming. However, it has one major limitation that does not allow it to be implemented in many other world languages. While the MTM can simulate the grapheme-to-phoneme mapping process, it does not have a component in its architecture that would deal with lexical stress. This is not problematic in French as this language does not have lexical stress, but rather utilizes prosodic stress (i.e., stress is placed on the final syllable of a string of words, or the next-to-final syllable, if the final syllable is a schwa). On the other hand, in languages like Spanish, Italian, Russian, or English, in which there is lexical stress and stress position is flexible in a word, the MTM would not be able to provide fully specified phonological output.

A connectionist approach to modeling the processing of polysyllables has also been implemented in the Junction model of Kello (2006). In this model, one simple recurrent network at the input level converts variable length sequences into fixed-width representations, and another simple recurrent network at the output level regenerates the sequence from the fixed-width representation. These representations and semantic representations are joined together via a set of intermediate nodes that are responsible for the mapping of graphemes onto phonemes. Thus, the mapping of orthography to phonology is mediated by semantics, rather than being direct as in the MTM model described above.

The Junction model was further elaborated by Sibley, Kello, and Seidenberg (2010) by including stress output nodes and by changing the input coding. At the moment, it is difficult to assess the theoretical and practical validity of the Junction model and its variants, as the models are still in their preliminary stages of development and have not been tested extensively. Mainly, researchers tested the Junction model on its ability to account for the variance in the response latency of the words in the ELP database (Yap & Balota, 2009). The model could account for about 30% of the variance in the RT data. The ability of this model to accurately generate pronunciations was far from the level of a skilled reader as the model produced errors in 70% of cases in its original version (Kello, 2006) and in 35% of cases in its later version (Sibley, Kello, & Seidenberg, 2010). Further, the specifics of the performance of the Junction model on stress assignment were not clear as the modelers did not specify whether the errors that the model committed were segmental (i.e., incorrect mapping of orthography onto phonology) or supra-segmental (i.e., incorrect mapping of orthography onto stress) in nature.

Next, descriptions and assessments of performance of two well-tested models of stress assignment (Rastle & Coltheart, 2000; Seva et al., 2010) and a model of reading that has a stress assignment component in its architecture (Perry et al., 2010) are provided. These models can be viewed as extensions of two competing approaches to computational modeling of reading processes, that is the dual-route approach (Rastle & Coltheart, 2000; Perry et al., 2010) and the connectionist, single-route approach (Seva et al., 2010).

2.2. The model by Rastle and Coltheart (2000)

The model of stress assignment by Rastle and Coltheart (2000) was conceived within the framework of the dual-route theory of reading (Coltheart et al., 1993). According to this theory, phonology can be assembled from spelling based on a set of rules (the non-lexical route) or retrieved from lexical memory (the lexical route). The rules the non-lexical route uses are derived on statistical grounds and reflect the most frequently associated grapheme-to-phoneme mappings. The original DRC model could simulate the naming of monosyllabic words only. In order to extend it to the domain of polysyllabic words, Rastle and Coltheart (2000) developed a model of lexical stress assignment for English disyllabic items.

The architecture of this model of stress assignment is very similar to that of the DRC as the assignment of stress can be completed lexically via retrieval of stress information from memory or as a result of computations by a non-lexical, rule-based system using an algorithm. The rules of the stress-assigning algorithm reflect previously reported findings of associations that exist in English between some morphemes and certain stress patterns (Fudge, 1984). The non-lexical route is utilized when readers assign stress to nonwords or regularly stressed words (i.e., words for which the proposed algorithm predicts stress patterns correctly), especially if the word is a low frequency word. The lexical route is used when readers assign stress to irregularly stressed words (i.e., words for which the proposed algorithm does not predict stress patterns correctly), and, to some extent, to regularly stressed words, if these are high frequency items.

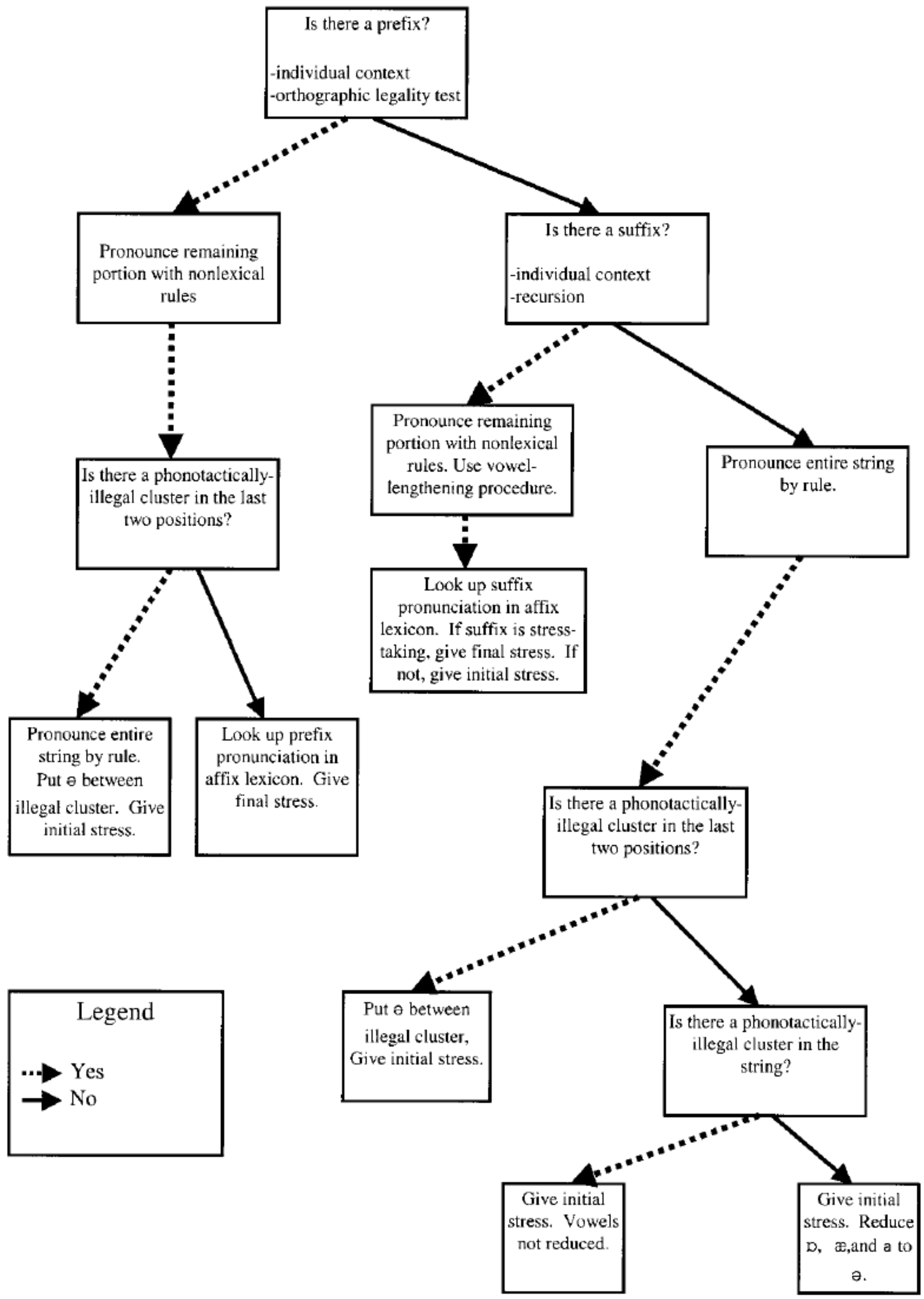
The algorithm goes through the following steps (see Figure 1). First, it determines whether a word has any prefixes. As prefixes are unstressed in English, any disyllabic word with a prefix will have stress on the second syllable. If no prefix is identified, then, the algorithm searches for the presence of suffixes. All prefixes and suffixes are checked for their legality to avoid the identification of affixes in monomorphemic words (e.g., -er in corner). If the algorithm concludes that a word does contain a legal suffix, then, this suffix is checked against the store of stress-taking suffixes. If the suffix is stress-taking, the word is assigned second syllable stress. If the suffix is not stress-taking, the word is assigned first syllable stress. Finally, if neither a prefix nor a suffix are identified, the algorithm assigns the most frequent stress pattern in English (i.e., stress on first syllable).

The algorithm proposed by Rastle and Coltheart (2000) was evaluated using a set of disyllabic words taken from the CELEX database (Baayen, Piepenbrock, & van Rijn, 1995). The algorithm assigned stress correctly to 90% of these English disyllabic words. However, the performance of the algorithm on words with a (common for English) trochaic stress versus a (less frequent) iambic stress was not identical. While the ability of the model to correctly predict trochaic stress was exceptional (95% correct), the model's hit rate for words with iambic stress was relatively low (67% correct).

The predictions of the algorithm were also compared to the performance of native speakers on a set of nonwords created for this purpose. The algorithm produced the same response as speakers in 84% of cases, although the performance of the algorithm on items with trochaic versus iambic stress was slightly different. The model predicted correctly the speakers' assignments in 81% of nonwords assigned trochaic stress and in 89% of nonwords assigned iambic stress, which stands in contrast to the results of simulations on words.

Figure 1

The set of non-lexical stress rules in the model of stress assignment by Rastle and Coltheart (2000)



This fact that the algorthim did as well as it did on iambically stressed nonwords might suggest that the nonwords were not created in an arbitrary way. In fact, the majority of them did contain stress-bearing affixes. Thus, the modelers were testing the items that were predisposed to be assigned iambic stress both by the readers and by the algorithm. Further, Seva et al. (2009) showed that the performance of the algorithm on a different set of nonwords (Kelly, 2004) was less impressive: the algorithm was correct in 78% of cases when nonwords were given trochaic stress by readers and only in 44% of cases when readers assigned iambic stress to nonwords.

In addition to the relatively modest results demonstrated by the algorithm, there are other points of criticism of this model. First, the distinction between lexical and non-lexical routes is not clear in the model as the non-lexical route is perceived as containing storage of affixes that carry lexically relevant information. Secondly, the researchers posit that the process of stress assignment in English is based on knowledge of the associations between morphemes and stress patterns. However, their stress-bearing suffixes include some word endings that are not suffixes at all (e.g., -oo, -ique), undermining the whole idea of morphologically based mechanism. Further, the system that checks on whether a string of graphemes is a valid affix or not implemented in the algorithm would run into problems handling pseudo-complex words (e.g., corner), words that the algorithm supposedly does not parse into pseudo-morphemes. In contrast, there is now substantial evidence suggesting that morphological parsing occurs pre-lexically for these types of words (Diependale, Sandra, & Grainger, 2005; Morris, Grainger, Holcomb, 2008). Note also that the algorithm in its present, rather complex, form can only explain stress assignment in disyllabic words. The extension of this model to words of other syllabic length would require addition of a significant number of new components to the model's architecture, making it even more complicated from a computational point of view. Finally, it is not clear whether this algorithm can be applied to polysyllabic words of any other language than English. To a certain extent, the model does perform satisfactorily in English due to the fact that it contains a default trochaic stress rule, which by itself can correctly predict stress assignment in 80% of English words. The ability of this algorithm to adequately explain stress assignment in languages that do not possess a default stress pattern or do not exhibit associative connections between morphology and stress patterns appears to be rather limited.

2.3. The model by Seva, Monaghan, and Arciuli (2009)

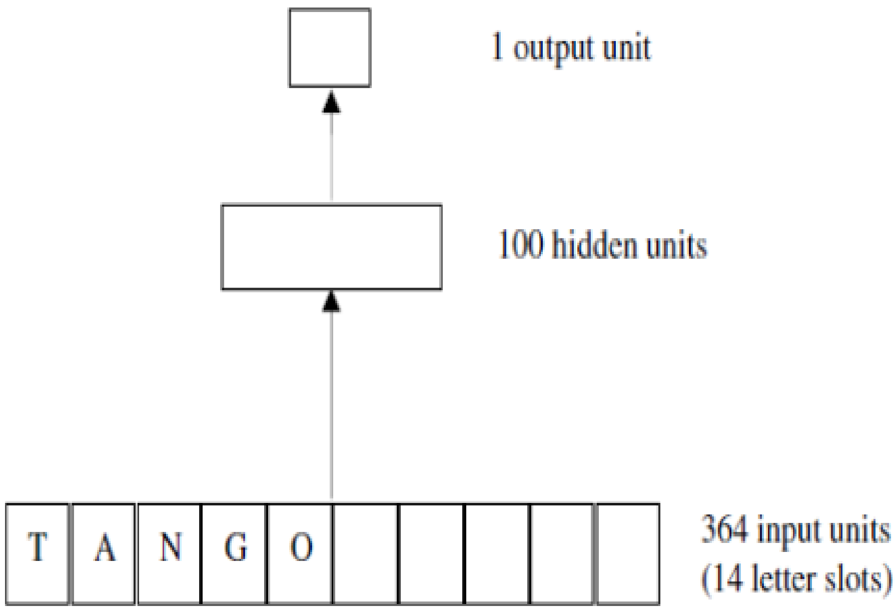
Seva, Monaghan, and Arciuli (2009) based the architecture of their model on the tenets of the connectionist model of reading (Plaut, McClelland, Seidenberg, & Patterson, 1996) that suggests that lexical and non-lexical processing, in fact, arise from a single connectionist mechanism. The knowledge of grapheme-to-phoneme correspondences, in the form of statistical probabilities, is stored in connections between input and output layers via a layer of hidden units. Upon being exposed to a corpus of words, the connectionist model adjusts weights on connections between units in a way that reflects associative relations between orthography and phonology. Similar principles are extended to the process of stress assignment in the model by Seva et al. (2009), which is based on the idea that orthographic patterns are probabilistically associated with stress patterns. With sufficient exposure to words, the model can discover the statistical regularities present between orthography and stress, and utilize them in the process of stress assignment.

The model is a simple supervised feed-forward connectionist network that maps orthography of English disyllables onto stress patterns (see Figure 2). The orthographic input layer is composed of 14 slots with 26 letter units per slot. Words are presented at the input layer left aligned. The input layer is connected to a layer of 100 hidden units, which in turn are connected to one stress output unit. For words with trochaic stress, the stress unit activity is 0, for words with iambic stress, its activity is 1. The model was judged to have assigned trochaic stress if the activation of output unit was less than .5, and iambic stress if the activation of the output unit was greater than .5. The model was trained on a set of disyllabic words with the weights on connections between units being adjusted by way of back-propagation based on errors.

The model was tested on words from the CELEX database and two sets of nonwords. The performance of the model on words used in the process of training was very high (99% correct for words with trochaic stress and 92% correct for words with iambic stress). The model's performance on words not used during training was slightly less accurate (97% correct for words with trochaic stress and 77% correct for words with iambic stress). The performance of the connectionist model on nonwords from the study by Rastle and Coltheart (2000) was not perfect (69% correct responses) mainly due to its inability to assign second syllable stress patterns correctly (88% correct predictions for trochaically stressed words and 50% correct predictions for iambically stressed words). The results of the testing of the model on nonwords from the study by Kelly (2004) were also modest (65% correct responses) again due to the model's poor performance on iambically stressed words (42% of correct responses in comparison to 89% on items that were assigned trochaic stress).

Figure 2

The architecture of the connectionist model of stress assignment by Seva et al. (2009)

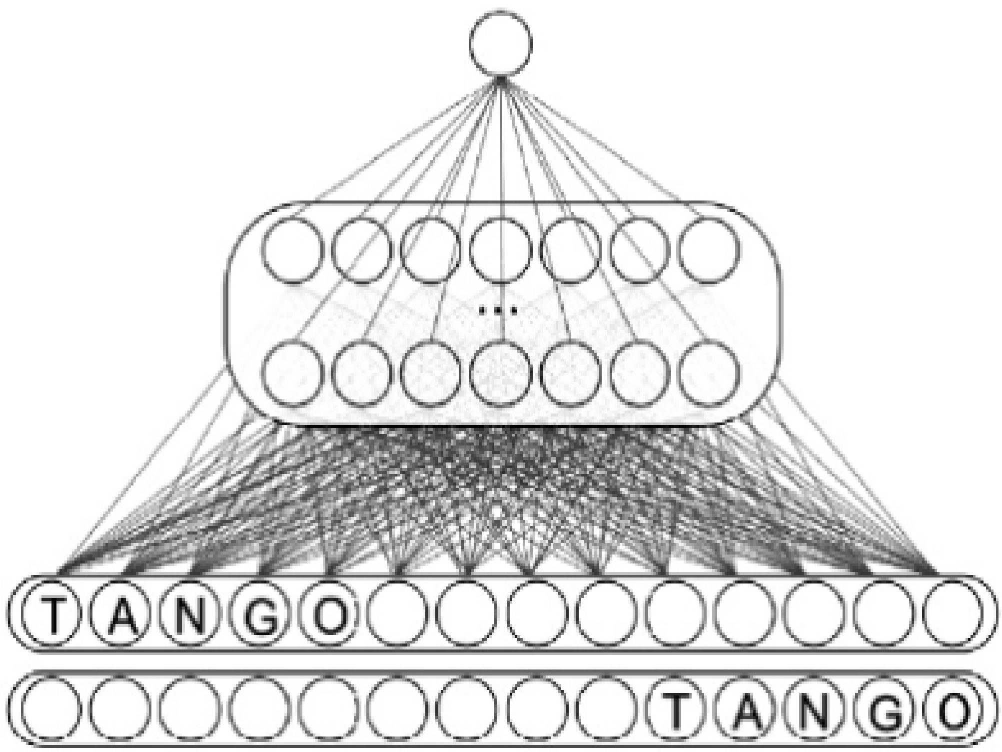


One concern was that this connectionist model might be performing poorly on nonwords due to the fact that the left-aligned model considered the statistical probabilities that exist between stress patterns and word beginnings only, while readers might be using probabilities that exist between stress patterns and other orthographic components (e.g., word endings). To make the regularities of both word beginnings and of word endings available to the model, the modelers included both left-aligned and a right-aligned orthographic input layers in the model (Arciuli et al., 2010; see Figure 3).

The model was trained on words from the Educator's Word Frequency Guide (Zeno, Ivens, Millard, & Duvvuri, 1995), reflecting the lexicons of children at different ages. The model exposed to the lexicon of a 5-6 year old child demonstrated a significant bias towards assigning a trochaic stress pattern to words, a bias that decreased with the incremental exposure of the model to a later age lexicon. Having received additional training, the model with left-aligned and right-aligned input layers assigned stress correctly in 99% of words, which is significantly better than the model with only a left-aligned (86%) or a right-aligned input layer (83%). Unfortunately, as the authors do not provide the details of the performance of the full model on words with first and second syllable stress separately (which is required for proper assessment of the performance of the model as words with different stress patterns were not represented in the lexicons proportionally), it might still be the case that the improved model has some difficulty in predicting second syllable stress correctly. Such was, indeed, the cases for the left-aligned model, which was correct on 96% of words with first syllable stress and only on 49% of words with second syllable stress and right-aligned model, which was correct on 96% of words with first syllable stress and 35% of words with second syllable stress.

Figure 3

The architecture of the connectionist model of stress assignment by Arciuli et al. (2010)



The full model was also tested against the behavioral performance of children of different age groups on 24 nonwords that contained orthographic strings that cued first or second syllable stress. Although the low number of tested items makes generalization difficult, the model underperformed on items to which participants assigned second syllable stress. Thus, in predicting the behavior of 11-12 year olds, the model was correct on 92% of nonwords that were given first syllable stress, and only on 67% of nonwords that were given second syllable stress.

In summary, Arciuli et al.'s (2010) model of stress assignment is an improvement over earlier models as it is not limited to an a priori determined set of rules. However, in its present implementation, the model seems to be sensitive to orthographic cues of word beginnings and word endings only, while readers might be paying attention to other orthographic components while assigning lexical stress. Further, the connectionist model does not perform well in assigning second syllable stress to either words or, especially, nonwords. This difficulty presumably arises from the fact that in English many orthographic cues are associated with first syllable stress, while the extent of the association between orthography and a second syllable stress pattern is not large. This difference in the scope of the probabilistic relation between orthography and stress patterns for two types of words occurs mainly due to there being a greater number of words with first syllable stress in English. In light of this fact, it might be difficult for the connectionist model to predict stress pattern assignment in languages that do not have a more frequent stress pattern. In such languages, the associations between orthographic cues and stress patterns might, in general, be weak and, therefore, the performance of the model might be only mediocre.

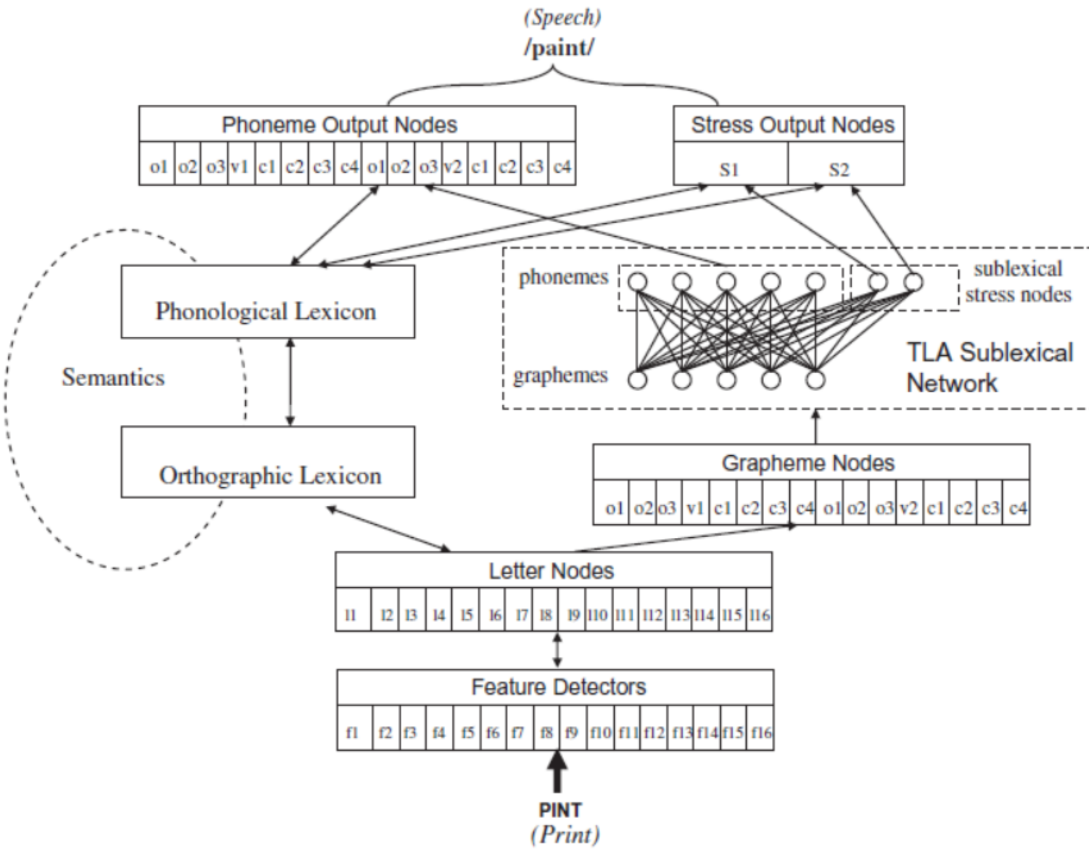
2.4. The Connectionist Dual Process ++ (CDP++) model (Perry et al., 2010)

The CDP++ (Perry et al., 2010) is a model of word reading built on the strengths of the dual-route and the connectionist models. Similar to the dual-route model, the CDP++ distinguishes between lexical and sub-lexical processing. However, the sub-lexical route is represented by a connectionist network, rather than by a set of rules. The architecture of the CDP++ is depicted in Figure 4. In the CDP++, a buildup of activation starts at the level of orthographic features which is, then, fed to the level of letters consisting of 16 letter slots. At further stages of processing, letters are mapped onto orthographic and, further, onto segmental phonemic and suprasegmental stress representations. This mapping may be achieved via lexical or sub-lexical routes.

The lexical route is a fully interactive network consisting of phonological and orthographic lexicons. The representation at the letter level activates orthographic entries in the lexicon on the basis of letter overlap. Orthographic entries that do not contain letters being activated at the letter level of the model are inhibited. Entries in the orthographic lexicon, then, activate whole-word representations in the phonological lexicon. Finally, lexical phonological representations activate corresponding phoneme output units and one of two stress output units in the phonological output buffer. In the lexical route of the CDP++, all levels are connected in a way that makes feedback possible. Thus, the activation of the stress or phoneme output unit in the phonological output buffer can be sent to the phonological lexicon, and activate phonological lexical representations.

Figure 4

The architecture of the CDP++



The sublexical route is represented by a graphemic buffer that organizes letters into a graphosyllabic template and the connectionist two-layer network of phonological assembly (TLA network) that encodes statistical regularities. In the graphemic buffer, a sublexical orthographic representation is constructed by a graphemic parser that analyzes letter input, transforms letters into graphemes, and maps them onto syllabic templates of the first and the second syllables. Each syllabic template has three onset slots, one vowel slot, and four coda slots. Thus, the complete template of a disyllabic word has the following structure: CCCVCCC.CCCVCCC. An issue of an ambiguity in syllabification present in English (e.g., the word *demand* can be segmented as *de.mand* or as *dem.and*) has been addressed by the modelers by applying a widely accepted phonological constraint, known as the Maximal Onset Principle (Kahn, 1976). According to this principle, consonants occurring between two vowels are assigned to the onset position of the second syllable, if this does not lead to the creation of codas or onsets that are illegal in the language. Thus, the word *demand* will be represented in the graphemic buffer in the following way: d**e***.m**and* (asterisk represents an empty slot).

A representation constructed in the graphemic buffer is next processed in the TLA network which is a simple two layer network of connections between orthographic input and phonological output. The orthographic input is encoded over 16 slots with 96 grapheme nodes per slot. The phonological output is encoded over 16 phoneme slots with 44 phoneme nodes per slot and a stress slot with two nodes. Two stress nodes have lateral inhibitory connections. Thus, the activation of one stress node inhibits the other. The activation from sub-lexical output nodes is sent to the phoneme output and stress output nodes. The naming of a word starts only if phonological as well as stress output units are activated. Unlike the lexical route, the sub-lexical route of the CDP++ is not interactive. The activation goes only in the direction described above with no feedback possible.

The CDP++ was trained on words from the CELEX database (Baayen et al., 1995) and, then, tested on the same words that were used during the training stage. The CDP++ showed outstanding performance on this corpus with 97% of stress patterns overall being predicted correctly. However, the accuracy of the model on words with a less common (in English) second syllable stress was slightly worse (88% correct) than on words with a more common (in English) first syllable stress (99% correct). The performance of the model on nonwords from the study by Rastle and Coltheart (2000) was less accurate. The model was correct in 92% of items with first syllable stress, and in 51% of items with second syllable stress. A similar pattern emerged when the model was tested on nonwords from the study by Kelly (2004), showing 93% accuracy for the nonwords stressed on their first syllable, but only 45% accuracy for nonword stressed on their second syllable.

To summarize, the CDP++ was able to perform well on the corpus of English disyllabic words, but it had substantial difficulty in simulating the nonword data as seen in a trend to overgeneralize a first-syllable stress pattern. So far, the CDP++ has only been used to simulate the performance of readers on English disyllabic words. The authors state that with minor changes the architecture of the CDP++ can be applied to words of other syllabic lengths and other languages. However, no modeling attempts of that kind have been completed yet, and the ability of the model to simulate stress assignment in languages in which, unlike in English, there is no dominant stress pattern present remains to be examined.

2.5. Conclusion

There has been some progress in modeling the reading of polysyllabic words and the process of stress assignment. In all of the reviewed models created to deal with English disyllabic words, it is suggested that orthographic (Seva et al., 2009; Perry et al., 2010) or morphological (Rastle & Coltheart, 2000) cues present in the written input are used in computing the correct stress pattern. In general, these computational models demonstrate good performance on word reading and high percentage agreement on stress assignment in nonwords that are named with first syllable stress by native speakers. The performance on the naming of nonwords that are empirically assigned second syllable stress is considerably less impressive.

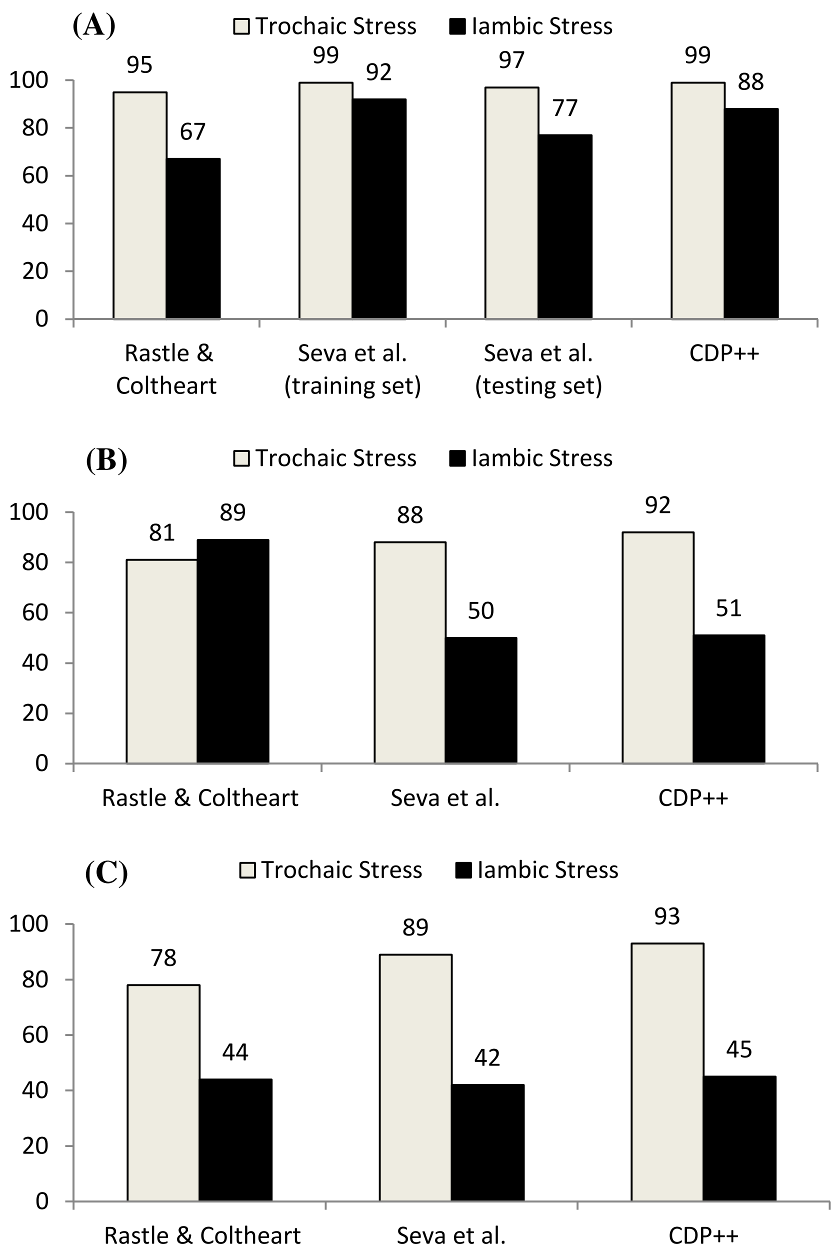
Figure 5 contains summary information concerning each model's performance on a corpus of disyllabic words (see Figure 5A), nonwords taken from the study by Rastle and Coltheart (2000) (see Figure 5B), and nonwords taken from the study by Kelly (2004) (see Figure 5C). While all models performed well in assigning correct stress pattern to words with stress on the first syllable, the CDP++ and the connectionist model by Seva et al. (2009) (when tested on words that were also used during training of the model) were the most successful in assigning stress to words with second syllable stress. The algorithm of Rastle and Coltheart demonstrated the least ability to predict second syllable stress in the corpus of English disyllabic words. On the other hand, that algorithm provided the best fit to the behavioral data using a set of nonwords taken from the study by Rastle and Coltheart. Moreover, the algorithm showed equally good performance on nonwords from this set of nonwords that were assigned first as well as second syllable stress. In contrast, the model by Seva et al. (2009) and the CDP++

performed poorly on these nonwords, especially nonwords that were assigned second syllable stress by readers. It has been suggested that this difference in the performance of the models is due to a somewhat biased choice of nonwords in the study by Rastle and Coltheart. Finally, the results of the simulations of the behavioral data taken from the study by Kelly showed that all three models performed poorly on nonwords that readers pronounced with second syllable stress. The CDP++ showed the best hit rate when the stress patterns of Kelly's nonwords with first syllable stress had to be predicted, while the algorithm of Rastle and Coltheart was the least successful in simulating the behavioral data for these stimuli.

Overall, it appears that the CDP++ performs better than the algorithm of Rastle and Coltheart (2000) and slightly better than the model of Seva et al. (2009). However, the performance of the CDP++ is still far from perfect, and it has not yet been tested extensively. The present thesis is not an attempt to directly examine the approach to stress assignment modeling proposed in the CDP++ but, instead, to consider an alternative, potentially equally plausible way to model this process. In the present thesis, it is suggested that stress assignment in reading can be viewed as a process of evaluation of probabilities of stress patterns. A probability of a stress pattern is computed by adjusting the prior belief about the likelihood of this stress pattern being present in a word as well as evidence for stress provided by the orthography of a word being read.

Figure 5

Correct stress agreement (percentage) for the model by Rastle & Coltheart (2000), the model by Seva et al. (2009), and the CDP++ on a set of disyllabic words (A), Rastle and Coltheart (2000) nonwords (B), and Kelly (2004) nonwords (C)



Chapter 3 – Bayesian Model of Stress Assignment

3.1. Introduction

People constantly face the challenge of interpreting uncertain signals coming from a noisy environment and acting in the face of incomplete knowledge. One of the ways of dealing with this uncertainty is to process information using a probabilistic framework. In the presence of uncertainty, a person can make intelligent decisions by considering estimates of the probabilities of events rather than accepting the idea that data is limited to two values only (e.g., true or false). Thus, the human mind can potentially be perceived as an evaluator of the likelihoods of events aiming at near optimal decisions (Anderson, 1991). The view of the human mind as a probability estimator, which is associated with the Bayesian theory, has been widely adopted to explain various cognitive processes (for a review see Griffiths, Kemp, & Tenenbaum, 2008), although this approach also finds its opponents (Bowers & Davis, 2012; Jones & Love, 2011).

This chapter starts with an introduction of the basic ideas of Bayesian probabilities that despite their simplicity appear to be very powerful in explaining many phenomena in our environment. Then, a review of previous research pointing at the probabilistic nature of human cognition overall as well as of specific cognitive processes, including language, is provided. Indeed, language is characterized by uncertainty and its processing can be viewed as a problem of probabilistic constraint satisfaction. The process of lexical stress assignment, the topic of investigation in the present thesis, is also often ambiguous and, thus, it might be useful to consider this process in a probabilistic rather than a deterministic framework. In this chapter, a model of stress assignment that is based on the principles of Bayesian probabilities is proposed and described.

3.2. Bayesian probability

Probability is a numerical measure of the relative frequency of an event or the strength of a belief in a certain proposition. In describing human cognition, the subjective interpretation of probability (i.e., belief strength), in which probability can be viewed as a mental phenomenon, appears to be more appropriate. By convention, probability ranges from 0 to 1, where 0 means that the belief is certainly false and 1 means that it is certainly true. In a probabilistic system, one considers the probability of various possible hypotheses about the state of the environment, based on the sensory input received from this environment and prior knowledge about the state of the world. Such probability calculations are typically based on some form of Bayesian inference.

Bayesian inference is based upon a simple formula known as Bayes' rule (Bayes, 1763/1958), which is traditionally presented in the following form:

$$P(h \mid d) = \frac{P(d \mid h)P(h)}{P(d)} \ , \tag{1}$$

where h refers to a hypothesis, and d stands for some data used as evidence in the process of inference. In computing the probability of the hypothesis given the data, also known as *posterior probability*, one uses the knowledge of the probability of the data given the hypothesis, or *likelihood of evidence*, $P(d \mid h)$, the probability of the hypothesis before the data was assessed, or *prior probability*, $P(h)$, and the total probability of the data regardless of the hypothesis, $P(d)$. The total probability of the data is calculated by summing the products of the likelihood of evidence and prior probabilities of all possible hypotheses about the process. Thus, the formula can be re-written as:

$$P(h \mid d) = \frac{P(d \mid h)P(h)}{\sum_{h' \in H} P(d \mid h')P(h')} \ , \tag{2}$$

where H refers to the *hypothesis space*, or the set of all nonzero probability hypotheses. Thus, the posterior probability is proportional to the product of prior probabilities and the likelihoods of evidence. The sum in the denominator is used to normalize the posterior probabilities in such a way that they all sum up to one. For the probabilities to sum up to one, the hypotheses considered as alternative explanations of the data should be mutually exclusive, that is, two or more cannot be true at the same time.

Here is an example to illustrate how the posterior probabilities of a hypothesis are computed. Imagine that a doctor assesses the probability that a patient has pneumonia considering a patient's positive X-ray test. In this case, a doctor has two alternative hypotheses: *pneumonia* and *no pneumonia*. The only evidence that he has at this point is the result of an X-ray *test*. First, the doctor measures the prior probability of a patient having this disease. He knows that only 5% of previously treated patients in his care had pneumonia, therefore, $P(pneumonia) = .05$, while $P(no\ pneumonia) = .95$. Next, the doctor calculates the likelihood that a patient has a positive X-ray test given pneumonia. The doctor finds that 70% of patients with pneumonia had positive X-ray tests, while only 10% of patients who did not have pneumonia had positive X-ray tests. Thus, $P(test \mid pneumonia) = .70$, while $P(test \mid no\ pneumonia) = .10$. Thus, the posterior probability that a patient has pneumonia given a positive X-ray test can be calculated:

$$P(pneumonia \mid test) = \frac{(.70)(.05)}{(.70)(.05) + (.10)(.95)} = .27 \tag{3}$$

3.3. The probabilistic nature of human cognition

The world we live in is highly probabilistic. The fact that we see dark clouds in the sky does not necessarily mean that it is going to rain, although this possibility may be reasonably high. If we drop a glass vase, the chances are high that it will break; however, it may stay intact. If we see someone crying, we are more likely to think that the person is upset, however, these might be tears of joy. Therefore, similar to the doctor who makes probabilistic diagnosis based on certain prior observations of patients in his care, people make inductive inferences by evaluating the probabilities of possible hypotheses and selecting what appears to be the most probable one based on some past observations.

The complexity of the world that our mind has to grasp makes such metaphors as the Bayesian brain or probabilistic mind very popular in cognitive and neuropsychology. In fact, the idea of the probabilistic nature of human cognition has been described as "the most exciting and revolutionary paradigm to hit cognitive science since connectionism" (Movellan & Nelson, 2001, p.691). According to this idea, people learn probabilities of various objects that they observe in the world very quickly (Peterson & Beach, 1967) or even encode them automatically (Zacks & Hasher, 2002). In this way, the human mind operates like a statistician, although people are often vulnerable to incorrect assumptions about the relevance of the observed sample to the population, which gives rise to incorrect assessments of probabilities and, therefore, various erroneous conclusions and biases (for a review, see Hansson, Juslin, & Winman, 2008). There is also a claim in the literature that the human mind is not only generally good in grasping probabilities from the environment, but it constantly engages in action-oriented predictive processing (Clark, 2013). More specifically, our brain forms expectancies based on prior experience that are adjusted by weighing various cues arriving from sensory modalities.

Originally, the Bayesian view of cognition was thought to be able to explain the computational level of the processing only. Currently, there is growing evidence that probabilistic analysis is relevant to human cognition at the neuronal level as well (for a review, see Doya, Ishii, Pouget, & Rao, 2007). It has been suggested that probability distributions may be encoded in neurons in such a way that inference is achieved by summing up the firing rates (Ma, Beck, Latham, & Pouget, 2006) and that spiking neurons reflect integration of information over time (Deneve, 2004). Further, evidence for the integration of top-down prior information and bottom-up sensory data has been demonstrated in recurrent loops in the visual cortex (Lee & Mumford, 2003). Thus, Bayesian models of cognition are likely to be biologically plausible.

The probabilistic approach has been widely applied to explain many areas of human cognition including visual perception (Feldman, 2001), object recognition (Kersten, Mamassian, & Yuille, 2004), motor control (Kording & Wolpert, 2006), and eye movements (Najemnik & Geisler, 2009), to memory (Dennis & Humphreys, 2001), and theory of mind (Baker, Saxe, & Tenenbaum, 2009). Most relevant to the current thesis, another aspect of cognition that many researchers have started evaluating using the Bayesian approach is language (for a review, see Jurafsky, 2003). Traditionally, language has been viewed as involving a set of abstract units that are generated according to some formal rules. These rules are deterministic in their nature. However, in reality, language is characterized by the presence of significant noise and ambiguity that speakers can successfully deal with. In other words, language processing can be viewed as a process of probabilistic constraint satisfaction (McRae, Spivey-Knowlton, & Tanenhaus, 1998; Seidenberg & MacDonald, 1999).

The principles of probabilistic inference have been applied by researchers to explain language perception, production, and learning. Thus, there are a number of models of speech recognition couched in the Bayesian framework (Charter & Maning, 2006; Norris, 2006; Norris & Kinoshita, 2008; Norris & McQueen, 2008). Further, there is a view that probabilistic knowledge plays a role in language production with more probable structures in grammar or in the mental lexicon being accessed faster or with more confidence than less probable ones. Finally, the knowledge of probabilities has been shown to be implicated in language acquisition (Saffran, 2002; Xu & Tenenbaum, 2007). In the present thesis, it is proposed that principles of probabilistic inference as underlying mechanisms of cognitive action can be extended to the process of stress assignment, a process which is characterized by a high degree of uncertainty in many languages.

3.4. The Bayesian model of stress assignment

Within the Bayesian framework, the process of stress assignment can be viewed as the process of posterior probability estimation for alternative hypotheses concerning the position of stress. There are as many hypotheses considered for a word as there are syllables in the word. The idea that in the process of stress assignment a reader examines the likelihoods of only those stress patterns that are possible for a word of certain syllabic length assumes that a reader is aware of the syllabic length of a word before the probability of each hypothesis is computed. Although there is currently no strong evidence showing a time-period when the discrimination of words according to their syllabic length occurs, it seems likely that it happens at early stages of processing, and there is some empirical support for this claim (Ashby & Rayner, 2004; Ashby & Martin, 2008). Further, the assumption that readers assess the probabilities of only those stress patterns that are possible in a word has been made in all previous models of polysyllabic word reading and models of stress assignment (Perry et al., 2010; Seva et al., 2009).

As in the CDP++ (Perry et al., 2010), a reasonable assumption is that the decisions concerning the number of syllables that a word has are most likely to be made based on the information about the number of vowel graphemes in a letter string. For example, the identification of two vowels in a string would indicate that this string should be processed as a disyllabic word, and, thus, two hypotheses about stress patterns would be assessed in the process of stress assignment. This assumption does raise the question of how readers cope with situations in which the number of syllables and the number of vowel graphemes differ (e.g., the silent vowel –e at the end of monosyllabic English words or the so-called "hiatus" words. Those types of words are likely to be more difficult for readers to deal with (Chetail & Content, 2012; Chetail & Content, 2013)).

The computation of the posterior probability of each stress pattern in a word given some (non-lexical) evidence, $P(stress \mid evidence)$, presupposes the assessment of the prior probability that a word of this language has a hypothesized stress pattern, $P(stress)$, and the likelihood with which evidence considered is associated with the hypothesized stress pattern, $P(evidence \mid stress)$. In the Bayesian calculation of the posterior probability of a stress pattern, the product of the prior probability of this stress pattern and likelihood of evidence given this probability is divided by the sum of the products of prior probabilities and likelihoods of evidence of all alternatives (*stress*') in the hypothesis space (*STRESS*). Thus, the general Bayes' formula given in the Equation 2 can be re-written as follows:

$$P(stress \mid evidence) = \frac{P(evidence \mid stress)P(stress)}{\sum_{stress' \in STRESS} P(evidence \mid stress')P(stress')} \tag{4}$$

The calculation of the prior probability of a stress pattern in a language, $P(stress)$, must involve readers estimating the frequencies of various stress patterns in the words of the language. The prior probability of a stress pattern does differ significantly from language to language. For example, in English, disyllabic words have trochaic stress pattern in 80% of cases and iambic stress pattern in 20% of cases, while, in Finnish, 100% of disyllabic words have trochaic stress. Thus, in English, the prior probability of a trochaic stress pattern, *P*(*trochaic)*, equals .80, while, in Finnish, it is 1.00. On the other hand, the prior probability of iambic stress pattern, *P*(*iambic*), is .20 in English and 0.00 in Finnish. What is assumed here is that readers have a good idea of these probabilities because they are sensitive to the frequencies of the patterns they personally experience.

Equating the prior probability of a stress pattern with the frequency of the stress patterns in the language is motivated by the fact that readers have been shown to be sensitive to frequency in many realms. First of all, frequencies of linguistic structures have been shown to impact the production and comprehension of speech. Thus, more frequent words enjoy a processing advantage over less frequent ones (Balota & Chumbley, 1985). In case of ambiguous words, more common meanings appear to be accessed first (Dell, 1990). Finally, people are aware of the frequencies with which words co-occur, and use these transitional probabilities in speech production and comprehension (Saffran, Newport, & Aslin, 1996). Therefore, it is quite likely that the frequency with which stress patterns occur in the language might be picked up by speakers and used in the processing of polysyllabic words. The utilization of this information seems to be ecologically plausible, especially if there is a dominant stress pattern in a language, as it would significantly decrease uncertainty in the system and would simplify the process of stress assignment.

Indeed, there have been a number of empirical studies showing that readers are aware of the statistical distribution of stress patterns in the language and use this information in the processing of polysyllabic words (Colombo, 1992; Monsell, Doyle, & Haggard, 1989). Some researchers have claimed that, in some languages, readers assign the most frequent stress pattern by default (Black & Byng, 1986; Colombo, 1992). Within the proposed model of stress assignment, exclusive use of a default mechanism of assigning stress is only possible if a hypothesized stress pattern is the only stress pattern realized in the words of a specific syllabic length (i.e., in a language where the stress pattern is always fixed to some syllable). In this case, the prior probability of this stress pattern, $P(stress)$, equals 1.00, while the prior probability of the stress pattern corresponding to the alternative hypothesis, $P(stress')$, equals 0.00. This means that further evaluation of the likelihood of evidence is not needed as it would not change the posterior probabilities of stress patterns. In all other cases, when stress can be assigned to any syllable in words of a certain length (i.e., a language where stress placement is flexible), the information about the frequency of stress patterns only establishes a bias towards the more frequent stress pattern (reflected in the $P(stress)$ values) that can be diminished or even reversed if some source of non-lexical evidence is strongly associated with the alternative stress pattern(s).

In the calculation of the posterior probability of a hypothesized stress pattern, therefore, non-lexical sources of evidence for stress are important. A reliable source of evidence should be in a significant probabilistic relation with a specific stress pattern. In other words, the presence of this evidence in a word should act as a cue signaling the presence of the hypothesized stress pattern. Thus, evidence for stress is assessed from the point of view of its informational value or its validity. For example, if in a language all disyllabic words having trochaic stress start with two consonants and words with an iambic stress pattern mainly have one consonant in their onset, the complexity of the onset is a highly valid stress cue. The validity of a stress cue can be estimated by multiple regression analysis, in which the values of a stress cue are regressed on stress patterns of all words of the language that might have this stress pattern.

The presence of a correlation between some cue and a stress pattern in the language does not necessarily mean that readers employ it in their stress assignment decisions. While informative, these cues might be ignored by the readers. Therefore, besides having high validity, proper stress cues that might be included in the model should also be used by readers (i.e., the cues should have high "utility"). The utility of the stress cue can be obtained by regressing values of a stress cue on the patterns of stress assignment performance demonstrated by readers.

The impact of stress cues is in a trade-off relationship with the impact of prior probabilities of stress patterns. The more reliable the stress cue is, the less the stress assignment performance is influenced by the prior probabilities. On the other hand, if a stress cue is only weakly reliable, the role of the prior probabilities of stress patterns increases. Similar to the prior probabilities of stress patterns that are language specific, the nature of the stress cues and the number of the stress cues with high validity and utility are expected to differ from language to language.

Readers might utilize multiple sources of evidence in making stress assignment decisions. The assumption in the model is that multiple stress cues are considered in a stepwise fashion, starting with the most informative cue to stress in a language and going to the least informative one. Thus, if there are two stress cues in the language A and B, and A is a more informative one, the model, first, calculates the posterior probability of the stress pattern given evidence A, $P(stress \mid A)$, by using the following equation:

$$P(stress \mid A) = \frac{P(A \mid stress)P(stress)}{\sum_{stress' \in STRESS} P(A \mid stress')P(stress')} \tag{5}$$

Next, the posterior probability of the stress pattern given both evidence A and B is calculated. To do this, the model incorporates the likelihood of evidence B given the stress pattern ($P(B \mid stress)$) along with the probability of that stress pattern that already reflects the likelihood of evidence A ($P(stress \mid A)$) that will be referred to as $P(stress)^*$. In other words, at this stage, the prior probabilities that the model uses are not those that reflect the frequency of various stress patterns in the language, but, rather are the probabilities based on the frequency of each stress pattern among the words of the language that are also characterized by the presence of cue A (i.e., the posterior probabilities calculated based on the existence of evidence A). Thus, at the second stage of the computation, the formula is:

$$P(stress \mid A, B) = \frac{P(B \mid stress)P(stress)^*}{\sum_{stress' \in STRESS} P(B \mid stress')(1 - P(stress)^*)} \tag{6}$$

Note that the stepwise approach in updating the posterior probabilities using several sources of evidence assumes that these two sources are conditionally independent of each other. The sources can be considered independent if the existence of one of them does not change the impact (i.e., the probability associated with the various possible stress assignments) of the other source. In the case of non-lexical cues to stress this is not always the case, and some sources might be correlated to some extent. Thus, the posterior probabilities computed by the model may be overestimated. However, it is possible to measure the degree of correlation between two cues and remove any statistical dependency that is due to confounding.

The computed estimates of posterior probabilities for alternative stress patterns are used by a reader in the selection of a response. This selection is likely to unfold in a way similar to random walk or multiple racing diffusion process (Ratcliff, 1978; Ratcliff & McKoon, 2008; Voss, Nagler, & Lerche, in press). In the diffusion process, there is a gradual drift toward decision boundaries. The response is initiated when a decision boundary (also known as response criterion) has been reached. There would need to be as many decision boundaries as there are possible stress patterns for a particular word. For example, for a disyllabic word, there are two decision boundaries and, thus, this decision making process is essentially similar to the one described in the diffusion model of binary decision making (Ratcliff, 1978). For a word consisting of three syllables, on the other hand, there are three decision boundaries and, thus, the prosess of selecting one of three stress patterns is similar to the one described by the models of decision making with multiple alternatives (Leite & Ratcliff, 2010; Ratcliff & Starns, 2013).

Each of the possible stress pattern choices has a posterior probability provided by the calculations inherent in the Bayesian model of stress assignment described in the present thesis. The evidence for each pattern accumulates during these calculations in such a way that evidence for one alternative is evidence against the others. The movement from the starting point of the random walk to one of the decision boundaries happens with a drift rate that is directly related to the quality of the evidence for a stress pattern extracted from the orthography of a stimulus (i.e., the calculated probabilities).

With a high drift rate, indicating that the evidence for certain stress pattern is very strong, a decision boundary of this stress pattern will be reached relatively rapidly. Hence, the likelihood of incorrect stress pattern choice should be low. In contrast, when the drift rate is low due to the fact that the evidence for neither stress pattern (i.e., the posterior probability) is very strong, the likelihood of the system producing an incorrect stress pattern response is somewhat higher.

The decision boundaries are flexible, as their position in relation to each other can be changed to reflect a speed-accuracy trade-off. Thus, when a task accentuates the importance of the correct stress assignment over speed of performance, the boundaries are moved farther apart. Doing so, of course, leads to a more accurate performance, but there is a delay in response time. On the other hand, when the speed of naming is a priority, the decision boundaries are moved closer, thus, allowing the process to reach a decision boundary relatively rapidly. However, performance is likely to be somewhat error prone.

For the purpose of illustration, the Bayesian model's computations of the posterior probabilities of trochaic and iambic stress patterns for a novel word *belpet* completed based on a corpus of disyllabic words of a fictitious language are described. This language has only 30 disyllabic words (see Table 1) and three sources of evidence for stress: the orthography of the ending of the second syllable (i.e., the second vowel of a word and all following consonants), the orthography of the first syllable, and, finally, the orthography of the beginning of the first syllable (i.e., all graphemes up to and including the vowel of the first syllable).

Table 1

The corpus of disyllabic words of a fictitious language used to illustrate the computation of the stress patterns by the Bayesian model of stress assignment

Words with Trochaic Stress	Words with Iambic Stress
BELTIK	BELTOP
BELKOP	BENRET
BETNIK	BELTET
BELSIK	DOLMAT
BENSET	DOLPIK
BELRAT	DOLNOP
BELMOT	FAPLOP
BERMAT	KILPIK
DOMRET	LIPSOP
FAPRET	MERLON
FAMLIK	
KOLTIK	
LIPSET	
MERLIK	
MOLTET	
MONPIK	
NERMET	
NELTIK	
POMLOP	
TERLIK	

First of all, the model assesses the prior distribution of stress patterns in this language. As 67 % of words have trochaic stress pattern, prior probability that a word has trochaic stress, *P*(*Stress1*), is .67, while prior probability that a word has iambic stress, *P*(*Stress2*), is .33. Next, the model consideres the evidence provided in the orthography of the word. The model computes that the ending *–et* of the word *belpet* is present in 30% of words with trochaic and 10% of words with iambic stress. Following the formula,

$$P(Stress1 \mid -et) = \frac{P(-et \mid Stress1)P(Stress1)}{P(-et \mid Stress1)P(Stress1) + P(-et \mid Stress2)P(Stress2)} \quad , \qquad (7)$$

the model calculates that the posterior probability of a word having a trochaic stress pattern given the presence of the ending *-et* as:

$$P(Stress1 \mid -et) = \frac{(.30)(.67)}{(.30)(.67) + (.10)(.33)} = \frac{.20}{.23} = .87 \qquad (8)$$

Hypotheses are in trade-off relations with each other in a way that increasing the belief in one hypothesis decreases the belief for the other hypotheses. As the model described here assesses two mutually exclusive hypotheses (i.e., a trochaic stress pattern vs. an iambic stress pattern), it is sufficient to calculate the probability of one hypothesis. The posterior probability of the other hypothesis can then be directly calculated:

$$P(Stress2 \mid -et) = 1 - P(Stress1 \mid -et) = 1 - .87 = .13 \qquad (9)$$

The model next accounts for the evidence provided by the first syllable *bel-* present in 25% of words with trochaic stress and 20% of words with iambic stress. The model uses this stress cue to update its earlier beliefs about stress patterns that were based on the presence of the evidence *–et* in the word. Thus, $P(Stress1 \mid -et)$, further referred to as *P*(*Stress1*)*, serves as the model's new prior probability of a trochaic stress pattern, while $P(Stress2 \mid -et)$, further referred to as P(Stress2)*, is the new prior probability of an iambic stress pattern. The posterior probability that the word *belpet* has trochaic stress given the presence of *–bel* and *-et* is calculated following the formula:

$$P(Stress1 \mid bel-,-et) = \frac{P(bel- \mid Stress1)P(Stress1)*}{P(bel- \mid Stress1)P(Stress1)*+P(bel- \mid Stress2)P(Stress2)*}\ , \tag{10}$$

$$P(Stress1 \mid bel-,-et) = \frac{(.25)(.87)}{(.25)(.87)+(.20)(.13)} = \frac{.22}{.25} = .88\ . \tag{11}$$

As the final step in the calculation, the model considers the evidence for trochaic and iambic stress patterns provided the beginning *be-*. In assessing the likelihood of evidence for this orthographic component, the model cannot simply base its decision on the scope of representation of this cue in words with trochaic versus iambic stress patterns due to the fact that the beginning *be-* is a part of the first syllable *bel-* that has been already accounted for by the model. This confound can be eliminated if the model considers the distribution of this cue in all words with trochaic versus iambic stress patterns except the words that have first syllable *bel-*. Out of words that meet abovementioned criterion, 15% have trochaic stress and 10 % have iambic stress. The model uses this stress cue to update its earlier beliefs about stress patterns that were based on the presence of the evidence *bel-* and *-et* in the word. Thus, *P*(*Stress1*|*bel-*,*-et*), further referred to as *P*(*Stress1*)**, serves as the model's new prior probability of a trochaic stress pattern, while *P*(*Stress2*|*bel-*,*-et*), further referred to as P(Stress2)**, is the new prior probability of an iambic stress pattern. The model calculates the posterior probability that the word *belpet* has a trochaic stress pattern given the evidence *be-*, *bel-*, and *-et*, using the formula:

$$P(Stress1 \mid be-, bel-, -et) = \frac{P(be- \mid Stress1)P(Stress1)^{**}}{P(be- \mid Stress1)P(Stress1)^{**} + P(be- \mid Stress2)P(Stress2)^{**}} \,, \tag{12}$$

$$P(Stress1 \mid be-, bel-, -et) = \frac{(.15)(.88)}{(.15)(.88)+(.10)(.12)} = \frac{.13}{.14} = .93 \,. \tag{13}$$

Thus, based on the prior knowledge of the distribution of stress patterns in the language and correlations that exist between three types of orthographic cues and stress patterns in the words of this language, the Bayesian model of stress assignment predicted that the novel word *belpet* is very likely to be assigned trochaic stress pattern.

The calculations of probabilities of stress patterns provided above reflect the behavior of an ideal observer, who computes the most probable stress pattern given the whole corpus of the language. The real patterns of behavior are expected to be correlated with the patterns produced by the model, but are unlikely to be identical. First of all, humans might be good statisticians, but they are not perfect, while the model's computation is error-free. As various errors, biases, and heuristics are common features of human cognition (Tversky & Kahneman, 1974), departures from optimal behavior are expected in human performance. Secondly, the Bayesian model of stress assignment is a model based only on non-lexical information and people might also use stress information stored in lexical memory, especially if in the result of the non-lexical computation of stress patterns, the calculated posterior probabilities are fairly similar.

As a final note, it should be mentioned that the Bayesian framework is essentially generative, meaning that observed data (evidence) is generated by some underlying source that relates it to a hypothesis. For example, in estimating the probability of pneumonia, a doctor might consider various symptoms that are generated by an underlying illness directly (e.g., fever, coughing, chest pain) or indirectly (e.g., positive X-ray test, positive blood culture test). In the proposed Bayesian model of stress assignment in reading, the evidence that is considered is the orthography of a word that readers implicitly believe is indirectly associated with various stress patterns. The underlying cause that brings together orthography and stress pattern is the phonology of the language. In the process of language acquisition, children first master aural speech with all of the probabilistic information that it provides. Among other information, children learn that some similar sounding words are more likely to have the same stress pattern. Later, children learn to map sounds onto abstract orthographic representations (to write) and to decode the orthography back to phonology (to read). In the process of reading, it is not enough just to construct the string of phonemes, one also needs to apply a stress pattern to this string. At the early stages of literacy acquisition, children might map graphemes onto phonemes first, and, then, use the earlier acquired knowledge of probabilistic relations between sounds and stress patterns to select the most likely stress pattern to be applied to a string of phonemes. With further improvements in literacy, readers might still be going through the same serial steps from orthography to phonology and, then, to stress patterns. Alternatively, they could be gradually switching to a more efficient serial way of processing with orthography being mapped onto phonology and stress pattern at the same time.

Chapter 4 – Non-lexical Sources of Evidence for Stress Patterns

4.1. Introduction

Within the proposed model of stress assignment, a prior belief about the likelihood with which a word has a certain stress pattern (reflecting the frequency of this stress pattern in a language) is adjusted by non-lexical evidence for stress patterns derived from the orthographic input. The first goal of this chapter is to substantiate the claim that readers do utilize information about the frequency of stress patterns in a language when they assign stress to words. This idea has been widely considered in prior research, however, the empirical findings have been somewhat mixed. Some researchers have demonstrated the effect of the frequency of stress patterns on naming, and, further, posit that a more frequent stress pattern is applied to words by default (Black & Byng, 1986; Breen & Clifton, 2011; Colombo, 1992). Others failed to provide behavioral support for the default stress pattern hypothesis, and state that the frequency of the stress patterns in a language plays little, if any, role (Burani & Arduino, 2004; Sulpizio, Job, & Burani, 2012; Sulpizio, Arduino, Paizi, & Burani, 2013). In the proposed model, an intermediate position is taken. On the one hand, there is a substantial amount of evidence suggesting that readers are likely to be impacted by the knowledge of the distribution of stress types in a language. However, this knowledge is not used as a default rule, but rather as a prior belief about the likelihood with which a word has a particular stress pattern. This prior belief can be easily changed by the assessment of non-lexical, orthographic cues present in a word that are probabilistically associated with certain stress patterns.

The second goal, therefore, is to consider a range of non-lexical cues to stress that might play a role in stress assignment. For example, in a selected number of languages (e.g., Greek, Spanish), readers can rely on diacritics, which are orthographic marks used to indicate the syllable to stress (Protopapas, 2006). In other languages (e.g., English, Russian), stress patterns may be signaled by the morphology of a word (Rastle & Coltheart, 2000), although this cue would be of use only when a polymorphemic word is being read. In this Chapter, only those cues that are likely to be used in a wide range of languages and that are likely to be relevant for words of various morphemic structures are considered. The first cue of such type is the orthographic complexity of word onsets and codas. In English, it has been suggested that disyllabic words with complex graphemic onsets (i.e., onsets containing more than one consonant grapheme) tend to have an iambic stress pattern (Kelly, Morris, & Verrekia, 1998), while words with complex graphemic codas (i.e., codas containing more than one consonant graphemes) tend to have a trochaic stress pattern (Kelly, 2004). Further, the orthography of word beginnings and endings has been shown to be utilized by readers as lexical stress indicator (Arciuli & Cupples, 2007). Finally, some researchers proposed that the knowledge of a word's grammatical category is also a cue to lexical stress as the frequency of the stress pattern within certain grammatical categories exerts more influence on stress assignment than overall stress type frequency (Kelly & Bock, 1988). A more detailed review of research related to a number of potential sources of evidence for word stress is provided below.

4.2. Frequency of stress patterns in the language

Languages differ significantly with respect to the distribution of stress patterns. In fixed-stress languages (e.g., Hungarian, Finnish), there is only one stress pattern.

Therefore, readers do not have to derive stress information from print or lexical knowledge. They can apply the only available stress pattern to a word by default and always be correct. In contrast, in free-stress languages (e.g., English, Spanish, Italian), stress assignment is a cognitively demanding task requiring stress pattern identification in each polysyllabic word. Readers of these languages do, however, possess the knowledge of the relative probability of occurrence of various stress patterns in a language. In so called bounded languages (i.e., languages that have the tendency for stress to be drawn to the right or to the left edge of a word), certain stress patterns would occur significantly more often than the others. These stress patterns would be considered “regular” or “typical”, while the other(s) would be called “irregular” or “atypical”. For example, in English, a trochaic stress pattern is regular as 80% of disyllabic words have stress on their first syllable (Cutler & Carter, 1987). Simply by applying the more frequent stress pattern to all words of the language, an English speaker would assign stress correctly in 80% of cases. On the other hand, there are unbounded languages (e.g., Russian) in which words with different stress patterns are represented in the lexicon in approximately equal proportions. The knowledge of frequencies of stress patterns in these languages is of reduced value as there is no regular (or irregular) stress.

As noted, stress regularity has often been considered to be an important variable affecting word processing. In one of the most influential models of spoken word production Weaver++, it was argued that the most frequent stress pattern is applied to a word’s syllabic structure by default (Levelt, 1989; Levelt, Roelofs, & Meyer, 1999). This idea was extended to the area of written word comprehension, where it was suggested that readers of languages with a regular stress pattern possess implicit knowledge about the frequency of that pattern. This knowledge forms a strong bias to apply a regular stress pattern as some type of default rule (Colombo, 1992; Monsell, Doyle, & Haggard, 1989). Essentially, these researchers proposed that there are differences in the way regular and irregular stress patterns are processed. While regular stress patterns are applied by default, irregular ones must be either computed non-lexically (typically for low frequency words) or retrieved from lexical memory (typically for high frequency words).

The presence of alleged differences in the way words with regular versus irregular stress patterns are processed suggests that speakers should behave differently when reading words with regular versus irregular stress patterns. If a regular stress pattern is applied essentially by default, then words that have this stress (i.e., regular words) should enjoy a processing advantage. On the other hand, words with an irregular stress pattern (i.e., irregular words) should be more difficult to process. In addition, similarly to the effect of the regularity of spelling-sound correspondences, which is observed with words of low frequency only (Seidenberg, Waters, Barnes, & Tanenhaus, 1984), stress regularity should interact with lexical frequency such that irregular words of low frequency should incur the most processing cost.

Evidence for a significant stress regularity effect and its interaction with lexical frequency has been reported in English (Brown, Lupker, & Colombo, 1994; Monsell, Doyle, & Haggard, 1989). It took readers longer to name less frequent iambic stress words compared to more frequent trochaic stress words. Further, the effect of stress regularity was evident when low frequency words were used as stimuli, while high frequency words were immune to a regularity effect. Colombo (1992) replicated the stress regularity effect and stress regularity by frequency interaction in Italian. Moreover, this effect was significant even when regular versus irregular words were presented in separate blocks, suggesting that the knowledge of the frequency of stress patterns is not reduced by strategic manipulations. Additionally, there were replications of a stress regularity effect in Dutch (Schiller, Fikkert, & Levelt, 2004) and in Greek (Protopapas, Gerakaki, & Alexandri, 2006). These replications in languages with different regular stress patterns demonstrate that the effect is driven by the frequency of stress pattern and not simply by a bias to the beginnings or endings of words.

Colombo (1992) provided a theoretical explanation for the stress regularity effect and its interaction with lexical frequency, similar, in essence, to the principles of the Dual Route Model of reading (Coltheart & Rastle, 1994). According to Colombo, stress in high-frequency words that have strong lexical connections, is assigned via the lexical route. On the other hand, low-frequency words have less established lexical links, allowing time for stress information to be computed by mapping spelling onto stress patterns; i.e., a non-lexical route is utilized with the most frequent stress pattern being assigned by default before the correct stress assignment can be produced by the lexical route. For low frequency regular words, the lexical and non-lexical reading procedures will produce the same response. On the other hand, if a low frequency word possesses an irregular stress pattern, the temporarily assigned default stress will not be correct. The conflicting outputs of the lexical and non-lexical routes result in a delay in pronunciation and a decline in accuracy.

Additional support for the processing advantage of regularly stressed words is provided by patient data. English-speaking deep dyslexic aphasic patients made fewer errors on regularly compared to irregularly stressed words (Black and Byng, 1986;

Nickels & Howard, 1999). Similar findings of poor accuracy in naming of irregularly stressed words were reported in Italian (Cappa, Nespor, Ielasi, & Miozo, 1997; Laganaro, Vacheresse, & Frauenfelder, 2002; Miceli & Caramazza, 1993).

There is also some evidence, from eye-tracking experiments, for the special status of a regular stress pattern in word reading (Breen & Clifton, 2011; Sulpizio & McQueen, 2012). In a study by Breen and Clifton (2011), English participants read limericks that had stress-alternating homographs (e.g., *prEsent* – *presEnt*) embedded in them, while the participants' eye-movements were recorded. The results demonstrated a reading cost when the lexical stress of the homograph, as determined by context, mismatched the metrical pattern of the limerick, but only in the case of irregularly stressed homographs (i.e., a word with iambic stress in trochaic metrical context). There were no processing costs when a word with a regular, trochaic stress pattern was presented in an iambic metrical context. Further, in a study by Sulpizio and McQueen (2012), Italian speakers learned tri-syllabic names of nonsense objects that they had to identify later on visual displays based on an auditory presentation that contained full or reduced acoustic stress cues. The researchers found that the acoustic manipulation of stress cues did not affect the speed of recognition of nonsense objects with regular, penultimate stress. Moreover, overall targets with penultimate stress were recognized faster than targets with ante-penultimate stress, signaling that there is a distributional stress bias toward the more frequent penultimate stress pattern in Italian.

Finally, there is an ERP study conducted in Turkish that provides evidence for differences in the processing of words with regular, final syllable stress and words with irregular, non-final syllable stress (Domahs, Genc, Knaus, Wiese, & Kabak, 2012). In this study, the visual presentation of a word was followed by the aural presentation of the same word with either a proper or an improper stress pattern. Stress violations involving the assignment of regular stress modulated the N400 ERP component, which is reflective of the difficulties in accessing the lexical representation of a word. More importantly, however, violations with irregular stress modulated the P300 ERP component, which is the signature of phonological reevaluation of the stress pattern. Thus, in the case of the regular stress pattern, participants have difficulty judging that this pattern is incorrect unless they access the word's lexical representation, while the incorrect usage of an irregular stress pattern is detected easily and very early in processing.

Not all results have been supportive of the "default" stress hypothesis, however (Kelly, Morris, & Verrekia, 1998; Rastle & Coltheart, 2000; Sulpizio, Job, & Burani, 2012). For example, Kelly et al. (1998) showed that readers named words with irregular iambic stress faster than words with regular trochaic stress. This unusual pattern could be attributed partially to the choice of stimuli. Kelly et al. proposed that words with an irregular (in English) iambic stress pattern are orthographically marked in that the endings of those words have more letters than needed for proper phonemic processing (e.g., -ette, -elle, -oo). The experimenters, therefore, manipulated not only stress patterns of the words but also the presence of orthographic markers of iambic stress. Thus, half of their words with trochaic stress and half of their words with iambic stress contained endings that were representative of the iambic stress pattern, while the presence or absence of orthographic markers of trochaic stress was not controlled for. This characteristic of the stimuli might have given rise to a strategy that produced the advantage in processing for irregularly stressed words.

The issue of the effect of stress regularity on word naming in English has also been investigated by Rastle and Coltheart (2000). The words used in their Experiment 1 were not explicitly selected to contain “orthographic markers” of an iambic stress pattern. In their experiment, there was no difference in the speed of processing of words with irregular iambic stress versus words with regular trochaic stress.

Further, there are other reports of failed attempts to find a processing advantage for words with more frequent compared to less frequent stress patterns in Spanish (Gutierrez-Palma & Palma-Reyes, 2008) and in Italian (Burani & Arduino, 2004; Sulpizio, Job, & Burani, 2012; Sulpizio, Arduino, Paizi, & Burani, 2013). Moreover, not only adult readers, but also children, who are expected to rely on sub-lexical processing to a greater extent (Ziegler & Goswami, 2005), failed to show sensitivity to stress dominance in other studies (Gutierrez-Palma & Palma-Reyes, 2004; Paizi, Zoccolotti, & Burani, 2011), although young children, who had just started learning to read, did apply a regular stress pattern to nonwords that they were asked to name (Arciuli et al., 2010). Thus, a tendency for stress regularization appears to decline gradually with age potentially due to the overall improvement in literacy and due to the acquisition of other stress cues present in the language. Indeed, dyslexic children, who have difficulty in acquiring reading skills, often show a similar pattern of stress regularization errors as novice readers (Paizi et al., 2011). Although knowledge of the existence of a regular stress pattern is likely still accessible in adults and young skilled readers, it may not be a leading source of evidence for stress patterns anymore and, therefore, the stress regularity effect can often not be registered behaviorally.

Finally, the idea that there is a strong default mechanism of regular stress assignment found no support in a study by Colombo and Zevin (2009). Using a “pathway priming” methodology, in which participants named a target word or a nonword preceded by a set of (prime) words or nonwords that either had or did not have the same stress pattern as the target, these researchers demonstrated that participants were more likely to be impacted by the stress pattern of the primes or by lexical knowledge than by the knowledge of a more frequent stress pattern in the language. Nevertheless, there was also some evidence for a bias to assign regular stress to words when the experimental manipulation made sub-lexical processing of stimuli more likely.

The suggestion that the most frequent stress pattern forms a bias in the stress assignment process and acts as a strong cue to stress is, therefore, open to debate. On the one hand, there are studies showing that there is a processing advantage for words with the more frequent stress patterns. These findings are often interpreted as denoting the presence of a default mechanism or rule, according to which the most frequent stress pattern is assigned by default to any word in a language. On the other hand, this idea of a default regular stress mechanism is not supported by investigations that failed to demonstrate a processing advantage for words with a regular stress pattern or that showed a processing disadvantage for words with regular stress. Based on those types of findings, one could argue that the knowledge of the distribution of stress patterns in a language is of little, if any, value or utility in the process of word recognition. Alternatively, one could easily argue that there is enough evidence suggesting that information about the frequency of stress patterns in the language is available to readers and impacts the processing of polysyllabic words. However, this impact is not in the form of a default rule that is applied to words, but rather in the form of prior belief that any word is more likely to have a more frequent than less frequent stress pattern. This information is easily accessible and at early stages of literacy acquisition it is the main source of evidence for stress. With the development of reading skills, it seems likely that readers acquire other orthographic cues that are probabilistically associated with stress patterns and these cues are used in order to adjust their prior beliefs formed by the knowledge of the distribution of stress patterns. Hence, the impact of the existence of regular stress pattern is muted, causing that impact to sometimes fail to be evident.

4.3. Orthographic complexity of word onsets and codas

Stress patterns can be marked in the orthography via associations that exist between graphemic combinations and stress patterns. One of the associations of this type is that of stress and complexity of words' codas (Kelly et al., 1998) and/or complexity of words' onsets (Kelly, 2004). A word's coda is defined as the ending of a word that includes all word final consonants that follow the vowel of the last syllable of a word (e.g., *effe-**ct***, *patte-**rn***, *lette-**r***). Onset corresponds to a consonant cluster that precedes the first vowel of a word (e.g., ***n**-umber*, ***bl**-ossom*, ***spl**-ashy*).

Thus, Kelly et al. (1998) found that many codas of disyllabic English words are correlated with stress patterns. For example, words containing coda –*t* are more likely to have trochaic stress pattern (e.g., comet, sonnet, market), while words containing coda –*tte* are more likely to have iambic stress (e.g. roulette, corvette, dinette). Based on these observations, Kelly et al. proposed that orthographic cues to stress are located in the second syllable of the disyllabic words and that these cues typically mark only the irregular (for English) iambic stress pattern by representing the information about the phoneme of the coda by using more letters than needed. As a result, irregular words with iambic stress that are marked by codas as having an iambic stress pattern should be as easily processed as regular trochaic stress words.

Indeed, Kelly et al. (1998) demonstrated that words with an iambic stress pattern orthographically marked for this type of stress by their codas and non-marked words with a trochaic stress pattern (i.e., words that did not contain codas associated with iambic stress) had a processing advantage in naming and lexical decision tasks over non-marked for iambic stress iambic words and trochaic words that contained iambic orthographic cues. These findings support a claim that orthographic cues to stress are learned by readers, and that the presence of these cues in words expedites their processing.

Further, Kelly (2004) showed that there is also a relationship between stress patterns and onsets in English disyllabic words. A corpus analysis revealed that the incidence of trochaic stress increased significantly with the number of consonants in word onset position (Kelly, 2004). Words that had no onset consonants had trochaic stress in 35% of the cases, while words with two consonants in their onset had trochaic stress in 83% of the cases. These results were further corroborated in a study by Arciuli and Cupples (2007). Moreover, it was demonstrated that English readers are sensitive to onset complexity as a stress cue as they assigned first syllable stress to disyllabic nonwords more often when they began with two consonants rather than one (e.g., *flormand* vs. *formand*; Kelly, 2004). In sum, the behavioral evidence indicates that speakers do consider the complexity of both word codas and word onsets in assigning lexical stress.

4.4. Orthography of word endings and beginnings

The hypothesis that orthography can implicitly provide information about stress patterns has been extended from word onsets and codas to orthographic elements of greater length: word endings and word beginnings. Most of the research concentrated on investigating the validity of word endings as stress cues. For a disyllabic word, word ending is defined as a fragment that includes a vowel of the second syllable and all following consonants (e.g., *wind-**ow***; *prod-**uce***; *nam-**ing***). Words with the same orthographic component in their structure are assumed to form neighborhoods (e.g., in English, *mark-**et***, *brack-**et***, *pack-**et***, *bask-**et***, *cad-**et***). Words with identical endings that map onto the same stress pattern are called "stress friends" (e.g., market: bracket). Words with identical endings that do not map onto the same stress pattern are called "stress enemies" (e.g., market: cadet). A word like "market" that has many "stress friends" is called consistent, while a word like "cadet" that has many "stress enemies" is called inconsistent.

The consistency with which graphemes map onto phonemes has been investigated in monosyllabic word reading (Jared, McRae, & Seidenberg, 1990; Jared, 2002), and it has been demonstrated that words with a high degree of consistency enjoy a processing advantage. Colombo (1992) extended this idea to the domain of polysyllabic word reading (in Italian) and proposed that the consistency of a word's orthography-to-stress mapping may have an effect on stress assignment. The presence of common letter clusters in words with different stress patterns ("stress enemies") may slow down the assignment of the correct stress due to the competition from partially activated, alternative variants of lexical stress compared to words that do not have "stress enemies".

An experimental investigation of the consistency effect in Italian demonstrated an interaction of consistency and regularity of stress (Colombo, 1992). The processing of regularly stressed words with many stress enemies was not slower than the processing of regularly stressed words with many friends. Only irregularly stressed words were subject to the influence of orthography-to-stress mapping consistency. When words with irregular stress pattern had many stress friends, that fact compensated for its irregularity with naming latencies being the same as the latencies of regularly stressed words. On the other hand, words with irregular stress patterns that had many stress enemies required more time for naming and were more likely to be pronounced with an incorrect stress pattern (Experiment 4, Colombo, 1992). Further, the reliance of readers on the knowledge of the overall distribution of stress patterns in the language and the distribution of stress patterns in words forming neighborhoods has been demonstrated in a nonword naming experiment (Experiment 5, Colombo, 1992). Thus, according to Colombo, there are two factors that influence stress assignment in Italian. The first factor is stress regularity: the most frequent stress pattern can be assigned by default. The second factor is stress consistency as defined by the distribution of stress patterns in a word's orthographic neighborhood formed on the basis of the orthography of the word's ending.

Burani and Arduino (2004) criticized Colombo's (1992) experiments on the grounds of an inappropriate matching of items on a number of variables including summed frequency of stress friends and initial phoneme characteristics. The performance of readers on naming of better matched Italian words that varied in stress consistency of word endings and stress regularity showed a significant consistency effect in both regularly and irregularly stressed words. Words with many stress friends were read faster and with fewer mistakes than words that had many stress enemies. There was, however, neither a regularity effect nor a consistency by regularity interaction.

There have been a number of replications of the effect of stress consistency of word endings in Italian. For example, in a naming study by Sulpizio, Arduino, Paizi, and Burani (2013), participants were sensitive to stress cues provided by word endings, although this sensitivity was greater for endings associated with the irregular (in Italian) antepenultimate stress pattern. Further, the effect of stress neighborhood on naming was also demonstrated in typically developing and developmental dyslexic Italian children (Paizi et al., 2011). Both participant groups read words with many stress friends more accurately than words with many stress enemies. These results suggest that stress assignment in Italian is driven by distributional information about the consistency of the stress pattern and the orthography of word endings.

Performance on regularly and irregularly stressed words with different degrees of stress consistency was also examined in English (Arciuli & Cupples, 2006; 2007; Arciuli et al., 2010). A large scale analysis of the corpus of disyllabic English words revealed that the orthography of many word endings is probabilistically associated with lexical stress (Arciuli & Cupples, 2006). For example, words ending in “-ock” tend to have a trochaic stress pattern (e.g., hammock, bullock, pollock), while words ending in “-oon” tend to have iambic stress pattern (e.g., baboon, lagoon, maroon). In fact, a discriminant function analysis of an English disyllabic corpus showed that the correct classification of word stress types based on the orthography of word endings occurred in 95% of cases. Further, adult and child participants were shown to be sensitive to the probabilistic stress cues provided by word endings (Arciuli & Cupples, 2006; Arciuli et al., 2010).

As noted, recently, it has been suggested that not only word endings, but also word beginnings, can serve as useful stress cues (Arciuli & Cupples, 2007; Arciuli et al., 2010). The word beginning of a disyllabic word is defined as the segment containing all graphemes up to and including the first vowel (e.g., ***fo****-rmer*, ***mo****-del*, ***e****-nding*). An analysis of the corpus of English disyllabic words showed that some word beginnings occur more often in trochaically stressed words, whereas other word beginnings occur more often in iambically stressed words (Arciuli & Cupples, 2007). In addition, the results of a discriminant function analysis with word beginnings considered as the only criterion for stress classification demonstrated that the correct grouping of words into trochaic versus iambic stress occurred in 90% of cases (Arciuli et al., 2010). In follow-up studies, empirical evidence was obtained showing that when reading nonwords containing orthographic cues to stress adults and children were sensitive to beginnings as well as endings (Arciuli & Cupples, 2007; Arciuli et al., 2010).

In summary, even in languages that do not use explicit orthographic markers of stress (i.e. diacritics), there are certain orthographic patterns that signal what stress type should be assigned to a word. Word beginnings and endings were empirically shown to be utilized as stress cues by readers. The limitation of these findings is that they were reported in a few languages only. To allow for greater generalization of the idea that lexical stress decisions can be made based on orthographic information, investigations of the role of orthography in stress assignment in other languages are needed.

4.5. Grammatical category

Another potential cue to stress is the grammatical category of a word. In some languages, the distribution of stress patterns in words of different grammatical categories might be different. For instance, in English, trochaic stress is more typical in disyllabic nouns, whereas most disyllabic verbs often exhibit iambic stress (Chomsky & Halle, 1968). Readers might be aware of these differences and might be more inclined to assign the most frequent (for words of certain grammatical category) stress pattern to a word belonging to a particular grammatical category. Thus, in English, nouns might be more likely assigned trochaic stress, while verbs might be more likely assigned iambic stress.

Kelly and Bock (1998) noted this characteristic of the English stress system and suggested that nouns with trochaic stress and verbs with iambic stress may be considered as having regular stress in English. Empirical evidence for the impact of grammatical category on stress assignment has been provided by Kelly and Bock in two experiments involving reading nonwords embedded in verb versus noun biasing contexts. The results showed that speakers were sensitive to the relation between grammatical category and stress patterns. Specifically, nonwords acting as nouns were more likely to be assigned trochaic stress, while nonwords acting as verbs were more likely to receive iambic stress.

Additional evidence for the impact of grammatical category on stress assignment has been provided by Arciuli and Cupples (2004, 2006, 2007). For example, Arciuli and Cupples (2004) showed that speakers of English classified visually presented stimuli as verbs or nouns faster and more accurately if items were what they call typically stressed (i.e., trochaic nouns and iambic verbs). Further, typically stressed nouns and verbs also enjoyed a processing advantage over atypically stressed iambic nouns and trochaic verbs in naming and lexical decision tasks (Arciuli & Cupples, 2006). Finally, in an onset-gating paradigm, in which words were presented aurally in increasing increments of length, participants were better at identifying words with a stress pattern typical for their grammatical category (Arciuli & Cupples, 2007).

In an analysis of the corpus of English disyllabic words, Arciuli and Cupples (2006) demonstrated that English word endings are probabilistically associated with certain stress patterns as well as with certain grammatical categories. Across all endings, correlations between grammatical category and stress patterns were highly significant (nouns and trochaic stress: $r = .70$; verbs and iambic stress: $r = .75$). Further, the researchers provided evidence that speakers of English use the cues to grammatical category and stress patterns provided by the word endings. Based on these findings, Arciuli and Cupples (2006) concluded that typically stressed English words may enjoy a processing advantage due to the fact that, in these cases, orthographic cues are often consistent with one another in terms of providing the correct combination of grammatical category and stress pattern information.

To conclude, grammatical category does appear to be probabilistically related to lexical stress. So far, this relation has been established and investigated in English only. However, even in English, it is not clear how exactly the knowledge of grammatical category is utilized in the process of stress assignment. On the one hand, it could be that orthography cues grammatical category directly, which in its turn influences assignment of stress. On the other hand, orthography might be cuing grammatical category and lexical stress at the same time and independently from each other. The correlation between grammatical category and stress pattern might be an artifact of the relationship between each of these factors and orthographic cues.

4.6. Conclusion

The goal of this chapter was to assess the empirical evidence for the claim that readers are sensitive to the distribution of stress patterns in a language and use this information in the process of stress assignment. The second goal was to discuss a set of stress cues that have been shown to signal proper stress patterns (i.e., to have high validity) and to be used by readers (i.e., to have high utility). Such cues might potentially be used in the proposed Bayesian model of stress assignment as evidence used to adjust any prior belief about a stress pattern, based on stress frequency. The following conclusions, concerning these factors, can be offered.

First of all, previous research does provide evidence that readers are aware of the distribution of stress patterns in the language. In some studies, these results are often interpreted as favoring the default stress hypothesis, an idea that the most frequent stress pattern is assigned to words automatically. This idea, however, contradicts the principles of the Bayesian model of stress assignment to be proposed here. In the model, there are no procedural differences in the way more frequent versus less frequent stress patterns are assigned to words. In both cases, readers evaluate evidence that is provided by the orthographic input and make decisions based on that evidence. The only difference between two stress patterns is that in order for a less frequent stress pattern to be assigned, readers require stronger evidence for this stress pattern than in case of a more frequent stress pattern. There have been a number of failed attempts to demonstrate that the most frequent stress pattern is assigned by default. However, none of those studies posit that the information about the frequency of stress patterns in the language is unavailable or unused by readers.

Secondly, this review detailed research examining various stress cues. Stress cues that have been shown to influence the processing of polysyllables in a greater number of languages and are relevant for all words regardless of their morphological status concern the orthography of a word. For example, orthographic complexity of word onsets and codas has been linked to the assignment of stress in English disyllabic words. Further, it was demonstrated that the orthography of word beginnings and word endings might be good cues to stress. Finally, there are some suggestions that the grammatical category of a word is a potential stress cue. However, at this point, it is unclear whether grammatical category cues stress directly or whether the orthography is cuing both grammatical category and lexical stress at the same time.

This list is not exhaustive as there might be some other stress cues that have not yet been investigated. Further, the presented research was mainly conducted in English and Italian, languages that are stress bounded, and, thus, these cues might be characteristic only of languages that have regular stress patterns. Therefore, further investigations of stress cues in other languages, especially in languages with no regular stress pattern, are required. A final point to be made is that although in making stress assignment decisions, readers can evaluate all sources of evidence available in the language, doing so might be a time-consuming process. Therefore, during routine word processing, which is usually time-constrained, the set of stress cues being analyzed is likely limited to only those sources of information that are highly indicative of the stress patterns in the language and ones that readers have learned to rely on.

Chapter 5 – Implementation of the Bayesian Model of Stress Assignment in Russian

5.1. Introduction

The present chapter represents the beginning of the process of implementing the Bayesian model of stress assignment in Russian. Stress in Russian is flexible and it often serves to distinguish between otherwise identical lexical items (e.g., *зАмок* (“castle”) – *замОк* (“lock”); *мУка* (“burden”) - *мукА* (“flour”)) or between grammatical forms of the same lexical item (e.g., *рУки* (plural, nominal “hands”) – *рукИ* (singular, genitive “hand”); *лЕсу* (dative, “forest) – *лесУ* (locative, “forest”). Despite the importance of lexical stress for word recognition, its assignment in Russian is complex and is often a source of speech errors as there are no clear rules to follow and there is no dominant stress pattern in this language. The complexity of the stress system in Russian has been taken by some researchers as indicating that lexical stress in Russian is assigned only following the retrieval of accurate stress information from the word’s lexical representation (Gouskova, 2010; Lukyanchenko, Idsardi, & Jiang, 2011). One of the goals of the present research was to assess whether this position is incorrect and, instead, there are at least some non-lexical cues that readers of Russian actually do use to assign stress. If the results confirm that stress in Russian can be and is computed non-lexicaly, then, these non-lexical cues can be considered as valid and potentially utilized sources of evidence for stress within a Bayesian model of stress assignment. Hence, a computational implementation of that model can be created and its performance on stress assignment can be assessed in a series of simulations. For the sake of simplicity, only the issue of stress assignment in disyllabic Russian words was investigated here.

Study 1 was a corpus analysis of the distribution of trochaic versus iambic stress patterns in a set of Russian disyllabic words. The goal was to determine if there are any distributional differences for these two stress patterns and whether there are grounds to expect that readers in Russian might be biased for a particular stress pattern. The analysis was conducted over all disyllabic words regardless of their grammatical category and separately for words of each grammatical category to see if stress regularity could be found in Russian when only words performing one grammatical function are considered. This analysis provided us with the information about prior biases to stress pattern that the Bayesian model of stress assignment requires.

The next goal was to identify a set of non-lexical sources of evidence for stress that are present in Russian and that are used by native speakers. This investigation involved the combination of factorial and regression approaches. First, a factorial study investigated the impact of a number of variables on performance in a naming task (Study 2). In this study, one question was whether there is any evidence for a bias to either a trochaic or an iambic stress pattern demonstrated by readers of Russian. A second question was whether readers are sensitive to the effect of two potential cues to stress: spelling-to-stress consistency of word endings and grammatical category.

Although a factorial design allows an investigator to claim that the manipulation of independent variables is responsible for significant effects, this approach has some limitations. The most important one is that it does not allow for the examination of effects of many variables within one study. A complementary approach allowing researchers to overcome this limitation and to conduct an investigation which is more exploratory in nature is regression analyses. In a regression study, the effect of many variables within a single data set, which usually includes a significant number of observations, is analyzed. Following the suggestions that it is useful to combine factorial and regression analyses (Balota, Yap, Hutchinson, & Cortese, 2012; Treiman et al., 1995), it seemed prudent not to limit the investigation to factorial studies only, but also to undertake what Balota et al. (2012) termed a “megastudy” approach in the attempt to establish a set of non-lexical cues to stress present in Russian and used by Russian readers.

Therefore, a binary logistic regression was run on a set of non-lexical predictor variables of stress patterns in the corpus of more than 13,942 words (Study 3). This study allowed the discovery of at least some of the non-lexical cues that are probabilistically associated with stress patterns in Russian. Then, a generalized linear mixed effects model (Study 4) that had the same set of predictors was applied to the results of stress assignment performance of readers on a set of 500 disyllabic words. Study 5 allowed an assessment of the actual utilization of the potential cues to stress. The expectation is that the combination of factorial and regression studies would allow identification of most of the non-lexical sources of evidence that could be used to predict stress assignment in Russian using the proposed Bayesian framework.

5.2. Study 1: Corpus analysis of prior probabilities of stress patterns in Russian

The goal of this study was to establish the prior probabilities of trochaic and iambic stress patterns in Russian by investigating the distribution of these stress patterns in the language. Both type-based (proportion of words with trochaic versus iambic stress patterns) and token-based (proportion of the summed logarithmic frequencies of words with trochaic versus iambic stress) distributions of stress patterns were calculated.

Method

All disyllabic words from the Frequency Dictionary of Modern Russian (Lyashevskaya & Sharov, 2009) were selected. The dictionary provides lemmatized forms of the words only. In the morphologically rich Russian language, however, readers are exposed to inflected forms more often than to lemmatized forms. Therefore, inflected forms of words were retrieved from the Dictionary of Russian Grammar (Zaliznyak, 2003) and added to the database. Only words with a frequency of at least 1 per million words according to the Russian National Corpus (http://ruscorpora.ru) were considered. The resulting database consisted of 13,942 words. The information about the grammatical category and frequency of each word was retrieved from the Frequency Dictionary of Modern Russian (Lyashevskaya & Sharov, 2009). The stress pattern information was verified by consulting the Dictionary of Russian Lexical Stress (Zarva, 2001).

Results and Discussion

Table 2 presents the proportion of each stress pattern calculated based on the number of words with trochaic versus iambic stress as a function of grammatical category. Table 3 presents the proportion of each stress pattern calculated based on the summed logarithmic frequency of words with trochaic versus iambic stress as a function of grammatical category. The results of both analyses showed that there is no dominant stress pattern in Russian. In the type-based analysis, a trochaic stress pattern was present in 55% of the words and an iambic stress pattern was present in 45% of the words, while in the token-based analysis 57% of the words had trochaic stress and 43% of the words had iambic stress. The analysis of the distribution of stress patterns in words of various grammatical categories demonstrated a potentially interesting result. Adjectives frequently had trochaic stress (type-based analysis: 80%; token based analysis: 81%).

Table 2

Number and Proportion of Each Stress Type for Russian Disyllabic Words in the Corpus

	Trochaic Stress		Iambic Stress	
Grammatical Category	Number	Proportion (%)	Number	Proportion (%)
Adjective	1707	80	401	20
Noun	4678	55	3884	45
Verb	1100	38	1844	62
Other	162	50	166	50
Total	7647	55	6295	45

Note. The stress type proportions are calculated based on the total number of words in the grammatical category in question in the corpus. Trochaic Stress refers to stress on the first syllable of a word. Iambic Stress refers to stress on the second syllable of a word.

Table 3

Summed Logarithmic Frequency and Proportion of Each Stress Type for Russian Disyllabic Words in the Corpus

	Trochaic Stress		Iambic Stress	
Grammatical Category	Summed Log Frequency	Proportion (%)	Summed Log Frequency	Proportion (%)
Adjective	2221	81	514	19
Noun	6110	56	4580	44
Verb	1248	38	2007	62
Other	655	49	679	51
Total	10234	57	7780	43

Note. The stress type proportions are calculated based on the summed logarithmic frequency of words in the grammatical category in question in the corpus. Trochaic Stress refers to stress on the first syllable of a word. Iambic Stress refers to stress on the second syllable of a word.

Verbs, in contrast, more often had iambic stress (type-based analysis: 62%; token-based analysis: 62%). For nouns, trochaic stress occurred approximately as often as iambic stress (type-based analysis: 55% vs. 45%; token-based analysis: 57% vs. 43%). Other grammatical categories (prepositions, pronouns, adverbs, etc.) showed an approximately 50:50 split, although there were only small numbers of words in each of these categories.

Based on these data, it appears that Russian does not possess a regular stress pattern, meaning that the prior probabilities of trochaic and iambic stress patterns are approximately the same. Therefore, the readers of Russian are unlikely to be biased toward either stress pattern when assigning stress to disyllabic words. At the same time there is a dominance of the trochaic stress pattern for adjectives which potentially might influence the processing of words belonging to that grammatical category. A small dominance of the opposite, iambic stress pattern does exist for verbs. Finally, there is no regular stress pattern for nouns. What remains to be investigated, of course, is whether the presence of differences in the distribution of stress patterns at the level of grammatical categories influences word processing.

5.3. Sources of evidence for stress patterns in Russian

5.3.1. Study 2: Factorial investigation of the role of stress regularity, stress consistency of word ending, and grammatical category on word naming

The goal of Study 2 was to examine the role that stress regularity, stress consistency of word ending, and grammatical category play in Russian word naming. As noted, the effect of these variables on stress assignment has been investigated in a limited number of languages (mainly English and Italian), and the results that were reported in these studies were somewhat inconsistent (Arcuili & Cupples, 2006; Burani & Arduino, 2004; Colombo, 1992). Therefore, it is not yet clear whether these variables have an impact on word processing and, hence, whether they could be considered valid and utilized stress cues that should be incorporated into a Bayesian model of stress assignment in Russian.

One issue investigated in Study 2 was whether Russian readers demonstrate an overall bias to either trochaic or iambic stress patterns in naming disyllabic words. Such a result seems unlikely because Russian does not have a regular stress that dominates the language. Therefore, if all other variables are equated, latency differences in reading words with first versus second syllable stress are unlikely.

The other issue concerns the readers' reliance on the consistency of the relationship between the orthography of the word ending and the stress pattern. Previous research has not fully established whether the differential latencies observed in naming of polysyllabic words reflect the effect of consistency of stress, regularity of stress or the combined effects of consistency and regularity. Because Russian nouns do not possess a regular stress pattern, those words should provide good grounds for examining the impact of consistency uncontaminated by regularity effects. If consistency matters, there should be faster response times to nouns that have consistent stress patterns. In contrast, adjectives and possibly verbs have regular stress patterns which will allow an examination of the potential interaction of regularity and consistency for these stimuli. The presence of any effect of consistency would indicate that the orthography of word ending serves as a reliable stress cue in Russian.

Study 2 also allowed an examination of the impact of grammatical category on word naming and, in particular, whether the different levels of regularity in adjectives, nouns, and verbs revealed in Russian might matter. The question is whether readers are sensitive to these differences, and whether they use this information in naming Russian disyllabic words. The evidence for a stress regularity effect at the level of grammatical category in Russian (e.g., a processing advantage for trochaic adjectives) would provide evidence that a word's grammatical category affects stress assignment.

The final issue concerns the more general claim that stress is assigned to words in Russian only as a result of lexical retrieval (Gouskova, 2010). If so, no significant differences in the processing times and accuracy of stress assignment as a function of consistency or regularity should emerge for words in any grammatical category. In contrast, the demonstration of an impact of regularity and/or consistency on word naming would signal utilization of non-lexical information by readers and, therefore, it would suggest that a Bayesian model (or some other type of non-lexical model of stress assignment) would be appropriate for modeling stress assignment in Russian.

Method

Participants

Twenty eight undergraduate students from Altay State University (Barnaul, Russia) took part in this experiment for a small monetary remuneration (age 17 – 35; M = 19). All were native speakers of Russian. None of the participants reported high proficiency in any second language.

Materials

A set of 192 disyllabic words (see Appendix A) was created by crossing of grammatical category (adjective vs. noun vs. verb), stress consistency of word ending (consistent vs. inconsistent), and stress type (first syllable stress vs. second syllable stress). None of the words contained morphemes that are associated with only one stress pattern; thus, the decisions about proper stress could not be biased by morphology. The stress pattern of each word was determined by consulting the Dictionary of Russian Lexical Stress (Zarva, 2001). Only the items with a frequency less than 20 per million as reported in the Frequency Dictionary of Modern Russian (Lyashevskaya & Sharov, 2009) were used. The sets were matched on length, word frequency, orthographic neighborhood size (Coltheart, Davelaar, Jonasson & Besner, 1977), and in a word-by-word manner on initial phoneme characteristics. Because it is unclear whether imageability affects performance in visual word recognition tasks (Cortese & Khanna, 2007; Zevin & Balota, 2000), no attempt was made to match the words on imageability. A post hoc analysis did, however, show that, as expected, nouns were rated as more imageable than adjectives or verbs. However, imageability did not vary as a function of consistency or regularity.

The consistency measures were calculated using the database created for Study 1. Consistency was based on the neighborhood created by words sharing an ending (i.e., the vowel of the second syllable and all following consonants). Words in the neighborhood that had the same stress patterns were categorized as stress friends. Stress enemies were neighbors with the opposite stress pattern. The method for calculating spelling-stress consistency was analogous to that used by Treiman et al. (1995) for spelling-sound consistency. The type consistency measure for each word was calculated as the number of stress friends divided by the number of all words with the same ending. The calculation of token consistency was carried out by dividing the summed frequency of friends by the summed frequency of all words with the same ending.

The words in conditions with consistent spelling-to-stress mappings were matched on type ($M = 0.72$) and token consistency ($M = 0.69$). Words in conditions with inconsistent spelling-to-stress mapping were also matched on these measures (type consistency: $M = 0.35$; token consistency: $M = 0.36$). Words with consistent versus inconsistent spelling-to-stress mappings differed significantly from each other when type, $F(1,191) = 1155.94$, $p < .001$, as well as token, $F(1,191) = 241.79$, $p < .001$, measures were compared. The mean characteristics of the word sets are shown in Table 4 for words with consistent (A) and inconsistent (B) spelling-to-stress mappings.

The 192 experimental items were mixed with 108 disyllabic filler words. The filler words had equal proportions of trochaic and iambic stress to reflect the absence of a dominant stress pattern in Russian. The number of filler words belonging to a specific grammatical category was varied to replicate the proportion of words of each category in the language. The distribution of stress within words of a certain grammatical category essentially reflected the frequency of stress type within each grammatical category.

Procedure

Participants were instructed to read aloud words presented on the screen one at a time as quickly and as accurately as possible. Instructions and stimuli were presented using the DMDX display system (Forster & Forster, 2003). The list of 300 items was presented in three blocks of trials. There was a preceding practice block of 20 words. The order of blocks and of items within blocks was randomized for each participant. Each trial started with the presentation of a fixation point for 500 ms. A target word in upper-case appeared in white on a black background (Courier New, 12 font) for 2000 ms or until the participant responded. The intertrial interval was 1000 ms.

Table 4

Mean characteristics of the words with consistent (A) and inconsistent (B) spelling-to-stress mappings used in Study 2

A.

	Adjectives		Nouns		Verbs	
Characteristics	Trochaic Stress	Iambic Stress	Trochaic Stress	Iambic Stress	Trochaic Stress	Iambic Stress
Words	16	16	16	16	16	16
Length	5.63	5.50	5.25	5.44	5.38	5.63
Frequency	3.27	2.82	3.37	3.32	3.03	3.17
N-size	2.69	3.31	3.88	2.88	3.31	3.06
Imageability	4.03	4.55	4.59	5.11	4.08	4.17
Type Consistency	0.70	0.76	0.70	0.69	0.69	0.76
Token Consistency	0.74	0.70	0.66	0.69	0.67	0.71

B.

	Adjectives		Nouns		Verbs	
Characteristics	Trochaic Stress	Iambic Stress	Trochaic Stress	Iambic Stress	Trochaic Stress	Iambic Stress
Words	16	16	16	16	16	16
Length	5.31	5.38	5.50	5.31	5.44	5.31
Frequency	2.96	3.35	3.58	3.22	3.47	2.85
N-size	2.94	3.50	2.53	3.63	3.00	3.38
Imageability	4.16	4.11	5.23	5.37	4.41	4.30
Type Consistency	0.36	0.35	0.36	0.36	0.33	0.37
Token Consistency	0.39	0.35	0.34	0.36	0.36	0.36

Results

Responses were marked using CheckVocal (Protopapas, 2007) by the author and two other native speakers of Russian. To reduce the effects of outliers, latencies slower than 1500 ms or faster than 200 ms were discarded from the analyses. The total percentage of discarded data-points was 2.4%. Latencies and error rates were analyzed using a linear mixed effects model with Subjects and Items entered as crossed random factors, and with Stress Type (trochaic vs. iambic), Stress Consistency (consistent vs. inconsistent), and Grammatical Category (adjectives vs. nouns vs. verbs) entered as fixed factors. The analysis was conducted using the R package *lme4* (Bates & Maechler, 2010). The mean latencies and percentage of errors are shown in Table 5.

As expected, latencies to words with trochaic stress (M = 684 ms, SD = 42) did not differ significantly from those for words with iambic stress (M = 686 ms, SD = 41), $t\ (5025) = 0.70$, $\beta = 2.44$, $p = .48$. However, participants were more likely to make stress assignment errors on the words with iambic (7.1%) than trochaic stress (4.5%), $z = 3.88$, $\beta = 0.99$, $p < .01$. Also as expected, there was a main effect of consistency in the analysis of latencies, $t\ (5025) = 4.89$, $\beta = 17.00$, $p < .01$, and in the analysis of errors, $z = 6.19$, $\beta = 1.62$, $p < .01$. Participants were faster (M = 676 ms, SD = 37) and more accurate (3% errors) in naming words with stress consistent endings in comparison to words with stress inconsistent endings (M = 693 ms, SD = 44; 8.6% errors). The main effect of grammatical category was also significant in both the latency, $t\ (5024) = 4.13$, $\beta = 17.50$, $p < .01$, and the error analyses, $z = 2.04$, $\beta = 0.63$, $p = .04$. None of the interactions reached significance either in the latency (all $ts < 1.39$) or the error analyses (all $zs < .93$).

Table 5

Mean naming latencies and percentage of errors as a function of type of stress, consistency of stress and grammatical category in Study 2 (word naming)

	Trochaic Stress				Iambic Stress			
	Consistent		Inconsistent		Consistent		Inconsistent	
Grammatical Category	RT	%Error	RT	%Error	RT	%Error	RT	%Error
Adjectives	667	1.1	668	3.1	663	3.6	693	8.5
Nouns	689	4.7	709	11.6	690	6.9	710	13.4
Verbs	678	1.2	689	5.8	668	1.6	691	8.4
Overall	678	2.3	689	6.8	674	4.0	698	10.1

Note. N = 28. Trochaic Stress refers to stress on the first syllable of a word. Iambic Stress refers to stress on the second syllable of a word. Latencies (RTs) are reported in ms.

Planned contrasts were carried out to compare mean latencies and error rates for the three grammatical categories. The mean latency for nouns (M = 700 ms, SD = 44) was significantly larger than that for adjectives (M = 673 ms, SD = 38), t (5025) = 4.59, β = 38.84, $p < .01$, or verbs (M = 681 ms, SD = 34), t (5025) = 2.45, β = 17.45, p = .01. The error rate for nouns (9.1%) was also significantly higher than that for adjectives (4.0%), z = 4.46, β = 0.04, p < .01, or verbs (4.2%), z = 3.45, β = 1.06, $p < .01$. The difference in naming latencies for verbs compared to adjectives was also significant, t (5025) = 2.35, β = 19.88, p = .02, although verbs and adjectives did not differ significantly in terms of error rates, z = 0.62, β = 0.20, p = .54.

Although the grammatical category factor did not interact with any other variables, it was decided to fit mixed effects models with Subjects and Items entered as crossed random factors, and with Stress Type (trochaic vs. iambic) and Stress Consistency (consistent vs. inconsistent) entered as fixed factors to the latency and error data of each grammatical category. This was done to assess if the presence of a regular stress pattern in adjectives leads to differential performance of readers on words of this category compared to nouns and verbs that do not have regular stress patterns.

For adjectives, there was a main effect of stress type in the latency analysis (M = 668 ms, SD = 37 vs. M = 679 ms, SD = 39), t (1655) = 2.80, β = 22.73, p = .01, and in the analysis of errors (2.4% vs. 5.7%), z (1655) = 5.17, β = 1.50, $p < .01$. The main effect of consistency was significant in the analysis of errors (2% vs. 6%), z = 2.27, β = 1.18, p = .02, but not in the latency analysis (M = 667 ms, SD = 33 vs. M = 690 ms, SD = 44), t (1655) = 0.22, β = 2.28, p = .77. Finally, there was a significant interaction between stress type and consistency for adjectives in the latency analysis, t (1654) = 2.26, β = 25.88, p = .03, although not in the analysis of errors, z = 0.63, β = 0.38, p = .52.

For nouns, the only significant main effect was that of consistency both in the latency analysis (M = 690 ms, SD = 45 vs. M = 710 ms, SD = 48), t (1655) = 1.98, β = 18.69, p = .05, and in the analyses of errors (5.8% vs. 12.4%), z = 3.18, β = 0.86, p < .01. The main effect of stress type was not significant either in the latency analysis, t (1655) = 0.13, β = 1.26, p = .90, or in the error analysis, z = 1.76, β = 0.32, p = .08. Similarly, there was no significant interaction of consistency and stress type in either analysis, t (1655) = 0.01, β = 0.06, p = .99; z = 0.06, β = 0.02, p = .95.

For verbs, there was a significant main effect of consistency in the error analysis (1.0% vs. 7.4%), z = 2.06, β = 1.77, p = .04, but not in the latency analyses (*M* = 673 ms, *SD* = 30 vs. *M* = 690 ms, *SD* = 36), t (1655) = 1.42, β = 11.20, p = .15. The main effect of stress type was not significant in either the latency or error analyses, t (1655) = 0.23, β = 2.01, p = .80; z = 1.68, β = 1.03, p = .09. Likewise, the interaction of stress type and consistency did not reach significance in either the latency or error analyses, t (1655) = 1.07, β = 11.78, p = .29; z = 0.49, β = 0.56, p = .62.

Discussion

The hypothesis that differences in processing of disyllabic words with stress on the first versus the second syllable are unlikely to appear in Russian was generally supported. There was no evidence of an overall latency difference between words with trochaic versus iambic stress. Although participants did make more stress assignment errors in naming words with second compared to first syllable stress, this difference was small in size (less than 1 error per participant). Further, a stress type effect was not realized for either nouns or verbs, grammatical categories that do not have a regular stress pattern. In contrast, readers were not only faster and more accurate in naming Russian adjectives than naming nouns and verbs, but they also showed a stress type effect, with shorter latencies and fewer errors when naming regular, first syllable stress adjectives than when naming irregular, second syllable stress adjectives.

The effect of consistency (of the stress pattern) was successfully demonstrated. Words with endings associated with their stress patterns were named faster and more accurately than words that had endings signaling a different stress pattern. This effect remained significant even when separate analyses of nouns and verbs were conducted. In contrast, in the analysis of adjectives, an interaction of consistency and stress type was observed. Consistency had no effect on the speed of processing of adjectives with regular trochaic stress, while adjectives with infrequent iambic stress showed a consistency effect in the latency analysis. Therefore, it is clear that stress consistency is an important cue in stress assignment.

Finally, with respect to the more general question of how stress is assigned in Russian, Study 2 provided evidence that that process is not simply a lexically based one. Instead, readers do use other types of information, in particular, stress regularity and stress consistency when naming Russian words.

5.3.2. Study 3: Binary logistic regression of a set of non-lexical predictors on stress patterns in a corpus of Russian disyllabic words.

The goal of Study 3 was to explore whether there are relationships between a range of non-lexical variables and stress patterns in Russian by running a binary logistic regression analysis with stress patterns of 13,943 disyllabic words entered as the criterion variable and eleven variables entered as predictors. The predictor variables were Grammatical Category, Log Frequency, Length, Word Onset Complexity, Word Coda Complexity, and a set of six orthographic components.

The choice of some of the variables entered into a regression model as predictors of stress patterns was, to some extent, empirically driven. Thus, Grammatical Category was included as a predictor as prior studies in English demonstrated the presence of a relationship between stress patterns and a word's grammatical role (Arciuli & Cupples, 2004, 2006). Further, as shown in Studies 1 and 2 of the present thesis, relations between grammatical category and stress patterns also exist in Russian. There have also been prior empirical demonstrations of associations existing between stress patterns and orthographic complexity of Word Onsets and Word Codas (Kelly et al., 1998; Kelly, 2004). Hence, these variables were entered as predictors into the regression. If the complexity of an orthographic segment matters in stress assignment, then, overall complexity of a word might also matter. Therefore, word length as a reflection of the overall structural complexity of a word was also included as a predictor in the analysis.

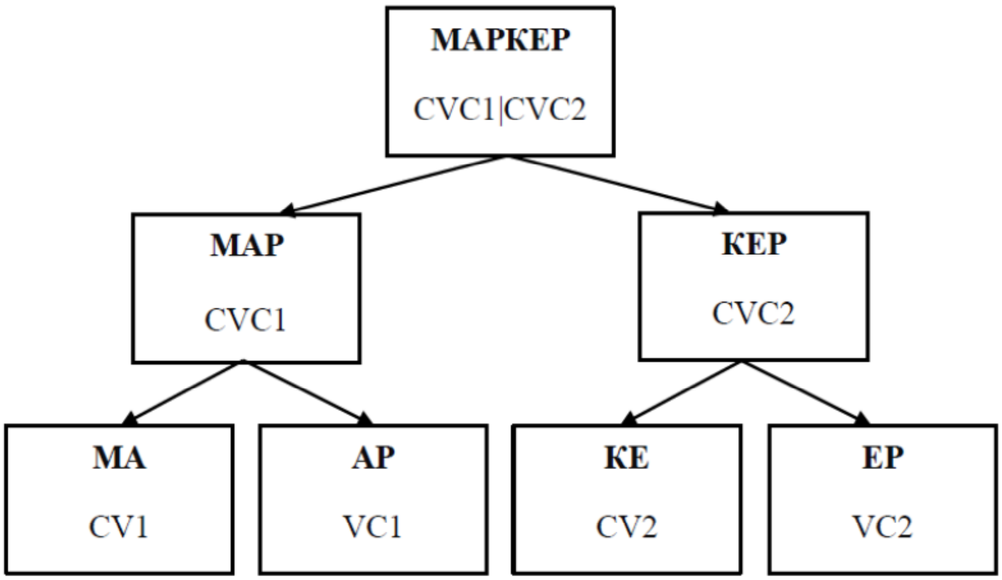
The present study also involved an exploratory approach as a variety of orthographic segments that might be associated with stress patterns were analyzed. The orthographic segments were the First Syllable (further referred to as CVC1), the Beginning of the First Syllable (CV1), the Ending of the First Syllable (VC1), the Second Syllable (CVC2), the Beginning of the Second Syllable (CV2), and the Ending of the Second Syllable (VC2). The symbols C and V refer not just to single consonants or vowels, but rather to all letters of that type before the next type is encountered. For example, in the word *крона*, the segment CV1 refers to *кро-*. An example of the division of a word into the segments that were used in the calculation of spelling-to-stress consistency measures entered into binary logistic regression as predictors of stress patterns is presented for the word *маркер* in Figure 6.

Syllables were included because there is a hypothesis that syllables do play an important role in visual recognition of polysyllabic words (Carreiras & Perea, 2002). For example, it has been demonstrated that readers require more time for naming disyllabic words than monosyllabic words (Balota et al., 2007; Yap & Balota, 2009). Further, syllable frequency has been demonstrated to influence response times in German and Spanish (Alvarez, Carreiras, & Taft, 2001; Conrad & Jacobs, 2004), with words having high-frequency syllables producing longer latencies than words having low-frequency syllables. These studies suggest that at least in some languages, readers parse polysyllabic words into syllabic units at early stages of the processing. Therefore, the orthography of syllables and, more specifically, information about the consistency with which orthography of syllables maps onto stress patterns might be available for readers and might assist them in establishing stress patterns of polysyllabic words.

Further, in this regression analysis, the ability of some components of syllables to predict stress patterns in Russian was assessed. The components of syllables considered were beginnings (i.e., all consonants preceding a nucleus vowel + a nucleus vowel) and endings (i.e., all consonants following a nucleus vowel + a nucleus vowel). The Beginning of the First Syllable (CV1) refers to the same orthographic component as previously investigated, the word beginning. The Ending of the Second Syllable (VC2) refers to the same orthographic component as previously investigated, the word ending.

Figure 6

The division of the word MARKEP into six orthographic segments for calculating spelling-stress consistency



Hence, the inclusion of CV1 and VC2 into the regression equation is driven by previous empirical findings. To obtain a broader picture of the impact of various orthographic components on the process of stress assignment, CV2 and VC1 orthographic components were also included as predictors of stress patterns.

The final variable was logarithmic frequency. This variable could be of theoretical interest if certain stress patterns are more likely to occur in words that readers encounter frequently or, alternatively, in words that occur rarely in the language.

Method

Materials

A corpus of 13,943 disyllabic Russian words was compiled for the present study. Both lemmatized (i.e., dictionary forms) and inflected forms of the words were included. Lemmatized forms of the words were taken from the Frequency Dictionary of Modern Russian (Lyashevskaya & Sharov, 2009), while inflected forms of the words were retrieved from the Dictionary of Russian Grammar (Zaliznyak, 2003). The only constraint on the choice of words was the frequency of word usage with words that have frequency of less than 1 per million words being excluded.

The words were used as items in a binary logistic regression. The binary dependent variable was a stress pattern of the word coded as “0” (trochaic stress pattern) or “1” (iambic stress pattern). The stress pattern information was verified in the Dictionary of Russian Lexical Stress (Zarva, 2001). The information about the grammatical category and the frequency of each word was retrieved from the Frequency Dictionary of Modern Russian (Lyashevskaya & Sharov, 2009). The length variable corresponded to the number of letters in a word. The onset complexity of each word was defined as the number of consonants in the word onset position. The coda complexity of each word was established as the number of consonants in the word coda position.

Spelling-stress consistency measures were calculated for six orthographic segments: CVC1, CV1, VC1, CVC2, CV2, and VC2. In making decisions about the division of words into syllables, a number of principles were followed. First of all, the Maximal Onset Principle, a widely recognized principle of syllabification in contemporary linguistics (Giegerich, 1992), was considered. According to the Maximal Onset Principle, intervocalic consonants are maximally assigned to the onsets of syllables in conformity with language-specific and universal conditions. In other words, in a disyllabic word, syllables should be divided in such a way that as many consonants as possible are assigned to the beginning of the second syllable rather than the ending of the first syllable (e.g., English: *a-fraid*, *ba-sics*, *so-fa*; Russian: *ка-ток*, *ро-тик*, *са-жа*). The main language-specific requirement is that words should be divided into syllables that have legal onsets and codas in their language. For example, the proper syllabification of the English word *kitchen* is not *ki-tchen*, but rather *kit-chen* as the letter cluster "tch" is an illegal onset in English. Similarly, a Russian word *близкий* is syllabified as *близ-кий* as the letter cluster "*зк*" is an illegal onset in Russian. A universal principle that was also considered is that syllabification should not violate morphemic divisions. Thus, the English word *artist* contains syllables *art-ist* rather than *ar-tist* and the Russian word *выслать* (meaning "send away") contains syllables *вы-слать* (the prefix *вы* ("away") + the root *слать* ("send")) rather than *выс-лать* as in the former cases syllable division agrees with morphemic division.

Following these principles, it was possible to determine unequivocally first and second syllable divisions for 92% of words in the corpus. The syllabification in the remaining 8% of words was less straightforward. These were words with intervocalic consonant clusters that could serve both as a legal coda if attached to the first syllable and as a legal onset if attached to the second syllable and, further, these words were made of one derivational morpheme. Thus, in deciding on the division of a word into syllables, neither distributional nor morphological information were useful. In the case of these words, a reader might establish the syllable division in one of the three ways: (1) by maximizing a coda of the first syllable (*маск-а*), (2) by maximizing an onset of the second syllable (*ма-ска*), or (3) by splitting a consonant cluster between a coda of the first syllable and an onset of the second syllable (*мас-ка*).

The method of syllabification preferred by Russian speakers was determined through a survey in which 23 native speakers of Russian had to indicate the way they would divide a disyllabic word into syllables by typing in the first and second syllables for each given word. One hundred words that were ambiguous from the point of view of syllable division were presented in this pilot experiment (see Appendix B). The results showed that Russian readers mainly divided disyllabic words containing intervocalic consonants by splitting a consonant cluster between a coda of the first syllable and an onset of the second syllable (84% of responses), followed by maximizing an onset of the second syllable (14% of responses), and, finally, by maximizing a coda of the first syllable (2%). Based on these findings, words with an ambiguous syllable boundary in the corpus were divided into syllabic units by splitting a consonant cluster between a coda of the first syllable and an onset of the second syllable.

The beginning of the first syllable (CV1) corresponded to all initial consonants of the first syllable preceding the vowel plus the vowel of that syllable. The beginning of the second syllable (CV2) corresponded to all initial consonants of the second syllable preceding the vowel plus the vowel of that syllable. The ending of the first syllable (VC1) corresponded to the vowel of the first syllable plus all consonants of that syllable following this vowel. The ending of the second syllable (VC2) corresponded to the vowel of the second syllable plus all consonants of that syllable following this vowel.

For each orthographic segment of interest, spelling-to-trochaic stress consistency measures were calculated, using the method analogous to that used by Treiman et al. (1995) for spelling-sound consistency. Words sharing a certain orthographic component were defined as the words in the target's neighborhood. In calculating the type consistency measure, the proportion of words with trochaic stress in the neighborhood was calculated. For example, all Russian disyllabic words with CVC1 *вра*- have a trochaic stress pattern, therefore, words in the neighborhood "вра" have a consistency measure for CVC1 that equals 1.00. On the other hand, all Russian disyllabic words with CVC1 *дя*- have an iambic stress pattern, therefore, for any word in that neighborhood the consistency measure of CVC1 equals 0.00. Cases when certain orthographic components were only associated with either trochaic or iambic stress pattern were rare. The majority of words belonged to neighborhoods consisting of words with both trochaic and iambic stress patterns. In addition to type consistency measures, token consistency measures, corresponding to the proportion of the summed frequency of words with iambic stress in certain orthographic neighborhood divided by the summed frequency of all words in this orthographic neighborhood, were calculated.

Results

A set of binary logistic regressions was run to predict stress patterns for words in the corpus using combinations of eleven predictors: *Grammatical Category*, *Log Frequency*, *Length*, *Onset Complexity*, *Ending Complexity*, and Consistency of *CVC1*, *CV1*, *VC1*, *CVC2*, *CV2*, and *VC2*. The goal was to find a model with a minimum number of factors that would still have high predictive power. In other words, the goal was to find a balance between the simplicity of a model and its goodness of fit. The full model was simplified in a backward stepwise fashion using $p \geq .05$ on the likelihood ratio test as an exclusion criterion. The backward design was selected over the frontward design as it provides an opportunity to look at all the variables in the model at once and to assess all possible subsets of the set of potential independent variables. Further, backward selection has been shown to produce regression models that provide a better fit to the data than models produced as the result of forward selection (Harrel, Lee, & Mark, 1996).

The goodness of fit of a model was assessed with the Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC), the Deviance Information Criterion (DIC), and the log likelihood (logL) that describe the trade-off between accuracy and complexity of a model. A model that minimizes AIC, BIC, DIC, and increases logL is a preferred choice. Further, to select amongst competing models a likelihood ratio test was completed. The analysis was conducted using the R package *lme4* (Bates & Maechler, 2010). Due to the fact that the stress consistency could be either a type or a token measure, two separate sets of regressions were conducted.

In the first analysis, type consistency measures were used. The measures of goodness of fit and the results of the likelihood ratio tests of the models tested are given in Table 6. A full model with all eleven predictors provided a significantly better fit to the data than a null model with intercept only, χ^2 (13) = 9873.83, *p* < .001. In the full model eight variables were significant predictors of stress patterns: *Grammatical Category* (*z* = -1.96, *p* = .05), *Onset Complexity* (*z* = -5.86, *p* < .001), *Ending Complexity* (*z* = 2.96, *p* = .003), *Log Frequency* (*z* = -1.98, *p* = .05), *CVC1* (*z* = -34.45, *p* < .001), *CVC2* (*z* = -32.51, *p* < .001), *CV2* (*z* = 3.30, *p* = .001), and *VC2* (*z* = -3.27, *p* = .001).

First, logistic regressions were run on eleven different models that had only one predictor entered. Doing so established the goodness of fit of each individual predictor and the following order of elimination of predictors: *Length* (*χ2(1) = 4.45, p = .04*), *Log Frequency* (*χ2 (1) = 13.70, p < .001*), *Onset Complexity* (*χ2 (1) = 172.71, p < .001*), *Ending Complexity* (*χ2 (1) = 361.07, p < .001*), *Grammatical Category* (*χ2 (3) = 864.07, p < .001*), *VC1* (*χ2 (1) = 1224.07*, *p* < .001), *CV1* (χ^2 (1) = 2318.78, *p* < .001), *CV2* (χ^2 (1) = 2730.03, *p* < .001), *VC2* (χ^2 (1) = 1440.61, *p* < .001), *CVC1* (χ^2 (1) = 4530.08, *p* < .001), and *CVC2* (χ^2 (1) = 6753.63, *p* < .001).

The model without *Length* did not lose in its ability to explain the data compared to the full model, χ^2 (1) = 3.51, *p* = .06. Therefore, *Length* was deleted from the model. On the other hand, there was a significant drop in goodness of fit for models when *Log Frequency*, χ^2 (1) = 6.11, *p* = .02, *Onset Complexity*, χ^2 (1) = 5.88, *p* = .02, *Ending Complexity*, χ^2 (1) = 26.98, *p* < .001, or *Grammatical Category*, χ^2 (3) = 16.05, *p* = .01 were eliminated. Hence, these variables were kept in the model as predictors. Next, two consistency variables that were not improving the power of the model were dropped, that is, *VC1*, χ^2 (1) = 3.56, *p* = .06, and *CV1*, χ^2 (1) = 0.01, *p* = .92. The removal of other consistency variables resulted in the decline of goodness of fit: *CV2*, χ^2 (1) = 16.21,

Table 6.

Measures of goodness of fit and likelihood ratio tests of binary logistic regressions predicting stress patterns in the corpus (consistency measures are based on type count).

		Goodness of Fit Measures				Likelihood Ratio Test	
#	Fixed Factors (* - $p < .05$)	AIC	BIC	LogL	DIC	Alternative Model (#)	Test Statistic
1.	Null Model						
2.	Grammatical Category* Log Frequency* Length Onset Complexity* Ending Complexity* CVC1*, CV1, VC1 CVC2*, CV2*, VC2*	8856	8953	-4415	8830	1	$\chi 2\ (12) = 9873.83$, $p < .001$
3.	Grammatical Category*	17280	17310	-8636	17272	1	χ^2 (3) = 864.07, $p < .001$
4.	Log Frequency*	18126	18141	-9061	18122	1	χ^2 (1) = 13.70, $p < .001$
5.	Length*	18135	18150	-9066	18131	1	$\chi 2$ (1) = 4.45, $p = .04$
6.	Onset Complexity*	17967	17982	-8982	17963	1	$\chi 2$ (1) = 172.71, $p < .001$
7.	Ending Complexity*	17779	17794	-8887	17775	1	χ^2 (1) = 361.07, $p < .001$
8.	CV1*	13610	13625	-6803	13606	1	χ^2 (1) = 2318.08, $p < .001$
9.	VC1*	16916	16931	-8456	16912	1	χ^2 (1) = 1224.07, $p < .001$
10.	CV2*	11386	11401	-5691	11382	1	χ^2 (1) = 2730.03, $p < .001$
11.	VC2*	15306	15836	-7908	15817	1	χ^2 (1) = 1440.61, $p < .001$
12.	CVC1*	13471	13485	-6733	13467	1	χ^2 (1) = 4530.08, $p < .001$
13.	CVC2*	12979	12994	-6487	12975	1	χ^2 (1) = 6753.63, $p < .001$

Note. Asterisk indicates fixed factors in the regression models that were significant predictors of stress patterns.

Table 6 (continued).

Measures of goodness of fit and likelihood ratio tests of binary logistic regressions predicting stress patterns in the corpus (consistency measures are based on type count).

		Goodness of Fit Measures				Likelihood Ratio Test	
#	Fixed Factors (* - $p < .05$)	AIC	BIC	LogL	DIC	Alternative Model (#)	Test Statistic
14	Grammatical Category* Log Frequency Onset Complexity* Ending Complexity* CVC1*, CV1*, VC1 CVC2*, CV2, VC2*	8857	8947	-4417	8833	2	$\chi2$ (1) = 3.51, $p = .06$
15	Grammatical Category* Onset Complexity* Ending Complexity* CVC1*, CV1, VC1 CVC2*, CV2*, VC2*	8868	8950	-4423	8840	14	$\chi2$ (1) = 6.11, $p = .02$
16	Grammatical Category* Log Frequency Ending Complexity* CVC1*, CV1*, VC1 CVC2*, CV2*, VC2*	8864	8947	-4421	8841	14	$\chi2$ (1) = 5.88, $p = .02$
17	Grammatical Category Log Frequency Onset Complexity* CVC1*, CV1*, VC1* CVC2*, CV2*, VC2*	8895	8977	-4436	8860	14	$\chi2$ (1) = 26.98, $p < .001$
18	Log Frequency* Onset Complexity* Ending Complexity* CVC1*, CV1*, VC1 CVC2*, CV2, VC2*	8862	8929	-4422	8849	14	$\chi2$ (3) = 16.05, $p = .01$

Note. Asterisk indicates that these fixed factors were significant predictors of stress assignment in the corresponding regression models.

Table 6 (continued).

Measures of goodness of fit and likelihood ratio tests of binary logistic regressions predicting stress patterns in the corpus (consistency measures are based on type count).

		Goodness of Fit Measures				Likelihood Ratio Test	
#	Fixed Factors (* - $p < .05$)	AIC	BIC	LogL	DIC	Alternative Model (#)	Test Statistic
19	Grammatical Category Log Frequency* Onset Complexity* Ending Complexity* CVC1*, CV1* CVC2*, CV2*, VC2*	8858	8940	-4418	8836	14	$\chi 2$ (1) = 3.56, $p = .06$
20	Grammatical Category Log Frequency* Onset Complexity* Ending Complexity* CVC1*, CVC2, CV2, VC2	8856	8930	-4418	8836	19	$\chi 2$ (1) = 0.01, $p = .92$
21	Grammatical Category* Log Frequency Onset Complexity* Ending Complexity* CVC1*, CVC2*, VC2*	8866	8933	-4424	8852	20	$\chi 2$ (1) = 16.21, $p < .001$
22	Grammatical Category Log Frequency* Onset Complexity* Ending Complexity* CVC1*, CVC2*, CV2*	8861	8930	-4428	8845	20	$\chi 2$ (1) = 8.50, $p < .001$
23	Grammatical Category Log Frequency* Onset Complexity* Ending Complexity* CVC2*, CV2*, VC2*	12305	12377	-3046	12338	20	$\chi 2$ (1) = 3502.70, $p < .001$
24	Grammatical Category Log Frequency* Onset Complexity* Ending Complexity* CVC1*, CV2*, VC2*	10816	10837	-3894	10319	20	$\chi 2$ (1) = 1482.60, $p < .001$

Note. Asterisk indicates that these fixed factors were significant predictors of stress assignment in the corresponding regression models.

Table 6 (continued).

Measures of goodness of fit and likelihood ratio tests of binary logistic regressions predicting stress patterns in the corpus (consistency measures are based on type count).

		Goodness of Fit Measures				Likelihood Ratio Test	
#	Fixed Factors (* - $p < .05$)	AIC	BIC	LogL	DIC	Alternative Model (#)	Test Statistic
25	Grammatical Category Onset Complexity* Ending Complexity* CVC1* CVC2*, CV2, VC2*	8859	8901	-4413	8840	20	χ^2 (1) = 3.63, p = .06
26	**Onset Complexity* Ending Complexity* CVC1* CVC2*, CV2*, VC2***	**8860**	**8913**	**-4423**	**8847**	**25**	**χ2 (3) = 7.32, p = .06**
27	Ending Complexity* CVC1* CVC2*, CV2*, VC2*	8868	8913	-4428	8853	26	χ2 (1) = 5.64, p = .02
28	Onset Complexity* CVC1* CVC2*, CV2*, VC2*	8878	8919	-4429	8872	26	χ2 (1) = 24.87, $p < .001$
29	Ending Complexity* Onset Complexity* CVC1*,CVC2*, VC2*	8890	8935	-4439	8872	26	χ2 (1) = 25.34, $p < .001$
30	Ending Complexity* Onset Complexity* CVC1*,CVC2*, VC2*	8868	8913	-4428	8852	26	χ2 (1) = 4.43, p = .04
31	Ending Complexity* Onset Complexity* CVC2*,CV2*, VC2*	11331	11376	-5660	11319	26	χ2 (1) = 2472.70, $p < .001$
32	Ending Complexity* Onset Complexity* CVC1*,CV2*, VC2*	10397	10372	-5557	10345	26	χ2 (1) = 1497.60, $p < .001$

Note. Asterisk indicates that these fixed factors were significant predictors of stress assignment in the corresponding regression models. The model in bold is the final simplified model with a minimum possible number of factors in it that still had high power to predict stress patterns.

$p < .001$, *VC2*, χ^2 (1) = 8.50, $p = .001$, *CVC1*, χ^2 (1) = 3502.70, $p < .001$, and *CVC2*, χ^2 (1) = 1482.60, $p < .001$. Thus, in the first round of simplification, the full model was reduced to a model with eight predictors: *Log Frequency*, *Onset Complexity*, *Ending Complexity*, *Grammatical Category*, *CVC1*, *CVC2*, *CV2*, and *VC2*.

Next, the possibility of simplifying the model further was examined. The model without *Log Frequency* fit the data as well as the model with this factor in it, χ^2 (1) = 3.63, $p = .06$. Similarly, the elimination of *Grammatical Category* from the model did not decrease the goodness of fit significantly, χ^2 (3) = 7.32, $p = .06$. Hence, these factors were deleted from the model. The exclusion of all other variables was associated with weakening of the power of the model: *Onset Complexity*, χ^2 (1) = 5.64, $p = .02$, *Ending Complexity*, χ^2 (1) = 24.87, $p < .001$, *CV2*, χ^2 (1) = 25.34, $p < .001$, *VC2*, χ^2 (1) = 4.43, $p = .04$, *CVC1*, χ^2 (1) = 2472.70, $p < .001$, and *CVC2*, χ^2 (1) = 1497.00, $p < .001$. As a result, the final simplified model that could explain the data as well as the full model had six variables in it that were all significant predictors of stress patterns in Russian disyllabic words: *Ending Complexity*, $z = 2.38$, $p = .02$, *Onset Complexity*, $z = -4.94$, $p < .001$, *CVC1*, $z = -46.54$, p < .001, *CV2*, $z = 5.14$, $p < .001$, *CVC2*, $z = -32.99$, $p < .001$, and *VC2*, $z = -2.11$, $p = .04$.

The regressions were run for a second time using token consistency measures. The measures of goodness of fit and the results of the likelihood ratio tests of the models are provided in Table 7. A full model with eleven predictors in it provided a better fit to the data in comparison to an intercept only model, χ^2 (13) = 8304.07, $p < .001$. In the full model nine variables were significant predictors of stress patterns in Russian disyllabic words: *Ending Complexity* ($z = 2.42$, $p = .02$), *Onset Complexity* ($z = -7.80$, $p < .001$),

Table 7.

Measures of goodness of fit and likelihood ratio tests of binary logistic regressions predicting stress patterns in the corpus (consistency measures are based on token count)

		Goodness of Fit Measures				Likelihood Ratio Test	
#	Fixed Factors (* - $p < .05$)	AIC	BIC	LogL	DIC	Alternative Model (#)	Test Statistic
1.	Null Model						
2.	Grammatical Category Log Frequency* Length* Onset Complexity* Ending Complexity* CVC1*, CV1, VC1* CVC2*, CV2*, VC2*	9858	9954	-4915	9831	1	$\chi 2\ (12) = 8304.07$, $p < .001$
3.	Grammatical Category Log Frequency* Onset Complexity Ending Complexity* CVC1*, CV1, VC1* CVC2*, CV2*, VC2*	9867	9957	-4922	9843	2	χ^2 (1) = 11.77, $p < .001$
4.	Grammatical Category Length* Onset Complexity* Ending Complexity* CVC1*, CV1, VC1* CVC2*, CV2*, VC2*	9867	9957	-4921	9843	2	χ^2 (1) = 11.32, $p < .001$
5.	Grammatical Category Log Frequency* Length* Ending Complexity* CVC1*, CV1*, VC1 CVC2*, CV2*, VC2*	9862	9951	-4919	9838	2	χ^2 (1) = 5.88, $p = .02$
6.	Grammatical Category Log Frequency Length* Onset Complexity* CVC1*, CV1*, VC1* CVC2*, CV2*, VC2*	9918	1000 8	-4971	9894	2	χ^2 (1) = 62.62, $p < .001$

Note. Asterisk indicates that these fixed factors were significant predictors of stress assignment in the corresponding regression models.

Table 7 (continued).

Measures of goodness of fit and likelihood ratio tests of binary logistic regressions predicting stress patterns in the corpus (consistency measures are based on token count)

		Goodness of Fit Measures				Likelihood Ratio Test	
#	Fixed Factors (* - $p < .05$)	AIC	BIC	LogL	DIC	Alternative Model (#)	Test Statistic
7.	Log Frequency Length* Onset Complexity* Ending Complexity* CVC1*, CV1*, VC1* CVC2*, CV2, VC2*	9859	9934	-4919	9839	2	χ^2 (3) = 7.07, $p = .07$
8.	Log Frequency Length* Onset Complexity* Ending Complexity* CVC1*, VC1* CVC2*, CV2*, VC2*	9858	9926	-4920	9847	7	χ^2 (1) = 6.85, $p = .01$
9.	Log Frequency* Length* Onset Complexity* Ending Complexity* CVC1*, CV1* CVC2*, CV2*, VC2*	9863	9923	-4924	9847	7	χ^2 (1) = 6.64, $p = .01$
10.	Log Frequency* Length* Onset Complexity* Ending Complexity* CVC1*, CV1*, VC1* CVC2*, VC2*	9961	9927	-4969	9923	8	χ^2 (1) = 80.14, $p = .01$
11.	Log Frequency* Length* Onset Complexity* Ending Complexity* CVC1*, CV1, VC1 CVC2*, CV2*	9959	10018	-4971	9942	8	χ^2 (1) = 102.14, $p < .001$

Note. Asterisk indicates that these fixed factors were significant predictors of stress assignment in the corresponding regression models.

Table 7 (continued).

Measures of goodness of fit and likelihood ratio tests of binary logistic regressions predicting stress patterns in the corpus (consistency measures are based on token count)

		Goodness of Fit Measures				Likelihood Ratio Test	
#	Fixed Factors (* - *p* < .05)	AIC	BIC	LogL	DIC	Alternative Model (#)	Test Statistic
12.	Log Frequency Length* Onset Complexity* Ending Complexity* CV1*, VC1 CVC2*, CV2, VC2*	11600	11660	-5792	1158 4	8	χ^2 (1) = 1743.30, $p < .001$
13.	Log Frequency Length* Onset Complexity* Ending Complexity* CVC1*, CV1*, VC1 CV2*, VC2*	11868	11928	-5926	1185 2	8	χ2 (1) = 2011.90, $p < .001$
14.	**Length*** **Onset Complexity*** **Ending Complexity*** **CVC1*, CV1*, VC1*** **CVC2*, CV2*, VC2***	**9858**	**9926**	**-4920**	**9849**	**8**	**χ^2 (1) = 2.96, $p = .09$**
15.	Onset Complexity* Ending Complexity* CVC1*, CV1*, VC1 CVC2*, CV2*, VC2*	9869	9943	-4900	9861	14	χ^2 (1) = 12.68, $p < .001$
16.	Length Ending Complexity* CVC1*, CV1*, VC1* CVC2*, CV2, VC2*	9863	9835	-4915	9855	14	χ^2 (1) = 6.21, $p = .01$
17.	Length* Onset Complexity* CVC1*, CV1*, VC1 CVC2*, CV2, VC2*	9885	9874	-5025	9910	14	χ^2 (1) = 60.17, $p < .001$

Note. Asterisk indicates that these fixed factors were significant predictors of stress assignment in the corresponding regression models. The model in bold is the final simplified model with a minimum possible number of factors in it that still had high power to predict stress patterns.

Table 7 (continued).

Measures of goodness of fit and likelihood ratio tests of binary logistic regressions predicting stress patterns in the corpus (consistency measures are based on token count)

		Goodness of Fit Measures				Likelihood Ratio Test	
#	Fixed Factors (* - $p < .05$)	AIC	BIC	LogL	DIC	Alternative Model (#)	Test Statistic
18.	Length Onset Complexity* Ending Complexity* CV1*, VC1* CVC2*, CV2*, VC2*	11379	11381	-6192	11409	14	χ^2 (1) = 1560.17, $p < .001$
19.	Length* Onset Complexity* Ending Complexity* CVC1*, VC1* CVC2*, CV2*, VC2*	9862	9835	-4913	9856	14	χ^2 (1) = 6.54, $p = .01$
20.	Length* Onset Complexity* Ending Complexity* CVC1*, CV1* CVC2*, CV2*, VC2	9863	9832	-4910	9857	14	χ^2 (1) = 7.28, $p = .001$
21.	Length Onset Complexity* Ending Complexity* CVC1*, CV1*, VC1* CV2*, VC2*	11309	11123	-6156	11323	14	χ^2 (1) = 1474.30, $p < .001$
22	Length* Onset Complexity* Ending Complexity* CVC1*, CV1*, VC1* CVC2*, VC2*	9854	9860	-4930	9866	14	χ^2 (1) = 16.15, $p < .001$
23	Length Onset Complexity* Ending Complexity* CVC1*, CV1*, VC1* CVC2*, CV2*	9917	9892	-4938	9909	14	χ^2 (1) = 60.17, $p < .001$

Note. Asterisk indicates that these fixed factors were significant predictors of stress assignment in the corresponding regression models.

Length (z = 3.42, p < .001), *Log Frequency* (z = -3.36, p < .001), *CVC1* (z = -25.45, p < .001), *VC1* (z = -2.61, p = .01), *CVC2* (z = -38.57, p < .001), *CV2* (z = -4.25, p < .001), and *VC2* (z = -19.95, p < .001).

The full model was further simplified following the same steps as in the analysis in which type consistency measures were used. The likelihood ratio tests showed a significant drop in the goodness of fit of models if *Length*, χ^2 (1) = 11.77, p < .001, *Log Frequency*, χ^2 (1) = 11.32, p < .001, *Onset Complexity*, χ^2 (1) = 5.88, p = .02, or *Ending Complexity*, χ^2 (1) = 62.62, p < .001 were eliminated. On the other hand, *Grammatical Category* did not add to the power of the model to explain the data, χ^2 (3) = 7.07, p = .07, and, thus, was removed. Attempts to further simplify the model were not successful. There was a significant decrease in the goodness of fit measures when the following variables were eliminated from the model: *CV1*, χ^2 (1) = 6.85, p = .01; *VC1*, χ^2 (1) = 6.64, p = .01; *CV2*, χ^2 (1) = 80.14, p = .01; *VC2*, χ^2 (1) = 102.14, p < .001; *CVC1*, χ^2 (1) = 1743.30, p < .001; and *CVC2*, χ^2 (1) = 2011.90, p < .001. Thus, in the first round of model reduction, the model included ten predictors: *Length*, *Log Frequency*, *Onset Complexity*, *Ending Complexity*, *CVC1*, *CV1*, *VC1*, *CVC2*, *CV2*, and *VC2*.

In the second round of model reduction, *Log Frequency,* which was not improving the goodness of fit of the model (χ^2 (1) = 2.96, p = .09), was eliminated. The elimination of other variables resulted in a significant decline in the power of the model to fit the data (*Length*, χ^2 (1) = 12.68, p < .001; *Onset Complexity*, χ^2 (1) = 6.21, p = .01; *Ending Complexity*, χ^2 (1) = 60.17, p < .001; *CVC1*, χ^2 (1) = 1560.17, p < .001; *CV1*, χ^2 (1) = 6.54, p = .01; *VC1*, χ^2 (1) = 7.28, p = .001; *CVC2*, χ^2 (1) = 1474.30, p < .001; *CV2*, χ^2 (1) = 16.15, p < .001; and *VC2*, χ^2 (1) = 60.17, p < .001). Thus, the final model that could explain the data as well as the full model contained nine predictors: *Onset Complexity* (z = -2.49, p = .02), *Ending Complexity* (z = -7.66, p < .001), *Length* (z = 3.59, p = .003), *CVC1* (z = -36.58, p < .001), *CV1* (z = -2.57, p = .01), *VC1* (z = -2.69, p = .01), *CVC2* (z = -38.67, p < .001), *CV2* (z = 3.70, p = .01), and *VC2* (z = -19.99, p < .001).

Discussion

Study 3 involved two sets of binary logistic regressions on stress patterns in a corpus of Russian disyllabic words. The variables evaluated as predictors of stress patterns were Length, Log Frequency, Grammatical Category, Onset Complexity, Ending Complexity, and Spelling-to-Stress Consistency of CVC1, CV1, VC1, CVC2, CV2, and VC2 that were estimated based either on type or token information. The goal was to simplify full models in such a way that a final model would fit the data with the minimum number of predictor variables possible. Variables that survive this simplification procedure and remain significant predictors of stress patterns in the corpus would be considered to have strong associative relationships with stress patterns, and, thus, may reliably be treated as valid stress cues in Russian.

A final model with type consistency measures contained six predictor variables (Onset Complexity, Ending Complexity, CVC1, CVC2, CV2, and VC2), while a final model with token consistency measures had nine predictors (Onset Complexity, Ending Complexity, Length, CVC1, CV1, VC1, CVC2, CV2, and VC2). Two simplified models (i.e., the model with type consistency measures vs. the model with token consistency measures) were compared on their ability to fit the data. The results showed that despite the fact that the final model with type consistency measures had fewer predictor variables in it (six vs. nine), this model provided a significantly better fit to the data compared to the model with token consistency measures, χ^2 (3) = 994.04, p < .001. All measures of goodness of fit point to the superiority of the model with type consistency variables (AIC = 8860, BIC = 8913, logLik = -4423, DIC = 8846) over the model with token consistency variables (AIC = 9858, BIC = 9926, logLik = -4920, DIC = 9849) to predict stress patterns in the corpus of Russian disyllabic words. Therefore, the variables that were significant predictors of stress patterns in the model with type consistency measures are more likely to be the relevant stress cues than variables that were significant predictors of stress patterns in the model with token consistency measures.

Thus, the results of the binary logistic regression suggest that there are six potential sources of stress pattern information in Russian. First, disyllabic words with complex onsets are more likely to have a trochaic than an iambic stress pattern. In contrast, the presence of complex codas appears to be associated more with an iambic than with a trochaic stress pattern. Further, four measures based on the orthography of a word were predictive of stress patterns in the corpus: CVC1, CVC2, CV2, and VC2. For three orthographic components (CVC1, CVC2, and VC2), a high score on the consistency of orthography to a trochaic stress pattern was associated with higher likelihood that a word does have a trochaic stress pattern. In other words, a word in an orthographic neighborhood that consists mainly of words with trochaic stress is more likely to have a trochaic stress pattern in comparison to a word from an orthographic neighborhood that consists mainly of words with iambic stress. On the other hand, for the orthographic component CV2, there was an unexpected reversed relationship between the consistency measure and stress pattern. More specifically, the analysis indicates that a high score on the consistency of orthography to a trochaic stress pattern was associated with a higher likelihood that a word has an iambic stress pattern. This result is counterintuitive and difficult to interpret from the perspective of the cognitive mechanisms that might cause it, suggesting that it is likely a statistical artifact. Therefore, although CV2 as a variable was a significant predictor of stress in the final equation, it seems unlikely that CV2 is a valid stress cue in Russian. In conclusion, the result of the binary logistic regression analysis singled out a set of five variables that are probabilistically associated with stress patterns in the corpus of Russian disyllabic words: Onset Complexity, Ending Complexity, CVC1, CVC2, and VC2.

5.3.4. Study 4: Generalized linear mixed effects regression of a set of non-lexical predictors on stress assignment performance by native speakers of Russian.

The main finding of Study 3 was that there are five non-lexical variables that are related to stress patterns in Russian. However, in order to conclude that any particular cue is a source of evidence that is used in the process of stress assignment (within the framework of the Bayesian model), it is necessary to demonstrate that this cue is not only of high validity, but also of high utility, that is, that readers are aware of this cue and use it in making stress assignment decisions. To assess the utility of the stress cues identified in Study 3, a generalized linear mixed effects model with the set of eleven non-lexical predictor variables was applied to stress assignment performance of readers who were asked to name 500 disyllabic words.

Method

Participants

Thirty four undergraduate students from Altay State University (Barnaul, Russia) took part in this experiment for a small monetary remuneration (age 17 – 23; M = 19). All were native speakers of Russian. None of the participants reported high proficiency in any second language.

Materials

A set of 500 disyllabic words (see Appendix C) was randomly selected from the database created for Study 3. Post-hoc analysis of the randomly selected words showed that the distribution of stress patterns and words according to grammatical category in this set of experimental items was similar to that in the language. Further, to make sure that this set of words is representative of the corpus of Russian disyllabic words from the point of view of associations existing between non-lexical cues and stress patterns, a binary logistic regression was carried out. In this analysis, the question was whether stress patterns for the 500 words selected can be predicted from a set of eleven predictor variables: Grammatical Category, Log Frequency, Length, Onset Complexity, Ending Complexity, and Consistency of six orthographic components (CVC1, CV1, VC1, CVC2, CV2, and VC2). The analysis was conducted using the R package *lme4* (Bates & Maechler, 2010). Similar to Study 3, two sets of binary logistic regressions were completed: one with type consistency measures and the other with token consistency measures. Both models were simplified using the same steps and rationale as in Study 3.

In a regression analysis in which type consistency measures were included, a full model was simplified to a model that contained six predictor variables: *Log Frequency*, *Onset Complexity*, *Ending Complexity*, *CVC1*, *CVC2*, and *VC2*. In this model, three variables were significant predictors of stress patterns (*Onset Complexity*: z = -2.14, p =

.03; *CVC1*: $z = -5.33$, $p < .001$; and *CVC2*: $z = -5.52$, $p < .03$), two were marginally significant (*Ending Complexity*: $z = 1.74$, $p = .08$; and *VC2*: $z = -1.86$, $p = .06$), and one was non-significant (*Log Frequency*: $z = -1.48$, $p = .14$). The simplified model with six predictors provided a significantly better fit to the data than intercept only model χ^2 (7) = 347.51, $p < .001$. Further, the simplified model did not differ significantly from the full model in its ability to fit the data, χ^2 (7) = 2.62, $p = .92$.

Next, an analysis in which token consistency measures were included was undertaken. A full model with eleven predictors was simplified to a model with six predictors: *Onset Complexity*, *Ending Complexity*, *CVC1*, *CV1*, *CVC2*, and *VC2*. In this model, four variables were significant predictors of stress (*Onset Complexity*: $z = -1.96$, $p = .05$; *CVC1*: $z = -4.13$, $p < .001$; *CVC2*: $z = -6.14$, $p < .001$; and *VC1*: $z = -2.86$, $p = .004$) and two variables were marginally significant predictors of stress (*Ending Complexity*: $z = 1.72$, $p = .09$; and *CV1*: $z = -1.83$, $p = .07$). The simplified model fit the data better than an intercept only model, χ^2 (7) = 320.29, $p < .001$. At the same time, the simplified model was as good in its power to predict stress patterns as a full model with all eleven predictors in it, χ^2 (6) = 3.72, $p = .72$.

Finally, similarly to the results observed in Study 3, the data were better fit by the model with type rather than token consistency, χ^2 (1) = 27.22, $p < .001$. Therefore, in assessing the variables from the point of view of their validity as stress cues, the focus is on the results of the regression with type consistency measures. In this analysis, five variables were probabilistically associated with stress patterns in the corpus of 500 words: *Onset Complexity*, *Ending Complexity*, *CVC1*, *CVC2*, and *VC2*. These are the same stress cues that were reported to have high validity in predicting stress patterns in

Study 3. The only variable that was a significant predictor of stress in Study 3, but did not make it to the final model in this analysis of the much smaller corpus was CV2. However, in Study 3, the CV2 variable demonstrated an unexpected reversed relationship with stress patterns that appears to have been an artifact. The fact that CV2 was not among the significant predictors of stress in the present analysis adds to the likelihood that in Study 3, the associative relationship between CV2 and stress patterns was artifactual. Overall, the results of the binary logistic regression on the corpus of 500 selected words suggest that this corpus is representative of a large corpus of Russian disyllabic words from the point of view of having stress cues with high validity.

Procedure

Participants were instructed to read aloud as quickly and as accurately as possible words presented on the screen one at a time. Instructions and stimuli were presented, and responses were recorded using the DMDX display system (Forster & Forster, 2003). The list of 500 items was presented over two blocks of trials. Every participant named both blocks of trials. The order of blocks and of items within blocks was randomized for each participant. Each trial started with the presentation of a fixation point for 500 ms. The target word in upper-case appeared in white on a black background (Courier New, 12 font) for 2000 ms or until the participant responded. The intertrial interval was 1000 ms.

Results

The author and two other native speakers of Russian listened to the responses and marked stress patterns that participants assigned to words. There were no cases that were treated by markers as ambiguous from the point of view of stress pattern implementation. A pronunciation of a word with a trochaic stress was coded as “0”; while a pronunciation of a word with an iambic stress was coded as "1". This categorical response variable was analyzed using a generalized linear mixed-effects model (GLMM), with Subjects and Items as random crossed factors. Fixed factors that were considered during this analysis were *Grammatical Category*, *Log Frequency*, *Length*, *Onset Complexity*, *Ending Complexity*, and consistency of six orthographic components (*CVC1*, *CV1*, *VC1*, *CVC2*, *CV2*, and *VC2*). Due to the fact that the stress consistency measure could be conceived either as type or token consistency, two separate sets of GLMMs were conducted.

The analysis was exploratory in nature as the goal was to find a model with a minimum possible number of factors that would still fit the data well. The goodness of fit of a model was assessed with the following measures describing the trade-off between accuracy and complexity of a model: the Akaike Information Criterion (*AIC*), the Bayesian Information Criterion (*BIC*), the Deviance Information Criterion (*DIC*), and the log likelihood (logL). To select amongst competing models a likelihood ratio test was used. The analysis was conducted using the R package *lme4* (Bates & Maechler, 2010).

First, the results of the analyses involving the model with type consistency measures are reported. The measures of goodness of fit and the summary of likelihood ratio tests of this model and other versions of this model are given in Table 8. The likelihood ratio test of the full model against a model that had no fixed factors entered (i.e., null model) showed that the full model fit the data significantly better, χ^2 (12) = 458.03, $p < .001$. Out of eleven, only four factors were significant predictors of stress assignment performance: *Ending Complexity* ($z = 2.12$, $p = .03$), *CVC1* ($z = -5.49$, $p < .001$), *CVC2* ($z = -9.59$, $p < .001$), and *VC2* ($z = -2.56$, $p = .01$).

Table 8

Measures of goodness of fit and likelihood ratio tests of linear mixed effects model predicting stress pattern assignment (consistency measures are based on type count)

#	Fixed Factors (* - $p < .05$)	Goodness of Fit Measures: AIC	BIC	LogL	DIC	Likelihood Ratio Test: Alternative Model (#)	Test Statistic
1.	Null Model	7917	7940	-3955	7911		
2.	Grammatical Category Log Frequency Length Onset Complexity Ending Complexity* CVC1*, CV1, VC1 CVC2*, CV2, VC2*	7481	7589	-3726	7453	1	χ^2 (12) = 458.03, $p < .001$
3.	Grammatical Category*	7890	7929	-3940	7880	1	χ^2 (2) = 30.63, $p < .001$
4.	Log Frequency*	7911	7942	-3951	7903	1	χ^2 (1) = 8.08, $p = .004$
5.	Length	7918	7949	-3955	7910	1	χ2 (1) = .83, p = .36
6.	Onset Complexity*	7908	7939	-3950	7900	1	χ2 (1) = 10.78, p = .001
7.	Ending Complexity*	7884	7915	-3938	7876	1	χ^2 (1) = 34.45, $p < .001$
8.	CVC1*	7707	7738	-3849	7699	1	χ^2 (1) = 211.93, $p < .001$
9.	VC1*	7875	7906	-3934	7867	1	χ^2 (1) = 43.66, $p < .001$
10.	CVC2*	7775	7806	-3883	7867	1	χ^2 (1) = 152.84, $p < .001$
11.	CV1*	7847	7878	-3919	7839	1	χ^2 (1) = 72.24, $p < .001$
12.	CV2*	7842	7901	-3941	7863	1	χ^2 (1) = 48.18, $p < .001$
13.	VC2*	7793	7824	-3893	7758	1	χ^2 (1) = 125.43, $p < .001$

Note. Asterisk indicates that these fixed factors were significant predictors of stress assignment in the corresponding regression models.

Table 8 (continued)

Measures of goodness of fit and likelihood ratio tests of linear mixed effects model predicting stress pattern assignment (consistency measures are based on type count)

		Goodness of Fit Measures				Likelihood Ratio Test	
#	Fixed Factors (* - $p < .05$)	AIC	BIC	LogL	DIC	Alternative Model (#)	Test Statistic
14.	Grammatical Category Log Frequency Onset Complexity Ending Complexity CVC1*, CV1*, VC1 CVC2*, CV2, VC2*	7482	7583	-3728	7456	2	χ^2 (1) = 3.15, $p = .07$
15.	Grammatical Category Onset Complexity Ending Complexity CVC1*, CV1, VC1 CVC2*, CV2, VC2*	7482	7575	-3729	7458	14	χ^2 (1) = 1.87, $p = .17$
16.	Grammatical Category Ending Complexity CVC1*, CV1, VC1 CVC2*, CV2, VC2*	7480	7566	-3729	7458	15	χ^2 (1) = .58, $p = .44$
17.	Ending Complexity CVC1*, CV1*, VC1 CVC2*, CV2, VC2*	7477	7546	-3729	7459	16	χ^2 (2) = .09, $p = .95$
18.	CVC1*, CV1, VC1 CVC2*, CV2, VC2*	7477	7539	-3730	7461	17	χ^2 (1) = 2.16, $p = .14$
19.	CVC1*, CV1* CVC2*, CV2, VC2*	7611	7665	-3799	7597	18	χ^2 (1) = 136.44, $p < .001$
20.	CVC1*, CV1*, VC1 CVC2*, VC2*	7474	7531	-3730	7460	18	χ^2 (1) = .02, $p = .89$
21.	**CVC1*, VC1 CVC2*, VC2***	**7475**	**7529**	**-3730**	**7461**	**20**	$\boldsymbol{\chi^2}$ **(1) = .16,** $\boldsymbol{p = .68}$
22.	CVC1*, VC1 CVC2*	7582	7628	-3785	7570	21	χ^2 (1) = 14.00, $p < .001$

Note. Asterisk indicates that these fixed factors were significant predictors of stress assignment in the corresponding regression models. The model in bold is the final simplified model with a minimum possible number of factors in it that still had high power to predict stress patterns.

Table 8 (continued)

Measures of goodness of fit and likelihood ratio tests of linear mixed effects model predicting stress pattern assignment (consistency measures are based on type count)

		Goodness of Fit Measures				Likelihood Ratio Test	
#	Fixed Factors (* - $p < .05$)	AIC	BIC	LogL	DIC	Alternative Model (#)	Statistical Test
23.	CVC1*, VC1* VC2*	7560	7606	-3774	7548	21	χ^2 (1) = 87.03, $p < .001$
24.	VC1 CVC2*, VC2*	7538	7584	-3763	7526	21	χ^2 (1) = 36.58, $p < .001$
25.	CVC1* CVC2*, VC2	7554	7600	-3771	7542	21	χ^2 (1) = 81.07, $p < .001$

Note. Asterisk indicates that these fixed factors were significant predictors of stress assignment in the corresponding regression models.

Next, the model was simplified in a backward stepwise fashion using $p \geq .05$ on the likelihood ratio test as the exclusion criterion. To identify the order of exclusion of factors from the full model, the individual ability of each predictor to fit the data was assessed by running GLMMs on eleven different models that had only one predictor variable entered as a fixed factor. Then, the goodness of fit of each model was contrasted with that of the null model. Following the results of this analysis, the complexity of the full model was reduced by eliminating the predictor variables in the following order: *Length* (χ^2 (1) = .83, p = .36), *Log Frequency* (χ^2 (1) = 8.08, p = .004), *Onset Complexity* (χ^2 (1) = 10.78, p = .001), *Grammatical Category* (χ^2 (2) = 30.63, p < .001), *Ending Complexity* (χ^2 (1) = 34.45, p < .001), *VC1* (χ^2 (1) = 43.66, p < .001), *CV2* (χ^2 (1) = 48.18, p < .001), *CV1* (χ^2 (1) = 72.24, p < .001), *VC2* (χ^2 (1) = 125.43, p < .001), *CVC2* (χ^2 (1) = 152.84, p < .001), and *CVC1* (χ^2 (1) = 211.93, p < .001).

In the process of model reduction, *Length* was the first factor excluded as a predictor as it did not improve goodness of a fit of the model, χ^2 (1) = 3.15, p = .07. Next, *Log Frequency*, χ^2 (1) = 1.87, p = .17, *Onset Complexity*, χ^2 (1) = .58, p = .44, *Grammatical Category*, χ^2 (2) = .09, p = .95, and *Ending Complexity*, χ^2 (1) = 2.16, p = .14, were excluded. As the omission of *VC1* lead to a significant decrease in explanatory power of the model, χ^2 (1) = 136.44, p < .001, this factor was kept in the equation. The following likelihood ratio tests showed that the model can be further simplified by eliminating *CV2*, χ^2 (1) = .02, p = .89, and *CV1*, χ^2 (1) = .16, p = .68. Further exclusion of the remaining consistency measures from the model resulted in a significant loss of goodness of fit: *VC2*, χ^2 (1) = 14.00, p < .001; *CVC2,* χ^2 (1) = 87.03, p < .001, and *CVC1,* χ^2 (1) = 36.58, p < .001. Attempts to further simplify this model by excluding any of the four predictors resulted in a decline of goodness of fit: *VC1*, χ^2 (1) = 81.05, $p < .001$, *VC2*, χ^2 (1) = 108.83, $p < .001$, *CVC2,* χ^2 (1) = 87.01, $p < .001$, and *CVC1*, χ^2 (1) = 64.79, $p < .001$. As a result, the original model with eleven predictors was simplified to a model with only four predictors: *VC1*, *VC2*, *CVC2*, and *CVC1*. Out of four factors in the final model, only three were significant predictors of stress assignment performance: *CVC1* (z = -5.49, $p < .001$), *CVC2* (z = -9.59, $p < .001$), and *VC2* (z = -2.56, p = .01).

The same set of models was tested for a second time using token consistency measures. The measures of goodness of fit and the results of the likelihood ratio tests of the full model and other simplified versions of this model are provided in Table 9. The comparison of the null model with no fixed factors and the model with all eleven predictors demonstrated that the full model provided a significantly better fit to the data, χ^2 (12) = 350.03, $p < .001$. Further, in the full model, only three factors were significant predictors of stress assignment performance: *CVC1* (z = -4.45, $p < .001$), *CVC2* (z = -7.01, $p < .001$), and *VC2* (z = -3.02, p = .003).

The full model was simplified following the same steps as in the analysis in which type consistency measures were used. *Length* was preserved as a factor in the model as its exclusion lead to the significant reduction in goodness of fit, χ^2 (1) = 163.10, $p < .001$. On the other hand, *Log Frequency* was discarded from the analysis as this variable did not assist in explaining the data, χ^2 (1) = 0.00, p = 1.00. Further, *Onset Complexity* and *Grammatical Category* predictors were kept in the equation as there was loss in explanatory power when they were removed (*Onset Complexity*: χ^2 (1) = -128.24, $p <$ .001; *Grammatical Category*, χ^2 (2) = 56.64, $p < .001$). In contrast, the models without *Ending Complexity*, χ^2 (1) = 0.00, p = 1.00, *VC1*, χ^2 (1) = 2.05, p = .15, *CV2*, χ^2 (1) =

Table 9

Measures of goodness of fit and likelihood ratio tests of linear mixed effects model predicting stress pattern assignment (consistency measures are based on token count)

		Goodness of Fit Measures				Likelihood Ratio Test	
#	Fixed Factors (* - $p < .05$)	AIC	BIC	LogL	DIC	Alternative Model (#)	Test Statistic
1.	Null Model	7917	7940	-3955	7911		
2.	Grammatical Category Log Frequency Length Onset Complexity Ending Complexity CVC1*, CV1, VC1 CVC2*, CV2, VC2*	7589	7697	-3780	7561	1	χ^2 (11) = 350.03, $p < .001$
3.	Grammatical Category Log Frequency Onset Complexity Ending Complexity CVC1*, CV1, VC1 CVC2*, CV2, VC2*	7750	7851	-3862	7724	2	χ^2 (1) = 163.10, $p < .001$
4.	Grammatical Category Length Onset Complexity Ending Complexity* CVC1*, CV1, VC1 CVC2*, CV2, VC2*	7557	7658	-3766	7531	2	χ^2 (1) = 0.00, $p = 1.00$
5.	Grammatical Category Length Ending Complexity* CVC1*, CV1, VC1 CVC2*, CV2, VC2*	7684	7777	-3830	7660	4	χ^2 (1) = 128.24, $p < .001$
6.	Length Onset Complexity Ending Complexity* CVC1*, CV1, VC1 CVC2*, CV2, VC2*	7700	7593	-3738	7476	4	χ^2 (2) = 56.64, $p < .001$

Note. Asterisk indicates that these fixed factors were significant predictors of stress assignment in the corresponding regression models.

Table 9 (continued)

Measures of goodness of fit and likelihood ratio tests of linear mixed effects model predicting stress pattern assignment (consistency measures are based on type count)

		Goodness of Fit Measures				Likelihood Ratio Test	
#	Fixed Factors (* - $p < .05$)	AIC	BIC	LogL	DIC	Alternative Model (#)	Statistical Test
7.	Grammatical Category Length Onset Complexity CVC1*, CV1, VC1 CVC2*, CV2, VC2*	7500	7593	-3738	7476	4	χ^2 (1) = 0.00, p = 1.00
8.	Grammatical Category Length Onset Complexity CVC1*, CV1 CVC2*, CV2, VC2*	7500	7585	-3739	7478	7	χ^2 (1) = 2.05, p = .15
9.	Grammatical Category Length Onset Complexity CVC1*, CV1 CVC2*, VC2*	7509	7582	-3735	7479	8	χ^2 (1) = 1.85, p = .17
10.	Grammatical Category Length Onset Complexity CVC1*,CVC2*, VC2*	7498	7575	-3739	7478	9	χ^2 (1) = 0.12, p = .73
11.	Grammatical Category* Length Onset Complexity CVC1*, CVC2*	7553	7603	-3758	7515	10	χ^2 (1) = 37.09, p < .001
12.	Grammatical Category Length Onset Complexity CVC1*, VC2*	7574	7644	-3778	7556	10	χ^2 (1) = 78.06, p < .001
13.	Grammatical Category Length Onset Complexity* CVC2*, VC2*	7678	7748	-3830	7660	10	χ^2 (1) = 181.83, p < .001

Note. Asterisk indicates that these fixed factors were significant predictors of stress assignment in the corresponding regression models.

Table 9 (continued)

Measures of goodness of fit and likelihood ratio tests of linear mixed effects model predicting stress pattern assignment (consistency measures are based on type count)

		Goodness of Fit Measures				Likelihood Ratio Test	
#	Fixed Factors (* - $p < .05$)	AIC	BIC	LogL	DIC	Alternative Model (#)	Test Statistic
14.	Length Onset Complexity CVC1*, CVC2*, VC2	7563	7625	-3773	7547	10	χ^2 (2) = 68.90, $p < .001$
15.	Grammatical Category Onset Complexity CVC1*, CVC2*,VC2*	7496	7566	-3739	7478	10	χ^2 (1) = 0.05, $p = .82$
16.	Grammatical Cateogry CVC1*, CVC2*,VC2*	7496	7558	-3740	7480	15	χ^2 (1) = 1.92, $p = .17$
17.	Grammatical Category CVC1*, CVC2*	7521	7576	-3754	7507	16	χ^2 (1) = 27.48, $p < .001$
18.	Grammatical Category CVC1*, VC2*	7573	7627	-3780	7559	16	χ^2 (1) = 72.27, $p < .001$
19.	Grammatical Category CVC2*, VC2*	8116	8170	-4051	8102	16	χ^2 (1) = 622.25, $p < .001$
20.	**CVC1*, CVC2*, VC2***	**7493**	**7539**	**-3740**	**7481**	**16**	$\boldsymbol{\chi^2}$ **(2) = 0.71,** $\boldsymbol{p = .70}$
21.	CVC2*, VC2*	7783	7822	-3887	7773	20	χ^2 (1) = 292.67, $p < .001$
22.	CVC1*, VC2*	7836	7875	-3913	7826	20	χ^2 (1) = 345.72, $p < .001$
23.	CVC1*, CVC2*	7518	7557	-3754	7508	20	χ^2 (1) = 27.15, $p < .001$

Note. Asterisk indicates that these fixed factors were significant predictors of stress assignment in the corresponding regression models. The model in bold is the final simplified model with a minimum possible number of factors in it that still had high power to predict stress patterns.

1.85, $p = .17$ and *CV1*, χ^2 (1) = 0.12, $p = .73$, provided as good a fit to the data as models that had these predictors. Therefore, these predictors were excluded from the model. Finally, there was a significant decrease in the goodness of fit of models that did not have *VC2*, χ^2 (1) = 37.09, $p < .001$, *CVC2*, χ^2 (1) = 78.06, $p < .001$, or *CVC1*, χ^2 (1) = 181.83, $p < .001$. Thus, at this point a simplified model contained six fixed factors: *Grammatical Category*, *Length*, *Onset Complexity*, *VC2*, *CVC2*, and *CVC1*.

The model obtained in the first round of likelihood ratio tests was then further simplified to a model that had four fixed effects predictors only. This was done by the exclusion of *Length* and *Onset Complexity* that as predictors were not decreasing information entropy significantly (*Length*: χ^2 (1) = 0.05, $p = .82$; *Onset Complexity*, χ^2 (1) = 1.92, $p = .17$). On the other hand, there was a decline in goodness of fit if the following predictors were eliminated from the model: *Grammatical Category*, χ^2 (2) = 68.90, $p < .001$, *VC2*, χ^2 (1) = 27.48, $p < .001$, *CVC2*, χ^2 (1) = 72.27, $p < .001$, and *CVC1*, χ^2 (1) = 622.25, $p < .001$. The final step was to determine whether it was possible to eliminate any of the four predictors left in the model without losing the ability to explain the data. While the elimination of *VC2*, χ^2 (1) = 27.15, $p < .001$, *CVC2*, χ^2 (1) = 345.72, $p < .001$, and *CVC1*, χ^2 (1) = 292.67, $p < .001$, appeared to be detrimental for the goodness of fit of the model, the exclusion of *Grammatical Category* as a predictor did not have the same effect, χ^2 (2) = 0.71, $p = .70$. As a result, the final model had three fixed factors and it could explain the data as well as the full model with all ten predictors entered. In this model all fixed factors were significant predictors of stress assignment performance: *VC2*, $z = -5.17$, $p < .001$, *CVC2*, $z = -9.15$, $p < .001$, and *CVC1*, $z = -9.61$, $p < .001$.

Discussion

The goal of Study 4 was to assess the utility of various stress cues in Russian; that is what non-lexical cues, if any, speakers of Russian use in making stress assignment decisions. Two sets of GLMMs on stress assignment performance for native speakers of Russian were undertaken. The predictor variables were Length, Log Frequency, Grammatical Category, Onset Complexity, Ending Complexity and Consistency measures for six orthographic components (CVC1, CV1, VC1, CVC2, CV2, and VC2). Type- and token-based consistency measures were entered in the two separate GLMMs. Each full model was simplified in a way that would provide the best balance between model's complexity and its ability to explain the data.

The first model with type-based consistency measures was simplified to a model with four predictor variables: *CVC1*, *VC1*, *CVC2*, and *VC2*. Out of four variables, only three (*CVC1*, *CVC2*, and *VC2*) were significant predictors of stress assignment performance. The second model in which consistency measures were based on token count was simplified to a model with three predictor variables: *CVC1*, *CVC2*, and *VC2*. In this simplified equation, all three variables were significant predictors of stress assignment performance. Thus, two models based on different methods of consistency calculation provided converging results, suggesting that in assigning stress to words in Russian readers make use of the knowledge of probabilistic distributions of stress patterns over three orthographic components: *CVC1*, *CVC2*, and *VC2*.

To assess whether the final model with type consistency measures provides a better fit to the data than the final model with token consistency measures, likelihood ratio tests were used to compare these two models. The results showed that the final model with consistency measures based on type count fit the data significantly better than the model with consistency measures based on token count, χ^2 (1) = 19.98, $p < .001$. Indeed, the former model provided considerably better measures of goodness of fit compared to the latter model (model with type consistency: AIC = 7474, BIC = 7528, logLik = -3730, DIC = 7461; model with token consistency: AIC = 7493, BIC = 7539, logLik = -3740, DIC = 7481).

The results of this analysis suggest that not all non-lexical cues that might be used as sources of evidence for lexical stress, due to the fact that they have high validity, as demonstrated in Study 3, are actually used by Russian readers. That is, in Study 3, it was determined that there are probabilistic relations between stress patterns and five non-lexical cues present in Russian. These cues are *Onset Complexity*, *Ending Complexity*, *CVC1*, *CVC2*, and *VC2*. In spite of the fact that these variables had high validity (i.e., they were significant predictors of stress patterns in the corpus of 500 selected words), only three of them appeared to be used by speakers in assigning stress in these 500 words. Apparently, *Onset Complexity* and *Ending Complexity* do not impact naming performance. The variables that had high validity and high utility were the consistency measures of three orthographic components: *CVC1*, *CVC2*, and *VC2*. Participants were more likely to name trochaically stressed words with incorrect iambic stress if a word's CVC1, CVC2, and/or VC2 consistency score was low (i.e., the majority of words having the same CVC1, CVC2, or VC2 component had iambic stress patterns). Similarly, participants made stress assignment errors on iambically iambically stressedstressed words if a word's CVC1, CVC2, and/or VC2 consistency score was high (i.e., the majority of words having the same CVC1, CVC2, or VC2 component had trochaic stress patterns).

5.4. Conclusion

To date, behavioral investigations of the stress assignment process have been conducted in a limited number of languages, languages that are all characterized by the presence of a dominant stress pattern that is believed to create a bias in assigning stress. The presence of a bias of this sort complicates the investigation of other factors as it becomes difficult to disentangle the effect of the bias from the effects of other potential cues to stress. In an attempt to circumvent this problem, the present thesis involved an investigation of mechanisms of stress assignment and an implementation of a proposed Bayesian model of stress assignment in Russian, a language in which the assumption has been that there is no dominant stress pattern.

The present Chapter contained the results of a corpus analysis, a factorial study, and two regression studies that were conducted with an overall goal of creating a computational implementation of the Bayesian model of stress assignment in Russian. At this point, the investigation has been limited to disyllabic words only. This research has had the following objectives: (1) establishing the distribution of trochaic versus iambic stress patterns in the Russian language (prior probabilities of stress patterns); (2) identifying a set of valid and utilized non-lexical cues to stress (sources of evidence taken into consideration in estimation of posterior probabilities of stress patterns); and (3) demonstrating that stress assignment in Russian can be completed non-lexically.

The analysis of the corpus of Russian disyllabic words (Study 1) provided evidence substantiating the assumption that, among the disyllabic words in Russian, trochaic and iambic stress patterns occur essentially equally often (55% vs. 45%). As the prior probabilities of two stress patterns are very similar, Russian readers should have no reason to demonstrate an overall bias toward either stress type. Further analysis of the distribution of stress patterns in words of various grammatical categories revealed that, although distribution of stress types in Russian nouns and verbs was not greatly different from the distribution observed in the language overall, a trochaic stress pattern was more frequent than an iambic stress pattern in adjectives. Thus, Russian provides a unique opportunity to observe, within the same language, the behavior of readers in situations when there is a regular stress pattern that could create a stress assignment bias (i.e., in case of adjectives), and when there would be no bias due to the absence of a regular stress pattern (i.e., in case of nouns and, potentially, verbs).

For this difference in the distribution of stress patterns for adjectives, nouns, and verbs to have impact on the processing, it would seem to be necessary that information about grammatical category becomes available early on, specifically before stress information could be retrieved following a successful lexical access. Prior research on grammatical category effects in isolated word recognition does, indeed, suggest that grammatical category information is accessed automatically during very early stages of lexical processing (Bornkessel & Schlesewski, 2006; Federmeier, Segal, Lombrozo, & Kutas, 2000; Vigliocco, Vinson, Arciuli, & Barber, 2008).

Although none of the experiments cited above had been carried out in Russian, it seems possible that information about grammatical category would also be readily available in Russian, and would assist readers in stress assignment. Indeed, the findings of Study 2 (word naming) provided good evidence that probabilistic distributions of stress patterns in words of specific grammatical categories in Russian do play an important role. When a certain stress type occurs more often (e.g., first syllable stress in adjectives), readers are sensitive to this information, and appear to be biased to the more frequent stress pattern. The stress bias is manifested in faster response times and higher accuracy rates in the processing of adjectives with regular first syllable stress compared to adjectives with stress on their second syllable. On the other hand, when the probabilities of the two stress patterns are nearly equal (e.g., nouns), readers do not demonstrate a preference for either stress pattern.

The lack of a regular stress pattern for nouns and verbs means that stress assignment for those words had to be based on other factor(s). Note that the presence of a regular stress pattern in one grammatical category did put the regularly stressed words belonging to that category into an advantageous position from the point of view of their processing compared to the words from other grammatical categories. Significantly faster and more accurate processing of adjectives compared to nouns and verbs, as demonstrated in Study 2, serves as evidence of the facilitating effect that the presence of a regular stress pattern in the language can produce.

This finding of a regularity effect at the level of grammatical category might suggest that in establishing prior probabilities of stress patterns one should consider the frequency of stress patterns not among all words of the language, but rather among words of the word’s grammatical category in that language. The idea just described is not endorsed in the proposed Bayesian model of stress assignment for a number of reasons. First of all, prior beliefs about probabilities of stress patterns exist in readers’ minds before any processing of a word has been initiated. As at this stage, the grammatical status of a word in a standard word naming experiment is generally unknown (unless the preceding context provides this information) and therefore, readers cannot adjust their prior beliefs respectively. Secondly, although the stress regularity effect in adjectives observed in Study 2 appears to be readily explained by an early activation of grammatical category information, there appears to be an alternative explanation. It is quite possible that the orthographic cues to grammatical category also provide useful information concerning stress assignment in the case of adjectives, but not in the case of nouns and verbs. If so, one would expect an overall adjective advantage and a stress regularity effect for adjectives but not for nouns and verbs even if the grammatical category was not actually activated early in processing. Finally, other empirical results reported here argue against the proposal that prior beliefs about likelihood of a stress pattern in a word are based on probabilities derived at the level of grammatical categories. Specifically, grammatical category did not serve as a significant predictor of stress patterns in Russian (Study 3) or as a predictor of stress assignment performance by speakers of this language (Study 4). To conclude, based on the results of the studies reported in this Chapter, the most likely possibility is that prior beliefs about stress patterns reflect the native speakers' knowledge of distribution of stress patterns in the language overall, rather than their knowledge of distribution of stress patterns in words of certain grammatical category. Therefore, the distribution of stress patterns overall (55% - trochaic stress vs. 45% - iambic stress), appears to be the best information that can be used in calculating prior probabilities of stress patterns in the Bayesian model of stress assignment in Russian.

The second goal of this Chapter was to identify valid and utilized stress cues in Russian based on a combination of the results provided in the factorial (Study 2) and the regression (Studies 3 and 4) studies. In Study 2, the effect of spelling-to-stress consistency of word endings on readers' naming performance was demonstrated. However, the scope of reliance on this stress cue appears to depend on the availability of other factors. Experimental results showed that participants were guided mainly by consistency cues if there was no dominant stress pattern present (as in case of nouns and verbs). On the other hand, in naming adjectives which tend to have trochaic stress, consistency only mattered when irregularly stressed iambic adjectives had to be named (or alternatively, regularity only mattered when considering adjectives with inconsistent endings). This pattern of results suggests that both consistency and regularity are reliable stress cues for adjectives and there is only a penalty to pay when neither is valid (i.e., an adjective containing an ending consistent with a first syllable stress assignment which, nonetheless, is stressed on the second syllable).

The finding of an interaction between stress regularity and stress consistency when naming adjectives does parallel previous results reported by Colombo (1992), who found that only irregular words were affected by the consistency of stress in a naming task in Italian. At the same time, the present results stand in contrast to those from another study conducted in Italian (Burani & Arduino, 2004) showing comparable effects of stress consistency on regularly and irregularly stressed words. Burani and Arduino explained the discrepancies between their results and Colombo's by pointing to a number of characteristics of the experimental items that were not controlled properly in Colombo's experiment. Although the stimuli were selected for the present experiments by taking into account Burani and Arduino's criticisms, nevertheless, the same interaction that Colombo observed arose here. That is, there was a differential effect of stress consistency on regularly versus irregularly stressed words when stress regularity is a meaningful concept (i.e., for Russian adjectives), suggesting that there may be an alternative reason why there were different patterns in the two Italian naming studies.

Thus, the results of Study 2 extend findings reported in Italian (Burani & Arduino, 2004; Colombo, 1992) and English (Arciuli et al., 2010) of the significant role that the spelling-to-stress consistency of word endings plays in Russian. Although the consistency of word endings as stress cues is a thoroughly investigated variable, it is likely not the only non-lexical stress cue that readers of Russian use in naming polysyllabic words. Therefore, a more exploratory investigation was undertaken by running a regression of a set of eleven predictor variables on stress patterns in the corpus of Russian disyllabic words (Study 3) and on stress assignment performance demonstrated by native speakers (Study 4).

The results of Study 3 showed that in the corpus of Russian disyllabic words there were six variables that were in strong associative relationships with stress patterns. In Russian, the stress cues with high validity are onset complexity, coda complexity, and spelling-to-stress consistency measures of the first syllable (CVC1), of the second syllable (CVC2), of the beginning of the second syllable (CV2), and of the ending of the second syllable (VC2).

Some of these variables have been shown to act as stress cues in other studies. For example, the variable CV2 corresponds to the same orthographic component as a word ending. As has been previously mentioned, there is consistent evidence that information about probabilistic relations between word endings and stress patterns is used by readers in naming words and nonwords (Arcuili et al., 2010). Similarly, there have been studies demonstrating that in English the complexity of words' onsets and codas is related to stress pattern information (Kelly et al., 1998; Kelly, 2004). Although the present results indicate significant relations between onset/coda complexity and stress patterns in Russian, these relations were exactly the opposite in nature to the ones reported by Kelly et al. in English. Thus, in English, a word with complex onset is more likely to have a trochaic stress, while in Russian a word with such characteristics is more likely to have an iambic stress. Further, in English, a word with complex coda is likely to be iambically stressed, while in Russian such a word is more likely to be trochaically stressed.

Spelling-to-stress consistency measures of the first syllable (CVC1), of the second syllable (CVC2), and of the beginning of the second syllable (CV2) are the variables that were also probabilistically associated with stress patterns in the analysis of the corpus of Russian disyllabic words. These variables have not been previously investigated as stress cues in any other language. Although all three of these variables were significant predictors of stress patterns in the corpus as per the results of the binary logistic regression, it is possible that only spelling-to-stress consistency of CVC1 and CVC2 are, in fact, stress cues with high validity in Russian. The significance of spelling-to-stress consistency of CV2 is likely to be an artifactual finding.

Study 4 involved an assessment of the utility of stress cues, that is, whether native speakers of Russian base their stress assignment decisions on information provided by these cues. The results showed that only three variables (consistency measures of the first syllable (CVC1), of the second syllable (CVC2), and of the ending of the second syllable (VC2)) were driving stress assignment performance of native speakers of Russian. Participants were more likely to make stress assignment errors on words with inconsistent spelling-to-stress mappings for these three orthographic components.

To conclude, it appears that in Russian there are three sources of evidence for stress that have high validity (i.e., strong probabilistic associations between cues and stress patterns exist in the language) and high utility (i.e., readers use the knowledge of these probabilistic associations between cues and stress patterns). Specifically, the consistency of the first syllable of a word (CVC1), of the second syllable of a word (CVC2), and of the ending of the second syllable of a word (VC2) appear to be the sources of evidence for stress patterns that should be included in a Bayesian model of stress assignment in Russian.

Three sources of evidence for stress were identified primarily based on the results of two regression studies. In light of this, one might argue that a simple regression model that was based on those studies would be as good of a model of stress assignment as the Bayesian model of stress assignment proposed in the present thesis. That claim does not seem plausible for the following reason. According to Marr (2010), a valid model of any information processing system must be characterized by three levels of analysis: a computational level (what the system does and why it does it), an algorithmic level (how the system does what it does), and a biological level (what neural structures implement it). A regression model might provide some information about the algorithmic level of implementation of the process of stress assignment, however, it neither has processing implications reflecting the computational level, nor does it appear to be biologicaly based. On the other hand, the proposed Bayesian model of stress assignment does describe the processes happening during the identification of stress patterns in polysyllabic words by readers and representational units (stress cues) implicated in these processes. Further, based on some neuropsychological evidence supporting the notion that the human mind constantly engages in probabilistic analysis (Doya, Ishii, Pouget, & Rao, 2007), one might expect that there are neural structures and neuronal activities that underlie the process of estimation of probabilities of stress patterns in reading. Hence, a Bayesian model of stress assignment would seem to supersede any related regression model in its ability to explain the process of stress assignment.

With respect to one other goal of this research, the present data provide strong evidence against the idea that stress assignment in Russian is accomplished only by retrieving stress information from the word's lexical representation. If this hypothesis were in fact true, there should not have been either stress regularity or stress consistency effects in the factorial study and none of the non-lexical variables would have been significant predictors of stress patterns in the regression studies. In contrast, the present experiments demonstrate that there are probabilistic, associative connections between non-lexical cues and stress patterns in Russian and that native speakers of Russian do utilize this non-lexical, distributional information about stress in naming and identifying disyllabic Russian words. That is not to deny, of course, the possibility that the specific retrieval of word-based stress knowledge in the process of stress assignment might exist for Russian speakers and that it might even be greater in Russian compared to other languages in which word stress is more predictable.

Chapter 6 – Simulations of the Bayesian model of stress assignment in Russian

6.1. Introduction

The Bayesian model of stress assignment described in Chapter 3 computes posterior probabilities of stress patterns in a polysyllabic word, $P(stress \mid evidence)$, based on the knowledge of the frequencies of stress patterns in a language (allowing estimates of prior probabilities, $P(stress)$) and of the likelihoods with which the non-lexical evidence considered is associated with a particular stress pattern, $P(evidence \mid stress)$. The computation is performed using the formula given in Equation 4, which is a modified version of the Bayes rule.

In the present thesis, the goal is to provide an implementation of the Bayesian model of stress assignment in naming Russian disyllabic words. This model produces an output in the form of posterior probabilities that a word has a trochaic stress pattern, $P(Stress1 \mid evidence)$, or an iambic stress pattern, $P(Stress2 \mid evidence)$. Studies reported in Chapter 5 provided the data required for the implementation of this model. Based on the results of the corpus analysis (Study 1), it was concluded that the prior probability of a trochaic stress pattern ($P(Stress1)$) in Russian is .55, while the prior probability of an iambic stress pattern ($P(Stress2)$) is .45. Further, the results of a factorial study (Study 2) and two regression studies (Study 3 and 4) suggested that there are three predominant sources of evidence that are probabilistically associated with stress patterns in Russian: spelling-to-stress consistency measures of the first syllable (*CVC1*), of the second syllable (*CVC2*), and of the ending of the second syllable (*VC2*).

Although the order in which the model considers these three sources of evidence does not matter for the final calculation, the model initially analyzes the impact of CVC2, then, CVC1, and finishes with VC2 as sources of evidence for stress. This order choice reflects the relative strength of association of these sources of evidence with stress patterns as seen from the results of the regression analysis of Study 4: CVC2: $z = -9.59$, $p < .001$ CVC1: $z = -5.49$, $p < .001$, and VC2: $z = -2.56$, $p = .01$. The specific formula that the model uses in computing the posterior probability that a word has, for example, the trochaic stress pattern considering evidence provided by the orthography of CVC2 is:

$$P(Stress1 \mid CVC2) = \frac{P(CVC2 \mid Stress1) \times .55}{P(CVC2 \mid Stress1) \times .55 + P(CVC2 \mid Stress2) \times .45} \tag{14}$$

Knowing the posterior probability of a trochaic stress pattern being present in a word, the model can estimate the posterior probability that a word has an iambic stress pattern:

$$P(Stress2 \mid CVC2) = 1 - P(Stress1 \mid CVC2) \tag{15}$$

Next, the model accounts for the evidence provided by CVC1. The model uses this additional evidence to update its probabilities of stress patterns computed previously based on the knowledge of CVC2. Thus, at this step, $P(Stress1 \mid CVC2)$, referred to as P(Stress1)*, serves as the new prior probability of a trochaic stress pattern in a word, while $P(Stress2 \mid CVC2)$, referred to as P(Stress2)*, is a prior probability that this word has an iambic stress pattern. The full equation used in the computation of the posterior probability that a word has trochaic stress given the evidence of the orthography of CVC2 and CVC1 is given below:

$$P(Stress1 \mid CVC2, CVC1) = \frac{P(CVC1 \mid Stress1) \times P(Stress1)^*}{P(CVC1 \mid Stress1) \times P(Stress1)^* + P(CVC1 \mid Stress2) \times P(Stress2)^*} \tag{16}$$

The posterior probability of an iambic stress given a particular CVC2 and CVC1 is further estimated:

$$P(Stress2 \mid CVC2, CVC1) = 1 - P(Stress1 \mid CVC2, CVC1) \qquad (17)$$

Finally, the model accounts for the evidence for a trochaic stress pattern provided by VC2. As VC2 is a constituent part of CVC2 that has earlier been considered by the model, some of the evidence provided by VC2 has already been accounted for. To avoid the problem of including the same evidence twice into the model's computations, the model calculates the likelihood of evidence VC2 given stress patterns by assessing only those words that were not used earlier in estimating the likelihood of evidence CVC2 given stress patterns. For example, in computing the posterior probabilities of stress patterns for the word *мастак*, the model first considers the evidence *–мак* (CVC2) that is present in 1 word with trochaic stress and 4 words with iambic stress. Next, it considers the evidence *–мас* (CVC1). Finally, the model evaluates the orthographic evidence *–ак* (VC2) present in 4 words with trochaic and 50 words with iambic stress patterns. However, as the model has already accounted partially for the evidence *–ак* (VC2) as a constituent part of *–мак* (CVC2), at this step, only words that were not included in the estimation of the likelihood of evidence *–мак* (CVC2) (i.e., words that have the evidence *–ак* (VC2), but not the evidence *–мак* (CVC2)) are considered by the model. In the corpus, there are 3 words with trochaic (= 4 – 1) and 46 words with iambic stress patterns (= 50 – 4) that meet this requirement and that the model examines in estimating the likelihood of evidence *–ак* (VC2) given stress pattern in the process of posterior probability estimations of stress for the word *мастак*.

The model uses this additional evidence to update its probabilities of stress patterns computed previously based on the knowledge of CVC2 and CVC1. Thus, at this step, $P(Stress1|CVC2,CVC1)$, further referred to as $P(Stress1)$**, serves as the new prior probability of a trochaic stress pattern in a word, while $P(Stress2|CVC2, CVC1)$, further referred to as P(Stress2)**, is a prior probability that this word has an iambic stress pattern. The posterior probability that a word has a trochaic stress pattern given the evidence of the orthography of CVC2, CVC1, and VC2 is calculated following the formula below:

$$P(Stress1 \mid CVC2, CVC1, VC2) = \frac{P(VC2 \mid Stress1) \times P(Stress1)^{**}}{P(VC2 \mid Stress1) \times P(Stress1)^{**} + P(VC2 \mid Stress2) \times P(Stress2)^{**}} \quad (18)$$

The posterior probability that a word has an iambic stress pattern given a particular CVC2, CVC1, and VC2 is further calculated:

$$P(Stress2 \mid CVC2, CVC1, VC2) = 1 - P(Stress1 \mid CVC2, CVC1, VC2) \quad (19)$$

Using the calculations described above, the model can make predictions about the probabilities of stress patterns. In this Chapter, the Bayesian model of stress assignment in Russian disyllabic words is evaluated via two sets of simulations. First, the predictions of the model about stress patterns are compared with actual stress patterns that words have and with the performance of native speakers of Russian on a set of 500 disyllabic words (Study 5). The model is expected to be able to predict stress patterns in words and to simulate readers' performance assigning stress to those words. That is, the model would be expected to assign higher probabilities to the actual stress pattern of words than to the incorrect pattern and to identify those words to which the participants are more likely to make stress assignment errors. For those "problematic" words, the model should compute posterior probabilities of correct stress patterns that deviate significantly from 1.0 (complete belief that a stress pattern is correct). There should then be a correlation between the size of the deviation of the posterior probability computed by the model for a correct stress of a word from 1.0 and the likelihood that a word is pronounced with an incorrect stress pattern in the behavioral data.

This approach of simulating actual stress assignment performance of native speakers naming words rather than only assessing the ability of a model to predict stress patterns in the corpus is a novel and, presumably, more critical way of evaluating a model's potential. The previous models of stress assignment that were reviewed in Chapter 2 (Rastle & Coltheart, 2000; Seva et al., 2009; Perry et al., 2010) were all tested on their ability to predict stress patterns for each word in the corpus of disyllabic words. The algorithm by Rastle and Coltheart is unable to simulate actual stress assignment performance as its output is deterministic (i.e., trochaic or iambic stress patterns) rather than probabilistic. On the other hand, the connectionist model by Seva et al. and the nested model by Perry et al. do produce the output in the form of relative activation levels of the trochaic versus the iambic stress nodes that can be interpreted as the probabilities with which these stress patterns would be assigned by readers to those words. However, the modelers preferred to transform the continuous probability values into binary stress outputs (with a stress node having the maximum level of activation being considered as the stress pattern that the model assigns to a word) and, hence, ran simulations against stress patterns in the corpus. In contrast, the predictions of the Bayesian model of stress assignment were compared with actual performance of readers on a set of words.

Further, in Study 6 of the present thesis, the predictions of the Bayesian model were compared with the behavioral performance of native speakers of Russian, naming a set of 200 disyllabic nonwords. Simulating stress assignment in nonwords is a gold standard in the assessment of the effectiveness of models of stress assignment (Perry et al., 2010). In contrast to real words that could potentially be stressed via a lexical lookup procedure (a mechanism that is not actually a part of the model), nonword pronunciation, including stress placement, is completed fully via non-lexical processing, processing that the Bayesian model of stress assignment is specifically created to explain.

All previously published models of stress assignment have been tested by the modelers on their ability to predict stress pattern placement in nonword naming. Stress assignment in nonword naming is characterized by great inter-subject variance (Zevin & Joanisse, 2000). However, as noted above, because the models produce binary, deterministic output (trochaic or iambic stress patterns) or modelers selected to transform continuous, probabilistic output into binary, deterministic output, they are unable to account for this variability. Therefore, the three most well-known models of stress assignment can only predict the most frequent stress pattern that participants assign to a nonword, rather than the ratio of responses with trochaic versus iambic stress patterns assigned to that nonword. In contrast, the Bayesian model of stress assignment can provide estimates of the distribution of trochaic and iambic responses that speakers should produce in naming nonwords as well as the most frequent response that should be given by participants.

The computations of the likelihood of evidence were completed using the lexicon compiled for the studies reported in Chapter 5. In this lexicon, only the words with a frequency of more than one per million were included. Further, only nouns that describe a class of entities (i.e., common nouns), but not unique entities (i.e., proper nouns) were included. Thus, the lexicon that was used for these calculations did not include all disyllabic words of the Russian language. The fact that the lexicon used was not exhaustive might lead to a slight distortion in the computation of the likelihoods of evidence. Although this limitation should not change the predictions of the model drastically in the majority of cases, it might matter when certain evidence is very low in frequency in the language overall (a certain orthographic component is present just in a few words) and, therefore, this evidence was not well represented in the selected lexicon. For example, in the selected lexicon, there is just one word *мольберт* that has the orthographic component *–берт* (CVC2). Thus, in calculating the posterior probability of a trochaic stress for this word based on the information provided by CVC2, the model will predict that there is no chance that this word is assigned a trochaic stress pattern:

$$P(Stress1 \mid -берт) = \frac{(0/7668) \times .55}{((0/7668) \times .55) + ((1/6274) \times .45)} = .00\,. \qquad (20)$$

At this point, the assessment of other sources of evidence is meaningless, as the model will never be able to move away from the prediction that this word has iambic stress no matter how strong some other evidence might be. This situation does not create a problem if the model is assessed on its ability to predict a stress pattern for the single word *мольбЕрт* that is a part of the selected lexicon. However, this situation can become a problem if the model is assessed on its ability to predict a stress pattern for another word with the orthographic component *–берт* (CVC2) that is not a part of the selected lexicon and has a trochaic stress pattern (e.g., the proper name *шУберт*). The model would not be able to predict the correct stress pattern for the word *шУберт* due to the fact that its computations are based on the information provided in the selected lexicon, which, in case of the likelihood of evidence *–берт* (CVC2), does not properly reflect the ratio of trochaically versus iambically stressed words with *–берт* (CVC2) in the language.

This issue of the distortion in the representation of evidence in the selected lexicon is less problematic when certain evidence is represented widely in the language. In that situation, even if a few words having a particular orthographic component do not make it to the lexicon, the relative strength of the evidence based on that component for one of two alternative hypotheses should not depart greatly from the distribution present in the language. The issue of incorrect calculations of posterior probabilities due to the underrepresentation of certain evidence in the lexicon was addressed in the following way. To reflect the possibility that there might be a word present in the language that has a certain orthographic component, but that simply did not make it to the lexicon, a constant that equals one was added in the calculations of likelihoods of evidence of both trochaic stress ($P(evidence{+}1|Stress1)$) and iambic stress ($P(evidence{+}1|Stress1)$). For instance, in calculating the posterior probability of a trochaic stress given *–берт* (CVC2), the evidence for trochaic versus iambic stress is estimated not as 0 and 1 (meaning that in the lexicon, 0 words have a trochaic stress pattern and 1 word has an iambic stress pattern), but rather as 1 and 2 (meaning that there is potentially 1 word with a trochaic stress pattern and 2 words with an iambic stress patterns). Following this way of estimating the likelihood of evidence, the posterior probability of a trochaic stress given the evidence *–берт* (CVC2) is:

$$P(Stress1\,|\,{-}\text{\textit{берт}}) = \frac{(1/7668)\times .55}{((1/7668)\times .55) + ((2/6274)\times .45)} = .33 \ . \qquad (21)$$

The implementation of a parameter reflecting the possibility that there might be words with certain evidence for stress that were simply not included in the lexicon allows the model to make proper estimations of probabilities of stress patterns not just for the word like *мольбЕрт*, but also for the word like *шУберт* (when other sources of evidence contribute to the computation).

6.2. Study 5: Simulating stress assignment performance in word naming task

Study 5 was conducted to assess the ability of the proposed Bayesian model of stress assignment to predict stress patterns in Russian disyllabic words and to simulate stress assignment performance of native speakers. Perfect performance from the model in terms of classifying words was not expected. However, the erroneous predictions that the model might make may not necessarily reflect a failure of the model, but rather its inability to identify words for which the correct stress assignment is completed via lexical retrieval of stress patterns from the memory. The words characterized by these inconsistencies in stress patterns assigned via lexical versus non-lexical processing, however, should be especially difficult for readers to process and, therefore, these words should be more likely to be stressed inappropriately overall compared to words for which the model makes stress predictions that are consistent with the actual stress patterns. Further, there should be increased error rates in participants' performance not only when the model's predictions of stress patterns are incorrect, but also when the model predicts the correct stress pattern overall, but the posterior probability of this correct stress pattern deviates significantly from 1.0. To assess this hypothesis, one can correlate the degree of inconsistency of each prediction (i.e., difference between 1.0 and posterior probability of a correct stress pattern as estimated by the model) with error rate.

Method

Participants

Thirty four undergraduate students from Altay State University (Barnaul, Russia) took part in this experiment for a small monetary remuneration (age 17 – 23; *M* = 19). All were native speakers of Russian. None of the participants reported high proficiency in any second language.

Materials

A set of 500 disyllabic words (see Appendix D) was randomly selected from the corpus created for Study 3. Post-hoc analysis showed that the distribution of words according to stress patterns and grammatical categories in this set of experimental items was similar to that in the language. There were thirty four words that had ambiguous stress because they corresponded to two lexical items that differed in stress pattern only (e.g., *пАром* – Instrumental case for "steam" vs. *парОм* – Nominative case for "ferry"). For each of these words, the stress pattern for the more frequent word was selected as the correct one.

Procedure

For each word, the Bayesian model of stress assignment in Russian was used to compute posterior probabilities of trochaic and iambic stress patterns. The posterior probability of a stress pattern that exceeded .55 was interpreted as providing significant evidence that a word has that stress pattern and does not have the alternative stress pattern. The posterior probability of a stress pattern that was less than .45 was interpreted as providing evidence that a word does not have that stress pattern and does have the alternative stress pattern. Finally, the posterior probability of a stress pattern that was within the range of .45 - .55 was interpreted to mean that the model cannot determine which of the two stress patterns should be assigned to the word.

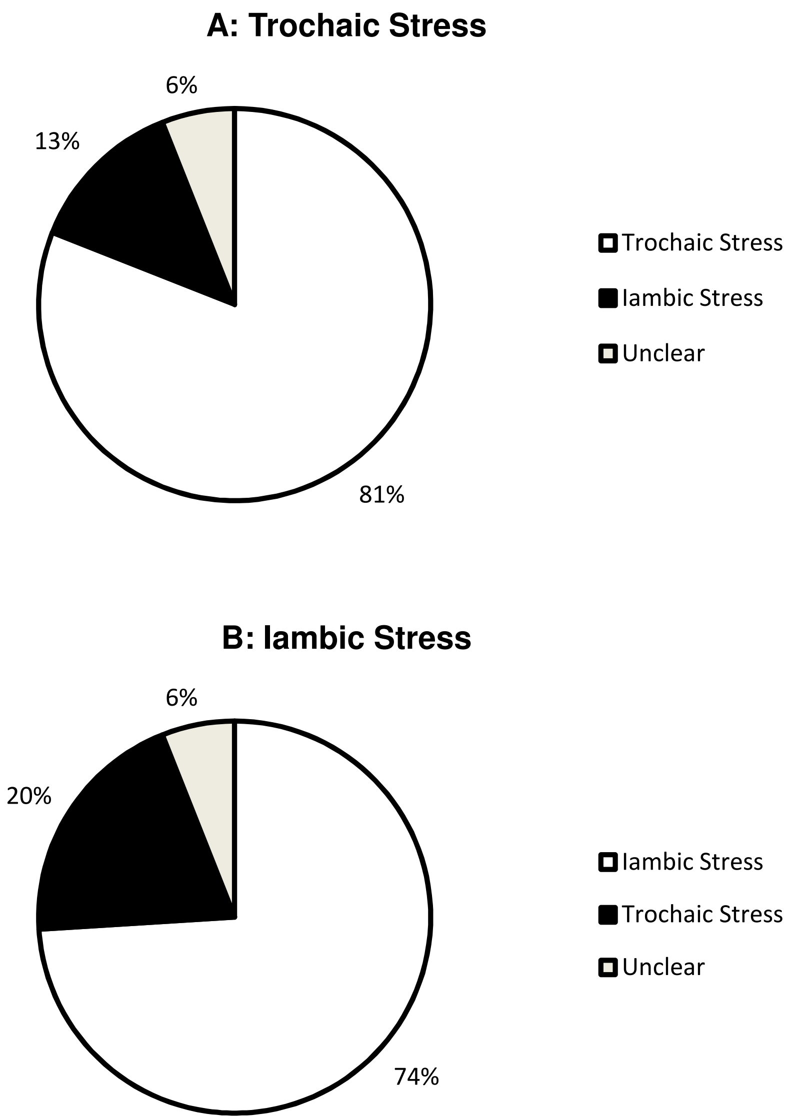
The behavioral data against which the simulation results were compared was collected in the following way. Participants were instructed to read aloud words presented on the screen as quickly and as accurately as possible. Instructions and stimuli were presented using the DMDX display system (Forster & Forster, 2003). The list of 500 items was presented in two blocks of trials. Every participant named all 500 items. The order of blocks and of items within blocks was randomized for each participant. Each trial started with the presentation of a fixation point for 500 ms. The target word in upper-case appeared in white on a black background (Courier New, 12 font) for 2000 ms or until the participant responded. The intertrial interval was 1000 ms.

Results

Responses were marked using CheckVocal (Protopapas, 2007) by the author and by two other native speakers of Russian. A response was coded as 0 if a word was pronounced with a trochaic stress and as 1 if a word was pronounced with an iambic stress. The Bayesian model of stress assignment could predict stress patterns in 78% of analyzed words (see Figure 7). Its performance on making correct predictions on trochaic stress words was slightly better (81%) than its ability to predict iambic stress (74%). Similarly, the model was more often wrong in predicting trochaic stress patterns for iambically stressed words (20%) than in incorrectly predicting iambic stress patterns for trochaically stressed words (13%). Based on the given evidence, the model could not conclude what stress pattern is more likely to be present in a word for 6% of words with trochaic stress and 6% of words with iambic stress. Thus, overall the Bayesian model of stress assignment could generally predict stress patterns based on non-lexical information only, although there were a number of cases when the model made erroneous predictions.

Figure 7

Stress pattern predictions of the Bayesian model of stress assignment in Russian for words with trochaic stress (A) and words with iambic stress (B)



The next question was whether there is a correlation between the model's predictions and stress assignment performance demonstrated by the readers. For this purpose, the posterior probability of an iambic stress pattern as calculated by the model was correlated with the proportion of responses with iambic stress that ranged from 0 (meaning that all participants named a word with a trochaic stress pattern) to 1 (meaning that all participants named a word with an iambic stress pattern). The regression analysis showed that the posterior probabilities of iambic stress patterns computed by the model were predictive of the likelihood that the readers would pronounce these words with iambic stress, r (498) = .76, F (1,498) = 681.25, $p < .001$.

The preceding analysis is potentially compromised because, for some words, the model does predict the incorrect stress. These are the words that are likely to be stressed by readers via lexical look-up procedure that is not implemented in the model. Therefore, one would expect that, for some of those words, participants would produce the correct stress even though non-lexical factors had biased them toward the wrong stress. These inconsistencies in stress patterns assigned via lexical versus non-lexical routes may cause difficulties in stress assignment. Similarly, one would expect that readers should be prone to stress assignment errors when processing words for which the model does predict the correct stress pattern; however, the posterior probability of this correct stress pattern as calculated by the model is not very high. To assess these predictions, a new variable referred to as the Degree of Inconsistency of stress pattern was computed. This variable reflects the difference between the probability of a correct stress pattern being assigned via a lexical look-up procedure (which equals 1.0) and the probability of a correct stress pattern being assigned via a non-lexical procedure (as estimated by the model).

The Degree of Inconsistency was entered as a fixed factor into a linear mixed effects model. Subjects and Items were entered as random factors. Stress assignment performance coded as 0 (correct) or 1 (incorrect) was used as the outcome variable. The analysis was conducted using the R package *lme4* (Bates & Maechler, 2010). Significance values were obtained via Markov Chain Monte Carlo (MCMC) sampling of the posterior parameter distributions (sample size = 10,000).

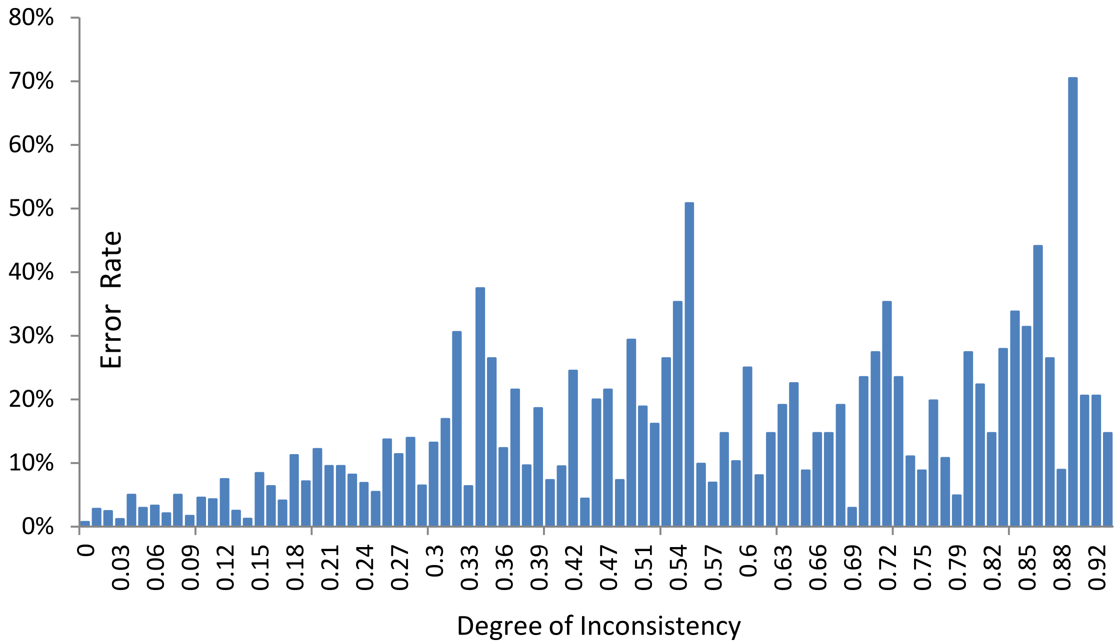
The model with the Degree of Inconsistency entered as a fixed factor and Subjects and Items entered as random factors provided a significantly better fit to the data than the model with random factors only, $\chi^2(1) = 194.10$, $p < .001$. Further, the Degree of Inconsistency was a significant predictor of error rate, $z = 14.76$, $p < .001$. Thus, the participants were more likely to assign stress incorrectly to words with a high Degree of Inconsistency compared to words with a low degree of Inconsistency (See Figure 8).

Discussion

In Study 5, the ability of the Bayesian model of stress assignment to predict stress patterns in Russian disyllabic words was assessed. Overall, the model was reasonably successful in predicting stress patterns in the language as 78% of words were assigned correct stress patterns. For about 6% of words, the model did not predict significant differences in the probabilities of trochaic versus iambic stress patterns based on the non-lexical evidence provided. Finally, for the remaining 16% of words, the model made incorrect predictions. These results provide further evidence that stress pattern information in Russian can be computed non-lexically in the majority of cases and that the proposed Bayesian model of stress assignment is likely to be a viable model for explaining non-lexical mechanisms of stress pattern identification.

Figure 8

Error rate as a function of the Degree of Inconsistency between stress pattern predictions of the Bayesian model of stress assignment based on the non-lexical evidence given and of the lexical look-up procedure



Note. A Degree of Inconsistency that equals 0 refers to complete consistency between the lexical information and the predictions made by the Bayesian model, while a Degree of Inconsistency that equals 1 refers to complete inconsistency between the lexical information and the predictions made by the Bayesian model.

The second goal of the study was to assess whether the model can simulate the patterns of stress assignment behavior demonstrated by readers. The question was whether the model makes predictions about difficulty in assigning stress patterns for the same words that readers tend to make stress errors on. From this perspective, words for which the model fails to assign stress correctly or for which it struggles in deciding what stress pattern is more probable are of special interest. These words are characterized by a high degree of inconsistency between the stress pattern predicted by the model, based on non-lexical information, compared to accurate lexical information. Often, a reader may pronounce such words correctly by retrieving a corresponding stress pattern from lexical memory. Although many readers may do exactly that, it does not mean that they will be immune to the influence of the non-lexical information that is, in fact, incorrect or ambiguous for these words. Therefore, readers are expected to make more stress assignment errors on words for which the predictions of the Bayesian model, based completely on non-lexical information, deviate significantly from the actual stress patterns (stored in lexical memory) for these words.

The results of Study 5 provided evidence, first of all, that the posterior probability of a certain stress pattern in a word computed by the model was predictive of the likelihood that this word is pronounced with this stress pattern by readers. Secondly, it was also found that the degree of inconsistency of predictions of non-lexical and lexical information was related to the probability that readers make stress assignment errors. More specifically, if the model predicted that there is a high probability of a certain stress pattern and this pattern was, in fact, the stress pattern stored for this word in lexical memory, participants rarely assigned an incorrect stress pattern to this word. On the other hand, if according to the model's computations there was some evidence for a stress pattern that is alternative to the one stored in lexical memory, participants were often misled by the non-lexical evidence and made stress assignment errors.

6.3. Study 6: Simulating stress assignment performance in a nonword naming task

Although the Bayesian model of stress assignment could successfully predict stress patterns in Russian and simulate the stress assignment performance of readers of this language, its performance was not perfect. In fact, a perfect performance on assigning stress to words is not expected from this model as it mimics non-lexical mechanisms of processing only, while stress assignment in words is not immune to the impact of lexical information. Thus, in simulating stress assignment in words, the model would fail to explain any variance that is due to readers using lexical information. The issue of utilization of lexical information does not arise if the model is assessed on its ability to simulate stress assignment in nonwords which do not have lexical representations in memory and, hence, their stress can only be assigned non-lexically. In Study 6, the Bayesian model was assessed on its ability to predict patterns of behavior demonstrated by native speakers of Russian assigning stress to nonwords. More specifically, the model was evaluated on its ability to predict the most frequent stress pattern that readers assign to a nonword, as well as the proportion of responses with trochaic and iambic stress that readers produce.

Method

Participants

Thirty undergraduate students from Altay State University (Barnaul, Russia) took part in this experiment for a small monetary remuneration (age 17 – 23; *M* = 19). All were native speakers of Russian. None of the participants reported high proficiency in any second language.

Materials

A set of 200 disyllabic nonwords (see Appendix E) was created by randomly combining first syllables and second syllables of Russian disyllabic words. All nonwords were pronounceable and did not violate any ortho-phonological constraints present in Russian. To minimize the possibility that stress assignment is completed by analogy to a real word, no nonword that is an orthographic neighbor of a real word (Coltheart et al., 1977) was included as a stimulus in this study.

Procedure

For each nonword, the Bayesian model of stress assignment in Russian was used to compute posterior probabilities of trochaic and iambic stress patterns. A posterior probability of a stress pattern that exceeded .55 is interpreted as providing significant evidence that a nonword is likely to be assigned that stress pattern. A posterior probability of a stress pattern that was less than .45 is interpreted as providing evidence that a nonword is likely to be assigned an alternative stress pattern. A posterior probability of a stress pattern that was within the range of .45 - .55 suggests that the model cannot determine which pattern is more likely to be assigned to a nonword.

The behavioral data against which the simulation results were compared was collected in the following way. Participants were instructed to read aloud novel words that would be presented on the screen as quickly as possible. Instructions and stimuli were presented using the DMDX display system (Forster & Forster, 2003). The list of 200 items was presented in two blocks of trials. Every participant named all 200 items.

The order of blocks and of items within blocks was randomized for each participant. Each trial started with the presentation of a fixation point for 500 ms. The target nonword in upper-case appeared in white on a black background (Courier New, 12 font) for 2000 ms or until the participant responded. The intertrial interval was 1000 ms.

Responses were marked using CheckVocal (Protopapas, 2007) by the author and by two other native speakers of Russian. A response was coded as “0” if a nonword was pronounced with a trochaic stress and as “1” if a nonword was pronounced with an iambic stress. If the mean response score for a nonword was less than .45, it was deemed that the majority of participants assigned trochaic stress to this nonword. If the mean response score for a nonword was more than .55, it was deemed that the majority of participants assigned iambic stress to this nonword. Finally, if the mean response score was between .45 and .55, it was thought that neither trochaic nor iambic stress pattern was a preferred choice in the behavioral data.

Results

As can be seen from Table 10, the model made correct predictions about a stress pattern that is more likely to be realized by participants for 184 out of 200 nonwords (90% correct). More specifically, for nonwords predicted to be given a trochaic stress, participants did produce that stress pattern 93% of the time. For nonwords predicted to be given iambic stress, participants did produce that stress pattern 88% of the time. The model could not decide on the preferred stress pattern for 16 nonwords and in the data participants also had trouble figuring out which stress pattern to assign to five of those nonwords. For the remaining 11 nonwords that the model found ambiguous, participants had a tendency of assigning one of the two stress patterns reasonably often.

Table 50

Stress pattern assignment predictions of the Bayesian model of stress assignment compared with stress pattern assignment performance of readers naming 200 disyllabic nonwords

	Predicted Stress			
	Trochaic	Iambic	No Preference	**Total**
Assigned Stress				
Trochaic	64	10	6	**80**
Iambic	5	101	5	**111**
No Preference	0	4	5	**9**
Total	**69**	**115**	**16**	**200**

Further, to assess the ability of the model to predict the proportion of responses with trochaic versus iambic stress patterns, the predictions of the model in the form of posterior probabilities of iambic stress pattern and the ratio of iambic stress responses made by participants to nonwords were submitted to a correlational analysis. The results showed that the model's estimations of posterior probabilities of iambic stress pattern were reflective of actual performance, r (198) = .87, F (1, 198) = 600.35, $p < .001$.

Discussion

Study 6 provided clear evidence that the Bayesian model of stress assignment can successfully predict what stress pattern participants are more likely to use when naming nonwords. One minor discrepancy between the results of the model's simulations and the behavioral data concerned a few nonwords that the model could not classify as either having trochaic or iambic stress based on the evidence given. Unlike the model, readers did demonstrate a preference for a stress pattern for 70% (11 out of 16) of these nonwords that the model failed to classify. The cause of this discrepancy is likely rooted in the fact that the model is limited in that it only uses three sources of evidence, sources that have been shown to provide highly valid and utilized stress cues in Russian (i.e., CVC1, CVC2, and VC2). However, readers are free to use any stress cues that are of value for the processing of a specific word/nonword, even if the general validity and utility of these cues in the language are relatively low. It is quite possible that readers may resort to those less reliable stress cues when information about the probability of stress patterns provided by more reliable cues is inconclusive. Overall, the predictions of the model about the choice of the most frequent stress pattern and about the proportions of trochaic versus iambic responses to nonwords made by readers were quite good.

6.4. Conclusion

In Chapter 6, simulations based on the Bayesian model of stress assignment in Russian were provided. First, the model's predictions about probabilities of stress patterns in a set of 500 disyllabic words were compared with actual stress assignment performance of native speakers of Russian on those words. In general, the model was capable of predicting the correct stress pattern realized for those words in the language. More importantly, the model's predictions were reflective of the patterns of behavior demonstrated by the readers. Thus, words for which the model failed to assign stress correctly (i.e., posterior probability of a correct stress pattern was low) or for which it had difficulty in deciding what stress is more likely to be correct (i.e., posterior probabilities of two alternative stress patterns were approximately equal), were, in fact, more likely to be pronounced by the readers with incorrect stress compared to words for which the model assigned stress correctly (i.e., posterior probability of a correct stress was high).

The model was also successful in its ability to predict the probabilities with which trochaic and iambic stress patterns are assigned to nonwords. That is, if the model concluded that for a nonword a particular stress pattern was more probable considering the non-lexical evidence available, readers were quite likely to assign that stress pattern. The model was also able to predict not just the most frequent stress pattern that the readers would assign to a nonword, but also the relative ratio of readers' trochaic versus iambic responses. Overall, the results of the simulations conducted with a set of words and nonwords allows one to conclude that the proposed Bayesian model of stress assignment is a viable model that is likely to provide a good approximation of the non-lexical processes involved when a speaker of Russian assigns stress to a disyllabic word.

Chapter 7 – General Discussion

7.1. Summary of Results

With the shift of interest from the investigation of monosyllabic words to that of more complex polysyllabic words that has taken place in the area of visual word recognition (Perry et al., 2010; Yap & Balota, 2009), new scientific questions have emerged. One such question concerns the principles and mechanisms of lexical stress assignment, that is, how is it that readers come to a decision that certain syllables should be pronounced with greater prominence than the others (i.e., stressed) in a polysyllabic word. Do the readers retrieve this information from memory? Is this information computed based on some cues that are present in the orthography of a word? If lexical stress is, in fact, computed, what are the cues that allow readers to make a decision about the stress pattern that a word has? All of these questions need to be considered by the modelers of visual word recognition who wish to account not only for monosyllabic, but also for polysyllabic word reading.

Most models of visual word recognition (e.g., Coltheart et al., 2001; Harm & Seidenberg, 2004) were originally created to explain reading of monosyllabic words and, thus, did not have in their architectures any mechanisms that could explain the process of stress assignment. In response to this limitation, a number of the modelers expanded the architecture of their models by introducing new modules aimed at imitating the mechanisms by which readers assign stress to words. In *Chapter 2*, a detailed description of the three most well-known models that have components capable of producing an output in the form of a stress pattern was given. These are the dual-route model of stress assignment by Rastle and Coltheart (2000), the connectionist model by Seva, Monaghan, and Arciuli (2009), and the CDP++, a model that combines some principles of the dual-route and of the connectionist-type models (Perry et al., 2010). In these models, it is suggested that stress patterns are identified based on written cues present in the orthography (Perry et al., 2010; Seva et al., 2009) or morphology (Rastle & Coltheart, 2000) of a word.

The models' abilities to simulate stress assignment performance on a set of English disyllabic words and nonwords were assessed. Although the performance of models on word reading was acceptable as a first pass, none of the models provided a particularly good fit to the data. While the models had no difficulty in predicting the presence of a more frequent (in English) trochaic stress pattern, the presence of a less frequent iambic stress pattern was often not identified properly. A similar pattern was registered in simulations run in an attempt to model nonword naming data. The models agreed on high percentage of stress assignment responses if participants preferred to name a nonword with a trochaic stress. On the other hand, nonwords that were pronounced by participants with a less common iambic stress were often incorrectly assigned a trochaic stress pattern by the models. Thus, all of the models tended to overgeneralize the more frequent trochaic stress pattern at the expense of the less common iambic stress pattern.

In *Chapter 3*, an alternative way to model the process of stress assignment in polysyllabic words was advanced. The proposal is that the human mind, which is essentially probabilistic, might be approaching the task of deciding where stress should be placed in a word by evaluating the likelihood of each hypothetical outcome, that is, the likelihood of each stress pattern that is potentially present in a word. The stress pattern likelihood estimation is completed following the principles of Bayesian probabilities. For this reason, the proposed model is referred to as a Bayesian model of stress assignment.

The Bayesian model of stress assignment can be seen as the process of evidence accumulation during the identification of stress patterns in polysyllabic words. The process of the actual selection of a stress pattern to be applied to a polysyllabic word can be thought of as random walk diffusion process (Ratcliff, 1978). In this situation, the decision process moves from a starting point towards decision boundaries with some drift rate. This movement is susceptible to the impact of noise in the system that gives rise to incorrect responses. The impact of the noise is directly related to the strength of the evidence accumulation process (i.e., the posterior probability) that is implemented in the Bayesian model of stress assignment (i.e., stronger evidence for a correct stress pattern is associated with higher accuracy, while weaker evidence for a correct stress pattern is associated with lower accuracy). The estimation of evidence for each stress pattern is done by considering prior beliefs about the likelihood of each stress pattern in a language and the evidence for each stress pattern provided in a word.

The prior probability of a stress pattern in a language refers to the frequency of this stress pattern in the words of the language. The evidence for stress involves any type of non-lexical information present in a word that is probabilistically associated with stress patterns in a language. In other words, evidence for stress considered by the model would be of high validity. In addition, readers should be sensitive to this evidence and use it in making their stress assignment decisions. Thus, the model considers those sources of evidence for stress that are not only highly valid, but also highly utilized. There is likely to be a set of stress cues with high validity and utility that is routinely analyzed by readers in the process of stress assignment.

In *Chapter 4*, empirical support for the assumptions made in the Bayesian model of stress assignment was considered. First of all, evidence for the effect of the frequency of stress patterns in a language on polysyllabic word naming was reviewed. Previously, the debated issue in this area was whether the most frequent stress pattern is assigned by default and, thus, whether there is an essential difference in the processing of words with more frequent versus less frequent stress patterns (Black & Byng, 1986; Colombo, 1992). The polar opposite view was that the frequency of stress patterns in the language plays no role in processing at all and, hence, the mechanisms of processing of words with a more frequent stress pattern are exactly the same as of words with a less frequent stress pattern (Burani & Arduino, 2004). Thus, there are two extreme positions on the issue and both positions find some empirical support. On one hand, there are studies showing that readers are aware of the distribution of stress patterns in the language and are influenced by it to certain extent (Breen & Clifton, 2011; Colombo, 1992). On the other hand, there are studies that fail to find any evidence that words with a more frequent stress pattern are processed via different mechanisms compared to words with less frequent stress patterns (Burani & Arduino, 2004; Sulpizio, Arduino, Paizi, & Burani, 2013).

A more viable approach would seem to be to take an intermediate position. There is a substantial amount of evidence suggesting that readers are aware of statistical probabilities of stress patterns in the language. However, that does not mean that a more frequent stress pattern is applied to all words automatically following some default rule, which, in its turn, gives rise to the processing differences for words with more versus less common stress patterns. Knowledge of the distribution of stress patterns in a language may be used as a prior belief about likelihoods with which words have a particular stress pattern or, in other words, as a baseline for further computations of probabilities of stress patterns. Thus, in the Bayesian model of stress assignment, there are no differences in the mechanisms of processing of words with more frequent versus less frequent stress patterns, although words with a more frequent stress pattern do enjoy somewhat of a head start. However, this initial advantage for words that do have a more frequent stress pattern can be easily changed by assessment of non-lexical, orthographic cues that are probabilistically associated with less frequent stress patterns.

Thus, in the proposed model of stress assignment, the most vital role is played by non-lexical cues to stress. In *Chapter 4*, a review of previous research on potential sources of evidence for stress in various languages was provided. More specifically, studies investigating graphemic complexity of onsets and codas (Kelly, 2004; Kelly, Morris, & Verrekia, 1998), orthography of word beginnings and endings (Arciuli et al., 2010), and grammatical status of a word (Arciuli & Cupples, 2004) as evidence for lexical stress were surveyed. It is very likely that this list of stress cues is not comprehensive, and that there are other stress cues that have not been investigated yet.

In making stress assignment decisions, readers might be evaluating all non-lexical sources of evidence for stress present in the language. However, due to time-constraints and due to the excessive amount of evidence for stress, some of which is redundant, readers, in general, are likely to rely on a limited set of highly informative stress cues. Doing so would allow readers to assign stress with high accuracy and speed to a majority of words. As the Bayesian model presented here is an attempt to explain this common, non-lexical processing of stress assignment, the model considers only those sources of evidence that are highly informative in a language.

The Bayesian model of stress assignment is a universal model that can be applied to any language that utilizes lexical stress, although its exact components are language-specific. In *Chapter 5*, the bases for implementation of the Bayesian model of stress assignment in Russian were outlined. The choice of the language for present research is explained by the fact that despite the importance of lexical stress for word recognition in Russian, its assignment is very complex and is often a source of speech errors. In Russian, there appear to be no clear rules of stress assignment and no dominant stress pattern. This complexity of the Russian stress system gave rise to the idea that, in that language, stress assignment can be completed only lexically, that is via retrieval of stress pattern information from memory (Gouskova, 2010). If this proposal is true, it should be extremely challenging, in fact, next to impossible, for a Bayesian model that is essentially non-lexical to predict stress pattern placement in Russian words and to simulate stress assignment performance for native speakers of Russian.

In creating the computational implementation of the model for Russian, the distribution of stress patterns in the language (i.e., prior probabilities of stress patterns) and the nature of cues that are probabilistically associated with stress patterns (i.e., sources of evidence for stress) were assessed. To simplify the computation, only disyllabic Russian words were considered. In Study 1, the distribution of trochaic versus iambic stress patterns in a corpus of Russian disyllabic words was analyzed. This analysis showed that the prior probability of a trochaic stress pattern is .55, while the prior probability of an iambic stress pattern is .45. Additionally, the analysis of the distribution of stress patterns in words of various grammatical categories showed an interesting picture. Adjectives were often associated with trochaic stress (80%), verbs were slightly more often associated with iambic stress (62%), and, finally, for nouns, trochaic stress occurred approximately as often as iambic stress (55% vs. 45%).

The evidence for the bias to either a trochaic or an iambic stress pattern was assessed in a word naming task (Study 2). More specifically, one question was whether words having a trochaic stress pattern, which is just slightly more frequent in Russian, are processed faster than words having an iambic stress pattern. A second question was whether there was any evidence for faster and more accurate processing of adjectives with trochaic stress due to the fact that this stress pattern is dominant for words of this grammatical category. The results showed no effect of stress type overall, but a significant main effect of stress type for adjectives, suggesting that readers are sensitive to the information about frequencies of stress patterns in the language. Further, due to the presence of a more frequent, trochaic stress pattern, adjectives as a grammatical category were named and identified as words faster and more accurately than nouns and verbs which do not have a more frequent stress pattern.

The finding of a significant main effect of stress type at the level of grammatical category could be interpreted as suggesting that prior probabilities of stress patterns reflect the distribution of stress patterns among words of certain grammatical category rather than among all words of a language. This proposal, that to some extent contradicts the principles of the Bayesian model of stress assignment, is unlikely to be correct. First of all, although prior beliefs about stress patterns exist in a reader’s mind before any processing has been initiated, in a word naming experiment, a reader is unaware of the grammatical category of a word before its presentation and, thus, this information cannot have any impact on reader's prior expectations. Secondly, it could be argued that the effect of grammatical category observed in Study 2 was not due to the early activation of grammatical category information, but rather due to the fact that, in the case of adjectives, orthographic cues to grammatical category also provide useful information about stress patterns, while orthographic cues to nouns and verbs do not. Therefore, these data are not actually inconsistent with the original view that prior beliefs about stress patterns reflect the knowledge of distributions of stress patterns in all words of the language, rather than in words of certain grammatical category.

To examine what non-lexical sources of evidence for stress are present in Russian and are used by native speakers, a factorial (Study 2) and two regression (Studies 3 and 4) studies were conducted. The results of Study 2 showed that word ending was an important stress cue as words that have word endings representative of correct stress patterns had a processing advantage over words with word endings that are representative of incorrect stress patterns. A more exploratory approach was taken in Studies 3 and 4 that were run to examine the power of eleven variables (*Length*, *Log Frequency*, *Grammatical Category*, *Onset Complexity*, *Coda Complexity*, and spelling-to-stress consistency of *CVC1*, *CV1*, *VC1*, *CVC2*, *CV2*, and *VC2*) to predict lexical stress in Russian. Study 3 was a binary logistic regression of this set of predictors on stress patterns in a corpus of Russian disyllabic words. The aim of this study was to identify stress cues having high validity. The results showed that there are six variables significantly associated with stress patterns in Russian: *Onset Complexity*, *Coda Complexity*, the spelling-to-stress consistency of *CVC1*, *CVC2*, *CV2*, and *VC2*. In Study

4, a generalized linear mixed effect model with the same eleven variables as predictors of stress assignment performance was applied to the word naming data with an aim of identifying stress cues that are of high utility in Russian. The results showed that native speakers of Russian essentially base their stress assignment decisions on the information provided by the spelling-to-stress consistency of *CVC1*, *CVC2*, and *VC2*.

Based on the combination of the results provided by the factorial and the regression studies, it was concluded that there are three sources of evidence for stress in Russian that have high validity (i.e., strong probabilistic associations between cues and the stress patterns exist in the language) and high utility (i.e., readers use the knowledge of these probabilistic associations between cues and stress patterns). These three sources of evidence are the spelling-to-stress consistency of the first syllable (CVC1), the spelling-to-stress consistency of the second syllable (CVC2), and the spelling-to-stress consistency of the ending of the second syllable (VC2).

The information about prior probabilities of stress patterns in Russian and about the sources of evidence that are considered by native readers of Russian assigning stress to disyllabic words was used to create the computational implementation of a Bayesian model of stress assignment in Russian. The performance of the model was tested in a series of simulations reported in *Chapter 6*. In Study 5, the predictions of the model were compared with stress assignment performance of native speakers of Russian naming disyllabic words. The results showed that the model was not only able to predict correctly the stress patterns for the majority of the words tested, but also to reflect the patterns of behavior demonstrated by the readers. More specifically, the model managed to identify those words that participants had difficulty in processing, that is, words that were often assigned incorrect stress patterns in the behavioral data. In Study 6, the model's ability to simulate stress assignment performance of readers naming nonwords was examined. The model's performance in this simulation was quite good as it managed to predict not only the most frequent stress pattern that readers assigned to a nonword, but also the relative ratio of trochaic versus iambic responses given by the participants.

7.2. Theoretical implications

In the present thesis, a new theoretical approach to the modeling of the process of stress assignment couched in the principles of Bayesian probabilities has been introduced. Within this approach, it is suggested that in deciding where to place stress in a word, a reader estimates posterior probabilities of each stress pattern occurring in words in the language. The posterior probability of a stress pattern occurring in a word is estimated by adjusting a prior belief about the likelihoods of each stress pattern (derived from the knowledge of the distribution of stress patterns in the language) based on various non-lexical sources of evidence for stress present in the orthographic input. The proposed Bayesian theoretical framework was implemented in a computational model of stress assignment that mapped orthography onto stress position for disyllabic words in Russian. This computational model was able to accomplish stress assignment for words and nonwords with a high degree of accuracy, implying that the principles underlying this model are likely to reflect the mechanisms that are implicated during the process of stress assignment.

The Bayesian model of stress assignment is a model based on non-lexical processing. In other words, this model describes the procedures that are likely to occur when readers compute stress pattern information based on orthographic input rather than retrieve it directly from the memory. As it turns out, 20% of words in Study 5 could not be assigned stress properly following the non-lexical computation. For these words, for a reader to properly assign stress, that process must involve lexical retrieval. In the behavioral data, it was observed that readers did make significantly more errors on these types of words, suggesting that the readers were impacted by misleading information provided as the result of the non-lexical computation. However, in general, the readers managed to assign stress properly even to those words that the model assigned the incorrect stress to. Therefore, similar to the dual-route theory of reading (Coltheart et al., 1993) and to the stress assignment algorithm by Rastle and Coltheart (2000), the model expressed here must incorporate an assumption that stress pattern information may be retrieved via a lexical route as well as being computed following the principles of the Bayesian model of stress assignment. Unlike the algorithm by Rastle and Coltheart, which is rule-driven, stress assignment in the Bayesian model is not governed by pre-defined linguistic rules, but rather by a combination of different cues that are statistically associated with stress patterns. A reliance on non-lexical cues that are probabilistically associated with stress patterns is also implemented in the connectionist model of stress assignment by Seva et al. (2009). However, the model proposed in this thesis differs from the connectionist model of stress assignment because the former model allows that stress assignment may happen via the retrieval of localized lexical representations, while the latter model denies such a possibility.

The Bayesian model of stress assignment is most similar to the CDP++ (Perry et al., 2011) as both models combine dual-route principles of processing with an idea that any non-lexical route would be driven by knowledge of statistical regularities, rather than rule-based algorithms. Despite those similarities, the CDP++ and the Bayesian model of stress assignment take different fundamental approaches. The task of the Bayesian model is to solve an inductive problem of deciding which of several alternative stress patterns is likely to be present in a word taking into consideration some non-lexical evidence that is present. The task of any model of stress assignment that utilizes connectionist networks is to learn a set of weights on connections among orthographic input and stress output that would generate the appropriate stress pattern. To conclude, although the Bayesian model of stress assignment does have a lot of features in its architecture and makes some theoretical assumptions that are shared with the earlier models of stress assignment, it is a novel computational approach that appears to be able to provide new insights into the process of stress assignment in a variety of languages.

In the present thesis, it was demonstrated that the Bayesian model of stress assignment can successfully account for the process of stress assignment in Russian disyllables. As this model is essentially a model of non-lexical processing, one could conclude that lexical stress can be assigned to Russian polysyllabic words non-lexically. That is, in Russian, there are stress cues present in the orthography of a word and the native speakers of Russian use these cues in computing stress pattern information. This finding contradicts a widely accepted view that Russian stress assignment is completed only via the retrieval of stress pattern information from the memory (Gouskova, 2010).

7.3. Limitations and future research

Although the Bayesian model of stress assignment was successful in the present research, there are, of course, a number of lines of research to pursue to further test and develop the model. First, in order to adjudicate between competing modeling approaches, one needs to create computational implementations of major models that reflect the stress assignment process in one common language. Indeed, it is hard to conclude that one model supersedes another if they are tested on words taken from different languages. While all previously existing models have been created to simulate stress assignment in English, the computational implementation of the Bayesian model described here makes predictions about probabilities of lexical stress in Russian. The logical step in this respect is to make an implementation of the Bayesian model of stress assignment in English. Thus, one could compare directly the ability of models to predict stress patterns in a language and patterns of performance of native speakers assigning stress to words.

As has been mentioned earlier, none of the existing models of stress assignment could overcome the issue of overgeneralization of a more frequent trochaic stress pattern in English. All models of stress assignment in English demonstrated almost perfect performance on words with the more common trochaic stress and less than satisfactory performance on words with the less common iambic stress. It is an empirically interesting question whether a model based on the Bayesian principles would provide a better fit to the English data than existing models do. Within the Bayesian approach, English speakers have a high prior belief that any disyllabic word should have trochaic stress. Thus, in order to pronounce an iambically-stressed word correctly, a reader may need to be provided with orthographic evidence that is very strongly associated with iambic stress, while in case of a trochaically stressed word even weak evidence for trochaic stress would suffice.

The Bayesian model of stress assignment should also be tested on its ability to predict stress for polysyllabic words of various syllabic lengths. It is an open question whether the model would be as successful in simulating stress assignment performance of speakers naming words of more than two syllables as it was in predicting stress patterns in disyllabic words. Although the architecture of the model remains the same regardless of the syllabic length of a word being read, there are some minor differences. First, there would be differences in the number of hypotheses (stress patterns) for which the model must compute posterior probabilities. That is, in establishing the likelihoods of stress patterns in a disyllabic word, the model has to compute a posterior probability only for one hypothesis as the probability of the other hypothesis is the complement of the other probability, while during the processing of a trisyllabic word, computations of probabilities for two hypotheses would need to be conducted. Secondly, one needs to determine whether the sources of evidence for stress remain the same for words of various syllabic lengths or whether certain differences in the number and types of cues to stress (dependent on the syllabic length of a word) exist.

Another question for future research concerns the relative time period during which lexical stress information is being processed. No assumptions are made about when stress is assigned to words in the model as it is not clear at the moment whether stress assignment precedes mapping of orthography onto segmental phonology, follows it, or whether these two processes occur in parallel during reading. Hence, the stress assignment model is not implemented yet as a module within a larger model of polysyllabic word reading.

An additional issue that has not been investigated within the scope of the present manuscript is whether the proposed model can account for individual differences in stress assignment performance. These differences are likely to emerge as individuals might be exposed to different statistical probabilities even in the same language due to variability in the contents and sizes of individuals' lexicons. Due to these differences in exposure, the stress assignment performance of a highly educated person might be quite different from the performance of a person with an impoverished lexicon. Similarly, the statistical probabilities of the lexicon of a 6-year old child might differ significantly from those of an adult. In fact, Arciuli et al. (2010) analyzed a corpus of children's literature appropriate for various age groups, and demonstrated successive changes in the distributions of stress patterns (prior probabilities) and in reliable stress cues (likelihoods of evidence) that were picked up by children. By learning the language, children adapted their predictions to the structure of the language. Further, individual differences in stress assignment might be observed due to the regional differences in the language. For example, if in a certain dialect many words are stressed differently than in the standard language, it is possible that the speakers of this dialect might be relying greatly on the probabilities reflected in that dialect rather than in the standard language. The model presented here is an approximation only reflecting a behavior of an "average" speaker of Russian with the lexicon that contains about 14,000 disyllabic words. However, the model can easily be used to simulate individual differences in stress assignment performance by varying the size and the content of the lexicon used by the model in the process of estimation of posterior probabilities of stress patterns.

A related question concerns the behavior of bilinguals, who are exposed to statistical probabilities of more than one language. At the moment, it is unclear whether stress-relevant statistical information is language selective in a way that only probabilities of one language are activated at one time, or whether this information is language nonselective, meaning that in defining the degree of belief that a word of one language has a specific stress pattern, a bilingual relies on the knowledge of stress pattern distributions and stress cues of all languages that he/she speaks.

7.4. Concluding statements

In the present thesis, a model of stress assignment in reading based on the ideas of Bayesian probabilities was advanced. The process of stress assignment is viewed within this model as the process of estimation of posterior probabilities of stress patterns. In the computation of posterior probabilities of stress patterns, the model adjusts prior probabilities of stress patterns reflecting the frequency of stress patterns in the language by considering various non-lexical sources of evidence for stress. This model was successfully tested in its ability to predict stress patterns in Russian disyllabic words and to simulate stress assignment performance of native speakers of Russian. One of the greatest advantages of the Bayesian model of stress assignment over all other existing models is that unlike other models that predict "average" behavior, the Bayesian model can provide simulations of individual differences. In fact, the model was not only able to predict the most common stress pattern response to a word, but also the difficulty/likelihood of assigning that stress pattern by individual readers.

References

Álvarez, C.J., Carreiras, M., & Taft, M. (2001). Syllables and morphemes: Contrasting frequency effects in Spanish. *Journal of Experimental Psychology: Learning, Memory and Cognition*, 27, 545-555.

Anderson, J. R. (1991). Is human cognition adaptive? *Behavioral and Brain Sciences, 14,* 471–485.

Ans, B., Carbonnel, S., & Valdois, S. (1998). A connectionist multiple-trace memory model for polysyllabic word reading. *Psychological Review, 105*(4), 678-723.

Arciuli, J. & Cupples, L. (2004). The effects of stress typicality during spoken word recognition by native and non-native speakers of English: Evidence from onset-gating. *Memory and Cognition*, *32* (1), 21-30.

Arciuli, J. & Cupples, L. (2006). The processing of lexical stress during visual word recognition: Typicality effects and orthographic correlates. *Quarterly Journal of Experimental Psychology*, *59* (5), 920-48.

Arciuli, J. & Cupples, L. (2007). Would you rather 'embert a cudsert' or 'cudsert an embert'? How spelling patterns at the beginning of English disyllables can cue grammatical category. In Schalley, A.C. & Khlentzos, D. (Eds.), *Mental States: Language and Cognitive Structure*, (pp. 213-238). Amsterdam, Netherlands: John Benjamins Publishing Company.

Arciuli, J., Monaghan, P., & Seva, N. (2010). Learning to assign lexical stress during reading aloud: Corpus, behavioural and computational investigations. *Journal of Memory and Language*, *63*, 180-196.

Ashby, J., & Clifton, C. (2005). The prosodic property of lexical stress affects eye movements during silent reading. *Cognition, 96*(3), B89-B100.

Ashby, J., & Martin, A. E. (2008). Prosodic phonological representations early in visual word recognition. *Journal of Experimental Psychology: Human Perception and Performance, 34*(1), 224-236.

Ashby, J., & Rayner, K. (2004). Representing syllable information during silent reading: Evidence from eye movements. *Language and Cognitive Processes, 19*(3), 391-426.

Baayen, R. H., Piepenbrock, R., & van Rijn, H. (1995). *The CELEX lexical database*. [CD-ROM: Release 2.] Philadelphia: Linguistic Data Consortium, University of Pennsylvania.

Baker, C. L., Saxe, R., & Tenenbaum, J. B. (2009). Action understanding as inverse planning. *Cognition, 113*(3), 329-349.

Balota, D. A., & Chumbley, J. I. (1985). The locus of word-frequency effects in the pronunciation task: Lexical access and/or production? *Journal of Memory and Language, 24*(1), 89-106.

Balota, D. A., Yap, M. J., Cortese, M. J., Hutchison, K. I., Kessler, B., Loftis, B., Neely, J. H., Nelson, D. L., Simpson, G. B., & Treiman, R. (2007). The English Lexicon Project. *Behavior Research Methods*, 39, 445-459.

Balota, D. A., Yap, M. J., Hutchison, K. A., & Cortese, M. J. (2013). Megastudies: What do millions (or so) of trials tell us about lexical processing? In J. S. Adelman (Ed.), *Visual Word Recognition Volume 1: Models and methods, orthography and phonology* (pp. 90-115). New York, NY: Psychology Press.

Bayes, T. (1763/1958). Studies in the history of probability and statistics: Thomas Bayes's essay towards solving a problem in the doctrine of chances. *Biometrika*, 45, 296-315.

Bates, D., & Maechler, M. (2010). *Package 'lme4'*. Reference manual for the package, available at: http://cran.r-project.org/web/packages/lme4/lme4.pdf

Black, M. & Byng, S. (1986). Prosodic constraints on lexical access in reading. *Cognitive Neuropsychology*, *3*, 369-409.

Bornkessel, I. & Schlesewsky, M. (2006). The Extended Argument Dependency Model: A neurocognitive approach to sentence comprehension across languages. *Psychological Review*, 113, 787–821.

Bowers, J. S. & Davis, C. J. (2012). Bayesian just-so stories in psychology and neuroscience. *Psychological Bulletin*, *138*(3), 389-414.

Breen, M., & Clifton, C. (2011). Stress matters: Effects of anticipated lexical stress on silent reading. *Journal of Memory and Language, 64*(2), 153-170.

Brown, P., Lupker, S. J. & Colombo, L. (1994). Sources of information in word naming: A study of individual differences. *Journal of Experimental Psychology: Human Perception and Performance*, 20, 537-554.

Burani, C., & Arduino, L. S. (2004). Stress regularity or consistency? Reading aloud Italian polysyllables with different stress patterns. *Brain and Language*, *90*, 318–325.

Cappa, S.F., Nespor, M., Ielasi, W., & Miozzo, A. (1997). The representation of stress: evidence form an aphasic patient, *Cognition*, 65, 1-13.

Carreiras, M., & Perea, M. (2002). Masked priming effects with syllabic neighbors in the lexical decision task. *Journal of Experimental Psychology: Human Perception and Performance*, *28*, 1228-1242.

Chater, N., & Manning, C. D. (2006). Probabilistic models of language processing and acquisition. *Trends in Cognitive Sciences*, *10*(7), 335-344.

Chetail, F., & Content, A. (2012). The internal structure of chaos: Letter category determines visual word perceptual units. Journal of Memory and Language, 67, 371-388.

Chetail, F. & Content, A. (2013). Segmentation of written words in French. *Language and Speech, 56,* 125-144.

Chomsky, N. & Halle, M. (1968). *The Sound Pattern of English*. New York: Harper & Row.

Clark, A. (2013). Whatever next? Predictive brains, situated agents, and the future of cognitive science. *Behavioral and Brain Sciences*, 36, 181-204.

Coats, H. B. (1976). *Stress assignment in Russian: Inflection*. Edmonton: Linguistic Research.

Colombo, L. (1992). Lexical stress and its interaction with frequency in word pronunciation. *Journal of Experimental Psychology: Human Perception and Performance*, *18*, 987–1003.

Colombo, L. & Zevin, J. (2009). Stress priming in reading and the selective modulation of lexical and sub-lexical pathways. *PLoS ONE*, 4, e7219.

Coltheart, M., Davelaar, E., Jonasson, J. F., & Besner, D. (1977). Access to the internal lexicon. In S. Dornic (Ed.), *Attention and performance VI* (pp. 535-555). Hillsdale, NJ: Erlbaum.

Coltheart, M. and Rastle, K. (1994). Serial Processing in Reading Aloud: Evidence for Dual-Route Models of Reading. *Journal of Experimental Psychology: Human Perception and Performance*, 20, 1197-1211.

Coltheart, M., Rastle, K., Perry, C., Langdon, R., & Ziegler, J. (2001). DRC: A dual route cascaded model of visual word recognition and reading aloud. *Psychological Review, 108*(1), 204-256.

Conrad, M., & Jacobs, A. M. (2004). Replicating syllable frequency effects in spanish in german: One more challenge to computational models of visual word recognition. *Language and Cognitive Processes, 19*(3), 369-390.

Cortese, M. J. & Khanna, M. M. (2007). Age of acquisition predicts naming and lexical-decision performance above and beyond 22 other predictor variables: An analysis of 2,342 words. *The Quarterly Journal of Experimental Psychology, 60,* 1072–1082.

Cubelli, R. & Beschin, N. (2005). The processing of the right-sided accent mark in left neglect dyslexia. *Brain and Language, 95*(2), 319-326.

Cutler, A. (1980). Errors of stress and intonation. In V.A. Fromkin (Ed.), *Errors in Linguistic Performance: Slips of the Tongue, Ear, Pen and Hand* (pp. 67-80). New York: Academic Press.

Cutler, A. & Carter, D.M. (1987). The predominance of strong initial syllables in the English vocabulary, *Computer Speech & Language*, *2*(3–4), 133-142.

Cutler, A., & Clifton, C. E. (1984). The use of prosodic information in word recognition. In H. Bouma & D. G. Bouwhuis (Eds.), *Attention and performance X* (pp. 183 – 196). Hillsdale: Erlbaum.

Cutler, A., & Norris, D. G. (1988). The role of strong syllables in segmentation for lexical access. *Journal of Experimental Psychology: Human Perception and Performance*, 14, 113–121.

Dell, G. (1990). Effects of frequency and vocabulary type on phonological speech errors. *Language and Cognitive Processes*, 5, 313–349.

Deneve, S. (2008). Bayesian inference in spiking neurons. *Neural Computation*, 20, 91-117.

Dennis, S., & Humphreys, M. S. (2001). A context noise model of episodic word recognition. *Psychological Review, 108*(2), 452-478.

Diependaele, K., Sandra, D., & Grainger, J. (2009). Semantic transparency and masked morphological priming: The case of prefixed words. *Memory & Cognition*, 37, 895-908.

Domahs U., Genc S., Knaus J., Wiese R., & Kabak B. (2012). Processing (un-predictable word stress: ERP evidence from Turkish. Language and Cognitive Processes, 28, 335 – 354.

Doya, K., Ishii, S., Pouget, A., & Rao, R. (2007). *Bayesian brain: Probabilistic approaches to neural coding*. Cambridge, MA: MIT Press.

Federmeier, K. D., Segal, J. B., Lombrozo, T., & Kutas, M. (2000). Brain responses to nouns, verbs and class ambiguous words in context. *Brain*, 123, 2552–2566.

Feldman, J. (2001). Bayesian contour integration. *Perception & Psychophysics, 63*(7), 1171-1182.

Forster K.I. & Forster, J.C. (2003). DMDX: A windows display program with millisecond accuracy. *Behavior Research Methods, Instruments, & Computers*, *35* (1), 116-124.

Fudge, E. (1984). *English word-stress*. London: George Allen & Unwin.

Giegerich, H. J. (1992).*English phonology: An introduction.* Cambridge: Cambridge University Press

Gouskova, M. (2010). The phonology of boundaries and secondary stress in Russian compounds. *The Linguistic Review* 17(4), 387–448.

Grainger, J., & Jacobs, A. M. (1996). Orthographic processing in visual word recognition: A multiple read-out model. *Psychological Review, 103*(3), 518-518.

Griffiths, T. L., Kemp, C., & Tenenbaum, J. B. (2008). Bayesian models of cognition. In Ron Sun (Ed.), *Cambridge handbook of computational cognitive modeling* (pp. 59–100). Cambridge, England: Cambridge University Press.

Gutierrez-Palma, N., & Palma-Reyes, A. (2008). On the use of lexical stress in reading Spanish. *Reading and Writing*, *21*, 645–660.

Hansson, P., Juslin, P., & Winman, A. (2008). The role of short-term memory capacity and task experience for overconfidence in judgment under uncertainty. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 34*(5), 1027-1042.

Harm, M. W., & Seidenberg, M. S. (2004). Computing the meanings of words in reading: Cooperative division of labor between visual and phonological processes. *Psychological Review, 111*(3), 662-720.

Harrell, F.E. Jr, Lee, K.L., & Mark, D.B. (1996). Multivariable prognostic models: issues in developing models, evaluating assumptions and adequacy, and measuring and reducing errors. *Statistics in Medicine*, *15*(4), 361 – 387.

Jared, D. (2002). Spelling–sound consistency and regularity effects in word naming. *Journal of Memory and Language*, *46*, 723–750.

Jared, D., McRae, K., & Seidenberg, M. S. (1990). The basis of consistency effects in word naming. *Journal of Memory and Language*, *29*, 687–715.

Jones, M., & Love, B. C. (2011). Bayesian fundamentalism or enlightenment? On the explanatory status and theoretical contributions of Bayesian models of cognition. *Behavioral and Brain Sciences, 34,* 169–188.

Jurafsky, D. (2003). Jurafsky, Dan. 2003. Probabilistic Modeling in Psycholinguistics: Linguistic Comprehension and Production. In R. Bod, J. Hay, and S. Jannedy, (Eds), *Probabilistic Linguistics* (pp. 39 – 97), London: MIT Press.

Kahn, D. (1976). *Syllable-based generalizations in English phonology*. Doctoral dissertation, MIT.

Kello, C. T. (2006). Considering the junction model of lexical processing. In S. Andrews (Ed.), *From inkmarks to ideas: Current issues in lexical processing* (pp. 50-75). New York: Psychology Press.

Kelly, M. (2004). Word onset patterns and lexical stress in English. *Journal of Memory and Language*, *50*, 231–244.

Kelly, M. & Bock, J. (1988). Stress in time. *Journal of Experimental Psychology: Human Perception and Performance*, 14, 389-403.

Kelly, M., Morris, J., & Verrekia, L. (1998). Orthographic cues to lexical stress: Effects on naming and lexical decision. *Memory & Cognition*, *26*, 822–832.

Kersten, D., Mamassian, P., & Yuille, A. (2004). Object perception as Bayesian inference. *Annual Review of Psychology, 55*, 271-304.

Körding, K. P., & Wolpert, D. M. (2006). Bayesian decision theory in sensorimotor control. *Trends in Cognitive Sciences, 10*(7), 319-326.

Ktori, M., & Pitchford, N. J. (2008). Effect of orthographic transparency on letter position encoding: A comparison of Greek and English monoscriptal and biscriptal readers. *Language & Cognitive Processes*, 23, 258 – 281.

Kuhn, M. R., & Stahl, S. A. (2003). Fluency: A review of developmental and remedial practices. *Journal of Educational Psychology, 95*(1), 3-21.

Laganaro, M., Vacheresse, F., & Frauenfelder, U. H. (2002). Selective impairment of lexical stress assignment in Italian-speaking aphasic patient. *Brain and Language*, *81*, 601–609.

Lagerberg, R. (1999). *Stress and suffixation in modern Russian: The development of uniform syllable stress.* Nottingham: Astra Press.

Lee, T., & Mumford, D. (2003). Hierarchical Bayesian inference in the visual cortex. *Journal of the Optical Society of America*, 20, 1434–1448.

Leite, F., & Ratcliff, R. (2010). Modeling reaction time and accuracy of multiple-alternative decisions. *Attention, Perception, & Psychophysics, 72*(1), 246-273.

Levelt, W. J. M. (1989). *Speaking: From intention to articulation*. Cambridge, MA: MIT Press.

Levelt, W. J. M., Roelofs, A., & Meyer, A. S. (1999). A theory of lexical access in speech production. *Behavioral and Brain Sciences, 22,* 1-75.

Lukyanchenko, A., Idsardi, W. J., & Jiang, N. (2011). Opening your ears: The role of L1 in processing of nonnative prosodic contrasts. In G. Granena, J. Koeth, S. Lee-Ellis, A. Lukyanchenko, G. Prieto Botana, & E. Rhoades (Eds.), *Selected proceedings of the Second Language Research Forum 2010*. (pp. 50 – 62). Somerville, MA: Cascadilla Press.

Lyashevskaya, O. & Sharov, S. (2009). *The frequency dictionary of modern Russian language*. Moscow: Azbukovnik.

Ma, W., Beck, J., Latham, P., & Pouget, A. (2006). Bayesian inference with probabilistic population codes. *Nature Neuroscience*, 9(11), 1432–1438.

Marr, D. (2010). *Vision. A Computational Investigation into the Human Representation and Processing of Visual Information*. The MIT Press.

McRae, K., Spivey-Knowlton, M.J., & Tanenhaus, M.K. (1998). Modeling the influence of thematic fit (and other constraints) in on-line sentence comprehension. *Journal of Memory and Language,* 38, 283–312.

Mens, L. H., & Povel, D. (1986). Evidence against a predictive role for rhythm in speech perception. *The Quarterly Journal of Experimental Psychology A: Human Experimental Psychology, 38A*(2), 177-192.

Miceli, G., & Caramazza, A. (1993). The assignment of word stress in oral reading: Evidence from a case of acquired dyslexia. *Cognitive Neuropsychology*, *10*, 273–296.

Monsell, S., Doyle, M. C., & Haggard, P. N. (1989). Effects of frequency on visual word recognition tasks: Where are they? *Journal of Experimental Psychology: General*, *118*, 43 – 71.

Morris, J., Grainger, J., & Holcomb, P. J. (2008). An electrophysiological investigation of early effects of masked morphological priming. *Language and Cognitive Processes, 23*(7-8), 1021-1056.

Movellan, J.R. & Nelson, J.D. (2001). Probabilistic functionalism: a unifying paradigm for cognitive science. *Behavioral and Brain Sciences*, *24*(4), 690-692.

Najemnik, J., & Geisler, W. S. (2009). Simple summation rule for optimal fixation selection in visual search. *Vision Research, 49*(10), 1286-1294.

Norris, D. (2006). The Bayesian reader: Explaining word recognition as an optimal Bayesian decision process. *Psychological Review, 113*(2), 327-357.

Norris, D., & Kinoshita, S. (2008). Perception as evidence accumulation and Bayesian inference: Insights from masked priming. *Journal of Experimental Psychology: General, 137*(3), 434-455.

Norris, D., & McQueen, J. M. (2008). Shortlist B: A Bayesian model of continuous speech recognition. *Psychological Review, 115*(2), 357.

Norris, D., McQueen, J. M., & Cutler, A. (1995). Competition and segmentation in spoken-word recognition. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 21*(5), 1209-1228.

Paizi D., Zoccolotti P., & Burani C. (2011). Lexical stress assignment in Italian developmental dyslexia. *Reading and Writing*, 24, 443 - 461.

Perry, C., Ziegler, J. C., & Zorzi, M. (2010). Beyond single syllables: Large-scale modeling of reading aloud with the Connectionist Dual Process (CDP++) model. *Cognitive Psychology*, *61*(2), 106-151.

Peterson, C. R., & Beach, L. R. (1967). Man as an intuitive statistician. *Psychological Bulletin, 68*(1), 29-46.

Pitt, M. A., & Samuel, A. G. (1990). Attentional allocation during speech perception: How fine is the focus? *Journal of Memory and Language, 29*(5), 611-632.

Plaut, D. C., McClelland, J. L., Seidenberg, M. S., & Patterson, K. (1996). Understanding normal and impaired word reading: Computational principles in quasi-regular domains. *Psychological Review, 103*(1), 56-56.

Protopapas, A. (2006). On the usefulness of stress diacritics in reading Greek. *Reading and Writing*, *19*, 171–198.

Protopapas A. (2007). CheckVocal: A program to facilitate checking the accuracy and response time of vocal responses from DMDX. *Behavior Research Methods*, *39*(4), 859–862.

Protopapas, A., Gerakaki, S., & Alexandri, S. (2006). Lexical and default stress assignment in reading Greek. *Journal of Research in Reading*, 29(4), 418-432.

Rastle, K., & Coltheart, M. (2000). Lexical and nonlexical print-to-sound translation of disyllabic words and nonwords. *Journal of Memory and Language*, *42*, 342–364.

Ratcliff, R. (1978). A theory of memory retrieval. *Psychological Review*, 85, 59-108.

Ratcliff, R., & McKoon, G. (2008). The diffusion decision model: Theory and data for two-choice decision tasks. *Neural Computation*, 20, 873-922.

Ratcliff, R., & Starns, J. J. (2013). Modeling confidence judgments, response times, and multiple choices in decision making: Recognition memory and motion discrimination. *Psychological Review, 120*(3), 697-719.

Saffran, J. R. (2002). Constraints on statistical language learning. *Journal of Memory and Language, 47*(1), 172-196.

Saffran, J. R., Newport, E.L., & Aslin, R.N. (1996). Word segmentation: The role of distributional cues. *Journal of Memory and Language*, 35, 606–621.

Schiller, N,, Fikkert, P., & Levelt C. (2004). Stress priming in picture naming. *Brain and Language*, 90, 231-240.

Seidenberg, M. S., & MacDonald, M.C. (1999). A probabilistic constraints approach to language acquisition and processing. *Cognitive Science*, 23, 569–588.

Seidenberg, M.S., Waters, G., Barnes, M.A. & Tanenhaus, M.K. (1984). When does spelling sound regularity influence visual word recognition? *Journal of Verbal Leaning and Verbal Behavior*, 23, 383-404.

Seva, N., Monaghan, P., & Arciuli, J. (2009). Stressing what is important: Orthographic cues and lexical stress assignment. *Journal of Neurolinguistics*, 22, 237–249.

Sibley, D. E., Kello, C. T., & Seidenberg, M. S. (2010). Learning orthographic and phonological representations in models of monosyllabic and bisyllabic naming. *European Journal of Cognitive Psychology, 22*(5), 650-668.

Sulpizio, S., Arduino, L. S., Paizi, D., Burani, C. (2013). Stress assignment in reading Italian polysyllabic pseudowords. *Journal of Experimental Psychology: Learning, Memory, Cognition. 39*(1), 51 – 68.

Sulpizio, S., Job, R., & Burani, C. (2012). Priming lexical stress in reading Italian aloud. *Language and Cognitive Processes. 27*(6), 808 – 820.

Sulpizio, S., & McQueen, J. M. (2012). Italians use abstract knowledge about lexical stress during spoken-word recognition. *Journal of Memory and Language*, 66, 177-193.

Treiman, R., Mullenix, J., Bijeljac-Babic, R., & Richmond-Welty, E. D. (1995). The special role of rimes in the description, use, and acquisition of English orthography. *Journal of Experimental Psychology: General*, *124*, 107–136.

Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. *Science, 185*(4157), 1124-1131.

van Donselaar, W., Koster, M., & Cutler, A. (2005). Exploring the role of lexical stress in lexical recognition. *The Quarterly Journal of Experimental Psychology A: Human Experimental Psychology, 58A*(2), 251-273.

Vigliocco, G., Vinson, D.P., Arciuli, J., & Barber, H. (2008). The role of grammatical class on word recognition. *Brain and Language*, 105, 175 – 184.

Voss, A., Nagler, M., & Lerche, V. (in press). Diffusion models in experimental psychology: A practical introduction. *Experimental Psychology.*

Whalley, K., & Hansen, J. (2006). The role of prosodic sensitivity in children's reading development. *Journal of Research in Reading, 29*(3), 288-303.

Xu, F., & Tenenbaum, J. B. (2007). Word learning as bayesian inference. *Psychological Review, 114*(2), 245-272.

Yap, M. J., & Balota, D. A. (2009). Visual word recognition of multisyllabic words. *Journal of Memory and Language, 60*(4), 502-529.

Zacks, R. T., & Hasher, L. (2002). Frequency processing: A twenty-five year perspective. (pp. 21-36). In Zacks, R. T., & Hasher, L. (Eds) *Frequency processing and cognition*, New York, NY, US: Oxford University Press, New York, NY.

Zaliznyak, A. (2003). *The Dictionary of Russian Grammar*. Moscow: Prosvesheniye.

Zarva, M. (2001). *The Dictionary of Russian Lexical Stress*. Moscow: ENAS.

Zeno, S. M., Ivens, S. H., Millard, R. T., & Duvvuri, R. (1995). *The educator's word frequency guide*. Brewster, NY: Touchstone Applied Science Associates.

Zevin, J.D. & Balota, D.A. (2000). Priming and attentional control of lexical and sublexical pathways during naming. *Journal of Experimental Psychology: Learning, Memory, & Cognition*, 26, 121-135.

Zevin, J.D. & Joanisse, M. (2000). Stress assignment in nonword reading. *Journal of Cognitive Neuroscience, 41B*, S5.

Ziegler, J. C., & Goswami, U. C. (2005). Reading acquisition, developmental dyslexia and skilled reading across languages: A psycholinguistic grain size theory. *Psychological Bulletin, 131*(1), 3-29.

Appendices

Appendix A

Russian Disyllabic Words Used in Study 2

Adjectives:

Trochaic Stress:

Consistent: ВИДНОМ, ДИКОМ, ЖАДЕН, ТРУДЕН, КРАТКОМ, ЛЕВОМ, РЕЗКОМ, СЛАЩЕ, ТОЧЕН, ОСТРОМ, ЯСНОМ, БЕДЕН, ГЛАВНОМ, ЗЕЛЕН, ГОРДОМ, ЧЕСТЕН; *Inconsistent:* БАБКИН, ВЕСЕЛ, БЛИЗОК, ДЕРЗОК, ЖАЛОК, КРАТОК, КРЕПОК, МОЛОД, РОБОК, СЛАДОК, ТОНОК, УЗОК, ЯРОК, ГИБОК, ЧЁРТОВ, ВЯЗОК

Iambic Stress:

Consistent: КРАСИВ, НЕПРАВ, РЕВНИВ, ЗАЧАТ, ГОРБАТ, СУРОВ, СМЕШОН, ТРУСЛИВ, ТЯЖЁЛ, УНЫЛ, БОГАТ, БОЛТЛИВ, ВЫСОК, ЗАЖАТ, ГЛУБОК, ЕДИН; *Inconsistent:* ПЕЧНОЙ, УМНЫ, ЯСНА, БЫЛОМ, ЧУЖОМ, РАВНЫ, СВЕЖО, БЛАГИМ, ЖИЛОМ, ЗАБИТ, ГУСТОМ, ДУРНА, ЗЕМНОМ, КРУТОМ, ЛЕГКИ, КРУТОМ

Nouns:

Trochaic Stress:

Consistent: ВАЛЬСЫ, ВЕКОМ, КРОВЛИ, КРЕМОМ, МИСКИ, ЖАНРОМ, СЛОГА, ТЕСТЯ, АКЦИЙ, ЯВКИ, РУСЛОМ, БАСНЮ, БЛАНКИ, ВАЛОМ, ГАЙКИ, ЧУКЧИ; *Inconsistent:* ОТРОК, ЯДОВ, ГРАМОТ, ГАДОВ, ЧЕХОВ, ЛИФТОВ, МАСОК, РЫБИН, СВОДОВ, ПОШЛИН, ВЕТОК, ВЫПЛАТ, БЕСОВ, ЖЕСТОВ, КРЕСЕЛ, ПРИСТАВ

Iambic Stress:

Consistent: ЗАБАВ, БОРОД, ГЛУБИН, БЫЛИН, ЧИНОВ, ДЕВЧАТ, ЖИДОВ, ЗАСТАВ, ПРУЖИН, КРУЖКОВ, ЛОПАТ, МОРЩИН, СТАНКОВ, КАБИН, ОВЕЦ, ЮНЦОВ; *Inconsistent:* ВЕРХИ, ЯДРОМ, БАШКЕ, ГЕРБОМ, ЧУЛКИ, ЛОТКИ, МЕШКИ, СТАНКА, ТИСКИ, ИСТЦОМ, ДВОРЫ, ВОЗНИ, ДУБЫ, ЖИЛЬЦА, КРЮЧКИ, КРЫЛОМ

Verbs:

Trochaic Stress:

Consistent: КРУТЯТ, ЛЕЗЛО, ЛЯЖЕШЬ, СБИЛИ, ПОМНИ, АХНУЛ, ЕЗДЯТ, БИЛО, ГОНЯТ, ГРЫЗЛО, ЧУЕШЬ, ВЫЙДИ, ВАЛЯТ, БУРКНЕШЬ, ЖАРЯТ, КЛАЛИ; *Inconsistent:* ЕЗДИЛ, ГИБНЕТ, ВЫПЕЙ, ДЛИЛИСЬ, ЧИСТИЛ, ВЕДАЛ, ВОЮТ, ДУШАТ, ЖАЖДЕТ, ПРЫГАЛ, КЛЮНУТЬ, НЮХАЛ, МЕЧЕТ, СНИМЕТ, ТОПАЛ, АХАЛ

Iambic Stress:

Consistent: ЯВИТЬ, ГАДАЛ, БРОСАЛ, ГОСТИЛ, ЧИНИЛ, МОЛИЛ, РЕВЕЛ, СТИРАЛ, ТОРЧАТ, УБРАЛ, ЗАДЕЛ, ВИЗЖАЛ, БЕРЕЧЬ, ЗАБИЛ, ТРЕЩАЛ, ПРОЩАЛ; *Inconsistent:* ВЕЗЛИ, БУДИ, ВЕЛЯТ, КЛАДИ, ВИНЯТ, ПЛЕСТИ, ЛЕГЛО, МАНИ, СНЕСТИ, ИКНУЛ, ПОЛЗТИ, ЮЛИТ, БОМБЯТ, ГОРЯТ, БЛЮСТИ, ЦАРИТ

Appendix B

Russian Disyllabic Words Used As Stimuli in Pilot Experiment Of Study 3

АКТЁР, БАСНИ, БАШМАК, БЕДРУ, БОДРОСТЬ, БУБЛИК, БУГРОМ, БУДНИ, БУКЛЕТ, БЫСТРОЙ, ВЕДРУ, ВЕКТОР, ВЕСНА, ВЕТРЕ, ВИСКОВ, ВИТРАЖ, ВИХРИ, ВИШНЯ, ВМЕСТО, ВОБЛА, ВОЖДЕЙ, ВОСТОК, ВОСКОМ, ГВОЗДЯ, ГЕКТАР, ГИПСА, ГНЕЗДЕ, ГОСТЯМ, ГУСЛЯР, ДЕСПОТ, ДИКТАТ, ДИСКЕ, ДОБРОМ, ДОЖДИ, ДОСКА, ДУБЛЯЖ, ДУПЛО, ЕВРЕЙ, ЕЗДИЛ, ЖАЖДЕТ, ЖЕСТОВ, ЗАВТРА, ЗВЕЗДЕ, ИГРАТЬ, ИГЛА, ИЗВЕРГ, ИСЛАМ, ИСКРА, КАДРЫ, КАЖДЫЙ, КАЗНА, КАКТУС, КАПЛЮ, КАСКИ, КАШЛЯЛ, КЕДРА, КИСЛО, КОБРА, КОВРОМ, КОЗЛЫ, КОПНЫ, КОСТЕЙ, КОТЛЕТ, КУКЛЫ, ЛАВКУ, ЛИСТОМ, ЛОВКОСТЬ, МАГНИТ, МАСКИ, МАТРОС, МЕТРАХ, МЕШКАТЬ, МИКСЕР, МОКРЫЙ, МУДРЫХ, МУСКАТ, НЕГРЫ, НИТРАТ, ОКТЯБРЬ, ОСТРЯК, ПАТРОН, ПЕСКОВ, ПЁСТРЫЙ, ПИНГВИН, ПРОСПЕКТ, ПУДРА, РЕФРЕН, РЕЗВЫЙ, САБЛЯ, СВИСТОМ, СМОТРИ, СПАЗМЫ, ТАБЛИЦ, ТЕСТЯ, УГЛОМ, ФАКТОМ, ХВОСТЫ, ХРАБРОСТЬ, ЯБЛОНЬ, ЭСКИЗ

Appendix C

Russian Disyllabic Words Used As Stimuli in Study 4

КРАЁВ, СДАЮТ, ЗАБАВ, КАБИН, ЧАБАН, АГАТ, ЗАЖАТ, САЖАЛ, НАЙДЁТ, ТАЛОН, АЛЬБОМ, КАНАВ, КАНАТ, ЦАРИТ, ЗАСАД, КРАСИВ, РАСПАД, ФАСОН, ЗАСТАЛ, КАСТЕТ, ФАШИЗМ, ДЕВЧАТ, ПЛЕВАЛ, БЕГЛЕЦ, ВЕДЁТ, ШЕДЕВР, ТЕЛЕЦ, БЕЛЬЯ, БЕРЕЧЬ, БЕРЁШЬ, ВЕРШАТ, СВЕРЛИТЬ, ПЕСКОВ, ЦВЕТКИ, ЖРЕЦОВ, ПЕЧАЛЬ, ТРЕЩАЛ, КЛИЕНТ, СИЯТЬ, ПРИБРАТЬ, ПИВКО, КИДАЛ, ЛИЗНУТЬ, ДЛИНУ, ИНЫМ, ПИНАТЬ, ЧИНИЛ, ШИПЕЛ, ПИРАТ, СТИРАЛ, ИСТЦОМ, ЦИТАТ, ЛИЦЕЙ, ПРИЧУД, КИШКА, ГРОБНИЦ, СОДРАТЬ, ВОЖДЮ, ДОЖДЕ, КОЛЁС, ПРОЛИВ, СТВОЛЫ, ТОЛЧКИ, БОЛТЛИВ, БЛОНДИН, МОНТАЖ, ВОРЧУН, ГОРЯТ, ДВОРЦЕ, МОРЩИН, ГОРБАТ, КОРСЕТ, БРОСАЛ, ПРОСПЕКТ, ГОСТИЛ, КОСТРОВ, МОТАЛ, ОТЁК, ОТЧЁТ, БРОШЮР, ВУАЛЬ, ДУБРАВ, УБРАЛ, УГАР, ЛУЖОК, ПРУЖИН, ЧУЖОМ, РУКОЙ, ЧУЛАН, УНЫЛ, КУПАТЬ, ЖУРЧАТ, ТРУСЛИВ, ГРУСТИТЬ, СУСТАВ, КРЫЛОМ, РЫЧАГ, РЫЧАТ, СМЫЧОК, ЭТАП, ЮНЦОВ, ПЛЯСАЛ, СТРЯХНУТЬ, МЯЧОМ, ТЕРПЛЮ, ЗВЕРЬЁ, КРИВЫХ, РОДИТЬ, ПОЛЗТИ, КОНТРАКТ, ПОПЕТЬ, ТРУДОВ, ДРУЖИТЬ, ПУТЕЙ, РАЗГУЛ, СКАЛА, ЗАПОР, ЗАСТЫЛ, ЛЕЖИТ, ТЕРЯТЬ, ВЕСТЕЙ, СМЕШНА, ЛИСТУ, ВОЗВРАТ, КОЛЕЦ, МОЛИЛ, ПРОЛЕЗТЬ, ТОННЕЛЬ, ЖОНГЛЁР, ГЛОТОК, ОТЦЫ, СУМЕЛ, МЫЧАТ, КЛЮЧА, ГАЗЕТ, РВАНУЛ, ЖАРА, СПАСТИСЬ, ДЕБОШ, СЛЕЗАЙ, НЕПРАВ, ДЕФЕКТ, СПЕШИЛ, ВИЗЖАЛ, ОГНЁМ, СМОЛЧАТЬ, КОТЛЫ, ЖУЮТ, ГУБАМ, КУРИ, ГЛУХОЙ, БРАЛА, АНТЕНН, РЕДИС, СЕДЛО, СБЕЖАТЬ, СТРЕЛОК,

МЕСИТЬ, ВЗИРАТЬ, ЛИЦЕ, ВОЙНОЙ, ГОНЕЦ, ВОПИЛ, КОПНА, БОРЦА, ГЛУБИН, ШУМОК, СУРОВ, ЮЛИТ, РАВНИН, ВРЕДИТЬ, БРЕЗЕНТ, РЕМНЁМ, СЛЕПЫМ, ВЕСАМ, СТОЛА, ПУГАЛ, СКЛАДНОЙ, КАТКОВ, ЕДЕ, ДОБРОМ, ПОДВОД, ХОЛОП, БАГОР, КОРА, ЯДРОМ, КАЗНЕ, КРАСЕ, ЕДИН, ПЛЕСТИ, ЖИЛОМ, ЗАЧАТ, СТРАШНЫ, ИМАМ, РАВНЫ, ПОЛОС, ОРУ, КРУТОМ, ЗЕРНЕ, ЖИЛА, СТОПАМ, ВОЛХВЫ, ПЛОТУ, ЗВОНИШЬ, СОСКИ, МУКЕ, ЯСНА, СТАНКА, СОНЕТ, ИСКРА, ВИРШИ, МОРДВЫ, ЛОТКИ, МЫСОК, МАНИ, ПОРТЫ, ВЕЛОСЬ, ЛИФТОВ, КОЛИ, ДЕЛИ, ДЕНЩИК, ОТРОК, СТРОЁВ, СЛОГА, БАЛАХ, ГЕРБОМ, ЛЕСУ, СПИНЫ, БОРОД, УГЛИ, СКЛАДУ, ПОЛКУ, ХЛОПОК, ЧАСА, АХАЛ, КОПНЫ, УХЕ, ИРОД, ГОНЯТ, СХВАТИТ, ПРИСТАВ, ГВОЗДИК, РОСЧЕРК, ВЕДАЛ, ГИБОК, СТИЛЮ, ТОПАЛ, РОЩУ, ТУШИ, ГРЫЗЛО, КЛЕТОК, ПЛАТНОМ, СТАТУЙ, ДОЛЖНЫМ, ПУХУ, ПРОВОД, САРЖА, СКВЕРНЫ, ПОШЛОЙ, ПЛЯСКИ, ВАЛЯТ, САМЫХ, ДАРИТ, НИЩЕЙ, ВОИН, ЛОБНОМ, ДОМУ, ПОШЛИН, ТОЩЕЙ, СУМА, ПЯТОМ, МАЗАЛ, ФРАЗА, КАПЛЮ, ПАРТЫ, ХАТЕ, ВЛЕЗЛИ, ВЕКОМ, СЕЛЬСКОЙ, СЦЕНОЙ, ПШЁННЫЙ, КРЕСЕЛ, МЕХОМ, ЧЕХОВ, БЛИЗОК, ВЗВОДЕ, РОДА, КОЙКАХ, ТРОЙКА, СКРОМНОЙ, НОСИШЬ, ДОСКУ, ОТРАСЛЬ, ГРУБОЙ, ГРУДУ, СКУЛЕ, КРУТЯТ, РУХЛЯДЬ, МЫСА, СЛЫШАЛ, БАБЬЕЙ, ВПАЛА, МАССЕ, СТРАСТНЫХ, БЕДЕН, СРЕДНЕ, СДЕЛАЛ, ВЕЧНЫМ, ГНИЛИ, МИЛО, ВВОДИТ, РОКА, ТОМЫ, ТОНУТ, ЩУКИ, ТРУПУ, ШКУРКИ, ВЗЯТКИ, ЖАДЕН, ДРАЛИ, ПАРА, БЕГЛО, ВЕРНЫХ, ИГРЫ, ХИЛЫЙ, ЛИСТЬЯ, СТОЕК, МОЩНЫМ, МУЖЕМ, УЗКИХ, СЫРОМ, СТЫЧКА, ТЯЖБА, СВЯЗЯХ, ЛАЯТЬ, ГРАБЛИ, ГЛАВНОМ, ДАВШИЙ, РАВЕН, ТРАВЛЯ, ЛАДНО, СТАДИЙ, СВАДЬБЕ,

ВЛАЖНОЙ, ЖАЖДЕТ, ПРАЗДНИК, ЗАЙЦЕВ, ГАЙКИ, АКЦИЙ, ПЛАКАЛ, ЖАЛКИ, ЗАЛПЫ, МАЛЬЧИК, ПАЛЬМА, ГРАМОТ, МАМИН, РАМКА, ШРАМОМ, ЛАНДЫШ, БЛАНКИ, СТРАННЫМ, БАНТИК, ШАПКАХ, ЖАРЯТ, БАРЖИ, ПАСХЕ, КАСКИ, ЧАСТО, КРАТОК, КРАТКОМ, ТРАТА, ХВАТКОЙ, ДАЧЕЙ, ПЛАЧА, БАШНЯ, СЛАЩЕ, НЕБА, ЛЕВОМ, БРЁВНА, ДЁГОТЬ, БЕДНОСТЬ, МЁДА, РЕЖУ, СВЕЖЫХ, ЛЕЗЛО, ГРЁЗЫ, ЕЗДИЛ, ЕЗДЯТ, ЗВЁЗДАХ, РЕЙСЫ, СМЕЛЫХ, ЦЕЛОСТЬ, ЖЁЛТЫМ, БРЕМЯ, ЦЕННОСТЬ, ЖЕНСКИХ, ЛЕНТЫ, ЦЕПЬЮ, ВЕРЕН, ДЕРЗОК, МЕРА, СЕРА, СЕРБЫ, ДЕРЖИМ, ЧЁРТОВ, КРЕСЛЕ, ПЕСЕН, ВСПЛЕСКИ, ЧЕСТЕН, СВЕТСКИЙ, ШЕФОМ, ВИДНОМ, КНИЖКАХ, СНИЗИТ, ВСКРИКНУЛ, ФИЛЬМОМ, ЗРИМЫЙ, ЛЬДИНУ, ПРИНЦЫ, ЛИРИК, МИСКИ, СПИСКАМ, МИСТЕР, ЧИСТИЛ, БИТЫХ, НИТКЕ, ПЛИТКИ, РИТМОМ, БИТЬСЯ, ПТИЧКИ, ВИШНИ, ПРОБКЕ, РОБКИМ, КОВРИК, ПОВОД, БРОДИМ, ВОДНОМ, ВХОДОМ, ЛОДКУ, СОДА, СХОДЯТ, ДРОЖЖИ, КОЖЕЙ, ПОЗЫ, СТРОЙНОСТЬ, СРОКИ, МОЛОД, ДОЛЛАР, ГРОМОМ, ЛОМОМ, ПОМНИ, ТОННА, ТОНОК, ОПЫТ, СТВОРКИ, СПОРТА, СНОСНО, ВОСКОМ, ПРОСЬБЕ, КРОТОСТЬ, СОТНИ, СМОТРИШЬ, ВЗДОХОВ, ТОЧКА, БУДНИ, СЛУЖАТ, ГРУЗНЫЙ, БУЛКА, СТУЛА, ТКНУЛА, ДУМА, ПУНКТАМ, ХМУРЫМ, КУРТКА, ВКУСНО, МУТНОЙ, СКУЧНОМ, ШТУЧКИ, ПУШКЕ, РЫБИН, ВЗРЫВУ, ССЫЛКА, ВЫПЛАТ, ВЫПЕЙ, ВЫПИВ, СЫТНЫЙ, ВЫШКА, КРЫШАМ, ПЫШНО, КЛЮНУТЬ, НЮХАЛ, ВЯЗКИЙ, СНЯЛИ, ПРЯНЫЙ, ДРЯНЬЮ, МЯСА, ЗЯТЯ, КЛЯЧА, ПРЯЧЕШЬ, ПЕЧАТЬ

Appendix D

Russian Disyllabic Words Used in Study 5

Actual Stress refers to the stress pattern that a word has in the language (1 = trochaic stress; 2 = iambic stress). Predicted Stress refers to the stress pattern that the Bayesian model of stress assignment predicted for a word (1 = trochaic stress; 2 = iambic stress; 0 = no conclusive prediction is made). Assigned Stress1 refers to the proportion of answers with trochaic stress given by participants. Predicted Stress1 refers to the proportion of answers with trochaic stress predicted by the model. Assigned Stress2 refers to the proportion of answers with iambic stress given by participants. Predicted Stress2 refers to the proportion of answers with iambic stress predicted by the model. Degree of Uncertainty refers to the strength of the belief that a factual stress pattern is the correct one as estimated by the model (0 = complete belief; 1 = complete disbelief). Error rate refers to the proportion of responses with incorrect stress being assigned to a word.

Word	Actual Stress (Predicted Stress)	Assigned Stress1 (Predicted Stress1)	Assigned Stress2 (Predicted Stress2)	Degree of Uncertainty	Error Rate
сводный	1 (1)	0.97 (1.00)	0.03 (0.00)	0.00	0.03
местный	1 (1)	1.00 (1.00)	0.00 (0.00)	0.00	0.00
судный	1 (1)	1.00 (1.00)	0.00 (0.00)	0.00	0.00
бранный	1 (1)	1.00 (1.00)	0.00 (0.00)	0.00	0.00
рослый	1 (1)	1.00 (1.00)	0.00 (0.00)	0.00	0.00
точность	1 (1)	1.00 (1.00)	0.00 (0.00)	0.00	0.00
людный	1 (1)	1.00 (1.00)	0.00 (0.00)	0.00	0.00
праздность	1 (1)	1.00 (1.00)	0.00 (0.00)	0.00	0.00
зоркость	1 (1)	1.00 (1.00)	0.00 (0.00)	0.00	0.00
ловкость	1 (1)	1.00 (1.00)	0.00 (0.00)	0.00	0.00
разный	1 (1)	1.00 (1.00)	0.00 (0.00)	0.00	0.00
дюжий	1 (1)	1.00 (1.00)	0.00 (0.00)	0.00	0.00
синий	1 (1)	1.00 (1.00)	0.00 (0.00)	0.00	0.00
стержнем	1 (1)	1.00 (1.00)	0.00 (0.00)	0.00	0.00

буркнешь	1 (1)	1.00 (0.99)	0.00 (0.01)	0.01	0.00
классом	1 (1)	1.00 (0.99)	0.00 (0.01)	0.01	0.00
ляжешь	1 (1)	1.00 (0.99)	0.00 (0.01)	0.01	0.00
русских	1 (1)	1.00 (0.99)	0.00 (0.01)	0.01	0.00
гулко	1 (1)	1.00 (0.99)	0.00 (0.01)	0.01	0.00
вышлет	1 (1)	0.97 (0.99)	0.03 (0.01)	0.01	0.03
тусклых	1 (1)	1.00 (0.99)	0.00 (0.01)	0.01	0.00
кончик	1 (1)	1.00 (0.98)	0.00 (0.02)	0.02	0.00
прочных	1 (1)	1.00 (0.98)	0.00 (0.02)	0.02	0.00
бункер	1 (1)	0.97 (0.98)	0.03 (0.02)	0.02	0.03
дивных	1 (1)	1.00 (0.98)	0.00 (0.02)	0.02	0.00
пачкой	1 (1)	0.91 (0.98)	0.09 (0.02)	0.02	0.09
внятно	1 (1)	1.00 (0.98)	0.00 (0.02)	0.02	0.00
твёрдом	1 (1)	0.91 (0.98)	0.09 (0.02)	0.02	0.09
дамских	1 (1)	1.00 (0.98)	0.00 (0.02)	0.02	0.00
риска	1 (1)	1.00 (0.97)	0.00 (0.03)	0.03	0.00
ложки	1 (1)	1.00 (0.97)	0.00 (0.03)	0.03	0.00
жирном	1 (1)	1.00 (0.97)	0.00 (0.03)	0.03	0.00
правом	1 (1)	1.00 (0.97)	0.00 (0.03)	0.03	0.00
строчку	1 (1)	1.00 (0.97)	0.00 (0.03)	0.03	0.00
встречных	1 (1)	1.00 (0.97)	0.00 (0.03)	0.03	0.00
устных	1 (1)	0.97 (0.97)	0.03 (0.03)	0.03	0.03
хрупкой	1 (1)	1.00 (0.97)	0.00 (0.03)	0.03	0.00
флангом	1 (1)	1.00 (0.97)	0.00 (0.03)	0.03	0.00
стенку	1 (1)	1.00 (0.97)	0.00 (0.03)	0.03	0.00
младшим	1 (1)	1.00 (0.97)	0.00 (0.03)	0.03	0.00
мрачным	1 (1)	1.00 (0.97)	0.00 (0.03)	0.03	0.00
чашек	1 (1)	1.00 (0.97)	0.00 (0.03)	0.03	0.00
пачек	1 (1)	1.00 (0.96)	0.00 (0.04)	0.04	0.00
южном	1 (1)	1.00 (0.96)	0.00 (0.04)	0.04	0.00
внучек	1 (1)	0.74 (0.96)	0.26 (0.04)	0.04	0.26
лунки	1 (1)	0.91 (0.96)	0.09 (0.04)	0.04	0.09
квасом	1 (1)	1.00 (0.96)	0.00 (0.04)	0.04	0.00
ясном	1 (1)	1.00 (0.96)	0.00 (0.04)	0.04	0.00
бабкин	1 (1)	1.00 (0.96)	0.00 (0.04)	0.04	0.00
блюдом	1 (1)	0.91 (0.96)	0.09 (0.04)	0.04	0.09
кровли	1 (1)	1.00 (0.96)	0.00 (0.04)	0.04	0.00
руслом	1 (1)	0.94 (0.96)	0.06 (0.04)	0.04	0.06
гибнет	1 (1)	1.00 (0.96)	0.00 (0.04)	0.04	0.00
брался	1 (1)	1.00 (0.96)	0.00 (0.04)	0.04	0.00
клялся	1 (1)	0.97 (0.96)	0.03 (0.04)	0.04	0.03

шляться	1 (1)	1.00 (0.96)	0.00 (0.04)	0.04	0.00
ставишь	1 (1)	0.94 (0.95)	0.06 (0.05)	0.05	0.06
щепка	1 (1)	0.91 (0.95)	0.09 (0.05)	0.05	0.09
сжаты	1 (1)	1.00 (0.95)	0.00 (0.05)	0.05	0.00
внешне	1 (1)	1.00 (0.95)	0.00 (0.05)	0.05	0.00
танка	1 (1)	0.97 (0.95)	0.03 (0.05)	0.05	0.03
сложных	1 (1)	1.00 (0.95)	0.00 (0.05)	0.05	0.00
ищем	1 (1)	1.00 (0.94)	0.00 (0.06)	0.06	0.00
свечкой	1 (1)	1.00 (0.94)	0.00 (0.06)	0.06	0.00
смете	1 (1)	0.91 (0.94)	0.09 (0.06)	0.06	0.09
старта	1 (1)	1.00 (0.94)	0.00 (0.06)	0.06	0.00
мачта	1 (1)	1.00 (0.94)	0.00 (0.06)	0.06	0.00
сферах	1 (1)	0.91 (0.94)	0.09 (0.06)	0.06	0.09
дует	1 (1)	0.88 (0.94)	0.12 (0.06)	0.06	0.12
кухня	1 (1)	1.00 (0.93)	0.00 (0.07)	0.07	0.00
фирмы	1 (1)	0.97 (0.93)	0.03 (0.07)	0.07	0.03
божьих	1 (1)	1.00 (0.93)	0.00 (0.07)	0.07	0.00
кочки	1 (1)	1.00 (0.93)	0.00 (0.07)	0.07	0.00
спички	1 (1)	1.00 (0.93)	0.00 (0.07)	0.07	0.00
важен	1 (1)	1.00 (0.93)	0.00 (0.07)	0.07	0.00
стало	1 (1)	1.00 (0.93)	0.00 (0.07)	0.07	0.00
съезда	1 (1)	0.91 (0.93)	0.09 (0.07)	0.07	0.09
хлама	1 (1)	0.94 (0.93)	0.06 (0.07)	0.07	0.06
знатной	1 (1)	0.88 (0.92)	0.12 (0.08)	0.08	0.12
резком	1 (1)	1.00 (0.92)	0.00 (0.08)	0.08	0.00
братстве	1 (1)	0.88 (0.92)	0.12 (0.08)	0.08	0.12
темпом	1 (1)	0.91 (0.92)	0.09 (0.08)	0.08	0.09
вылет	1 (1)	1.00 (0.92)	0.00 (0.08)	0.08	0.00
дырки	1 (1)	1.00 (0.92)	0.00 (0.08)	0.08	0.00
пешку	1 (1)	0.91 (0.92)	0.09 (0.08)	0.08	0.09
чуешь	1 (1)	1.00 (0.91)	0.00 (0.09)	0.09	0.00
босса	1 (1)	0.94 (0.91)	0.06 (0.09)	0.09	0.06
кисло	1 (1)	1.00 (0.91)	0.00 (0.09)	0.09	0.00
нервам	1 (1)	1.00 (0.91)	0.00 (0.09)	0.09	0.00
шторы	1 (1)	1.00 (0.91)	0.00 (0.09)	0.09	0.00
точен	1 (1)	1.00 (0.91)	0.00 (0.09)	0.09	0.00
шутке	1 (1)	1.00 (0.91)	0.00 (0.09)	0.09	0.00
взносы	1 (1)	1.00 (0.91)	0.00 (0.09)	0.09	0.00
жанром	1 (1)	1.00 (0.91)	0.00 (0.09)	0.09	0.00
фронте	1 (1)	0.91 (0.91)	0.09 (0.09)	0.09	0.09
лапа	1 (1)	1.00 (0.90)	0.00 (0.10)	0.10	0.00

фонде	1 (1)	0.88 (0.90)	0.12 (0.10)	0.10	0.12
членам	1 (1)	0.91 (0.90)	0.09 (0.10)	0.10	0.09
школой	1 (1)	0.94 (0.90)	0.06 (0.10)	0.10	0.06
тестя	1 (1)	0.97 (0.90)	0.03 (0.10)	0.10	0.03
почве	1 (1)	1.00 (0.90)	0.00 (0.10)	0.10	0.00
прежней	1 (1)	0.97 (0.90)	0.03 (0.10)	0.10	0.03
труден	1 (1)	0.97 (0.89)	0.03 (0.11)	0.11	0.03
йоги	1 (1)	1.00 (0.89)	0.00 (0.11)	0.11	0.00
гордом	1 (1)	0.97 (0.89)	0.03 (0.11)	0.11	0.03
явки	1 (1)	0.97 (0.89)	0.03 (0.11)	0.11	0.03
склонны	1 (1)	1.00 (0.89)	0.00 (0.11)	0.11	0.00
спорах	1 (1)	1.00 (0.89)	0.00 (0.11)	0.11	0.00
тигры	1 (1)	1.00 (0.89)	0.00 (0.11)	0.11	0.00
мышцу	1 (1)	0.82 (0.89)	0.18 (0.11)	0.11	0.18
знаком*	1 (1)	0.85 (0.89)	0.15 (0.11)	0.11	0.15
губка	1 (1)	1.00 (0.88)	0.00 (0.12)	0.12	0.00
клином	1 (1)	0.97 (0.88)	0.03 (0.12)	0.12	0.03
здешней	1 (1)	1.00 (0.88)	0.00 (0.12)	0.12	0.00
некой	1 (1)	0.85 (0.88)	0.15 (0.12)	0.12	0.15
шёлком	1 (1)	0.91 (0.88)	0.09 (0.12)	0.12	0.09
низки*	1 (1)	0.74 (0.88)	0.26 (0.12)	0.12	0.26
казус	1 (1)	0.97 (0.88)	0.03 (0.12)	0.12	0.03
секта	1 (1)	1.00 (0.88)	0.00 (0.12)	0.12	0.00
скопом	1 (1)	0.85 (0.88)	0.15 (0.12)	0.12	0.15
било	1 (1)	1.00 (0.87)	0.00 (0.13)	0.13	0.00
спазмы	1 (1)	1.00 (0.87)	0.00 (0.13)	0.13	0.00
шашки	1 (1)	0.97 (0.87)	0.03 (0.13)	0.13	0.03
зёрен	1 (1)	1.00 (0.87)	0.00 (0.13)	0.13	0.00
дрогнет	1 (1)	1.00 (0.87)	0.00 (0.13)	0.13	0.00
окрик	1 (1)	0.94 (0.87)	0.06 (0.13)	0.13	0.06
парке	1 (1)	0.94 (0.86)	0.06 (0.14)	0.14	0.06
скачет	1 (1)	0.97 (0.86)	0.03 (0.14)	0.14	0.03
ножны	1 (1)	1.00 (0.86)	0.00 (0.14)	0.14	0.00
выйди	1 (1)	1.00 (0.86)	0.00 (0.14)	0.14	0.00
ждало	1 (1)	0.59 (0.85)	0.41 (0.15)	0.15	0.41
прессы	1 (1)	1.00 (0.85)	0.00 (0.15)	0.15	0.00
банда	1 (1)	1.00 (0.85)	0.00 (0.15)	0.15	0.00
валим	1 (1)	0.94 (0.85)	0.06 (0.15)	0.15	0.06
дали*	1 (1)	0.91 (0.85)	0.09 (0.15)	0.15	0.09
выжил	1 (1)	1.00 (0.85)	0.00 (0.15)	0.15	0.00
мечет	1 (1)	0.76 (0.84)	0.24 (0.16)	0.16	0.24

ведьму	1 (1)	1.00 (0.84)	0.00 (0.16)	0.16	0.00
номер	1 (1)	1.00 (0.84)	0.00 (0.16)	0.16	0.00
вольной	1 (1)	0.85 (0.84)	0.15 (0.16)	0.16	0.15
клубом	1 (1)	0.97 (0.84)	0.03 (0.16)	0.16	0.03
цапля	1 (1)	1.00 (0.84)	0.00 (0.16)	0.16	0.00
ветра*	1 (1)	0.76 (0.84)	0.24 (0.16)	0.16	0.24
ручка	1 (1)	1.00 (0.84)	0.00 (0.16)	0.16	0.00
сварка	1 (1)	1.00 (0.84)	0.00 (0.16)	0.16	0.00
лыжи	1 (1)	1.00 (0.83)	0.00 (0.17)	0.17	0.00
чукчи	1 (1)	1.00 (0.82)	0.00 (0.18)	0.18	0.00
рожа	1 (1)	1.00 (0.81)	0.00 (0.19)	0.19	0.00
схожесть	1 (1)	1.00 (0.81)	0.00 (0.19)	0.19	0.00
речке	1 (1)	1.00 (0.81)	0.00 (0.19)	0.19	0.00
спросу	1 (1)	0.88 (0.80)	0.12 (0.20)	0.20	0.12
эра	1 (1)	1.00 (0.80)	0.00 (0.20)	0.20	0.00
муха	1 (1)	1.00 (0.80)	0.00 (0.20)	0.20	0.00
чека*	1 (1)	0.65 (0.80)	0.35 (0.20)	0.20	0.35
ахнул	1 (1)	0.97 (0.79)	0.03 (0.21)	0.21	0.03
клали	1 (1)	0.88 (0.79)	0.12 (0.21)	0.21	0.12
чая	1 (1)	1.00 (0.78)	0.00 (0.22)	0.22	0.00
фаза	1 (1)	1.00 (0.78)	0.00 (0.22)	0.22	0.00
паром*	1 (1)	0.82 (0.78)	0.18 (0.22)	0.22	0.18
долге	1 (1)	0.88 (0.77)	0.12 (0.23)	0.23	0.12
грызла	1 (1)	1.00 (0.77)	0.00 (0.23)	0.23	0.00
маслу	1 (1)	0.91 (0.77)	0.09 (0.23)	0.23	0.09
строгим	1 (1)	1.00 (0.77)	0.00 (0.23)	0.23	0.00
края*	1 (1)	0.56 (0.77)	0.44 (0.23)	0.23	0.44
сучья	1 (1)	0.91 (0.77)	0.09 (0.23)	0.23	0.09
кукиш	1 (1)	1.00 (0.77)	0.00 (0.23)	0.23	0.00
мылом	1 (1)	1.00 (0.77)	0.00 (0.23)	0.23	0.00
диком	1 (1)	0.97 (0.76)	0.03 (0.24)	0.24	0.03
остром	1 (1)	0.85 (0.76)	0.15 (0.24)	0.24	0.15
валом	1 (1)	0.97 (0.76)	0.03 (0.24)	0.24	0.03
сизым	1 (1)	0.76 (0.76)	0.24 (0.24)	0.24	0.24
звукам	1 (1)	1.00 (0.76)	0.00 (0.24)	0.24	0.00
кремом	1 (1)	1.00 (0.76)	0.00 (0.24)	0.24	0.00
горной	1 (1)	1.00 (0.76)	0.00 (0.24)	0.24	0.00
горле	1 (1)	0.85 (0.76)	0.15 (0.24)	0.24	0.15
виллы	1 (1)	0.97 (0.76)	0.03 (0.24)	0.24	0.03
гнева	1 (1)	1.00 (0.75)	0.00 (0.25)	0.25	0.00
вече	1 (1)	0.91 (0.75)	0.09 (0.25)	0.25	0.09

скажут	1 (1)	0.97 (0.74)	0.03 (0.26)	0.26	0.03
толща	1 (1)	0.82 (0.74)	0.18 (0.26)	0.26	0.18
конном	1 (1)	0.82 (0.73)	0.18 (0.27)	0.27	0.18
символ	1 (1)	1.00 (0.73)	0.00 (0.27)	0.27	0.00
тура	1 (1)	0.74 (0.73)	0.26 (0.27)	0.27	0.26
храмом	1 (1)	1.00 (0.73)	0.00 (0.27)	0.27	0.00
базой	1 (1)	0.82 (0.73)	0.18 (0.27)	0.27	0.18
трону	1 (1)	1.00 (0.73)	0.00 (0.27)	0.27	0.00
сбили	1 (1)	1.00 (0.72)	0.00 (0.28)	0.28	0.00
реже	1 (1)	1.00 (0.72)	0.00 (0.28)	0.28	0.00
клала	1 (1)	0.47 (0.72)	0.53 (0.28)	0.28	0.53
матчей	1 (1)	0.97 (0.71)	0.03 (0.29)	0.29	0.03
вязок	1 (1)	0.94 (0.71)	0.06 (0.29)	0.29	0.06
шарфом	1 (1)	0.53 (0.70)	0.47 (0.30)	0.30	0.47
дверцы	1 (1)	1.00 (0.70)	0.00 (0.30)	0.30	0.00
дымом	1 (1)	1.00 (0.70)	0.00 (0.30)	0.30	0.00
цену	1 (1)	1.00 (0.69)	0.00 (0.31)	0.31	0.00
стоят*	1 (1)	0.65 (0.69)	0.35 (0.31)	0.31	0.35
пуска	1 (1)	0.82 (0.69)	0.18 (0.31)	0.31	0.18
года*	1 (1)	0.56 (0.68)	0.44 (0.32)	0.32	0.44
цвета*	1 (1)	0.50 (0.68)	0.50 (0.32)	0.32	0.50
ядов	1 (1)	0.85 (0.67)	0.15 (0.33)	0.33	0.15
сопли*	1 (1)	0.97 (0.67)	0.03 (0.33)	0.33	0.03
деле	1 (1)	1.00 (0.67)	0.00 (0.33)	0.33	0.00
дую	1 (1)	0.91 (0.67)	0.09 (0.33)	0.33	0.09
ноги*	1 (1)	0.94 (0.67)	0.06 (0.33)	0.33	0.06
мозга	1 (1)	0.71 (0.66)	0.29 (0.34)	0.34	0.29
нужды*	1 (1)	0.56 (0.66)	0.44 (0.34)	0.34	0.44
борта	1 (1)	0.47 (0.65)	0.53 (0.35)	0.35	0.53
тётей	1 (1)	0.91 (0.65)	0.09 (0.35)	0.35	0.09
пятна*	1 (1)	0.91 (0.64)	0.09 (0.36)	0.36	0.09
гонор	1 (1)	0.82 (0.64)	0.18 (0.36)	0.36	0.18
долгу*	1 (1)	0.68 (0.63)	0.32 (0.37)	0.37	0.32
басню	1 (1)	1.00 (0.63)	0.00 (0.37)	0.37	0.00
воле*	1 (1)	1.00 (0.62)	0.00 (0.38)	0.38	0.00
стражи	1 (1)	0.91 (0.62)	0.09 (0.38)	0.38	0.09
воду	1 (1)	0.97 (0.62)	0.03 (0.38)	0.38	0.03
душах	1 (1)	0.65 (0.61)	0.35 (0.39)	0.39	0.35
кудри	1 (1)	0.94 (0.61)	0.06 (0.39)	0.39	0.06
дозу	1 (1)	0.97 (0.59)	0.03 (0.41)	0.41	0.03
обществ	1 (1)	0.97 (0.59)	0.03 (0.41)	0.41	0.03

графы*	1 (1)	0.76 (0.59)	0.24 (0.41)	0.41	0.24
клюнет	1 (1)	0.94 (0.59)	0.06 (0.41)	0.41	0.06
боком	1 (1)	0.94 (0.59)	0.06 (0.41)	0.41	0.06
села*	1 (1)	0.59 (0.58)	0.41 (0.42)	0.42	0.41
косы*	1 (1)	0.76 (0.56)	0.24 (0.44)	0.44	0.24
балла	1 (1)	0.94 (0.56)	0.06 (0.44)	0.44	0.06
ходу*	1 (0)	0.79 (0.53)	0.21 (0.47)	0.47	0.21
слухах	1 (0)	0.97 (0.53)	0.03 (0.47)	0.47	0.03
развит	1 (0)	0.59 (0.53)	0.41 (0.47)	0.47	0.41
пищей	1 (0)	0.91 (0.52)	0.09 (0.48)	0.48	0.09
кашлял	1 (0)	0.94 (0.52)	0.06 (0.48)	0.48	0.06
жестов	1 (0)	0.88 (0.49)	0.12 (0.51)	0.51	0.12
боги	1 (0)	0.94 (0.49)	0.06 (0.51)	0.51	0.06
свистом	1 (0)	0.91 (0.49)	0.09 (0.51)	0.51	0.09
пену	1 (0)	0.91 (0.48)	0.09 (0.52)	0.52	0.09
снимет	1 (0)	0.97 (0.48)	0.03 (0.52)	0.52	0.03
зелен	1 (0)	0.85 (0.47)	0.15 (0.53)	0.53	0.15
тикать	1 (0)	0.50 (0.47)	0.50 (0.53)	0.53	0.50
кашу	1 (0)	0.79 (0.47)	0.21 (0.53)	0.53	0.21
крепок	1 (0)	0.97 (0.46)	0.03 (0.54)	0.54	0.03
робок	1 (2)	0.85 (0.41)	0.15 (0.59)	0.59	0.15
ярок	1 (2)	0.94 (0.41)	0.06 (0.59)	0.59	0.06
жалок	1 (2)	0.94 (0.40)	0.06 (0.60)	0.60	0.06
палок	1 (2)	0.74 (0.40)	0.26 (0.60)	0.60	0.26
сладок	1 (2)	0.91 (0.40)	0.09 (0.60)	0.60	0.09
подлой	1 (2)	0.82 (0.39)	0.18 (0.61)	0.61	0.18
гадов	1 (2)	0.97 (0.39)	0.03 (0.61)	0.61	0.03
прыгал	1 (2)	0.94 (0.37)	0.06 (0.63)	0.63	0.06
бури*	1 (2)	0.68 (0.37)	0.32 (0.63)	0.63	0.32
плохи*	1 (2)	0.68 (0.36)	0.32 (0.64)	0.64	0.32
бабок	1 (2)	0.91 (0.36)	0.09 (0.64)	0.64	0.09
змеи*	1 (2)	0.71 (0.33)	0.29 (0.67)	0.67	0.29
судьбах	1 (2)	0.97 (0.33)	0.03 (0.67)	0.67	0.03
сглазить	1 (2)	0.94 (0.32)	0.06 (0.68)	0.68	0.06
сводов	1 (2)	0.76 (0.30)	0.24 (0.70)	0.70	0.24
елей*	1 (2)	0.44 (0.29)	0.56 (0.71)	0.71	0.56
трубок	1 (2)	0.88 (0.26)	0.12 (0.74)	0.74	0.12
перьях	1 (2)	0.91 (0.26)	0.09 (0.74)	0.74	0.09
воют	1 (2)	0.82 (0.26)	0.18 (0.74)	0.74	0.18
актов	1 (2)	0.94 (0.26)	0.06 (0.74)	0.74	0.06
пьяниц	1 (2)	0.91 (0.25)	0.09 (0.75)	0.75	0.09

веток	1 (2)	0.79 (0.23)	0.21 (0.77)	0.77	0.21
звери	1 (2)	0.94 (0.22)	0.06 (0.78)	0.78	0.06
клеить	1 (2)	1.00 (0.21)	0.00 (0.79)	0.79	0.00
длились	1 (2)	1.00 (0.21)	0.00 (0.79)	0.79	0.00
бесов	1 (2)	0.76 (0.20)	0.24 (0.80)	0.80	0.24
принял	1 (2)	0.65 (0.20)	0.35 (0.80)	0.80	0.35
душат	1 (2)	0.85 (0.18)	0.15 (0.82)	0.82	0.15
встретить	1 (2)	0.85 (0.18)	0.15 (0.82)	0.82	0.15
масок	1 (2)	0.79 (0.17)	0.21 (0.83)	0.83	0.21
скрипок	1 (2)	0.74 (0.17)	0.26 (0.83)	0.83	0.26
весел	1 (2)	0.71 (0.17)	0.29 (0.83)	0.83	0.29
всыпать*	1 (2)	0.59 (0.15)	0.41 (0.85)	0.85	0.41
тискал	1 (2)	0.74 (0.13)	0.26 (0.87)	0.87	0.26
детях	1 (2)	0.97 (0.12)	0.03 (0.88)	0.88	0.03
узок	1 (2)	0.97 (0.12)	0.03 (0.88)	0.88	0.03
лоцман	1 (2)	0.82 (0.10)	0.18 (0.90)	0.90	0.18
таять	1 (2)	0.85 (0.05)	0.15 (0.95)	0.95	0.15
резня	2 (1)	0.21 (0.92)	0.79 (0.08)	0.92	0.21
высок	2 (1)	0.24 (0.90)	0.76 (0.10)	0.90	0.24
дружке	2 (1)	0.76 (0.89)	0.24 (0.11)	0.89	0.76
мелки*	2 (1)	0.50 (0.86)	0.50 (0.14)	0.86	0.50
нежна	2 (1)	0.38 (0.86)	0.62 (0.14)	0.86	0.38
ночник	2 (1)	0.15 (0.85)	0.85 (0.15)	0.85	0.15
тиски	2 (1)	0.38 (0.85)	0.62 (0.15)	0.85	0.38
минут*	2 (1)	0.18 (0.84)	0.82 (0.16)	0.84	0.18
джинса	2 (1)	0.50 (0.84)	0.50 (0.16)	0.84	0.50
корма*	2 (1)	0.35 (0.83)	0.65 (0.17)	0.83	0.35
глаза*	2 (1)	0.18 (0.81)	0.82 (0.19)	0.81	0.18
велят	2 (1)	0.29 (0.81)	0.71 (0.19)	0.81	0.29
летишь	2 (1)	0.09 (0.81)	0.91 (0.19)	0.81	0.09
близки*	2 (1)	0.32 (0.81)	0.68 (0.19)	0.81	0.32
грозе	2 (1)	0.24 (0.81)	0.76 (0.19)	0.81	0.24
пыльца	2 (1)	0.24 (0.80)	0.76 (0.20)	0.80	0.24
планет	2 (1)	0.15 (0.79)	0.85 (0.21)	0.79	0.15
штаны	2 (1)	0.09 (0.78)	0.91 (0.22)	0.78	0.09
печной	2 (1)	0.18 (0.78)	0.82 (0.22)	0.78	0.18
умны	2 (1)	0.18 (0.77)	0.82 (0.23)	0.77	0.18
большим*	2 (1)	0.15 (0.77)	0.85 (0.23)	0.77	0.15
укус	2 (1)	0.26 (0.77)	0.74 (0.23)	0.77	0.26
любом	2 (1)	0.21 (0.73)	0.79 (0.27)	0.73	0.21
дубы	2 (1)	0.26 (0.73)	0.74 (0.27)	0.73	0.26

парной*	2 (1)	0.35 (0.72)	0.65 (0.28)	0.72	0.35
кружком	2 (1)	0.15 (0.71)	0.85 (0.29)	0.71	0.15
дыра	2 (1)	0.12 (0.71)	0.88 (0.29)	0.71	0.12
хотят	2 (1)	0.03 (0.69)	0.97 (0.31)	0.69	0.03
кайма	2 (1)	0.32 (0.68)	0.68 (0.32)	0.68	0.32
ступень	2 (1)	0.18 (0.67)	0.82 (0.33)	0.67	0.18
бомбят	2 (1)	0.09 (0.67)	0.91 (0.33)	0.67	0.09
горах	2 (1)	0.09 (0.66)	0.91 (0.34)	0.66	0.09
толпу	2 (1)	0.24 (0.66)	0.76 (0.34)	0.66	0.24
тянул	2 (1)	0.12 (0.66)	0.88 (0.34)	0.66	0.12
вдова	2 (1)	0.09 (0.65)	0.91 (0.35)	0.65	0.09
грехом	2 (1)	0.26 (0.64)	0.74 (0.36)	0.64	0.26
земном	2 (1)	0.24 (0.63)	0.76 (0.37)	0.63	0.24
холмы	2 (1)	0.15 (0.63)	0.85 (0.37)	0.63	0.15
взрывных	2 (1)	0.15 (0.62)	0.85 (0.38)	0.62	0.15
пустых	2 (1)	0.06 (0.61)	0.94 (0.39)	0.61	0.06
винят	2 (1)	0.06 (0.61)	0.94 (0.39)	0.61	0.06
метлы	2 (1)	0.59 (0.60)	0.41 (0.40)	0.60	0.59
взяла	2 (1)	0.15 (0.58)	0.85 (0.42)	0.58	0.15
окне	2 (1)	0.03 (0.57)	0.97 (0.43)	0.57	0.03
тащи	2 (1)	0.06 (0.56)	0.94 (0.44)	0.56	0.06
аду*	2 (0)	0.59 (0.55)	0.41 (0.45)	0.55	0.59
корню*	2 (0)	0.53 (0.54)	0.47 (0.46)	0.54	0.53
борзой*	2 (0)	0.50 (0.54)	0.50 (0.46)	0.54	0.50
верста	2 (0)	0.29 (0.53)	0.71 (0.47)	0.53	0.29
князей	2 (0)	0.38 (0.53)	0.62 (0.47)	0.53	0.38
смола	2 (0)	0.12 (0.53)	0.88 (0.47)	0.53	0.12
густом	2 (0)	0.21 (0.53)	0.79 (0.47)	0.53	0.21
возни	2 (0)	0.32 (0.52)	0.68 (0.48)	0.52	0.32
гроши	2 (0)	0.21 (0.52)	0.79 (0.48)	0.52	0.21
голы*	2 (0)	0.56 (0.51)	0.44 (0.49)	0.51	0.56
бомжи	2 (0)	0.15 (0.51)	0.85 (0.49)	0.51	0.15
былом	2 (0)	0.29 (0.51)	0.71 (0.49)	0.51	0.29
фойе	2 (0)	0.06 (0.51)	0.94 (0.49)	0.51	0.06
жука	2 (0)	0.29 (0.50)	0.71 (0.50)	0.50	0.29
виске	2 (2)	0.44 (0.44)	0.56 (0.56)	0.44	0.44
гнилой	2 (2)	0.06 (0.44)	0.94 (0.56)	0.44	0.06
мешки	2 (2)	0.21 (0.44)	0.79 (0.56)	0.44	0.21
рублей	2 (2)	0.00 (0.43)	1.00 (0.57)	0.43	0.00
стрельба	2 (2)	0.09 (0.43)	0.91 (0.57)	0.43	0.09
верхи	2 (2)	0.32 (0.42)	0.68 (0.58)	0.42	0.32

уйти	2 (2)	0.00 (0.42)	1.00 (0.58)	0.42	0.00
стена	2 (2)	0.09 (0.41)	0.91 (0.59)	0.41	0.09
судам	2 (2)	0.12 (0.41)	0.88 (0.59)	0.41	0.12
чулки	2 (2)	0.06 (0.41)	0.94 (0.59)	0.41	0.06
бруски	2 (2)	0.18 (0.41)	0.82 (0.59)	0.41	0.18
софе	2 (2)	0.15 (0.40)	0.85 (0.60)	0.40	0.15
письмо	2 (2)	0.00 (0.40)	1.00 (0.60)	0.40	0.00
струну	2 (2)	0.15 (0.39)	0.85 (0.61)	0.39	0.15
явить	2 (2)	0.18 (0.38)	0.82 (0.62)	0.38	0.18
багром	2 (2)	0.15 (0.38)	0.85 (0.62)	0.38	0.15
блинов	2 (2)	0.03 (0.38)	0.97 (0.62)	0.38	0.03
замкнуть	2 (2)	0.21 (0.38)	0.79 (0.62)	0.38	0.21
щекам	2 (2)	0.32 (0.37)	0.68 (0.63)	0.37	0.32
металл	2 (2)	0.00 (0.36)	1.00 (0.64)	0.36	0.00
буди	2 (2)	0.24 (0.36)	0.76 (0.64)	0.36	0.24
шкалу	2 (2)	0.12 (0.36)	0.88 (0.64)	0.36	0.12
горшки	2 (2)	0.24 (0.35)	0.76 (0.65)	0.35	0.24
взглянуть	2 (2)	0.21 (0.35)	0.79 (0.65)	0.35	0.21
руды*	2 (2)	0.41 (0.34)	0.59 (0.66)	0.34	0.41
штабов	2 (2)	0.35 (0.34)	0.65 (0.66)	0.34	0.35
слюной	2 (2)	0.06 (0.33)	0.94 (0.67)	0.33	0.06
блоху	2 (2)	0.06 (0.32)	0.94 (0.68)	0.32	0.06
рядам	2 (2)	0.41 (0.32)	0.59 (0.68)	0.32	0.41
дворы	2 (2)	0.12 (0.32)	0.88 (0.68)	0.32	0.12
крючки	2 (2)	0.15 (0.31)	0.85 (0.69)	0.31	0.15
везли	2 (2)	0.06 (0.30)	0.94 (0.70)	0.30	0.06
проси	2 (2)	0.00 (0.29)	1.00 (0.71)	0.29	0.00
фольга	2 (2)	0.15 (0.29)	0.85 (0.71)	0.29	0.15
заре	2 (2)	0.09 (0.29)	0.91 (0.71)	0.29	0.09
нажим	2 (2)	0.03 (0.28)	0.97 (0.72)	0.28	0.03
чинов	2 (2)	0.26 (0.27)	0.74 (0.73)	0.27	0.26
блюсти	2 (2)	0.03 (0.27)	0.97 (0.73)	0.27	0.03
редут	2 (2)	0.21 (0.26)	0.79 (0.74)	0.26	0.21
курорт	2 (2)	0.00 (0.25)	1.00 (0.75)	0.25	0.00
глубок	2 (2)	0.21 (0.25)	0.79 (0.75)	0.25	0.21
родня	2 (2)	0.09 (0.25)	0.91 (0.75)	0.25	0.09
хребту	2 (2)	0.00 (0.25)	1.00 (0.75)	0.25	0.00
фуршет	2 (2)	0.00 (0.25)	1.00 (0.75)	0.25	0.00
рыдал	2 (2)	0.00 (0.23)	1.00 (0.77)	0.23	0.00
икнул	2 (2)	0.21 (0.22)	0.79 (0.78)	0.22	0.21
варяг	2 (2)	0.18 (0.21)	0.82 (0.79)	0.21	0.18

коньках	2 (2)	0.06 (0.21)	0.94 (0.79)	0.21	0.06
послы	2 (2)	0.18 (0.20)	0.82 (0.80)	0.20	0.18
кружков	2 (2)	0.12 (0.20)	0.88 (0.80)	0.20	0.12
снести	2 (2)	0.09 (0.20)	0.91 (0.80)	0.20	0.09
артель	2 (2)	0.00 (0.19)	1.00 (0.81)	0.19	0.00
просты	2 (2)	0.18 (0.19)	0.82 (0.81)	0.19	0.18
забит	2 (2)	0.15 (0.19)	0.85 (0.81)	0.19	0.15
бросок*	2 (2)	0.18 (0.19)	0.82 (0.81)	0.19	0.18
вакцин	2 (2)	0.15 (0.18)	0.85 (0.82)	0.18	0.15
жидов	2 (2)	0.24 (0.18)	0.76 (0.82)	0.18	0.24
сменил	2 (2)	0.06 (0.18)	0.94 (0.82)	0.18	0.06
грибов	2 (2)	0.09 (0.18)	0.91 (0.82)	0.18	0.09
былин	2 (2)	0.15 (0.18)	0.85 (0.82)	0.18	0.15
банкет	2 (2)	0.00 (0.17)	1.00 (0.83)	0.17	0.00
поймут	2 (2)	0.00 (0.17)	1.00 (0.83)	0.17	0.00
ступай	2 (2)	0.06 (0.17)	0.94 (0.83)	0.17	0.06
вносить	2 (2)	0.15 (0.17)	0.85 (0.83)	0.17	0.15
парнас	2 (2)	0.00 (0.16)	1.00 (0.84)	0.16	0.00
виток	2 (2)	0.12 (0.16)	0.88 (0.84)	0.16	0.12
измен	2 (2)	0.00 (0.16)	1.00 (0.84)	0.16	0.00
кивок	2 (2)	0.09 (0.15)	0.91 (0.85)	0.15	0.09
кадастр	2 (2)	0.03 (0.15)	0.97 (0.85)	0.15	0.03
жилья	2 (2)	0.00 (0.14)	1.00 (0.86)	0.14	0.00
киоск	2 (2)	0.00 (0.14)	1.00 (0.86)	0.14	0.00
графин	2 (2)	0.00 (0.14)	1.00 (0.86)	0.14	0.00
трепать	2 (2)	0.09 (0.13)	0.91 (0.87)	0.13	0.09
зовут	2 (2)	0.00 (0.12)	1.00 (0.88)	0.12	0.00
лопат	2 (2)	0.12 (0.12)	0.88 (0.88)	0.12	0.12
мерцал	2 (2)	0.00 (0.11)	1.00 (0.89)	0.11	0.00
каков	2 (2)	0.12 (0.11)	0.88 (0.89)	0.11	0.12
ларец	2 (2)	0.03 (0.11)	0.97 (0.89)	0.11	0.03
полям	2 (2)	0.00 (0.11)	1.00 (0.89)	0.11	0.00
террор	2 (2)	0.09 (0.10)	0.91 (0.90)	0.10	0.09
дурён	2 (2)	0.00 (0.10)	1.00 (0.90)	0.10	0.00
жильца	2 (2)	0.06 (0.09)	0.94 (0.91)	0.09	0.06
дремал	2 (2)	0.00 (0.09)	1.00 (0.91)	0.09	0.00
скрывал	2 (2)	0.00 (0.08)	1.00 (0.92)	0.08	0.00
ревел	2 (2)	0.09 (0.08)	0.91 (0.92)	0.08	0.09
застрял	2 (2)	0.00 (0.08)	1.00 (0.92)	0.08	0.00
конверт	2 (2)	0.00 (0.08)	1.00 (0.92)	0.08	0.00
зубрить	2 (2)	0.06 (0.08)	0.94 (0.92)	0.08	0.06

сетям	2 (2)	0.15 (0.08)	0.85 (0.92)	0.08	0.15
могил	2 (2)	0.00 (0.08)	1.00 (0.92)	0.08	0.00
мастак	2 (2)	0.06 (0.07)	0.94 (0.93)	0.07	0.06
сапог	2 (2)	0.00 (0.07)	1.00 (0.93)	0.07	0.00
стакан	2 (2)	0.00 (0.07)	1.00 (0.93)	0.07	0.00
станков	2 (2)	0.06 (0.07)	0.94 (0.93)	0.07	0.06
шуршал	2 (2)	0.00 (0.07)	1.00 (0.93)	0.07	0.00
утюг	2 (2)	0.00 (0.06)	1.00 (0.94)	0.06	0.00
смешон	2 (2)	0.06 (0.06)	0.94 (0.94)	0.06	0.06
копал	2 (2)	0.00 (0.06)	1.00 (0.94)	0.06	0.00
ревнив	2 (2)	0.00 (0.06)	1.00 (0.94)	0.06	0.00
плывут	2 (2)	0.06 (0.06)	0.94 (0.94)	0.06	0.06
желток	2 (2)	0.06 (0.06)	0.94 (0.94)	0.06	0.06
тяжёл	2 (2)	0.00 (0.06)	1.00 (0.94)	0.06	0.00
вставать	2 (2)	0.06 (0.06)	0.94 (0.94)	0.06	0.06
пингвин	2 (2)	0.00 (0.06)	1.00 (0.94)	0.06	0.00
червя	2 (2)	0.09 (0.05)	0.91 (0.95)	0.05	0.09
смущён	2 (2)	0.00 (0.05)	1.00 (0.95)	0.05	0.00
значок	2 (2)	0.00 (0.05)	1.00 (0.95)	0.05	0.00
стоять	2 (2)	0.00 (0.04)	1.00 (0.96)	0.04	0.00
пропал	2 (2)	0.00 (0.04)	1.00 (0.96)	0.04	0.00
палат	2 (2)	0.06 (0.04)	0.94 (0.96)	0.04	0.06
цыган	2 (2)	0.18 (0.04)	0.82 (0.96)	0.04	0.18
вогнать	2 (2)	0.06 (0.04)	0.94 (0.96)	0.04	0.06
картечь	2 (2)	0.06 (0.04)	0.94 (0.96)	0.04	0.06
засесть	2 (2)	0.18 (0.04)	0.82 (0.96)	0.04	0.18
солить	2 (2)	0.00 (0.03)	1.00 (0.97)	0.03	0.00
борец	2 (2)	0.00 (0.03)	1.00 (0.97)	0.03	0.00
заход	2 (2)	0.03 (0.03)	0.97 (0.97)	0.03	0.03
глотать	2 (2)	0.00 (0.03)	1.00 (0.97)	0.03	0.00
диктат	2 (2)	0.00 (0.03)	1.00 (0.97)	0.03	0.00
придал	2 (2)	0.03 (0.03)	0.97 (0.97)	0.03	0.03
обман	2 (2)	0.00 (0.03)	1.00 (0.97)	0.03	0.00
торчат	2 (2)	0.03 (0.03)	0.97 (0.97)	0.03	0.03
клеймить	2 (2)	0.15 (0.03)	0.85 (0.97)	0.03	0.15
валун	2 (2)	0.00 (0.02)	1.00 (0.98)	0.02	0.00
видать	2 (2)	0.03 (0.02)	0.97 (0.98)	0.02	0.03
загиб	2 (2)	0.00 (0.02)	1.00 (0.98)	0.02	0.00
мускат	2 (2)	0.00 (0.02)	1.00 (0.98)	0.02	0.00
богат	2 (2)	0.00 (0.02)	1.00 (0.98)	0.02	0.00
сазан	2 (2)	0.06 (0.02)	0.94 (0.98)	0.02	0.06

шажок	2 (2)	0.15 (0.02)	0.85 (0.98)	0.02	0.15
болтал	2 (2)	0.00 (0.02)	1.00 (0.98)	0.02	0.00
залить	2 (2)	0.00 (0.02)	1.00 (0.98)	0.02	0.00
жилец	2 (2)	0.00 (0.02)	1.00 (0.98)	0.02	0.00
забыл	2 (2)	0.03 (0.01)	0.97 (0.99)	0.01	0.03
призвать	2 (2)	0.00 (0.01)	1.00 (0.99)	0.01	0.00
шпинат	2 (2)	0.00 (0.01)	1.00 (0.99)	0.01	0.00
бледнеть	2 (2)	0.00 (0.01)	1.00 (0.99)	0.01	0.00
ворон*	2 (2)	0.35 (0.01)	0.65 (0.99)	0.01	0.35
овец	2 (2)	0.00 (0.01)	1.00 (0.99)	0.01	0.00
башмак	2 (2)	0.03 (0.01)	0.97 (0.99)	0.01	0.03
задел	2 (2)	0.00 (0.01)	1.00 (0.99)	0.01	0.00
гектар	2 (2)	0.06 (0.01)	0.94 (0.99)	0.01	0.06
показ	2 (2)	0.06 (0.01)	0.94 (0.99)	0.01	0.06
разбив	2 (2)	0.00 (0.01)	1.00 (0.99)	0.01	0.00
скорбеть	2 (2)	0.00 (0.01)	1.00 (0.99)	0.01	0.00
навар	2 (2)	0.06 (0.01)	0.94 (0.99)	0.01	0.06
экран	2 (2)	0.00 (0.01)	1.00 (0.99)	0.01	0.00
намёк	2 (2)	0.00 (0.01)	1.00 (0.99)	0.01	0.00
зарыть	2 (2)	0.06 (0.01)	0.94 (0.99)	0.01	0.06
закон	2 (2)	0.00 (0.01)	1.00 (0.99)	0.01	0.00
застав	2 (2)	0.03 (0.00)	0.97 (1.00)	0.00	0.03
мелькнёт	2 (2)	0.00 (0.00)	1.00 (1.00)	0.00	0.00
дерёт	2 (2)	0.00 (0.00)	1.00 (1.00)	0.00	0.00
начнешь	2 (2)	0.00 (0.00)	1.00 (1.00)	0.00	0.00
загон	2 (2)	0.00 (0.00)	1.00 (1.00)	0.00	0.00
начать	2 (2)	0.00 (0.00)	1.00 (1.00)	0.00	0.00
убьём	2 (2)	0.00 (0.00)	1.00 (1.00)	0.00	0.00
заснёт	2 (2)	0.06 (0.00)	0.94 (1.00)	0.00	0.06
пришлёт	2 (2)	0.00 (0.00)	1.00 (1.00)	0.00	0.00
зайдёт	2 (2)	0.00 (0.00)	1.00 (1.00)	0.00	0.00
внесёт	2 (2)	0.00 (0.00)	1.00 (1.00)	0.00	0.00
жуёт	2 (2)	0.00 (0.00)	1.00 (1.00)	0.00	0.00
отсчёт	2 (2)	0.06 (0.00)	0.94 (1.00)	0.00	0.06
отлёт	2 (2)	0.03 (0.00)	0.97 (1.00)	0.00	0.03

Appendix E

Nonwords Used in Study 6

Assigned Stress refers to the stress pattern that the majority of readers assigned to a nonword (1 = trochaic stress; 2 = iambic stress; 0 = trochaic and iambic stress patterns are assigned equally often). Predicted Stress refers to the stress pattern that the Bayesian model of stress assignment predicted for a nonword (1 = trochaic stress; 2 = iambic stress; 0 = no conclusive prediction is made). Assigned Stress1 refers to the proportion of answers with trochaic stress given by participants. Predicted Stress1 refers to the proportion of answers with trochaic stress predicted by the model. Assigned Stress2 refers to the proportion of answers with iambic stress given by participants. Predicted Stress2 refers to the proportion of answers with iambic stress predicted by the model.

Word	**Assigned Stress**	**Predicted Stress**	**Assigned Stress1**	**Predicted Stress1**	**Assigned Stress2**	**Predicted Stress2**
актить	2	2	0.27	0.11	0.73	0.89
анбель	2	2	0.43	0.43	0.57	0.57
балвор	0	2	0.53	0.33	0.47	0.67
бижей	2	1	0.33	0.69	0.67	0.31
блемах	1	1	0.57	0.65	0.43	0.35
блозан	2	2	0.07	0.01	0.93	0.99
бомтель	2	2	0.40	0.37	0.60	0.63
бражнем	1	1	0.87	1.00	0.13	0.00
бротах	1	1	0.63	0.62	0.37	0.38
брювал	2	2	0.13	0.10	0.87	0.90
буйче	1	1	0.87	0.97	0.13	0.03
вазыв	2	2	0.20	0.07	0.80	0.93
вамать	2	2	0.40	0.11	0.60	0.89
вахри	1	1	0.73	0.74	0.27	0.26
вдолун	2	2	0.10	0.02	0.90	0.98
вдорать	2	2	0.10	0.02	0.90	0.98
венлам	2	2	0.23	0.36	0.77	0.64
взагом	2	0	0.30	0.48	0.70	0.52
взвожен	1	1	0.97	0.97	0.03	0.03
взилон	2	2	0.10	0.00	0.90	1.00
взопал	2	2	0.10	0.18	0.90	0.82

взрыжешь	1	1	0.97	0.99	0.03	0.01
вкужесть	1	1	0.90	0.93	0.10	0.07
влемок	2	2	0.40	0.32	0.60	0.68
впразе	1	1	0.83	0.88	0.17	0.12
врубень	1	1	0.80	0.71	0.20	0.29
врукарь	2	2	0.27	0.19	0.73	0.81
встрегой	2	1	0.30	0.78	0.70	0.22
вхожал	2	2	0.13	0.02	0.87	0.98
вяже	1	1	0.87	0.95	0.13	0.05
вязчей	1	1	0.90	0.87	0.10	0.13
гвозках	0	0	0.50	0.50	0.50	0.50
гежил	2	2	0.43	0.25	0.57	0.75
гларю	0	0	0.47	0.49	0.53	0.51
глулем	1	1	0.77	0.96	0.23	0.04
гничать	2	2	0.10	0.00	0.90	1.00
гокут	0	2	0.53	0.40	0.47	0.60
горлет	2	2	0.30	0.37	0.70	0.63
граход	2	2	0.20	0.19	0.80	0.81
греман	1	2	0.63	0.09	0.37	0.91
грошизм	2	2	0.07	0.02	0.93	0.98
грунец	2	2	0.27	0.24	0.73	0.76
гунить	2	2	0.13	0.07	0.87	0.93
гутать	2	2	0.23	0.04	0.77	0.96
дажень	1	1	0.77	0.93	0.23	0.07
дамтик	1	1	0.97	1.00	0.03	0.00
данкиз	2	2	0.27	0.13	0.73	0.87
дапасть	2	2	0.33	0.30	0.67	0.70
дведить	0	2	0.53	0.09	0.47	0.91
двобеть	2	2	0.30	0.00	0.70	1.00
дворстак	2	2	0.27	0.01	0.73	0.99
дёвишь	1	1	0.93	0.95	0.07	0.05
дёчен	1	1	0.90	0.96	0.10	0.04
длирец	2	2	0.33	0.08	0.67	0.92
дойхим	1	1	0.60	0.64	0.40	0.36
долцы	1	1	0.63	0.66	0.37	0.34
драшим	0	1	0.47	0.95	0.53	0.05
дроше	0	1	0.50	0.71	0.50	0.29
дрямый	1	1	1.00	1.00	0.00	0.00
думбик	1	1	0.83	1.00	0.17	0.00
дючешь	1	1	0.97	1.00	0.03	0.00
дябор	0	1	0.47	0.64	0.53	0.36
жеран	2	2	0.13	0.00	0.87	1.00
жерба	1	1	0.83	0.85	0.17	0.15

жрелёт	2	2	0.03	0.00	0.97	1.00
журбу	2	2	0.37	0.42	0.63	0.58
журец	2	2	0.03	0.02	0.97	0.98
замтар	2	2	0.03	0.03	0.97	0.97
звекой	2	1	0.40	0.77	0.60	0.23
зверан	2	2	0.07	0.01	0.93	0.99
звосал	2	2	0.07	0.02	0.93	0.98
звубор	2	2	0.43	0.29	0.57	0.71
звурон	2	2	0.03	0.03	0.97	0.97
земтит	2	2	0.30	0.44	0.70	0.56
земчать	2	2	0.03	0.00	0.97	1.00
зергат	2	2	0.10	0.01	0.90	0.99
зетет	2	2	0.27	0.16	0.73	0.84
змешей	2	0	0.30	0.46	0.70	0.54
знарог	2	2	0.13	0.24	0.87	0.76
зобук	2	2	0.33	0.27	0.67	0.73
зорва	1	1	0.93	0.94	0.07	0.06
зревен	1	1	0.90	0.98	0.10	0.02
зриность	1	1	1.00	1.00	0.00	0.00
изгель	2	0	0.37	0.45	0.63	0.55
инкарь	2	2	0.20	0.20	0.80	0.80
иским	2	1	0.17	0.89	0.83	0.11
исман	2	2	0.20	0.05	0.80	0.95
казлать	2	2	0.03	0.07	0.97	0.93
кармец	2	2	0.20	0.31	0.80	0.69
кашмом	2	1	0.20	0.80	0.80	0.20
кваней	2	1	0.23	0.75	0.77	0.25
кипасть	2	2	0.38	0.35	0.62	0.65
кирон	2	2	0.03	0.01	0.97	0.99
клашок	2	2	0.07	0.07	0.93	0.93
клейпор	2	2	0.43	0.17	0.57	0.83
клений	1	1	0.97	1.00	0.03	0.00
клюрам	2	1	0.23	0.62	0.77	0.38
княлом	1	1	0.67	0.91	0.33	0.09
княсечь	1	2	0.70	0.16	0.30	0.84
конрат	2	2	0.20	0.03	0.80	0.97
корщик	1	1	0.93	0.97	0.07	0.03
котерн	2	2	0.13	0.10	0.87	0.90
крамыть	2	2	0.33	0.05	0.67	0.95
кребат	2	2	0.10	0.07	0.90	0.93
кригай	2	2	0.17	0.42	0.83	0.58
крудал	2	2	0.23	0.10	0.77	0.90
круезд	2	2	0.30	0.18	0.70	0.82

крыня	1	1	0.90	0.91	0.10	0.09
кульзу	0	0	0.50	0.49	0.50	0.51
лазыв	2	2	0.10	0.09	0.90	0.91
легный	1	1	0.93	1.00	0.07	0.00
лемей	2	2	0.13	0.16	0.87	0.84
ленраж	2	2	0.03	0.02	0.97	0.98
лираль	2	2	0.10	0.08	0.90	0.92
лиссак	2	2	0.03	0.00	0.97	1.00
ловчек	1	1	0.93	0.99	0.07	0.01
лодаль	1	2	0.63	0.31	0.37	0.69
лофель	1	1	0.67	0.87	0.33	0.13
люмер	0	1	0.50	0.91	0.50	0.09
ляно	1	1	0.97	0.98	0.03	0.02
марлить	2	2	0.40	0.17	0.60	0.83
марлов	2	2	0.40	0.28	0.60	0.72
мельна	1	1	0.73	0.59	0.27	0.41
мёрный	1	1	1.00	1.00	0.00	0.00
миртель	0	1	0.47	0.74	0.53	0.26
морлась	2	2	0.30	0.20	0.70	0.80
мохарь	2	2	0.43	0.26	0.57	0.74
мулог	2	2	0.33	0.13	0.67	0.87
мытень	1	1	0.70	0.67	0.30	0.33
мятырь	1	1	0.63	0.79	0.37	0.21
навюр	2	2	0.03	0.04	0.97	0.96
нербок	1	1	0.63	0.78	0.37	0.22
нилун	2	2	0.07	0.04	0.93	0.96
ныраж	2	2	0.07	0.01	0.93	0.99
общур	0	0	0.47	0.50	0.53	0.50
овлам	2	2	0.17	0.27	0.83	0.73
оклать	2	2	0.23	0.11	0.77	0.89
орант	2	2	0.17	0.02	0.83	0.98
орман	2	2	0.43	0.03	0.57	0.97
пагель	1	1	0.67	0.80	0.33	0.20
паркон	2	2	0.10	0.05	0.90	0.95
певчить	1	2	0.67	0.07	0.33	0.93
пелон	2	2	0.07	0.01	0.93	0.99
первисть	1	1	0.80	0.92	0.20	0.08
петвы	0	2	0.53	0.43	0.47	0.57
пижей	2	0	0.17	0.50	0.83	0.50
племан	2	2	0.43	0.04	0.57	0.96
плепеть	2	2	0.20	0.00	0.80	1.00
плиным	0	1	0.47	0.91	0.53	0.09
пличёт	2	2	0.07	0.00	0.93	1.00

плорем	1	1	0.70	0.92	0.30	0.08
пойвых	1	1	0.80	0.64	0.20	0.36
потырь	2	2	0.37	0.33	0.63	0.67
прелак	2	2	0.07	0.02	0.93	0.98
прилец	2	2	0.07	0.01	0.93	0.99
пруёв	2	2	0.13	0.07	0.87	0.93
прулат	2	2	0.00	0.02	1.00	0.98
пулень	1	1	0.73	0.75	0.27	0.25
пытен	1	2	0.70	0.31	0.30	0.69
раверт	0	2	0.47	0.26	0.53	0.74
разварь	2	2	0.17	0.07	0.83	0.93
райдал	2	2	0.23	0.19	0.77	0.81
рикиш	1	1	0.93	0.96	0.07	0.04
сампить	0	0	0.50	0.49	0.50	0.51
сверщей	2	2	0.33	0.36	0.67	0.64
свяпор	2	2	0.21	0.32	0.79	0.68
сгобам	1	1	0.60	0.63	0.40	0.37
слачерк	1	1	0.87	0.94	0.13	0.06
слыкость	1	1	0.97	1.00	0.03	0.00
слютаж	2	2	0.10	0.00	0.90	1.00
смычишь	1	1	0.63	0.57	0.37	0.43
сойтят	2	1	0.30	0.62	0.70	0.38
спатат	2	2	0.03	0.02	0.97	0.98
сроций	1	1	0.97	1.00	0.03	0.00
стебно	1	1	0.97	0.96	0.03	0.04
стрезент	2	2	0.20	0.02	0.80	0.98
стрельщал	2	2	0.07	0.02	0.93	0.98
стручаг	2	2	0.07	0.06	0.93	0.94
стрявец	2	2	0.33	0.06	0.67	0.94
съезнем	1	1	0.87	1.00	0.13	0.00
тверщик	1	1	0.77	0.89	0.23	0.11
тикон	2	2	0.23	0.12	0.77	0.88
толнер	1	1	0.80	0.91	0.20	0.09
томент	2	2	0.37	0.05	0.63	0.95
торлий	1	1	0.97	0.99	0.03	0.01
трувал	2	2	0.13	0.03	0.87	0.97
успект	2	2	0.03	0.01	0.97	0.99
фавит	2	1	0.30	0.73	0.70	0.27
фарлый	1	1	0.97	1.00	0.03	0.00
фибом	2	1	0.40	0.84	0.60	0.16
фильсы	1	1	0.93	0.98	0.07	0.02
фралость	1	1	0.93	1.00	0.07	0.00
хвопы	1	1	0.70	0.68	0.30	0.32

храбне	1	1	0.80	0.96	0.20	0.04
хражет	1	1	0.60	0.75	0.40	0.25
хрупцев	1	1	0.93	0.97	0.07	0.03
черпость	1	1	0.90	0.98	0.10	0.02
шайвать	2	2	0.23	0.08	0.77	0.92
шпирять	2	2	0.07	0.01	0.93	0.99
юкиш	1	1	0.93	0.92	0.07	0.08

Appendix F

Letter of Information (in Russian)

Информационное письмо

Исследование механизмов постановки ударения в русском языке

В данном эксперименте на экране компьютера Вам будут представлены комбинации букв русского языка. В зависимости от того в какую экспериментальную группу Вы попали, Вам нужно будет решить являются ли данные комбинации словами русского языка или прочитать их вслух. Постарайтесь выполнять задание как можно правильнее и быстрее. В случае публикации результатов, Ваша личная информация останется конфиденциальной. Участие в эксперименте не связано с риском. В эксперименте не используется обман или скрытые манипуляции. Экспериментаторо объяснит цель эксперимента по окончанию сессии. Ваше участие добровольное и Вы в праве прекратить выполнение задания в любой момент. За участе в эксперименте Вам будет выплачено вознаграждение в размере $5.

Я прочитал/а информационное письмо и согласен/согласна принять участие в нем. Экспериментатор ответил на все мои вопросы.

__________________________ ______________________________

Подпись участника Подпись экспериментатора

__________________________ ______________________________

ФИО участника ФИО экспериментатора

____

Дата

Olessia Jouravlev **Curriculum Vitae**

Education

present-2009 University of Western Ontario, PhD in Psychology (Cognition and Perception) expected in 2013

Thesis: *Bayesian Model of Stress Assignment*

2002-1999 Altay State University, Barnaul, Russia, Candidate of Science Degree in Linguistics,

Thesis: *Creative use of language in written speech: cognitive mechanisms*

1999-1994 Barnaul State Pedagogical University, Barnaul, Russia, MA in Humanities, Majoring in Linguistics and Psychology

Thesis: *Psycholinguistic basis of the process of abbreviation*

Employment

present – 2013 **University of Western Ontario**, Canada, **Instructor**

present - 2009 **University of Western Ontario**, Canada, **Teaching Assistant**

2009 - 2002 **Altay State Technical University**, Russia, the Department of Humanities and Social Sciences, **Assistant Professor**

2002 - 1999 **Altay State Technical University**, Russia, the Department of Humanities and Social Sciences, **Instructor/ Teaching Assistant**

Teaching experience

- *Course Instructor*:

  Introduction to Cognition (2013); **Introduction to Psycholinguistics** (2004, 2005, 2006, 2007); **Lexicology** (2003, 2004, 2006, 2007); **Research Methods in Language Studies** (2002, 2003); **Second Language Acquisition** (2003); **History of Language Research** (2003); **Philosophy of Language** (2003, 2004, 2005, 2006)

- *Lab Instructor*:

  Statistics using SPSS (2013); **Research Design** (2011, 2012, 2013)

- *Teaching Assistant,*

  Introduction to Psychology (2011); **Introduction to Test and Measurement** (2010); **Sensation and Perception** (2010); **Introduction to Cognitive Psychology** (2009); **Introduction to Psycholinguistics** (2010); **Psychology of Thinking** (2010, 2012)

Awards and Grants

2012 Graduate Thesis Research Award, University of Western Ontario, $750

2012 Honorary Mention for the Best Poster Presentation at 8th International Conference on the Mental Lexicon, Montreal, QC

2011 Graduate Thesis Research Award, University of Western Ontario, $750

2005 Fulbright Visiting Scholar, University of Maryland, College Park, $18,000

2003 Junior Faculty of the Year Award, Altay State Technical University

2002 Soros Foundation travel Grant to attend a workshop “Language & Cognition”, Novosibirsk State Universiy, $800

Publications

Refereed Articles:

1. Jouravlev, O. & Jared, D. (2014). Reading Russian-English homographs in sentence context: Evidence from ERPs. *Bilingualism: Language and Cognition*, 17, 153 – 168.
2. Jouravlev, O. & Lupker, S. J. (in press). Stress consistency and stress regularity effects in Russian. *Language and Cognitive Processes*.
3. Jouravlev, O., Lupker, S. J., & Jared, D. (re-submitted). Cross-language phonological activation: Evidence from masked onset priming and ERPs. *Brain & Language*.
4. Jouravlev, O. & Lupker, S. J. (submitted). Predicting stress patterns in an unpredictable stress language: Non-lexical sources of evidence for stress in Russian. *Journal of Memory and Language*

Conference Proceedings:

1. Jouravlev, O. (2007). Play on words as a way of language generation. In Proceedings of the Conference “*Text: Structure and Functioning”*, (pp. 38-45).
2. Jouravlev, O. (2003). L. Vitgenstein’s conception of play on words as a base of cognitive approach to the phenomenon. In *Proceedings of the Third Annual Siberian Conference of Young Scientists*, Tomsk, Russia, (pp. 200-215).
3. Jouravlev, O. (2004). Mental structures of political debates. In *Proceedings of the Conference “Text: Structure and Functioning”*, (pp. 96-106).
4. Jouravlev, O. (2002). Associative potential of abbreviation in prose. In *Proceedings of the Conference “Language. System. Personality”*, Yekaterinburg, Russia, (pp. 59-71).
5. Jouravlev, O. (2002). Psycholinguistic foundations of the process of abbreviation. In *Proceedings of the Conference on Lingvosynergetics*, Barnaul, Russia, (pp. 117-132).
6. Jouravlev, O. (2000). Intertextual connections in newspaper articles. In *Proceedings of the Conference “Conceptual Image of the World”*, Barnaul, Russia, 2000. (pp. 43 – 49)
7. Jouravlev, O. (2000). The main difficulties in translating American newspaper headlines into Russian. In *Proceedings of the Conference on the Problems of Foreign Language Teaching*, Barnaul, Russia, (pp. 34-38).

Presentations

1. Jouravlev, O., Lupker, S., & Jared, D. (2013). *Cross-language phonological effects: Evidence from masked onset priming and ERPs*. Poster presented at the 54th Annual Meeting of the Psychonomic Society, Toronto, ON.
2. Jouravlev, O. & Lupker, S. (2013). *A Bayesian model of stress assignment in reading*. Talk presented at the 7th Tucson Lexical Processing Workshop, London, ON.
3. Jouravlev, O. & Lupker, S. J. (2013). *Activation of nonnative language during native language processing.* Poster presented at the 42nd Annual Meeting of Lake Ontario Visionary Establishment (LOVE), Niagara Falls, ON.
4. Jouravlev, O. & Lupker, S. J. (2012). *In - cite' or In' - sight: Stress consistency and regularity effects in disyllabic Russian word naming.* Poster presented at the 53rd Annual Meeting of the Psychonomic Society, Minneapolis, MN.
5. Jouravlev, O. & Jared, D. (2012, October). *Reading Russian-English homographs in sentence context: Evidence from ERP.* Poster presented at the 8th International Conference on the Mental Lexicon, Montreal, QC
6. Jouravlev, O. & Lupker, S. J. (2012). *The impact of L2-activated phonological and orthographic codes when bilinguals read in L1: ERP Investigation.* Talk presented at the 22nd Annual Meeting of the Canadian Society for Brain, Behaviour and Cognitive Science (CSBBCS), Kingston, ON.
7. Jouravlev, O. & Lupker, S. J. (2012). *Effects of stress consistency and regularity on polysyllabic word reading.* Poster presented at the 24th Annual Convention of the Association for Psychological Science (APS), Chicago, IL.
8. Jouravlev, O. & Lupker, S. J. (2012). *Regularity and consistency in the computation of lexical stress in reading.* Poster presented at 41st Annual Meeting of the Lake Ontario Visionary Establishment (LOVE), Niagara Falls, ON.
9. Jouravlev, O. (2007). *Play on words as a way of language generation.* Talk presented at the Annual Conference of Psycholinguistic Society, Barnaul, Russia
10. Jouravlev, O. (2004). *Mental structures of political debates.* Talk presented at the Annual Conference of Psycholinguistic Society: Structure and Functioning, Barnaul, Russia
11. Jouravlev, O. (2003). *L.Vitgensyein's conception of play on words as a base of cognitive approach to the phenomenon*. Talk presented at the Third Annual Siberian Conference of Young Scientists, Tomsk, Russia.
12. Jouravlev, O. (2002). *Associative potential of abbreviation in prose*. Talk presented at the Conference "Language. System. Personality", Yekaterinburg, Russia.
13. Jouravlev, O. (2002). *The cognitive mechanisms of abbreviation*. Talk presented at the Workshop on Lingvosinergetics in Barnaul, Russia.
14. Jouravlev, O. (2000). *Intertextual connections in newspaper articles*. Poster presented at the Conference "Conceptual Image of the World", Barnaul, Russia.
15. Jouravlev, O. (2000). *The main difficulties in translating American newspaper headlines into Russian*. Poster presented at the Conference on the Problems of

Foreign Language Teaching, Barnaul, Russia.

Editorial Service

Ad hoc Reviewer

Bilingualism: Language and Cognition: 2013
Scientific Studies of Reading, 2013
Language. System. Personality: 2006
Text: Structure and Functioning: 2005, 2006, 2007

Conference Committee Membership and Service

Member of the Organizing Committee, Siberian Conference of Young Scientists: 2004, 2005, 2006

Language Skills

Russian (native); English (advance); German (intermediate); French (basic)

Other Expertise

Statistical Software: SPSS, R, MPlus
Advanced Statistical Methods: HLM, MLM, SEM
Experiment Delivery Software: E-Prime, DMDX, OpenSesame
EEG/ERP Acquisition Hardware & Software: Biosemi ActiveTwo
EEG/ERP Analysis Software: ERPLAB, EEGLAB, EMSE Suite
fMRI Analysis Software: BrainVoyager, AFNI
Scripting Languages: Python, Matlab