An exploratory study of L1-specific non-words

David Alfter

Abstract

In this paper, we explore L1-specific non-words, i.e. non-words in a target language (in this case Swedish) that are re-ranked by a different-language language model. We surmise that speakers of a certain L1 will react different to L1-specific non-words than to general non-words. We present the results from two small case studies exploring whether re-ranking non-words with different language models leads to a perceived difference in ‘Swedishness’ (pilot study 1) and whether German and English native speakers have longer reaction times in a lexical decision task when presented with their respective L1-specific non-words (pilot study 2). Tentative results seem to indicate that L1-specific non-words are processed second-slowest, after purely Swedish-looking non-words.

1 General Swedish non-words

Non-word, i.e. strings of characters that look like words but actually are not, are often used for diagnostic testing purposes as in LexTale (Lemhöfer and Broersma, 2012) or in psycholinguistic studies. In the past, researchers often came up with non-words that suited their specific purposes by changing single letters in existing words. However, this is a very subjective judgment of goodness and often there is a rather specific use-case beyond which the non-words have little use.

Besides this manual generation of non-words, there are some resources which allow for lookup or generation of non-words. For English, there is the ARC database which contains 358,534 monosyllabic non-words (Rastle et al., 2002). It offers a very fine-grained search engine for selecting non-words. There are also other resources such as WordGen (Duyck et al., 2004) and Wuggy (Keuleers and Brysbaert, 2010) which allow for the generation of (non-)words in Dutch, English, German, French, Spanish, Serbian, and Basque. However, Wuggy requires a syllabified corpus in order to learn how to generate words. Another drawback with most non-word generation programs is that they generate non-words but do not rank them according to goodness; this is often left to the researcher. Recent work by Hamed and Zesch (2018) focuses on generation of English non-words but additionally investigates how automatically generated non-words can be assessed for goodness in an objective manner.
Non-words are quite language-specific, as a certain non-word in one language can be a valid, existing word in another language. To the best of our knowledge, there is no previous work on Swedish non-words.

In this work we first propose a general non-word generation pipeline for Swedish non-words that builds on and extends previous efforts. We then investigate the potential of L1-specific non-words in the target language Swedish, i.e. non-words that not only are valid letter combinations according to the Swedish language but additionally also according to another language.

For L1-specific non-words, we explore two research questions. Research question one asks whether non-words generated based on a Swedish language model but ranked by a non-Swedish language model can be perceived as less Swedish. Research question two asks whether L1-specific non-words result in longer response times in speakers of that specific L1, in comparison to general Swedish non-words. We present the results from two pilot studies on L1-specific non-words that aim at answering these research questions.

2 Methodology

For non-word generation, we use a three-step approach. The first step is generation, the second step is filtering and the third step is ordering/ranking.

We use an exhaustive generation approach for candidate generation of non-words between length two and up to length five, i.e. we generate all possible combinations (with repetition) of letters up to length five. We use a random non-exhaustive generation for candidate generation of non-words of length six to eleven, as the number of possible combinations increases from about 20 million for sequences of length five to about 600 million for sequences of length six.

Candidates of length six and up are generated using a position-aware character-based 4-gram Swedish language model trained on newspaper and fiction corpora. The model is position-aware inasmuch as it learns which characters tend to typically occur at the front, middle and end of words.

When generating non-words, the first character is chosen randomly. After that, the language model uses n-gram probabilities to predict the next character(s) according to the algorithm presented in algorithm 1. The model uses the highest available n-gram order at each step and stops when the length of the sequence matches the required target length.

With $s$ being the current stub. The stub consists of the last $n$ generated characters, ranging from one character at the beginning of generation to three characters after having generated at least 3 characters. After this, the stub will always be of length 3 and the 4-gram language model will predict the continuation character. In algorithm 1 $\text{cont}(s)$ is the continuation function that, based on the length of $s$, returns the set of all continuation characters for the stub $s$ according to the current n-gram language model.
Algorithm 1 Generating sequences

```
function NEXT(s)
    c ← cont(s)  \(\triangleright\)  c is continuation set
    c ← order(c)
    for all x in c do
        r ← random number \(\triangleright\)  between 0 and 1
        if r ≥ 0.5 then
            return x
        end if
    end for
    return last(c)
end function
```

Continuation characters are single characters that have been observed as following after the stub in the training data. After that, continuation characters are ordered by their log-likelihood, from most probable to least probable. Then, for each continuation character, we return it with a probability of 50% or go down to the next character, which again has a 50% chance of being returned, etc. If the loop terminates without returning, the last (and least probable) continuation character is returned. In case the continuation function returns the empty set, i.e. no continuation characters have been observed for the current stub, the method aborts, a new stub is randomly generated and generation is attempted again.

After the generation step, we filter out all words that are present in the 1 million word form database Saldo’s morphology\(^1\) (Saldom) \(^1\) (Borin et al., 2013). We also exclude common names and abbreviations. For words of up to length five, we also exclude all words that have a low language model probability, such as “xxxxx” or “äääää”.

Next, all candidates are ordered using the position-aware language model for Swedish. We experimented with orthographic neighborhood size but, as in Hamed and Zesch (2018), we found this feature to be low-performing and discarded it. The only ordering criterion is the n-gram probability.

In contrast to previous work on automatic non-word generation, we assign each word a part-of-speech and a target proficiency label. For part-of-speech assignment, we train an LSTM sequence-to-multi-label neural network that captures character-based position-specific features. In this way, we hope to learn sensible word to part-of-speech associations.

We also assign each generated non-word a target CEFR level, i.e. the level at which a learner of this level should be able to deal with the word. We expect that extending non-words with such information can lead to more sensible non-word exercises for learners of different levels. For this, we adapt

\(^1\)The resource contains roughly 2 million word forms but only 1 million unique word forms.
previous work by Alfter and Volodina (2018) that assigns each word a target label.

3 L1-specific Swedish non-words

After the generation of Swedish non-words, we want to explore whether we can use different L1 language models to re-rank the Swedish non-words for learners of Swedish with different L1 background. The intuition is that for example in lexical decision tasks, if a non-word is perceived both as having Swedish qualities as well as having qualities of one’s own L1, the decision takes longer and requires a higher proficiency of Swedish. Faster correct decisions could potentially yield more expressive power than general non-word tests.

We have formulated two research questions in relation to L1-specific non-words, namely:

1. Can Swedish non-words be perceived as less Swedish?
2. Do speakers of L1 X react more slowly on non-words that look Swedish but also X?

3.1 Related work

The theory of the dual-route approach to reading aloud seems to have been first proposed by de Saussure in 1922 (Saussure, 1983), formalized by Forster and Chambers (1973) and later adapted by Baron (1977) to also cover reading comprehension. The theory states that when encountering a word in reading, two routes are activated simultaneously: the lexical route uses only the visual stimulus from the word to retrieve the word from the mental lexicon, if it can be found in the mental lexicon. The non-lexical route uses grapheme-to-phoneme mappings to transform the visual stimulus into a mental phonological representation which is then used to either pronounce or retrieve the word from the mental lexicon. The result of encountering a word in reading is then whichever of the two processes returns a result first. The theory was later adapted into a computational model by Coltheart et al. (2001).

Furthermore it as been shown that if a non-word is orthographically similar to many entries in the mental lexicon, its reading time will be faster than if is has few or no orthographic neighbors in the mental lexicon (McCann and Besner, 1987). Since non-words activate similar words in the mental lexicon, orthographic neighborhood could be interesting in generating qualitatively high non-word lists. Indeed, if a non-word has a lot of potential words it could be confused with, it would increase cognitive load when trying to decide whether the non-word is a word or not. However, it has been
found that the number of orthographic neighbors of non-words does not influence response time in lexical decision tasks (Coltheart, 2005). This is consistent with the findings in Hamed and Zesch (2018) where they found neighborhood size to be performing rather modestly in ranking non-words for word-likeness.

With bilinguals, it has been shown that in monolingual lexical decision tasks where non-words can be valid words in their other language or at least form valid letter combinations in the other language, response time was slower on these non-words, suggesting an activation and inhibitory effect of the other language system (Thomas and Allport, 2000).

3.2 Pilot study 1

In the first pilot study, we want to answer the question whether Swedish non-words re-ranked by an Arabic language model are perceived as more Arabic.

Written Arabic is typically not vocalized (i.e. short vowels are not indicated in writing). However, in order to make the two language models similar to each other, we need vocalizations in Arabic. We used the vocalized Tashkeela corpus (Zerrouki and Balla, 2017). We use a heavily simplified non-standard transliteration scheme in order to have more overlap between the two language models.

For the study, we used non-words of length six. We generate 10000 random non-words of length six. We then rank this list with different language models as follows: first, we select the top twenty words as ranked by the Swedish language model (group 1). Next, we select the top twenty non-words as ranked by the Arabic language model (group 2). Finally, we also take the intersection of the first 1000 items in both lists, which gives us 138 items. From this set, we select twenty random words for inclusion in the study (group 3).

Using a Google Forms form, we ask people to indicate for each word whether it looks more Swedish or more Arabic. The words are ordered in the following manner: first a word from group 1, then a word from group 2, then a word from group 3, then a word from group 1, and so on until the end of each list. All the words were presented as a single list on one page. The task was not timed.

The number of participants was five, with two of the participants speaking Arabic as L1 but having no knowledge of Swedish, two participants speaking Swedish as L1 with no knowledge of Arabic and one participant speaking Swedish as L1 and having advanced knowledge of Arabic as L2.

The expected outcome of the study is that the non-words ranked by the Swedish model are perceived as more Swedish (group 1), non-words rated by the Arabic language model are perceived as more Arabic (group 2) while items in group 3 could be freely assigned to either language since they share
Table 1: Swedish-ness and Arabic-ness ratings

| Group   | Swedish | Arabic |
|---------|---------|--------|
| Group 1 | 14      | 6      |
| Group 2 | 5       | 15     |
| Group 3 | 17      | 3      |

orthographic features of both languages.

Table 1 shows the results. The table shows how many words of each group were rated as either Swedish or Arabic by the majority of voters.

We can see that the majority of raters rated Swedish-looking non-words as Swedish with 14 out of 20, and Arabic-looking non-words as Arabic with 15 of 20. Concerning group 3, which has both Swedish and Arabic features, only five words were rated as more Arabic than Swedish by the majority of raters. This seems to confirm our hypothesis that reordering Swedish non-words using a different-language language model leads to a perceived difference in Swedish-ness.

3.3 Pilot study 2

In pilot study 2, we want to investigate how reading times differ in speakers of different L1s when confronted with L1-specific non-words. The dependent variable is reaction time while the independent variable is L1. In order to increase the internal validity of the experiment, the experiment itself was designed as simple as possible.

In the study, we target two different L1 speaker groups, namely German and English L1 speakers.

We build the English language model from the Brown corpus, accessed through the NLTK Python toolkit (Bird et al., 2009). We build the German language model from the German Mixed 2011 part of the corpus by Goldhahn et al. (2012).

For this study, we re-use the 10000 item non-word list of length six mentioned in pilot study 1. We rank the list using the Swedish, German and English language models. We take the top 20 words of each ranking, replacing words that are already in one of the other lists with words from further down the current list, i.e. if we have already collected twenty non-words for Swedish and we are working on the German list, if a word from the top twenty German list is already in the top twenty Swedish list, we ignore the word and continue down the list until we have twenty non-words for the German setting. As fillers, we add twenty random existing Swedish words of length six from Saldom.

The words are ordered in blocks of size four where each block contains one non-word from each language model plus a filler. The words inside each
block are in random order and the words are presented one after another as a self-paced lexical decision task. Before starting the task, participants have to indicate their mother tongue as well as their self-reported proficiency in Swedish on a 3-point scale from beginner (A1/A2) to intermediate (B1/B2) to advanced (C1/C2). The options for mother tongue are “Swedish”, “German”, “English” and “Other”. In order to obfuscate the true aim of the task, namely the impact of L1-specific non-words, participants are asked to identify existing Swedish words from non-existing Swedish words.

The control group consists of three native Swedish speakers. For the control group, we expect the lexical route to outperform the non-lexical route on existing Swedish words and thus we expect fasted reaction times on existing Swedish words and slowest reaction times on non-word rated by the Swedish language model. For Swedish-looking non-words, we expect the control group to take longest, since non-words, by default, activate the non-lexical route.

However, response times for English- and German-looking non-words should lie in-between, as the Swedish grapheme-to-phoneme mental model should be able to discard those words as non-Swedish.

For German, we have eight participants with German as native language of which five have a high proficiency in Swedish, one informant has intermediate Swedish knowledge and one informant has basic Swedish knowledge.

For English, we have four participants with English as native language, two beginner level learners, one intermediate and one advanced.

We also have three participants whose native language was neither of the tested ones. One participant has an intermediate level of Swedish and two participants have an advanced level of Swedish.

3.3.1 Results

Table 2 shows the results for the control group. The table shows the average time taken (in seconds) for each rater and each of the groups: German, English, Swedish and Filler (existing words), as well as the normalized average of the three raters. The normalized average is calculated by first calculating each rater’s average of averages and then dividing each rater’s average by their average of averages. We then sum up averages for the different groups and divide the result by the number of raters. The normalized average is a dimensionless number.

As we can see from table 2, the control group was always slowest on Swedish-looking non-words ranked high by the Swedish language model. Raters 1 and 2 were fastest on existing Swedish words, while rater 3 shows a slight deviance from this tendency, being slightly quicker on English words. This may well be due to faster rejection times of more non-Swedish-looking words as opposed to slower recognition times of real existing Swedish words.
We will look deeper into this dichotomy for the German and English participants.

Table 2: Results: Control group

| Group    | R1  | R2  | R3  | nAvg |
|----------|-----|-----|-----|------|
| German   | 4.75| 1.60| 2.50| 1.10 |
| English  | 3.50| 1.60| 2.15| 0.94 |
| Swedish  | 4.85| 1.80| 3.05| 1.23 |
| Filler   | 1.45| 1.30| 2.40| 0.72 |

Table 3: Rater accuracy in percent

Table 3 shows the rater accuracy by category of non-words. The headers DE, EN and SV stand for German-looking, English-looking and Swedish-looking non-words and FI stands for fillers, i.e. existing Swedish words. Accuracy indicates how many non-words raters correctly discarded as non-existing words for columns DE, EN and SV whereas it indicates how many existing Swedish words raters recognized as existing words for fillers. Raters R1 to R8 are German native speakers, raters R9 to R12 are English native speakers and raters R13 to R15 are native speakers of unspecified other languages. As can be gathered from the table, accuracy in rejecting non-words and recognizing existing words is quite high in the German-speaking rater group. Values drop a bit for English and other-language native speakers,
especially for the rejection of Swedish-looking non-words.

Table 4 shows the reaction time results from the German and English native speakers, and for completeness also includes the participants whose mother tongue was neither of the targeted. Due to space constraints, the table header has been abbreviated to the format \( xy \). The first letter \( x \) takes the values D, E, S and F stand for German, English, Swedish (non-words) and Fillers (existing words) respectively. The second letter \( y \) has either the numbers 0 and 1 which correspond to rejection and acceptance times or C which stands for the combined reaction time. Thus, \( D0 \) stands for the rejection time of German-looking non-words, \( F1 \) stands for the acceptance time of existing Swedish words, etc. Note that the \( xC \) columns are not the arithmetic mean of the \( x0 \) and \( x1 \) columns due to differing size. Values of 0 indicate that the rater never accepted a word of this column as existing word (values of 0 only occur in \( x1 \) columns). The columns ‘R’ denotes the different raters with their respective self-indicated proficiency of Swedish (\( B = \) beginner, \( I = \) intermediate, \( A = \) advanced). We also indicate the normalized average \( nA (=nAvg) \) as well as the normalized average excluding beginner learners \( nA2 (=nAvg (I+A)) \).

Beginning learners seem not to show any predictable pattern. However, if we look at intermediate and advanced learners of Swedish, we see some interesting patterns.

For German speakers, we can see that on average (\( nAvg (I+A) \)) their rejection time of German-looking non-words (\( D0 \)) is higher than their rejection time of English-looking non-words (\( E0 \)). On average their reaction time to German-looking non-words (\( DC \)) is also higher than their reaction time to English-looking non-words (\( EC \)).

For English speakers, rejection time of English-looking non-words (\( E0 \)) is slightly higher than rejection time of German-looking non-words (\( D0 \)).

For non-target participants, we can see no clear pattern. However, they never react fastest on existing Swedish words. The fastest reaction times are on English non-words for raters R13 and R14, possibly due to the larger typological distance between Swedish and English. Rater R15 was marginally faster on rejection of German non-words than on recognition of Swedish words.

German and English intermediate and advanced participants follow the expected pattern of recognizing existing Swedish words fastest and reacting slowest on Swedish looking non-words. However, this small scale study hints at the possibility that L1-specific non-words are processed second-slowest, possibly due to the activation of the native language system. However, the low number of participants in this study does not allow us to draw any reliable conclusions.
|   | D0 | D1 | DC | E0 | E1 | EC | S0 | S1 | SC | F0 | F1 | FC |
|---|---|---|----|----|----|----|----|----|----|----|----|----|
| **German participants** |   |   |    |    |    |    |    |    |    |    |    |    |
| R1 (B) | 2.14 | 3.09 | 2.40 | 2.7 | 3.3 | 2.85 | 2.58 | 2.33 | 2.45 | 2.83 | 3.14 | 3.00 |
| R2 (I) | 2.57 | 4.67 | 3.20 | 2.78 | 7.00 | 3.20 | 3.18 | 5.00 | 3.45 | 3.00 | 3.35 | 3.30 |
| R3 (I) | 2.29 | 5.33 | 2.75 | 2.00 | 0 | 2.00 | 4.69 | 4.00 | 4.45 | 3.67 | 2.00 | 2.25 |
| R4 (A) | 4.35 | 0 | 4.35 | 4.21 | 0 | 4.21 | 4.95 | 0 | 4.95 | 4.83 | 2.64 | 3.30 |
| R5 (A) | 7.31 | 7.5 | 7.35 | 5.60 | 0 | 5.60 | 5.60 | 0 | 5.60 | 12.00 | 3.26 | 3.70 |
| R6 (A) | 2.47 | 3.00 | 2.50 | 2.65 | 0 | 2.65 | 3.53 | 7.00 | 3.70 | 2.50 | 1.65 | 1.75 |
| R7 (A) | 1.83 | 4.50 | 2.10 | 2.10 | 0 | 2.10 | 4.12 | 3.33 | 4.00 | 3.33 | 1.82 | 2.05 |
| R8 (A) | 10.20 | 0 | 10.20 | 3.89 | 7.00 | 4.05 | 8.00 | 0 | 8.00 | 14.40 | 5.33 | 7.60 |
| nA2 | 0.92 | 0.91 | 0.98 | 0.77 | 0.37 | 0.79 | 1.14 | 0.81 | 0.14 | 0.12 | 0.64 | 0.75 |
| **English participants** |   |   |    |    |    |    |    |    |    |    |    |    |
| R9 (B) | 3.42 | 3.88 | 3.60 | 3.11 | 6.50 | 3.45 | 2.75 | 3.25 | 2.50 | 5.50 | 1.75 | 3.15 |
| R10 (B) | 2.80 | 2.90 | 2.85 | 3.15 | 1.43 | 2.55 | 4.60 | 2.13 | 2.75 | 1.375 | 1.67 | 1.55 |
| R11 (I) | 1.71 | 3.00 | 2.10 | 1.76 | 2.33 | 1.85 | 5.29 | 2.46 | 3.45 | 4.50 | 1.89 | 2.15 |
| R12 (A) | 2.80 | 4.80 | 3.30 | 3.19 | 3.75 | 3.30 | 5.40 | 2.90 | 4.15 | 2.00 | 1.74 | 1.75 |
| nA2 | 0.60 | 0.81 | 0.66 | 0.63 | 0.73 | 0.62 | 1.04 | 0.59 | 0.73 | 0.73 | 0.40 | 0.47 |
| **Other participants** |   |   |    |    |    |    |    |    |    |    |    |    |
| R13 (I) | 2.44 | 1.75 | 2.30 | 1.50 | 3.00 | 1.65 | 1.44 | 1.82 | 1.65 | 3.80 | 1.93 | 2.40 |
| R14 (A) | 2.30 | 0 | 2.30 | 1.90 | 2.00 | 1.90 | 2.15 | 0 | 2.15 | 2.00 | 2.06 | 2.05 |
| R15 (A) | 1.21 | 2.00 | 1.25 | 1.55 | 0 | 1.55 | 1.58 | 2.00 | 1.60 | 3.00 | 1.22 | 1.40 |
| nA2 | 0.81 | 0.53 | 0.80 | 0.70 | 0.64 | 0.72 | 0.74 | 0.54 | 0.76 | 1.22 | 0.72 | 0.80 |

*Since this group does not contain any beginner learners, the normalized average corresponds to nAvg (I+A). However, due to the mixed nature of this group, these results should be taken with a grain of salt; we included the normalized average for completeness’ sake.*

Table 4: Results by rater and mother tongue
4 User interface and API

We have created a web-based graphical user interface that facilitates generation of non-words as shown in figure 1. The interface is kept simple, with the standard view offering a choice of length of non-words and the number of non-words to generate, including sensible default values as well as boundaries. It is also possible to access additional options such as L1-specific language ordering and the possibility to generate words that look like nouns, verbs, adjectives or adverbs.

We also provide a REST API (Application Programming Interface) for easy integration with other services.

*https://spraakbanken.gu.se/larkalabb/nonwords*
5 Discussion

During our experiments, we encountered the notoriously difficult-to-solve problem of accidentally generating existing words. These generated words might be colloquial, slang or non-standard words, technical jargon, words used only in certain areas, names, abbreviations, compounds, and many more. In order to exclude more existing words, we could either use a larger resource to check against or use the language model to find neither too highly rated nor too poorly rated non-words, in the hope that by excluding highly rated words, more existing words are excluded. However, this would probably not exclude rare words. Another approach would be to manually sift through all generated non-words and exclude all existing words. However, that would be labor-intensive; crowd-sourcing could potentially help with this task.

Even though accuracy in recognition of existing Swedish words was not the aim of this study, post-experimental interviews revealed that a lot of people had problems with words that could be confused for a misspelled version of an existing word despite the word in question being an existing word as well, such as for example the word *komman*. If analyzed as the commonly used verb *komma* ‘to come’ with an *n* at the end, rejection rates are high. However, it can also be analyzed as noun *komma* ‘comma’, of which *komman* is the definite form (viz. *the comma*). Some people also had difficulties with spelling, not being sure how exactly a word was spelled. Finally, there were some problematic words such as *kanden*, which, according to Saldom should be an existing Swedish word but was not identified as Swedish word by any of the native speakers. This is due to the automatic paradigm expansion used in Saldom which, for the entry *fil. kand.* (= Filosofi kandidat) ‘Bachelor of Arts’ generated ‘kanden’ from the second part. Similarly, non-Swedish words and expressions present in Saldom, such as *grande dame*, lead to nonsensical forms.

External validity certainly is a concern in these studies, as the number of participants as well as their selection was not randomized. However, results seem promising. Internal validity could also be problematized, as part of the instructions, for example in study 2, where participants where asked to perform a word recognition task, could have biased them towards more ‘actively’ activating their L2 mental lexicon. However, as the participants were unaware that the variable being measured was their reaction time to L1-specific non-words, we claim that the internal validity is sufficiently high.
References

Alfter, D. and Volodina, E. (2018). Towards Single Word Lexical Complexity Prediction. In Proceedings of the Thirteenth Workshop on Innovative Use of NLP for Building Educational Applications, pages 79–88.

Baron, J. (1977). Mechanisms for pronouncing printed words: Use and acquisition. Basic processes in reading: Perception and comprehension, pages 175–216.

Bird, S., Klein, E., and Loper, E. (2009). Natural language processing with Python: analyzing text with the natural language toolkit. O’Reilly Media, Inc.

Borin, L., Forsberg, M., and Lönngren, L. (2013). Saldo: a touch of yin to wordnets yang. Language resources and evaluation, 47(4):1191–1211.

Coltheart, M. (2005). Modeling Reading: The Dual-Route Approach. In Snowling, M. J. and Hulme, C., editors, The Science of Reading - A Handbook, chapter 1, pages 6–23. Blackwell Publishing.

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

Duyck, W., Desmet, T., Verbeke, L. P., and Brysbaert, M. (2004). WordGen: A tool for word selection and nonword generation in Dutch, English, German, and French. Behavior Research Methods, Instruments, & Computers, 36(3):488–499.

Forster, K. I. and Chambers, S. M. (1973). Lexical access and naming time. Journal of Memory and Language, 12(6):627.

Goldhahn, D., Eckart, T., and Quasthoff, U. (2012). Building Large Monolingual Dictionaries at the Leipzig Corpora Collection: From 100 to 200 Languages. In LREC, volume 29, pages 31–43.

Hamed, O. and Zesch, T. (2018). The automatic generation of nonwords for lexical recognition tests. In Vetulani, Z., Mariani, J., and Kubis, M., editors, Human Language Technology. Challenges for Computer Science and Linguistics, pages 321–331, Cham. Springer International Publishing.

Keuleers, E. and Brysbaert, M. (2010). Wuggy: A multilingual pseudoword generator. Behavior Research Methods, 42(3):627–633.

Lemhöfer, K. and Broersma, M. (2012). Introducing lextale: A quick and valid lexical test for advanced learners of english. Behavior research methods, 44(2):325–343.
McCann, R. S. and Besner, D. (1987). Reading pseudohomophones: Implications for models of pronunciation assembly and the locus of word-frequency effects in naming. *Journal of Experimental Psychology: Human Perception and Performance*, 13(1):14.

Rastle, K., Harrington, J., and Coltheart, M. (2002). 358,534 nonwords: The ARC nonword database. *The Quarterly Journal of Experimental Psychology Section A*, 55(4):1339–1362.

Saussure, F. d. (1983). Course in general linguistics. ed. charles bally and albert sechehaye with the collaboration of albert riedlinger. *Translation by Roy Harris. London: Duckworth*.

Thomas, M. S. and Allport, A. (2000). Language switching costs in bilingual visual word recognition. *Journal of Memory and Language*, 43(1):44–66.

Zerrouki, T. and Balla, A. (2017). Tashkeela: Novel corpus of Arabic vocalized texts, data for auto-diacritization systems. *Data in brief*, 11:147.