The Multilink model for word translation: Similarity effects in word recognition and word translation

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Contents

1. Abstract

The Multilink Model for word translation is developed by Dijkstra & Rekké (2012). We have made several adaptations to the model in order to make it fit the data better and to make it more psychologically plausible. I have tested the performance of the improved model on both word recognition tasks as well as on word translation tasks. I have primarily looked at the cognacy effect and the effect of word length on reaction time. Most results I have found are well in line with the literature; cognates are recognised and translated considerably faster than other words. False friends still are a problem for Multilink.

2. Introduction

Word translation is one of the most difficult and least-understood cognitive tasks a human can perform. Whereas talking and understanding one another in one language already are impressive feats of human cognition, it is all the more remarkable that humans can communicate in multiple languages. The fact that humans are able to learn different languages—sometimes just two, but sometimes three or more—implies that humans are able to retrieve words from different lexicons that are interconnected, yet can nonetheless be kept separate in one's daily speech. This interconnectedness is apparent from our ability to translate back and forth between different languages.

Whatever the future will bring, for coming centuries, it makes sense to study multilingualism and word translation in humans. This is not simply the case because there are many languages in general—this has always been the case. Rather, there arguably is no point in history in which an average person would come in contact with so many languages in their daily life; there currently are 200 different countries for more than 6000 different languages. The progression of European and international collaboration is one of the causes of this, and whether one approves or disapproves of this development, it is bound to expose communication barriers. These barriers have to be dealt with, and as a consequence many people are using word translation—on either a personal or professional level—to increase mutual understanding.

As word translation becomes more and more apparent, it makes sense to study it at the cognitive level. Many computational models—amongst which Multilink—have already been developed to explain the human cognitive capabilities of word recognition and word translation. I will discuss several more influential ones and subsequently explain why Multilink is a timely next step in the field.

Following this introduction, I will first explain the more important notions of my thesis. These include: some of the more influential models in section 3, cognates and interlingual homographs in section 4, and general information about the important factors involved in word translation as well as how Multilink incorporates these factors in section 5. Finally, in section 6 I will introduce the part of my thesis in which I will compare Multilink simulations with empirical studies.

The core of my thesis will consist of several simulation sessions with Multilink. In section 7, I will perform model-to-model comparison between the Interactive Activation (IA) and the Multilink model on word comprehension for the recognition of English words, as well as model-to-model comparison between the Bilingual Interactive Activation (BIA) model and Multilink for the recognition of Dutch words. This will be followed by section 8 in which I will run simulations in Multilink on word comparison and then perform model-to-data comparison on the empirical data by Vanlangendonck (2014) and Dijkstra et al. (2010). Then, in section 9, I will run simulations in Multilink on word translation and compare these results with the empirical data collected by Pruijn (2015). After that, in section 10, I will run Multilink with control words and interlingual homographs and verbally relate the findings to Dijkstra, Jaarsveld, & Brinke (1998). Section 11 will consist of my conclusion and discussion, and in chapter 12, I will present options for future research. The references are listed in section 13 and the appendices are included in section 14.

3. Models

There are several influential models regarding language comprehension and translation. I will discuss three of them here, after which I will describe Multilink.

3.1. Revised Hierarchical Model

The Revised Hierarchical Model (RHM) is a model explaining the human capability of word translation. It was developed in 1994 by Kroll and Stewart (1994). The model assumes "asymmetrical connections between bilingual memory representations" (Kroll & Stewart, 1994, p.149). This means that the model assumes there is an asymmetry in translation proficiency in unbalanced bilinguals, which will be further explained later in this section. Translation proficiency refers to the speed with which a person can translate a word from one language to another. Unbalanced bilinguals are people that are not raised bilingually but rather have acquired their second language at a later point in time. The RHM assumes that unbalanced bilinguals translate more quickly from L2 to L1 than in the other direction. This is the translation proficiency asymmetry mentioned beforehand. The cause of this is the way in which the RHM explains word translation. Specifically, the Revised Hierarchical Model splits up the translation process into two different routes. The two notions to explain these routes are "Conceptual Mediation" and "Word Association".

Conceptual Mediation means that we have to access the meaning of a word in order to translate it. Conceptual Mediation is what Kroll and Stewart believe to be the explaining factor in forward word translation—that is, translation from one's first to one's second language. A decade before the development of the RHM, a group of researchers already spoke about this idea of conceptual mediation (Potter, So, Von Eckhardt, & Feldman, 1984).

In contrast, translation by means of Word Association makes use of direct lexical links from the word form to be translated in one language to the output word form in the other language. Word Association is said to be prominently used in backward translation (i.e., translation from L2 to L1).

Figure 1 gives a graphical representation of the model. The thick lines represent the strong conceptual links in L1 and the strong lexical links from L2 to L1. The dotted show that there are (weaker) lexical links from L1 to L2 as well, and likewise (weaker) concept mediation is possible from L2. The reason the lexical link from L2 to L1 is stronger than from L1 to L2 is that in early stages of L2 learning, the L2 words were very strongly associated with L1. Correspondingly, when children learn their L1, the only link they have is to the actual concepts itself; this is why the conceptual links are stronger in L1 than in L2.

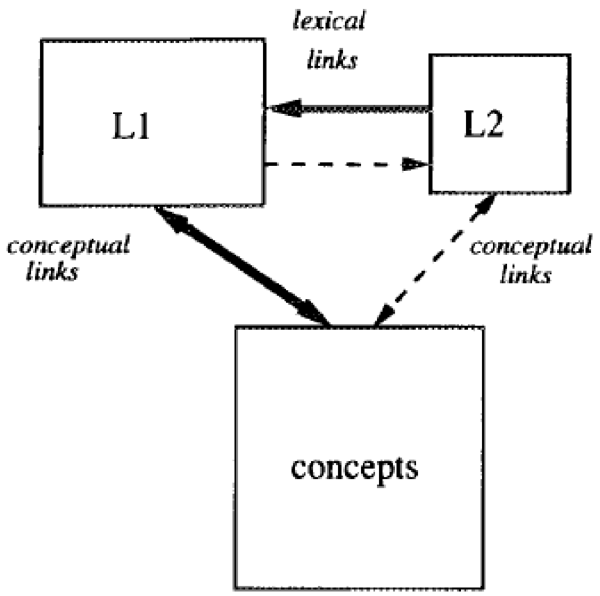

Figure 1: The Revised Hierarchical Model (Kroll & Stewart, 1994)

3.2. Bilingual Interactive Activation and BIA+ Models

The Bilingual Interactive Activation (BIA, figure 2) and Bilingual Interactive Activation Plus (BIA+, figure 2 and 3) Models are models for visual word recognition (i.e., word reading). They are bilingual extensions of the original monolingual Interactive Activation (IA) Model by McClelland and Rumelhart (McClelland & Rumelhart, 1981). As such, they incorporate words from two languages in their integrated lexicon.

When a letter string is presented to this type of model as visual input, activations start spreading in the network and representations become activated. Initially, the visual orthographic input sends activation to a letter level comprising nodes that correspond to individual letters; this activation can be either excitatory (in the case of matching features between input and letter nodes) or inhibitory (in the case of a mismatch). At this moment, all features will send activation to all letter nodes. Then, the letter nodes, depending on their activation, will start sending activation to a word level (comprising word nodes). These will in turn send activation to their language nodes, which denote either the L1 or the L2 and are linked to every word node in that language's lexicon.

Nodes at the word level inhibit other nodes at the word level. The reason for this lateral inhibition is that the visual input refers to exactly one word; for every input string, there is only one correct concept it refers to. Lateral inhibition is a logical consequence from this; if one knows only one concept is correct and one considers it likely that "dog" is the correct concept, the activation of "log", "dot" and all other (neighboring) words should be inhibited, because those concepts cannot be correct as well.

When the activation starts going through the network, many nodes start influencing each other and eventually one word node reaches a threshold activation level, after which we can say it is recognized.

The BIA+ Model (Dijkstra & Heuven, 2002) is a further development of the original BIA Model and incorporates phonological and sublexical levels of processing. The role of the language nodes has been altered as well. Thus, the BIA+ Model basically adds extra dimensions that we know are there (phonology and semantics). As stated by Dijkstra and Van Heuven (2002, p.182): "bilingual word recognition is affected not only by cross-linguistic orthographic similarity effects", in which case the BIA Model would be a perfect representation, "but also by cross-linguistic phonological and semantic overlap". To account for phonology and meaning, and for effects of different tasks, the BIA+ Model had to be developed from the BIA model.

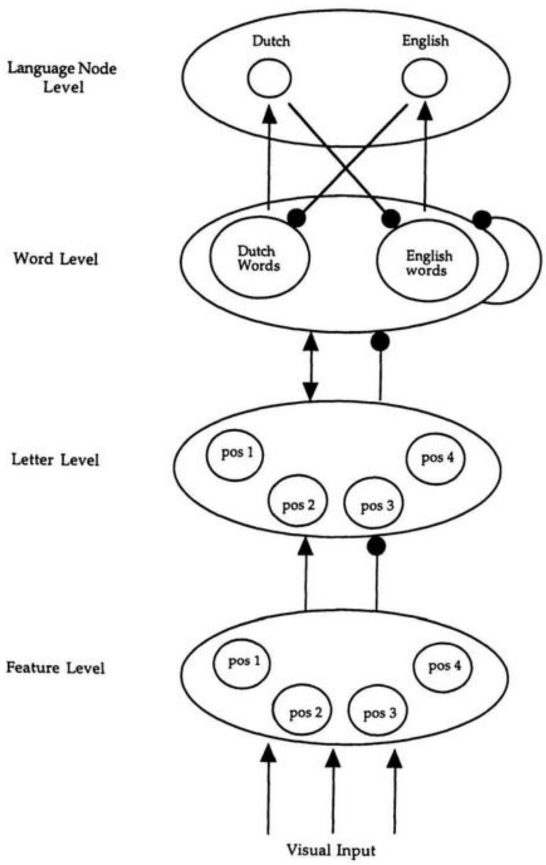

Figure 2: The Bilingual Interactive Activation Model (McClelland & Rumelhart, 1981)

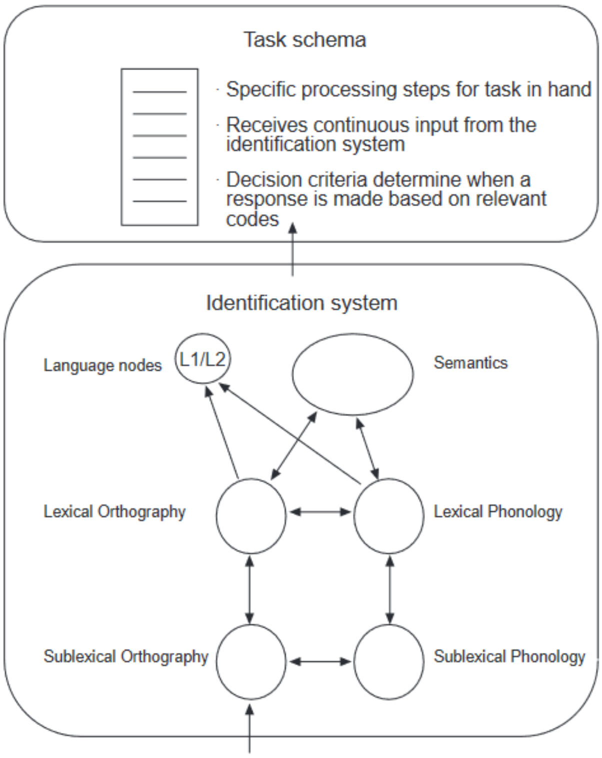

Figure 3: Extensions in the BIA+ Model
(Dijkstra & Van Heuven, 2002)

3.3. Multilink Model

The Multilink Model (Dijkstra & Rekké, 2012) is the most recently developed model concerning translation of words from English into Dutch, and vice versa, in balanced bilinguals. It is a state-of-the-art model for word translation. It is the only model of its kind in the sense that it is not a mere verbal model, but rather it is an implementation and can actually predict word translation times in (balanced) bilinguals. The model receives orthographic word representations and it returns the corresponding phonological representation in the target language. This model has been revised by Rekké, Al-Jibouri, Buytenhuijs, De Korte, and Van Halem in collaboration with Dijkstra in 2016. I will first provide a diagram of what Multilink currently looks like, after which I will describe the adjustments made and explain Multilink in its current shape.

3.3.1. Development of Multilink

Several adjustments have been made to improve the performance and validity of Multilink. Those adjustments can be split up in different parts. I will discuss: The lexicon; the similarity index; and the word frequency representation.

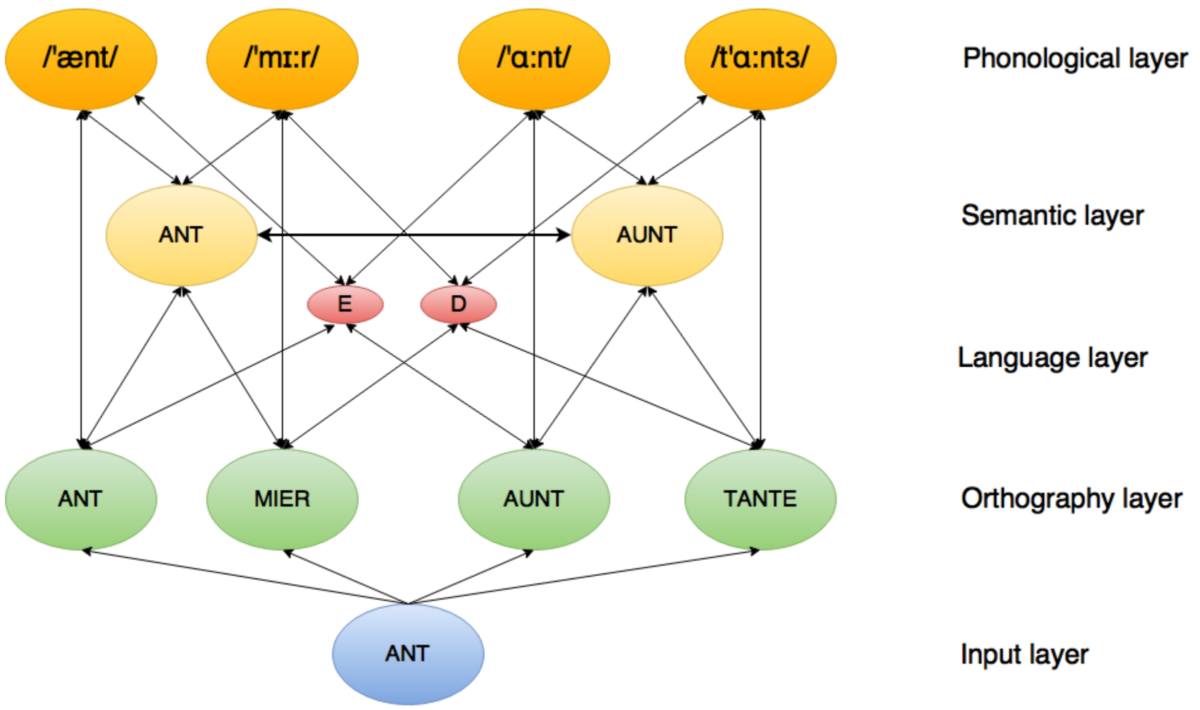

Figure 4: Current version of the Multilink Model

- The Lexicon

The Lexicon has been changed substantially, both with respect to its contents (the included words) and its organization. The most important change in the lexicon is the addition of phonological representations of the words. In former versions of Multilink, the phonological pool was a copy of the orthographic pool. With the adjustments to the lexicon, the phonological pool consists of the phonological word representations as can be seen in the upper row of figure 4. Furthermore, the lexicon was stripped in such a way that only the nouns are left. Words that can be either a noun or a verb (e.g. “walk”) have been removed as well. This is done in order to get the word frequencies absolutely right. The word frequencies are the last change made in the lexicon. The word counts originally came from the CELEX database, but those word counts have been replaced by SUBTLEX, which is much more up-to-date and provides better fits to empirical data.

- The similarity index

The score is something that has been changed as well. The similarity metric originally was computed by means of equation 1, which has been changed to equation 2.

$$score = \begin{cases} IO_{Multiplier} * \left(\frac{MAX_L - LD}{MAX_L}\right)^2 & if \left(\frac{MAX_L - LD}{MAX_L}\right) > 0.5 \\ 0 & otherwise \end{cases} \quad (1)$$

$$score = IO\_Multiplier * \left(\frac{MAX_L - LD}{MAX_L}\right)^3 \quad (2)$$

There were two sub-optimalities in the former score function. Firstly, if the total similarity would not reach 50%, no similarity effect would be regarded at all. To clarify this with an example, the words “sound” and “saint” would be considered equally similar as “sound” and “hedgehog”; the reason for this is that in both of these word pairs, less than 50% of the letters are the same (further explanation of this will follow in section 4.1). Figure 5 shows this effect. Although this difference might not seem to be substantial, there is no psychological reason to discard the word similarity effect of words that are less than 50% similar, therefore that boundary was removed.

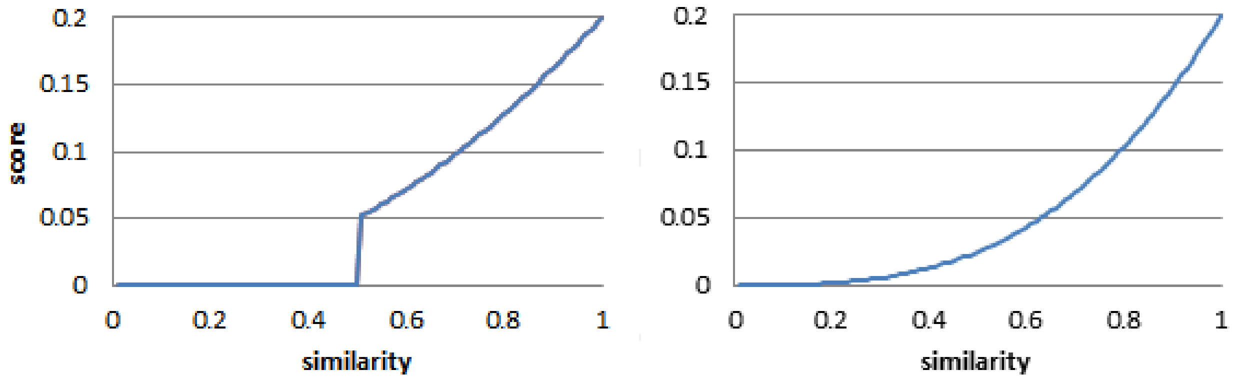

Figure 5: Old similarity score function in Multilink on the left versus the new similarity score function in Multilink on the right

The second sub-optimality in the score function was the overrepresentation of word similarity in general. This caused wrong translation to be produced simply because random words were highly similar to the input word. By cubing instead of squaring the similarity function, this problem can be overcome; word pairs need to have high similarity to receive a meaningful boost in their score function, and this way only translation pairs that are very similar to an input word that differs a lot from its own translation could be mistranslated. I will address this problem in more detail later in my thesis.

- The word frequency representation

Another aspect of the model we have successfully improved is the underestimation and misrepresentation of the word frequency effect. Word frequency is known to have a substantial effect on reaction time in both lexical decision tasks (Dijkstra et al., 2010) as well as in translation tasks (Christoffels, de Groot, & Kroll, 2006). The way word frequency is implemented in Multilink is in terms of a resting level activation for each word. By giving each word a different starting activation varying just below zero, lower frequency words need more time to reach the so-called translation criterion threshold of 0.7. The values of the starting activations ranged from -.05 to 0 initially, with the most frequently-occurring word in the lexicon having a starting activation of 0 and, conversely, the least frequently-occurring word having a starting activation of -.05. This was implausible for different reasons.

Firstly, the starting activations of the words were dependent on the frequency of other words in the lexicon. This is undesirable if one wants to simulate differences in L2 proficiency, which entails different frequency ranges for L2 words. Furthermore, it had consequences for the words' rank ordering; the difference in activation was the same for the most frequently-occurring word and the second most frequently-occurring word, and the least frequently-occurring word and the second least frequently-occurring word. This may seem obvious, but the absolute difference in occurrences per million (OPM) differs in such a way that a rank-wise representation was undesirable. Finally, there was an underestimation of the word frequency effect. Compared to the similarity effect, the word frequency effect barely influenced the Multilink cycle times.

Because of these objections, we changed the frequency representation so that the starting activation for each word becomes independent from all factors except from the frequency of the most occurring word in both English and Dutch ("the"). We have set the log10(occurrences per billion) of "the" which equals about 7.7 to have a starting activation of 0. Lastly, we have changed the range of starting activations to start at -.2 instead of -.05, so the range is quadrupled, causing more differentiation between words based on OPM/OPB, resulting in a higher frequency effect. The logging of the words replaces the artificial rank ordering system and the computation of the starting activation for a word now works as follows: the log10(OPB) for a word is computed (e.g. 2.6). Now this word has to receive a starting activation based on this value (2.6). The minimal starting activation is -.2, and the size of the range is 0.2. The starting activation of the word taken as an example is shown in equation 3. Equation 4 shows the general function for the computation of the resting level activation (RLA) of a word.

$$-0.2 + 0.2 * \left(\frac{2.6}{7.7}\right) \approx -0.13 \tag{3}$$

$$RLA = minrest + |minrest - maxrest| * \left(\frac{log10(OPB)}{7.7}\right) \tag{4}$$

3.3.2. Current version of Multilink

After the adjustments mentioned in section 3.3.1, Multilink has changed substantially. Figure 4 shows the architecture of the current version of Multilink.

The input of the model generally – when no priming is used – looks like this “0:WORD”, in which WORD is substituted by ANT in figure 4. This means that the word ANT is presented to the model at timestep 0. Subsequently, all orthographic nodes that have at least some resemblance to the input string get activated. The rate at which the orthographic nodes get activated is determined by the similarity index as described in section 3.3.1. The more orthographic overlap between the input and the orthographic node, the faster it gets activation. More information about how this activation works will follow in chapter 3.3.3. In figure 4, only the target word “ANT” and a neighbour “AUNT” are given as example.

When the orthographic representations become activated, they start spreading their activation to the semantic nodes. This activation determines how fast the semantic node’s activation rises. Once the activation of the semantic node becomes positive, the semantic node starts spreading activation to its corresponding phonology and orthography nodes.

When any phonologic node reaches the activation threshold of 0.7, it is recognised as correct answer/translation for the input word. The phonology however, should be in the right language, hence the language nodes.

3.3.3. Node activation processes in Multilink

In this whole process of activation and spreading activation, some nodes send excitatory activation, and some send inhibitory activation. The activation a node receives at any point in time is computed as shown in equation 5.

$$n_i(t) = \sum_j \alpha_{ij} e_j(t) - \sum_k \gamma_{ik} i_k(t) \tag{5}$$

This formula shows the net input of a node and is clarified in equation 6. All activations, either excitatory or inhibitory, are summed, and the result of this is the net input of a certain node at a certain timestep.

$$\begin{aligned} &Net\ input\ of\ node\ i\ on\ timestep\ t \\ &\quad = \sum_j (exitatory\ connection\ strength\ between\ node\ i\ and\ j) \\ &\quad * (activation\ of\ node\ j\ on\ timestep\ t) \\ &\quad - \sum_k (inhibitory\ connection\ strength\ between\ node\ i\ and\ k) \\ &\quad * (activation\ of\ node\ k\ on\ timestep\ t) \end{aligned} \tag{6}$$

The net input is not the value with which the node changes however. This rate is determined by the effect. The formula to compute the effect is given in equation 7.

$$\epsilon_i(t) = \begin{cases} n_i(t)\big(M - a_i(t)\big); & if\ n_i(t) > 0 \\ n_i(t)(a_i(t) - m); & if\ n_i(t) \leq 0 \end{cases} \tag{7}$$

This formula (7) causes a damping effect on the net input in case of an already positive activation, and an enlarging effect on the net input when the current activation is negative. The M stands for maximum activation of a node and the m stands for minimal activation of a node. If we would take a positive net input of 0.2 as an example, the effect would be different for different current activations.

With a current activation of -0.1, the effect would be: $0.2 * (1 - -0.1) = 0.22$.

With a current activation of 0.4, the effect would be: $0.2 * (1 - 0.4) = 0.12$.

The maximum activation in this example is set to 1. This means that a current activation of 1 causes the effect to be 0 for any positive net input. Because of this effect, the activation will never increase exponentially and the effect size difference will approach 0.

This effect will be added to the current activation of a node to acquire the new activation level. However, there is built-in decay of all activations, which is set to 0.07 by default to match the corresponding parameter in IB/BIA/BIA+ models. Hence, the change in activation is given by equation 8.

$$\alpha_i(t + \Delta t) = \alpha_i(t) - \Theta_i(\alpha_i(t) - rla_i) + \epsilon_i(t) \tag{8}$$

In equation 8, "Θ" stands for the decay rate and rla_i equals the resting level activation of node I (as described in equation 2). So the activation on next timestep equals the current activation plus the effect, but with the subtraction of the term $\Theta_i(\alpha_i(t) - rla_i)$. This term will rise linearly with the current level of activation.

4. Cognates and interlingual homographs

Cognates and interlingual homographs are words that differ from regular words in the sense that they orthographically resemble words in another language. If two words only have form overlap (e.g., Dutch-English ROOM), they are called interlingual homographs; if they have both form and meaning overlap, they are called cognates (e.g., Dutch-English FILM). Some translation equivalents have only partial form overlap (e.g., English RAIN – Dutch REGEN), so there is a continuum between cognates and interlingual homographs (in fact, some people consider cognates as a special type of interlingual homographs). I will start with explaining the notion of Levenshtein distance, as this is the determining factor in analyzing whether two words are cognates or not. I will then proceed by giving the definition for cognates I will use in the rest of my work, and lastly I will explain the concept of interlingual homographs.

4.1. Levenshtein distance

To determine whether a word should be called a cognate or interlingual homograph, we need to compute the word pair's Levenshtein distance (LD). The LD is a number that indicates how many transformations are needed to get from one word to another. There are three possible transformations:

1. Insertion; a letter is added somewhere in the word.
2. Deletion; a letter from the word is deleted.
3. Substitution; a letter from the word is replaced by another letter.

The Levenshtein distance is the lowest amount of transformations needed to get from one word to the other. Equation 9 shows the Levenshtein distance mathematically.

$$LD(x,y) = min\begin{Bmatrix} LD(|x|-1,|y|)+1 \\ LD(|x|,|y|-1)+1 \\ LD(|x|-1,|y|-1)+1_{(x_{|x|}\neq y_{|y|})} \end{Bmatrix} \quad (9)$$

The LD between word x and word y is the minimum of three smaller factors. If we want to change word x into word y: The first factor corresponds to deletion, the second factor corresponds to insertion of a letter and the third factor corresponds to replacement. Furthermore, "|x|" means "the length of word x" and $+1_{(x_{|x|}\neq y_{|y|})}$ means; add 1 if the last letter of word x is not equal to the last letter of word y, else add 0. This formula recursively computes the minimum number of transformations needed to get from word x to word y.

4.2. Cognates

There are two criteria determining whether two words are cognates or not. The definition of the linguistic criterion is found on dictionary.cambridge.org and is as follows; "[Cognates are] words [that] have the same origin, or are related in some way similar". This relation has to be of an etymological nature and more accurately means that the two words have the same root. The example that is given is the cognate status of the Italian and French words for "to eat", respectively "*mangiare*" and "*manger*". In the same way, the English noun "*snow*" would be cognate with its Dutch and German translations, respectively "*sneeuw*" and "*Schnee*". With this definition, the cognate pair does not really have to overlap in spelling, but only needs to have a common origin; that is what defines a cognate according to this linguistic definition of cognates.

Because of the orthographically-focused nature of the Multilink model, our definition for cognate will be closer to the definition used in psycholinguistics, which is slightly different from the linguistic criterion mentioned above. For two translation equivalents to be cognates, the LD between the two can be at most as large as half the length of the longest word. For example, English "*tea*" and Dutch "*thee*" are cognates because the Levenshtein distance between the two words is at most 2 (half the length of "*thee*"). To be more precise, the Levenshtein distance is in this case exactly 2 (to get from "*tea*" to "*thee*", we insert an "*h*" in "tea", and change the "*a*" into an "*e*"). The words "*snow*" and "*Schnee*" would not be considered cognates since we would need to do more than 3 (half the length of "*Schnee*") manipulations on the word "*snow*" to change it into the word "*Schnee*".

There are different kinds of cognate pairs as described by Dijkstra et al. (Dijkstra, Grainger, & van Heuven, 1999). Words can overlap in semantics and orthography (SO cognates, e.g. "water"); in semantics and phonology (SP cognates, e.g. "cliff" and "klif"); and in all three areas (SOP cognates, e.g. "net"). The previous version of Multilink did not take phonology into account at all, and therefore there was a major underrepresentation of the effect of SP cognates. The example given of an SP cognate in English-Dutch word pairs is "cliff" versus "klif"; the spelling of both words is only 60% similar, whereas the phonology is the same. Because the model lacked phonological representation, SP cognates did not receive as much benefit (faster modeled RT) from their cognate status as SOP and SO cognates did; the model simply did not recognize SP cognates as being cognate-like.

People are known to be able to translate cognate words faster than non-cognates words, but the Multilink model currently does not capture this effect as it is supposed to. If the input word is (almost) the same as the target word, the model generates too much activation. One way to improve this is by looking at which connections there are in the model, and to what extent they are active, as well as analyzing the effects that the strengths of those connections have. It would also be interesting to see if there are factors contributing to the cognate facilitation effect left unconsidered and thus not implemented in the model.

A complicating factor in this matter is the purely orthographically-based nature of the old model. This means that only cognates that have overlap in orthography (SOP and SO) were considered as cognates, whereas on the other hand, SP cognates were not recognized as being cognates by the model. The inclusion of phonology in the current model is a valuable addition and serves as a beginning solution for the underrepresentation of phonology. However, orthography still has a larger influence in determining whether two words are cognates or not.

4.3. Interlingual homographs

Interlingual homographs are words in two languages that are orthographically similar, but differ semantically. For example, the English word "*room*" would translate into the Dutch word "*kamer*"; however, the orthographic form "*room*" is also a word in Dutch, which translates to the English word "*cream*". This word form ambiguity can cause a lot of confusion for second language learners, as the resemblance in orthography combined with the discrepancy in meaning complicate understanding and translation. This confusion shows from empirical studies (Vanlangendonck, 2014); in English lexical decision tasks with Dutch distractor words, people respond slower to interlingual homographs than to English control words.

At the very end of this thesis, I will address interlingual homographs. I will discuss how Multilink deals with those word pairs and how this could possibly be improved upon in the future.

5. Most prominent variables in word translation

The Multilink model is built as a large network with different nodes influencing one another at different points in time. There are many variables that influence the differences in empirical reaction data, and the aim is to account for as many of them as possible in Multilink simulations. Of course, it is hard to capture all reaction time variance between words, and capturing variance between different subjects is essentially impossible. Although modeling human cognition with regard to word translation is challenging, some variables that influence empirical reaction time have successfully been incorporated into Multilink. Here, I detail these variables.

5.1. Word Similarity

Monolingual and bilingual word retrieval studies indicate that response times in many tasks are most affected by the similarity of the input letter string to stored representations and the frequency of usage of the items in daily life. In the bilingual domain, the similarity of the input is important relative to words in both languages of the bilingual. In fact, the cognate effect is strongly dependent on cross-linguistic similarity (and on the frequency of the cognate readings).

The cross-linguistic similarity effect is implemented in the model by means of the score function as seen in equation 10. The score is dependent on two factors. The first factor is the IO_Multiplier, which is chosen arbitrarily; if this value is raised, all words will reach activation faster. The "IO" in IO_Multiplier stands for "Input-output"; this factor is multiplied with the second factor. The second factor is the cube of the similarity value between the input word and the candidate output (hence "IO" in IO_Multiplier) words, calculated in terms of Levenshtein distance.

$$score = IO\_Multiplier * \left(\frac{MAX_L - DIST}{MAX_L}\right)^3 \quad (10)$$

One potential flaw in this representation is that, in a case where there is such a high activation for a translation pair that is not the target word; the wrong output could be selected. For example, both English "yacht" and Dutch "jacht" obtain high scores when the input word is Dutch "zacht" (meaning "soft"), since for both of these words, the similarity with "zacht" is 80%. The target word "soft" however does not receive much activation based on orthographic similarity (the "t" in the end is the only matching letter, so the similarity value is 20%). Later on, the semantic node of yacht/jacht will receive more activation than that of soft/zacht, simply because both words in a translation pair had a very high resemblance to the input word, whereas the correct translation did not particularly look like the input.

In this case, the combined cubed similarity value of "jacht" and "yacht" will be higher than that of "zacht" and "soft": $0.8^3 + 0.8^3 = 1.024$ versus $1^3 + 0.2^3 = 1.008$. Consequentially, the semantic node of jacht/yacht will have a head start, which results in the victory of "yacht" instead of "soft". Explorations with different parameter settings indicate that this currently is the only word that is not translated correctly.

5.2. Word Frequency

Word frequency is another variable implemented in the model; word frequency answers the question of how many times a word occurs in normal speech. This value is a strong indicator of word recognition speed and was the most important variable in the earlier word recognition models. In Multilink, this variable determines the starting activation for each word. Word frequency was implemented by means of a rank system. In this system, the most frequent word has the highest starting activation, the second most frequent word the second highest, and so forth. However, a consequence of this rank system was that there is no difference between whether the most frequent word is used 100,000 times per million words or 5,000 times per million. For this reason, the transition to the log10(OPB) as a measure for word frequency has been made.

Using a rank ordering instead of the occurrences per million (OPM) value was a helpful simplification from a computational standpoint, but the correlation between word occurrences per million words (OPM) and the rank the different words in the empirical study have is only $r = -0.77$, with $p < 0.001$. The correlation with the natural logarithm of OPM with rank is $r = -0.99$, with $p < 0.001$. This was an indication that rather than the rank ordering of the words determining their starting activation, a function applied to the OPM should be used. The logarithm of the OPM/OPB value made sense here, since that value seemed to be extremely correlated with the rank ordering. It also had the advantage that the starting activation of words would not change depending on other words. Lastly, logging of word frequencies is common practice in psycholinguistic studies.

5.3. Word length

The third major effect on word translation that is not implemented as such in the model, but must be mentioned, is the word length effect. The word length effect is to a certain extent incorporated in the LD; the maximum LD two words can have is limited by the length of the longest word. Several monolingual studies of lexical decision and word naming have found significant positive correlations between the word length of the input word and the reaction time of the subjects. These studies have been reviewed by New et al. (2006).

Some of the reviewed studies (New et al., 2006) have found an inhibitory effect of length. That is, the longer the word is, the slower the reaction on that word will be. This implies a positive correlation between length and reaction time. At the same time, there is little agreement about this effect: about half of the studies have not found a significant effect, whereas the other half has found a significant inhibitory effect.

The situation of word translation differs from the monolingual studies listed above because two languages are concerned. If we assume the inhibitory effect of input word length found in many studies, then it is to be expected that there should be a positive correlation between the length of the input word and the reaction time. The reason we examine the input words is because those are the words that have to be understood and parsed. The lengths of the output words might be correlated with the reaction time as well, but the above studies do not give us any information about output word lengths. The only indication for this would be the correlation between the length of the input and the output words ($r=.44$, $p < .001$). This would lead to a correlation between the output words and reaction time.

The empirical data (Pruijn, 2015) indeed provide evidence of an effect of input word length on reaction time. I will elaborate on this effect in chapter 9.

6. Comparison of Multilink with empirical data

Multiple experimental studies with human participants have been conducted involving lexical decision or word translation tasks. In both of these, the word recognition time is part of what is being measured. However, in lexical decision, the goal of the task is to determine how long it takes for people to recognize letter strings as being words or non-words. As such, lexical decision is a comprehension task. In contrast, in word translation tasks, the response time is the time that it takes to name the correct translation of the input word. This means that the input word has to be recognized, the other language's lexicon has to be accessed, and the translation equivalent has to be retrieved and produced.

In sections 7 and 8 I will compare Multilink respectively with the IA and the BIA models, and with empirical lexical decision studies. Chapter 9 will be dedicated to an explanation of the results found in word translation studies, and in section 10, I will run the word translation function of Multilink and make a comparison with the empirical data once again. Section 11 will be an exploration of interlingual homographs in Multilink.

In the appendix, all lexicons and word lists used in sections 7 to 10 are attached. The word lists used in the simulations with BIA and IA are not included; in these simulations the entire lexicon was used as input.

7. Comparison of Multilink with IA and BIA

In addition to the word translation function of Multilink, there is also the possibility for word recognition or lexical decision. In order to connect Multilink with the existing models for word recognition as described in existing literature, I will run batch jobs using Multilink. Those batch jobs will consist of all of the 4-letter words that are included in the English and Dutch lexicons in the IA and the BIA models, respectively. I will also run batch jobs using the IA and the BIA models, and subsequently I will correlate the output cycle times of Multilink with the output cycle times of BIA/IA. To get the RTs for the BIA model, I have used the most recent implementation of jIAM by Van Heuven (2015). jIAM is an online implementation of the BIA/IA model. I have altered the standard settings such that the recognition threshold is set to 0.7. This matches the Multilink settings and also increases accuracy. Furthermore, the integration rate / step size parameter is reduced to 10% of its original value. Because of this, a higher accuracy in display of cycle times can be reached. The reason for this is that, with the integration rate / step size parameter set to its original value, all recognition times would be between 17 and 21 cycles (integer values only). By multiplying the parameter by 10, the cycle times fall between 170 and 210. This bigger range (40 versus 4) is desirable, because this makes differentiation possible; words that are recognized in 171-180 cycles in the larger range are all recognized in exactly 18 cycles in the smaller range. The RTs of ML are obtained with the most recent version of Multilink.

7.1. Lexical decision by English monolinguals

To compare Multilink with the IA model, it is best that most variables remain the same so that variance found can be totally attributed to the difference in how the models work. Therefore, I created a new lexicon on which to run the Multilink simulations; this lexicon includes the same words and only the same words as those found in the lexicon of the IA model. The task is as follows: both models are run with in batch mode and include all of the words in their lexicons. In the new lexicon that I have created, I have used almost all of the words from the lexicon of the IA model, which totals 889 words.

After creating these lexicons that include phonological representations, I ran the Multilink model and the IA model. I also include data from the British Lexicon Project (BLP) (Keuleers, Lacey, Rastle, & Brysbaert, 2012) to compare the models based on how well they predict empirical data. The BLP contains the average reaction times of monolingual speakers of (British) English for almost 30,000 words (all 889 words I have used are included among them).

First, I will present a table (table 1) to give an overview of what the data look like. In this tabular representation of the data, I have normalized the reaction times so that the mean of IA and ML are the same as the mean of the BLP RTs. This way, the data is more easily interpretable. The most striking difference between the three groups is in the standard deviation: the standard deviation of the empirical data is more than twice the standard deviation of IA. This may imply that a lot of variance is still not covered by IA, or at least the factors causing that variance are underestimated. The standard deviation of the ML RTs is closer to that of the BLP RTs, but it still differs considerably. Boxplots are provided in figure 6.

	IA	ML	BLP
Min	492	455	478
Max	647	626	935
Std	22	37	49
Mean	560	560	560
Median	559	563	550

Table 1: Reaction time data by the IA model, Multilink, and the empirical data obtained from the BLP

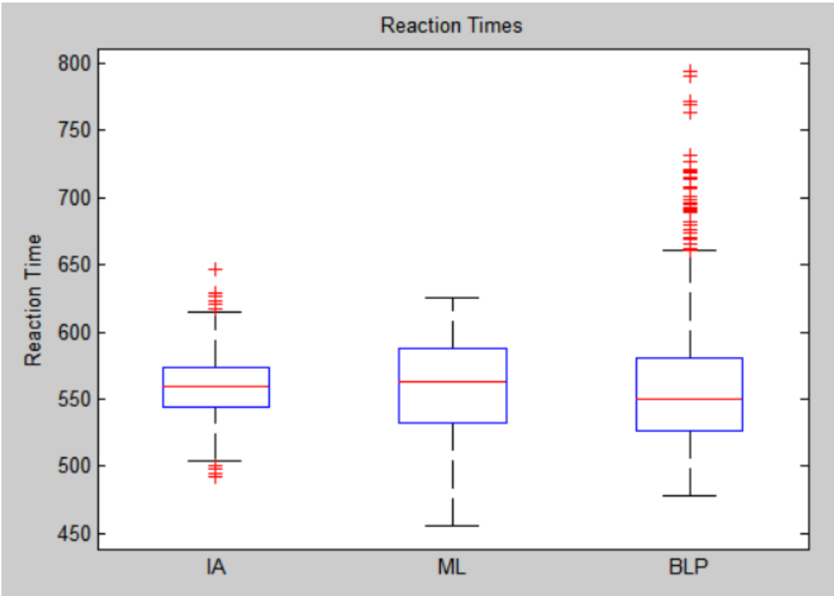

Figure 6: Reaction time data by the IA model, Multilink, and the empirical data obtained from the BLP

I will proceed by giving a direct comparison between the IA and the BLP data, followed by a comparison between the ML and the BLP data. Ultimately, I will perform a model-to-model comparison between BIA and ML.

The correlation between the outputs of the IA model and the BLP data is highly significant (r= 0.29, p < .001). The left plot in figure 7 shows the relation between the IA reaction times and the BLP reaction times. I have left out one data point for which the BLP value was 934 for the sake of clarity and so the axes would fit the data better.

The red diagonal line represents the formula:
$IA\ reaction\ time = BLP\ reaction\ time$. If all data points would be located on this line then IA would be a perfect predictor for the empirical BLP data. However, they are not and one reason for this is the very small dispersion in the IA data in combination with the much larger dispersion in the empirical data. Another reason is that Pearson's r is only 0.29; this means that a lot of variance remains unexplained by the model.

Another interesting relation to look at is the relation between Levenshtein distance (between the English word that has to be recognized and its Dutch translation equivalent) and IA RT. This correlation is not significant ($r= 0.05$, $p > 0.1$) as expected; the comparison between BLP data and Levenshtein Distance (and thus between IA RT and Levenshtein distance) should yield no significant correlation, but the comparison between Dutch Lexicon Project (DLP) data and Levenshtein Distance (which I will come to speak about in section 7.2) should yield a significant correlation. The DLP is the Flemish (bilingual) counterpart of the BLP. The reason for these expectations is that most English natives do not speak Dutch, but Flemish natives do speak English; bilinguals are helped by cognates, whereas monolinguals do not even detect cognates. In the BLP data, we indeed find no correlation between Levenshtein Distance and RT ($r= .02$, $p >.5$).

In essence, ML is a word translation model, however, it also provides the option of word recognition and this option should be sound in order for the word translation option to work properly. I will now use the same kinds of data as I did before with the comparison between IA and the BLP Data.

The correlation between ML and the BLP data is highly significant ($r= 0.35$, $p < .001$), and stronger than the correlation between IA and BLP. In the middle plot in figure 7, this is visually displayed. The largest difference between this plot and the first plot in figure 7 is the dispersion of the model data; that dispersion is larger in this plot than it is in the left plot. This increased dispersion is coming closer to the amount of dispersion in the BLP data. This could be a reason for the better correlation of ML with the BLP data compared to the correlation of AI with the BLP data. This increased dispersion however, does not necessarily increase the correlation; it could also be caused by noise which would not contribute to the fit at all.

Concerning the relation between Levenshtein distance and reaction times in the model, there is a noteworthy difference between IA and ML. Whereas IA did not show a significant correlation between the two ($r= 0.05$, $p > 0.1$), ML does ($r= .24$, $p < .001$). The reason for this is that in ML, the word that has to be recognized can activate both Dutch and English orthographic representations. In the case of a cognate for example, the Dutch equivalent of the target word will get activated as much as the (English) target word itself, speeding up the activation process of the semantic nodes and thereby speeding up recognition time. Although a significant relation between LD and RT is found in ML, but not in IA and the empirical data ($r= 0.02$, $p > 0.5$), the ML RT data correlates better with the BLP data than the AI RT data does.

Since we have compared both the IA and ML models on word recognition with empirical data, I will now compare the two models directly with each other. In the right plot in figure 7 I have plotted the AI RT against the ML RT. As can be seen from this plot, the AI and ML RTs correlate much better with one another (r= .54, p < .001) than either one does with the BLP data. The reason for this probably is that both models use some of the same techniques to compute output times; orthographic overlap is an especially important factor in both models. Empirical reaction times most likely include a lot of components that neither of the models captures, including noise.

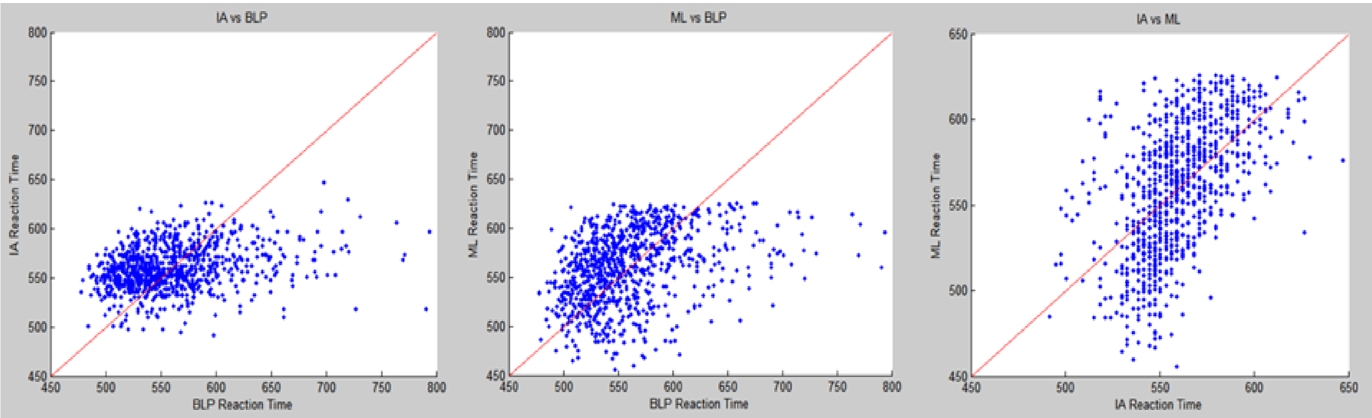

Figure 7: From left to right: IA vs. BLP; ML vs. BLP; IA vs. ML

7.2. Lexical decision by Dutch bilinguals

Here I will compare models and data in the same way as I did in section 7.1, with some differences. The first difference is the language of the words that will be tested on RT; in this section, I will be covering Dutch instead of English. The second difference is the model with which I will compare ML. For the English words, I used the IA model, but for the Dutch words I will use the bilingual version--the BIA model. The third difference is that I will not use all the words with which I ran batch jobs because many words (158) were not recognized by the BIA model at all. Therefore, I will only use the remaining 499 words; these are the words that both BIA and ML were run on. The fourth and last difference is that I will not use the BLP, since we are working with Dutch words; instead, I will be using the Dutch Lexicon Project (DLP) (Keuleers, Diependaele, & Brysbaert, 2010).

The further procedure is roughly the same; I have created a unique lexicon for ML that includes all those words—and only those words—that are included in the BIA lexicon. I then ran both models on the lexicon; the results can be found in table 2 with their boxplot representations in figure 8. I normalized the scores so that the means for all categories would be the same.

There are a few things that stand out when we compare the results here to those in table 1. First, the standard deviation of the ML RTs is a lot higher and lies a lot closer to the standard deviation of the empirical data (DLP in this case)—in fact, the ML standard deviation even is a bit higher. The standard deviation in the BIA RT data is even smaller than it was in its English counterpart. The effect the standard deviation has on the dispersion of RTs can be seen in the boxplots in figure 8 (compare figure 6). Later in this section, I will compare BIA with DLP, then ML with DLP, and finally I will compare the models with each other. I will also relate these findings to the ones from the previous section (7.1.) to explain why some things work and others do not.

	BIA	ML	BLP
Min	529	451	472
Max	647	763	789
Std	19	53	51
Mean	583	583	583
Median	583	580	571

Table 2: Reaction time data by the BIA model, Multilink, and the empirical data obtained from the DLP

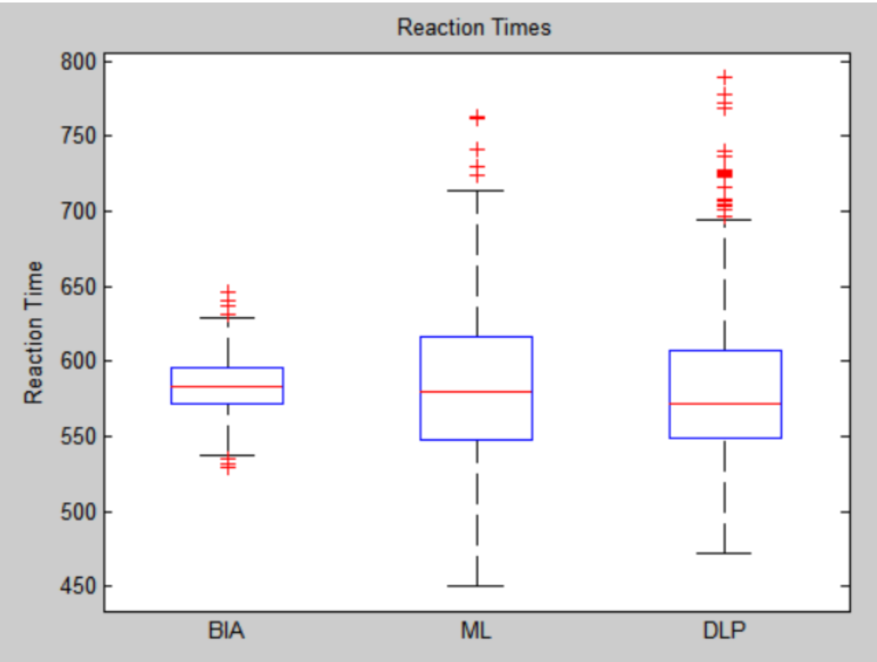

Figure 8: Reaction time data by the BIA model, Multilink, and the empirical data obtained from the DLP

The relation between BIA and DLP is best understood by referring to the first plot in figure 9. This plot closely resembles the left plot in figure 7 (in which I compare IA with BLP). The reason for this resemblance is the fact that IA and BIA use the same approach. BIA however comprises two lexicons (as opposed to one in IA), but the (Flemish) subjects tested in the DLP also have access to two lexicons (as opposed to the English subjects that only speak one language). So, the number of lexicons is the matched similarly, and the approach is the same; this causes the plots to resemble each other.

The items that take relatively long to be recognized in the DLP data are recognized too quickly by BIA. Furthermore, the dispersion in BIA RTs is smaller than in DLP and these factors all contribute to a low correlation between BIA and DLP (r= .3, p < .001). Levenshtein distance does not influence BIA RT.[1]

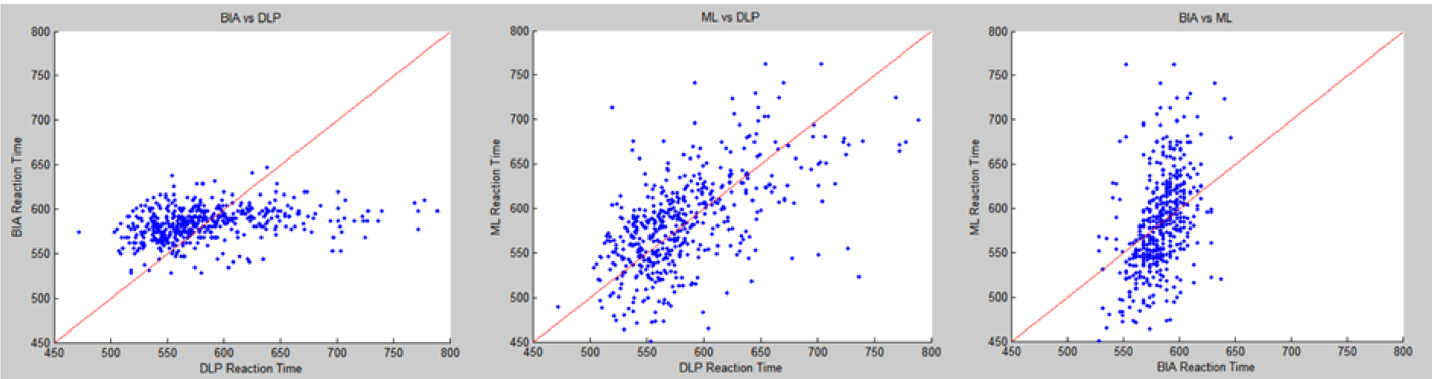

Figure 9: From left to right: BIA vs. DLP; ML vs. DLP; BIA vs. ML

[1] The correlation between LD and BIA RT is insignificant (r= .03, p > .5), based on the fact that the correlation between LD and IA RT was insignificant as well, this was to be expected.

Multilink, as a model for word translation in bilinguals, should perform more target-like on the recognition of Dutch words (targets being the DLP average RTs) than on the recognition of English words (targets being the BLP average RTs). There are two reasons for this expectation. On the one hand, the definition of "target" I use (BLP average RTs in previous section, and DLP average RTs now) is defined by either a group of monolingual British people or bilingual Belgian people. On the other hand, since ML takes into account the LD between translation equivalents, it is built to work like bilingual people and thus will perform better on Dutch words than on English words.

In the middle plot in figure 9, the relation is visible between ML and DLP. Its correlation indeed is a lot stronger ($r= .58$, $p < .001$) than any other (IA vs. BLP / ML vs. BLP / BIA vs. DLP). The data points, despite somewhat shattered, are nicely located around the red line. The formula for the red line is:

$ML\ reaction\ time = DLP\ reaction\ time.$

The correlation between LD and ML is expected to be significant and positive again. ML (incorrectly) took LD into account in its recognition of English words and it indeed does so on the recognition of Dutch words as well ($r= .15$, $p < .001$). This correlation is thus positive; the more similar the words (low LD), the faster the subject responds in general (low RT). This is what we would expect, since similar words or even cognates receive (more) facilitation from their translation equivalent (than less similar words).

The comparison between the RTs of the two models on Dutch words ($r= .45$, $p < .001$) yields a lower correlation than it did on the English words ($r= .54$, $p < .001$). One reason for this could be the reduced standard deviation of BIA RT data in combination with the increased standard deviation and better empirical fit of ML RT data. These different sized standard deviations become really clear from the oblong area in which the data points are located (right plot in figure 9).

8. Comparison of Multilink with empirical studies

In the previous section, the comparison was made between Multilink and other models of word recognition. In this section, I will compare the Multilink output data to data from empirical studies. In each subsection, I will summarize the study before moving on to my simulations and results. The first study with which I will compare Multilink is Dijkstra et al. (2010); the second one is Vanlangendonck (2014).

8.1. Lexical decision with cognates by Dijkstra et al. (2010)

Dijkstra et al. (2010) performed English lexical decision, which is the task I simulate in ML. Before starting this English lexical decision experiment, a rating experiment was conducted. This rating study aimed to measure perceived similarity (orthographic, semantic and phonological). The results of the rating experiment were used to select appropriate stimulus materials.

The stimuli in the English lexical decision experiment consisted of 194 words and 194 non-words. The participants were presented all of the experimental data in four blocks. These blocks never included four words of the same category (non-word, cognate, non-cognate) after each other.

There were two main findings concerning similarity. First, there was a negative correlation between perceived orthographic similarity and RT. This is interesting, because this indicates that there is a correlation between the extent to which people grade words as orthographically similar; which is a conscious process, and their reaction times on those words. Second, higher perceived phonological similarity went together with much faster RTs, but this was only the case for identical cognates; no effect was found for non-identical cognates. The interesting aspect about this finding is that it suggests that overlap in phonology is important, but this is only the case when orthography already overlaps completely. This would imply that SP-cognates should not be considered cognates at all in terms of reaction time, and SOP-cognates should be responded to significantly faster than SO-cognates; this would make the order as follows: SOP-cognate RT < SO-cognate RT < SP-cognate RT = control word RT.

The simulations I have run and the figures I will present in this section are based upon the raw data, and the data presented in the paper are acquired after data cleaning. Therefore, my data slightly deviate from the results as presented in the paper by Dijkstra et al. (2010).

8.1.1. Correlation between Dijkstra et al. data and Multilink output

Since all the words in the study are relatively short (either 4, 5, or 6 letters in length) I will consider words that have a Levenshtein Distance of 3 or higher to be control words; the reason for this is that such short words combined with such high LD (> 3) have less than 50% similarity and thus cannot be considered cognates anymore. From this, we can derive four categories: Identical cognates, cognates with a Levenshtein Distance of 1 (LD1 cognates), cognates with a Levenshtein Distance of 2 (LD 2 cognates) and control words. I will start by presenting table 3 and figure 10; these represent the results I have found. In the data I present, I have rescaled the Multilink cycle times to reaction times in milliseconds in the same way as I have done in previous sections.

	Identical Cognate	LD1 Cognate	LD2 Cognate	Controls
Dijkstra et al.	497	548	541	545
Multilink	517	541	535	544

Table 3: Average reaction times on different categories according to Dijkstra et al. (2010) and Multilink

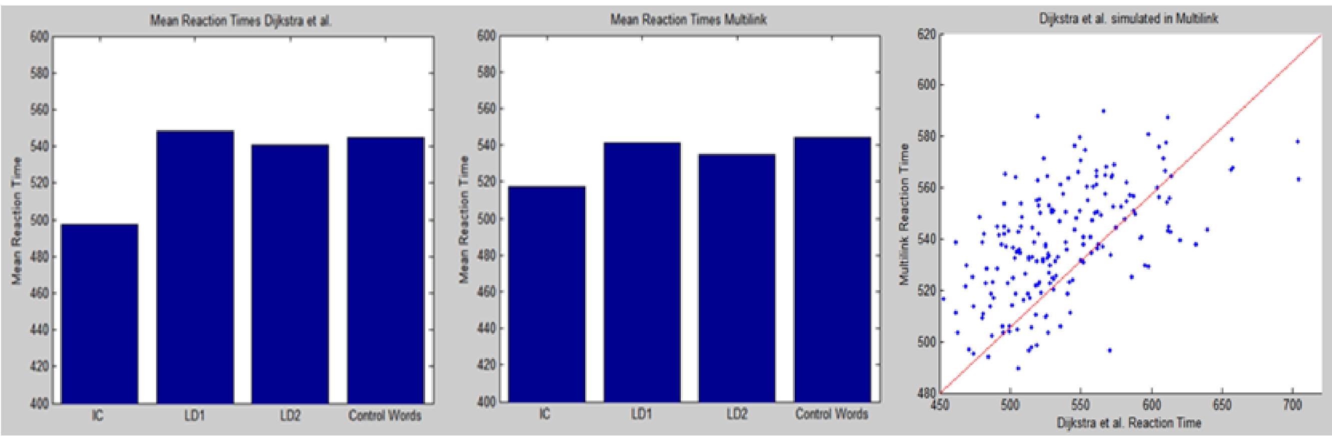

Figure 10: Reaction time data by Dijkstra et al. and Multilink graphically represented in the first two plots, and plotted against each other in the right plot

Table 3 is a summary of the two left plots in figure 10, with the first row of the table corresponding to the leftmost plot and the second row corresponding to the middle plot. Note that the y-axis does not start at 0, so the differences between bars may appear larger than they are. However, there still is an effect that is visible; both the empirical data as well as the ML data show RTs for ICs that are shorter than the RTs for the other categories.

It was to be expected that ICs would be responded to faster, and it is desirable that ML shows this. Furthermore, it would also be probable that this effect would carry over to LD1 and LD2 cognates. This however is not the case: the reason for this probably is that there is no considerable difference between LD1 cognates, LD2 cognates and control words in either the ML RT data or the Dijkstra et al. data. The Dijkstra et al. and the ML RTs dataset have correlations of respectively $r = .23$ ($p < .002$) and $r = .28$ ($p < .001$) with the LD, so there is a significant similarity effect to be found, and it is correctly represented in Multilink.

The model is quite successful in fitting the data. We see the same pattern in both figures and the correlation between the two datasets is .55 ($p < .001$). In the rightmost plot of figure 10, the relation between the empirical data and the ML data is visualized. We can see that it is impossible for ML to simulate outlier words well (the two rightmost data points for example). The source of this variance seems not to be included in Multilink.

8.1.2. Correlation between word length and reaction time

As mentioned before in section 5.3, many studies have been conducted on word length and RT. About half of them found an inhibitory effect (longer words take longer to recognize, thus meaning slower RTs) and the other half found no effect. (New et al., 2006)

Searching for this effect in the empirical data and the ML data that we are currently examining yields both results: in the empirical data we find no significant correlation between word length and RT ($r= -.03$, $p > .65$), and in the ML data we find a positive correlation between word length and RT ($r= .22$, $p < .005$).

In figure 11, the relation between word length and RT can be seen. This figure also clearly shows the relatively small dispersion of the ML data compared to the empirical data.

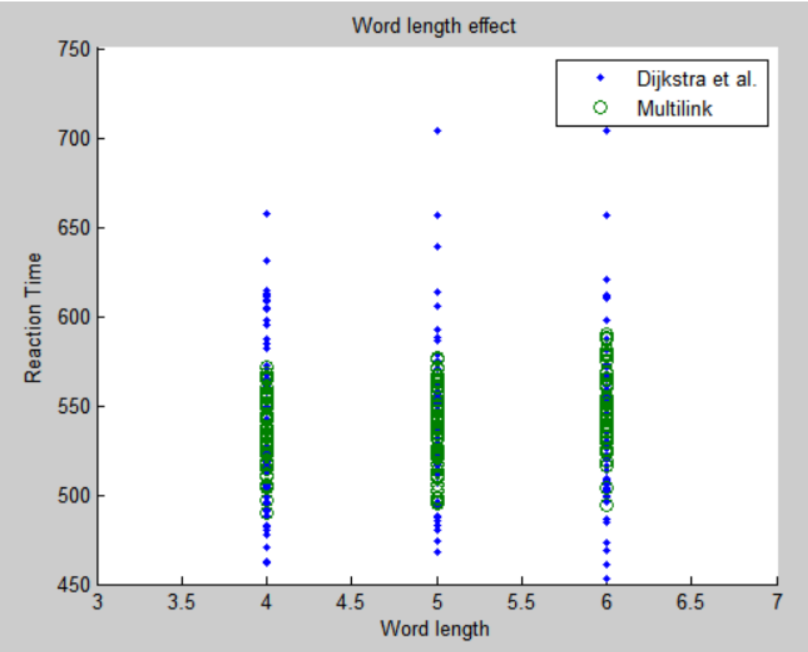

Figure 11: Word length vs. reaction time

8.2. Lexical decision with cognates by Vanlangendonck

A study by Vanlangendonck (2014) performed similar experiments to the study discussed above (Dijkstra et al., 2010). However, the author did not perform a preceding rating task, so the only information available regarding (orthographic) similarity is the LD.[2]

The first task – and the one that I will simulate – was English lexical decision. The stimulus material included: false friends, identical cognates, non-identical cognates with Levenshtein Distances of 1 and 2 and English control words; this study thus adds false friends to the categories used by Dijkstra et al. (2010). In the study by Vanlangendonck (2014), significant differences were found between the control words and the identical cognates and between the control words and the non-identical cognates with LD of 1 (identical cognates and non-identical cognates both have lower RTs than control words). These findings are only partially in line with the results Dijkstra et al. (2010): the significant difference in RT between control words and LD1 words was not found in the 2010 study.

[2] The additional value of this study is that in addition to measuring reaction times, the author used fMRI techniques as well.

8.2.1. Correlation between Vanlangendonck data and Multilink output

In contrast to the study in the previous section (Dijkstra et al., 2010), which used perceived similarity as judged by the participants, Vanlangendonck (2014) made word categories herself. She also reported the averages for each category. Table 4 shows these averages along with the ML averages, and the upper two plots in figure 12 show the bar graphs corresponding to the data in table 4. The averages of the raw data are presented in figure 12 as well.[3]

	False Friends	Identical Cognates	LD1	LD2	Controls
VL	649	612	632	634	647
ML	633	611	635	648	648

Table 4: Average reaction times on different categories according to Vanlangendonck (2014) and Multilink

As we can see in the figure 12, all five bars in the upper two plots generally resemble each other. When we take a look at the heights of the bars (Identical Cognate < LD1 Cognate < LD2 Cognate < Controls) there is reason to believe that there is a positive correlation between LD and RT, thus a cognate effect. This is the case because in both upper plots in figure 12, the larger the LD, the larger the RT. While this is not the case for the raw empirical data ($r = .03$, $p > .65$), it is for the ML data ($r = .30$, $p < .001$). In the raw empirical data, the cognate effect is visibly absent; if we were to leave out the Identical Cognates, there would even be an opposite effect (Controls < LD2 < LD1). Despite this, there still is a strong correlation between the raw empirical data and the ML data ($r = .64$, $p < .001$). A scatterplot of this is provided in figure 12 as well.

[3] I did not have access to the raw RT data for the false friends so this part of the figure only contains four classes.

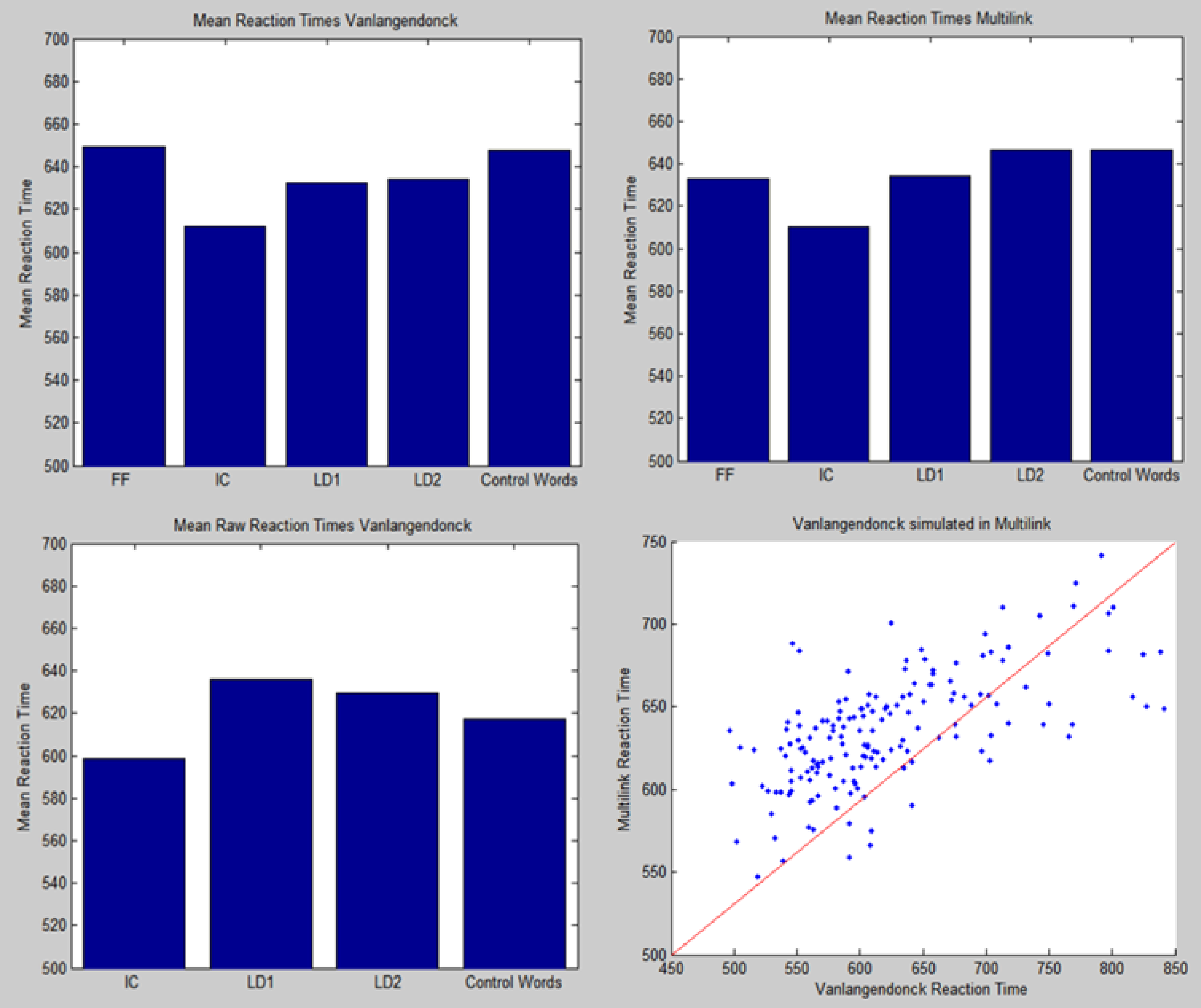

Figure 12: Clockwise, starting at the top left plot: Graphical representation of the reaction time data on different word categories as Vanlangendonck reported in her paper; graphical representation of the reaction time data on different word categories by Multilink; Multilink reaction time data plotted against empirical reaction time data; graphical representation of raw reaction times by Vanlangendonck

8.2.2. Correlation between word length and reaction time

As I did in the previous section with the Dijkstra et al. (2010) data, I will also compute the correlation between word length and RT for the data from the study by Vanlangendonck (2014). This time, both correlations are insignificant. The correlations between word length and RT for the empirical data and the ML data respectively are r= -.06 (p > .4) and r= .06 (p > .4). Data is shown in figure 13.

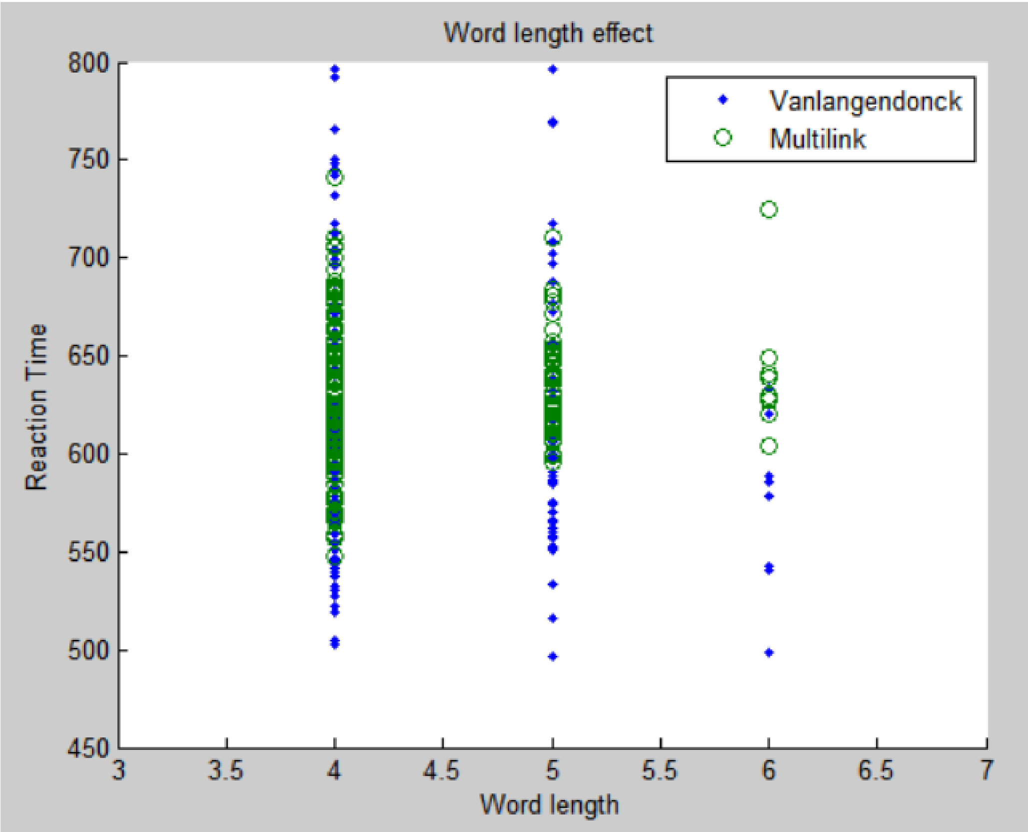

Figure 13: Word length vs. reaction time

8.3. Discussion

The comparisons with the empirical data of Dijkstra et al. (2010) and Vanlangendonck (2014) teach us something about the model we had not yet learned from the comparison with the BLP and the DLP data. In these former studies, Dutch people were tested on their performance of recognizing English words, as opposed to testing Dutch people on Dutch words or English people on English words. This bilingual component really is important in Multilink, and, considering the correlations between the RT data from the studies and the RT data of ML, we see that ML succeeds reasonably well in capturing a lot of variance in RTs for this kind of task (English lexical decision by Dutch people).

What we see in both studies, as well as in Multilink is that identical cognates are recognized considerably faster than all other word categories. Multilink sometimes has trouble with the other categories (LD1 cognates, LD2 cognates and control words) but the studies do not show a clear RT order for these categories either. The reason Multilink struggles with these words might be that the words were relatively short (4 to 6 letters) so a LD of 1 or 2 has substantial impact on the percentage similarity of two translation equivalents (which is the measure ML uses to generate cognate effects).

In terms of word length effects, Multilink only took length effects into account on the data of Dijkstra et al. (2010); Pearson's r for the correlation between ML RT and word length was .22 ($p < .005$). Multilink did not show length effects on the data from Vanlangendonck (2014). In both Dijkstra et al.'s (2010) and Vanlangendonck's (2014) empirical RT data, no effect of input word length on RT was found either.

9. Word translation simulation in Multilink

In sections 7 and 8, we have only considered word recognition and in this section the word translation functionality of Multilink will be used. This functionality of Multilink will be run with the words used in and empirical study by Pruijn (2015) and the cycle times output by the model will be compared to the RTs in this study. First, I will discuss two important papers with regard to word translation. I will summarize Christoffels et al.'s study (2006), of which Pruijn's was a partial reproduction, as well as Pruijn's study (2015).

9.1. Word translation by Christoffels et al. (2006)

The study I will cover in this section is that by Christoffels et al. (2006). This paper is titled "Memory and language skills in simultaneous interpreters: The role of expertise and language proficiency". This study involved the comparison of three different groups (students, highly proficient teachers of English, and interpreters) on different tasks (picture naming, word translation, and reading/speaking/word span tasks).

The most important group with regard to my thesis is the students group, since the participants Pruijn used are comparable in proficiency with the students group. The task I will look at is the word translation task, which involved 72 Dutch and 72 English words. Cognate status and word frequency were controlled for, and 8 groups of words were obtained in the end (varying translation direction, cognate status, and frequency). The groups were matched on word length and word concreteness as well.

In the student group, there was a clear effect of language found; English to Dutch translation went 66 milliseconds faster than Dutch to English translation. In the teacher and interpreter groups, no such effects were found. The RT differences between translation directions for these two groups were respectively 2ms and 0ms. This means that in Multilink we expect to see a translation direction effect in favor of Dutch to English.

The second finding I want to mention is the presence of the cognate effect. In all groups this effect was highly significant, so it is anticipated that some sort of cognate effect should appear in ML.

9.2. Word translation by Pruijn (2015)

The experimental data of Pruijn (Pruijn, 2015) is what I will be using in next chapter for the Multilink simulations. Pruijn has made the same division in groups as Christoffels et al. (2006) did: 8 groups of 32 words each were created by means of varying translation direction, cognate status, and frequency.

Pruijn's participants were 42 unbalanced Dutch university students. This group resembles the group Christoffels et al. used for their experiment, so we would expect to find the same results.

For all four groups (varying cognate status and frequency), an effect was found regarding translation direction. Furthermore, this effect always was in favor of Dutch to English translation direction. The average effect was 35ms and it was significant.

Also, the cognate effect was significant in all four groups (varying translation direction and frequency), cognates being translated more than 100ms faster than non cognates. All of these results are very well in line with the findings of Christoffels et al. (2006).

9.3. Simulating word translation

Based on what we learned from New et al.(2006) and the word recognition simulations, as well as the Christoffels et al. (2006) and Pruijn (2015) studies, we expect ML to show several effects. First, based on the ML simulations on the Dijkstra et al. (2010) data, as described in section 8.1.2, we expect to find a word length effect. Although the study by Dijkstra et al. was a word recognition study, I believe that this effect should also be found in word translation, since word recognition is a component of the word translation process. Second, there should be a translation direction effect with Dutch to English translation being faster than English to Dutch translation, since this effect was found by both Christoffels et al. (2006) and by Pruijn (2015). Lastly, there should be an effect of cognate status, since this is reported in the previously mentioned studies as well.

Tables 5 and 6 present the data from the Multilink simulations as well as Pruijn's data, while figure 14 shows the data plotted in a coordinate system. The cognate effect in ML is already visible from this table, but a translation direction effect is absent.

In subsections 9.4 and 9.5, I discuss the simulations of English-to-Dutch and Dutch-to-English word translation, respectively. Each of these subsections is further subdivided into two parts, corresponding to displays of non-cognate results and cognate results. In section 9.6 I will draw a conclusion about the results discussed in sections 9.4 and 9.5.

	Multilink			
	English to Dutch		Dutch to English	
	Non-Cognate	Cognate	Non-Cognate	Cognate
Min	809	675	808	675
Max	925	903	926	895
Std	30	54	31	53
Mean	872	789	869	795
Median	875	795	866	805

Table 5: Reaction time data of the Multilink simulations, divided in four groups

	Pruijn			
	English to Dutch		Dutch to English	
	Non-Cognate	Cognate	Non-Cognate	Cognate
Min	669	631	663	621
Max	1203	1034	1093	1105
Std	116	90	117	97
Mean	910	784	861	771
Median	908	764	836	745

Table 6: Reaction time data of the empirical study, divided in four groups

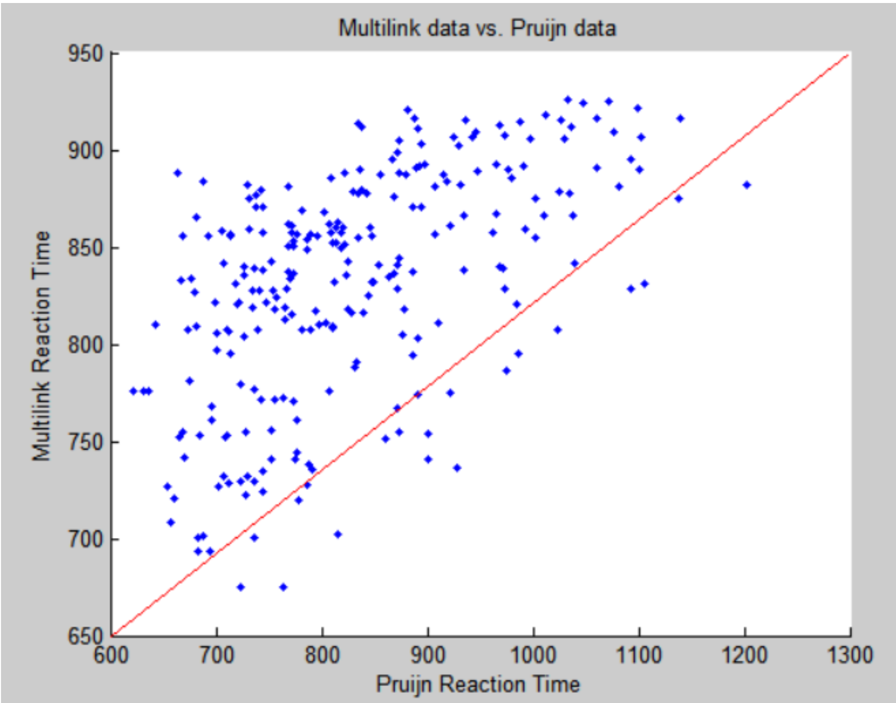

Figure 14: All words; Empirical reaction time vs. Multilink reaction time

9.4. English to Dutch translation

In section 8, we looked at English word recognition by Dutch unbalanced bilinguals. In this section, we will move a step further and look at word translation, which comprises, in order, the processes of word recognition, semantic lookup, and word production. When referring to reaction time or RT in this section, I mean the time it on average took one to translate the word (in Pruijn's (2015) experiment). Multilink RT refers to the ML output for this word (rescaled from cycle times).

9.4.1. Non-Cognates

The first category I will discuss is non-cognates. The correlation between ML and Pruijn's data on this category is very high; Pearson's r score is .6 ($p < .001$). Despite this very high correlation, the figure plotting this (15) barely shows any fit. The reason the correlation is that high, is that although the model underestimates the magnitude of the variance in the RT data, it does capture a substantial amount of it; the data points on the right are higher than the data points on the left, but not high enough.

		R	p
Pruijn RT	in_length	0.21	0.11
	out_length	0.3	0.02
ML RT	in_length	0.15	0.25
	out_length	0.05	0.72

Table 7: English to Dutch translation of non-cognates; correlations between word length and reaction time

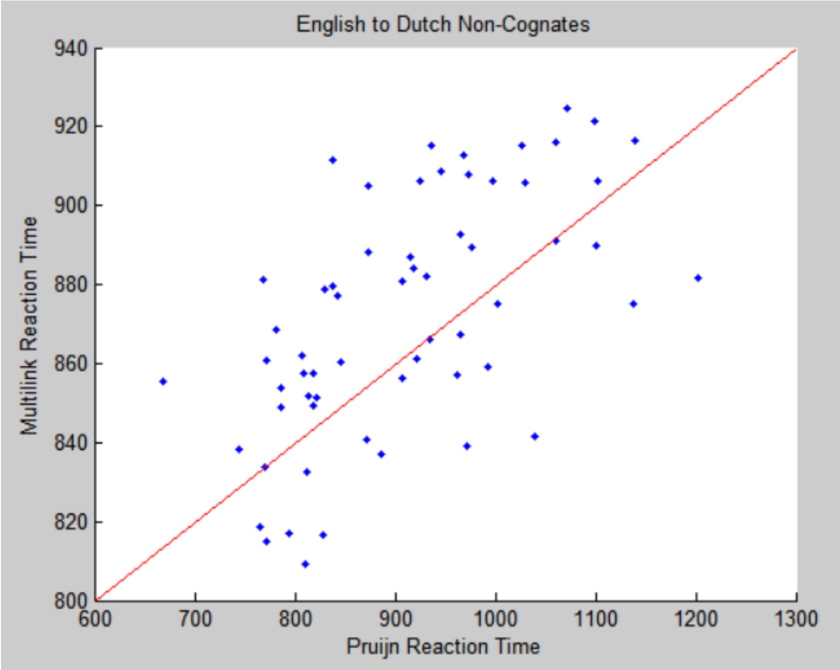

Figure 15: English to Dutch translation of non-cognates; Empirical reaction time vs. Multilink reaction time

The data of the correlations regarding word length are shown in table 7. Table 7 shows correlation between (from top to bottom): The empirical RT on a word and the length of the shown word; the empirical RT on a word and the word that had to be produced; the ML RT on a word and the length of the shown word; the ML RT on a word and the word that had to be produced. I will be using similar tables in next sections. The p value indicating the strength of the correlation is provided next to it.

The data in table 7 is as expected: there are positive correlations between word length and RT; however, they are insignificant with the exception of the one between empirical RT and output length. Multilink fails to capture this trend. In a later section, I will compare my findings to this table.

9.4.2. Cognates

The performance of ML on cognates in English to Dutch translation is worse than on non-cognates, the correlation between ML and the empirical data on this word category is plotted in figure 16.

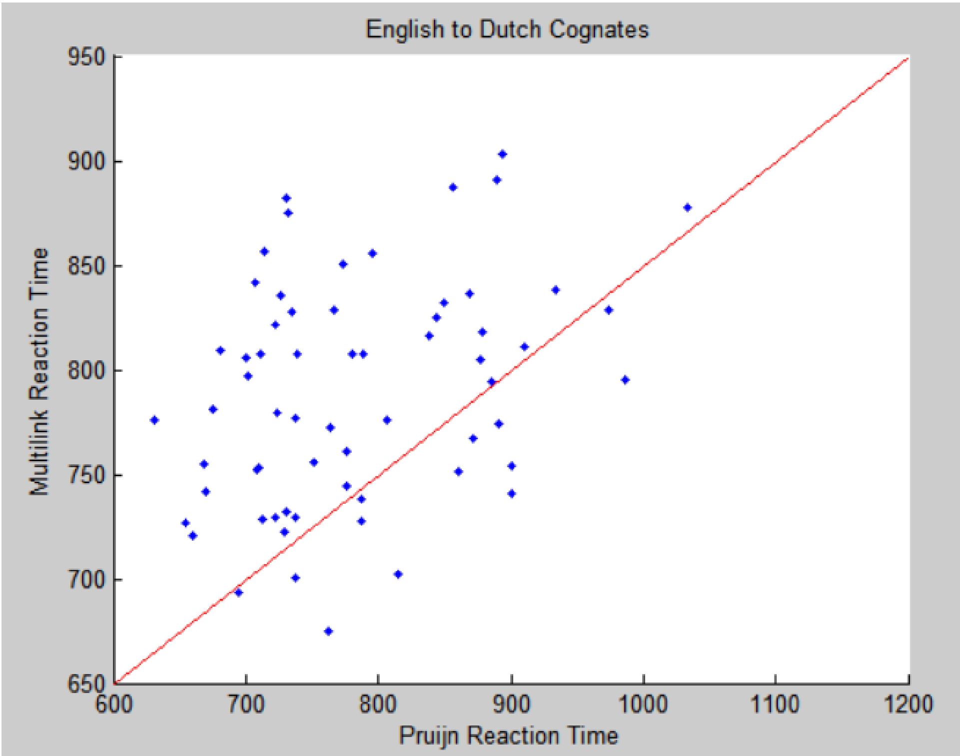

Figure 16: English to Dutch translation of cognates; Empirical reaction time vs. Multilink reaction time

Although this figure (16) may appear to show an equally strong pattern as figure 15 does, the correlation is in fact lower; r= .35 ($p < .005$). The upper right data point creates an illusion of a steep slope, when leaving out that data point; it becomes clearer that the slope is not as steep as it appears to be.

ML appears to capture the dispersion better in this category than it did in figure 15. It apparently does not do so successfully, but the (vertical) dispersion is larger than it was with the non-cognates. A reason for this might be that Pruijn did not totally base his definition of cognate on LD, and very small words were included. The word (EAR – OOR) for example is considered a cognate; however, the non-cognate (SHARK – HAAI) is more similar according to the equation ML uses. EAR and OOR have 33% overlap in spelling, whereas SHARK and HAAI overlap for 40%. This means some words considered as cognates are not seen as cognates by ML, in the sense that they do not receive a considerable boost in activation, which would eventually result in faster ML RT. This causes the RT of those words to be a lot higher than the RT of the words that are near-cognates and this division never occurs with non-cognates (where all RTs are relatively high), hence the larger dispersion in this case.

		R	p
Pruijn RT	in_length	0.1	0.46
	out_length	0.08	0.52
ML RT	in_length	-0.33	0.008
	out_length	-0.4	0.001

Table 8: English to Dutch translation of cognates; correlations between word length and reaction time

Table 8 shows the word length effects in English to Dutch translations of cognates. It is interesting to note that the ML data correlates negatively and very significantly with the word length, whereas none of these correlations exist in the empirical data. This negative correlation means that the longer the word, the faster the ML RT. This would imply that short cognates take longer to translate then long cognates.

The reason for this behavior probably has the same cause I just mentioned for the larger dispersion; small words that are a cognate in the sense that they have the same origin and resemble each other (e.g. LD =< 2) and thus are included in the cognates group, probably are not really similar when taking the percentage overlap into account (e.g. EAR – OOR only have 33% overlap). For smaller words, an absolute difference (LD) has more impact on the percentage similarity than for longer words. This causes the percentage similarity for a cognate pair of short words to decline faster when the LD increases.

9.5. Dutch to English translation

In this section, we will turn things around and start with a Dutch word as input instead of an English word. If the findings of Christoffels et al. (2006) and Pruijn (2015) hold, we will see slower RTs in general here than we saw in previous chapter.

9.5.1. Non-Cognates

In the previous section on English-to-Dutch translation, we saw that the correlation between ML and the empirical data was much better for non-cognates ($r = .6$ vs. $r = .35$) than for cognates ($r = .35$, $p < .05$). In translation from Dutch to English this also seems to be the case. The correlation of RTs on non-cognates between ML and the empirical data for Dutch to English translation is $r = .55$ ($p < .001$), versus $r = .22$ ($p > .05$) for cognates. The scatterplot of data points is visualized in figure 17. As in the scatterplot in the English-to-Dutch analysis, there does not seem to be a perfect fit, yet it is reasonably good. The reason the fit does not seem to be good is that the slope is far from steep enough, this however does not directly affect the correlation.

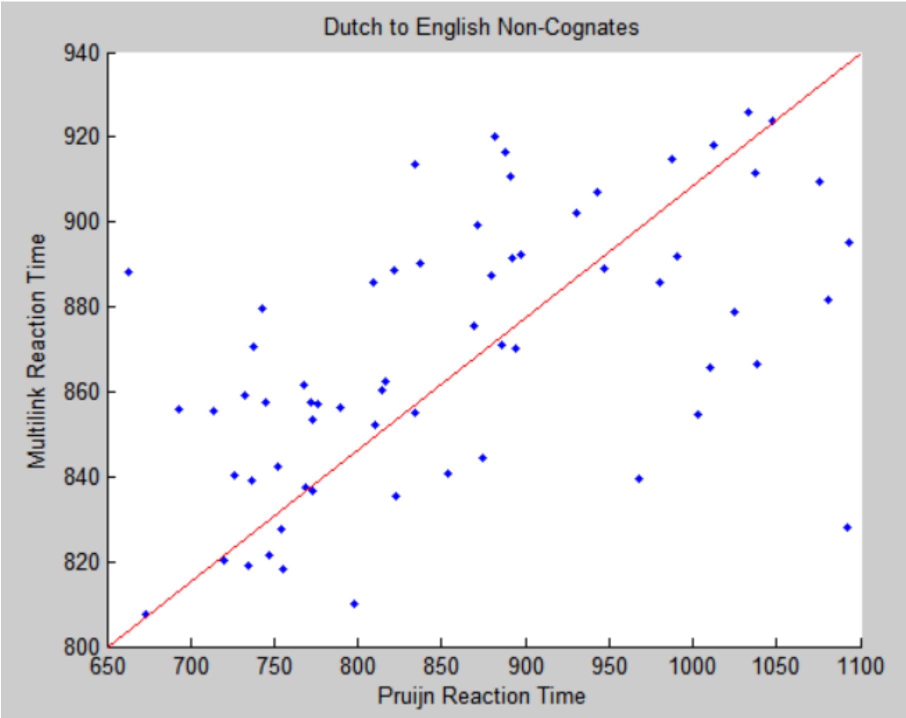

Figure 17: Dutch to English translation of non-cognates; Empirical reaction time vs. Multilink reaction time

		R	p
Pruijn RT	in_length	-0.09	0.48
	out_length	0.06	0.66
ML RT	in_length	-0.12	0.34
	out_length	0.16	0.2

Table 9: Dutch to English translation of non-cognates; correlations between word length and reaction time

In table 9, the correlations between the RTs and word lengths are shown. No significant values are observed here; the lowest p value is 0.2. However, unlike the patterns of correlations in the English-to-Dutch data, the direction of the effects of empirical and model input word lengths are both negative, while the direction of output word lengths are both positive. The fact that this input/output effect reversal is observed in both the empirical and model data is desirable (even if the effects are non-significant), since we want Multilink to perform like people do.

9.5.2. Cognates

The last condition I will discuss is cognates in Dutch to English translation. This dataset has the worst fit of all conditions; the correlation between ML data and empirical data did not even reach significance ($r= .22$, $p > .05$). Figure 18 shows this. Even more so than figure (EDC), this scatterplot looks like a random cloud. Many words that are responded to relatively quickly by human participants are responded to relatively slowly by ML (many data points are located in the upper left part of the coordinate system).

The table containing the correlation data between RTs and word lengths is shown below (table 10).

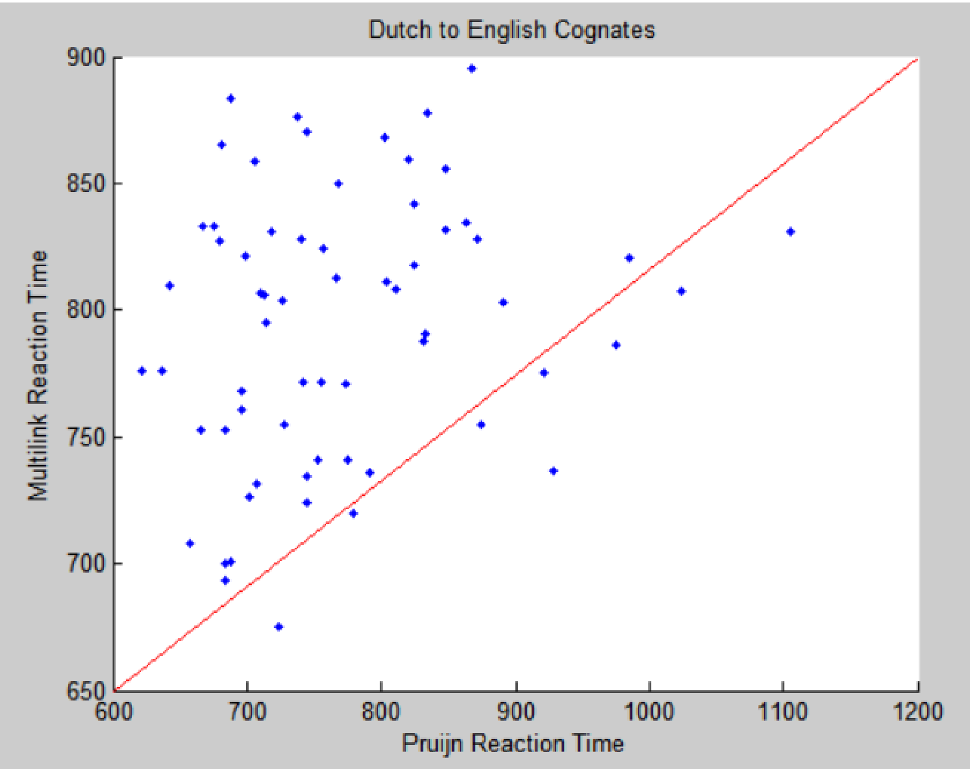

Figure 18: Dutch to English translation of cognates; Empirical reaction time vs. Multilink reaction time

		R	p
Pruijn RT	in_length	-0.25	0.06
	out_length	-0.11	0.4
ML RT	in_length	-0.3	0.02
	out_length	-0.27	0.03

Table 10: Dutch to English translation of cognates; correlations between word length and reaction time

In the table, we see that the only values reaching significance are the correlations between the word lengths and the RTs of Multilink. The reason for this probably is the same I mentioned in the section about English to Dutch cognate translation.

Some the words marked as cognates by Pruijn (2015) are not really cognates orthographically. This causes a division in the cognates group: On the one hand, cognates for which Multilink receives a considerable amount of extra activation, resulting in a faster than average RT; e.g. (BAKER - BAKKER), (RIVER - RIVIER), and on the other hand cognates that Multilink does not receive considerable extra activation for (e.g., (SEA – ZEE), (EAR – OOR)). Shorter words generally are in the second group, because one letter difference in e.g. a three letter word is 33% of the word, whereas one letter in a six letter word is only 16.66% and ML computes the extra activation based on percentage overlap.

9.6. Conclusion

There is a considerable difference in the fit Multilink has with the empirical data between the translation of cognates and the translation of non-cognates. The correlations for the four categories are shown in table 11.

		R	p
English to Dutch	Non-cognates	0.6	0.000...
	Cognates	0.35	0.005
Dutch to English	Non-cognates	0.55	0.000...
	Cognates	0.22	0.078

Table 11: Correlations between Multilink reaction time and Empirical reaction time, divided in four groups

This difference between cognates and non-cognates is caused by the difference in the definition of cognate by Pruijn (2015) and Multilink. The definition used by Pruijn is as follows: "A word was classified as a cognate if its translation had a Levenshtein's distance of 3 or less. A Levenshtein's distance of 4 or more resulted in the word being classified as a non-cognate." (Pruijn, 2015, p.20). Multilink does not divide the words in two categories but rather uses a similarity index to determine the boost in activation a word should receive. This similarity measure may provide non-cognates with a larger boost in activation than cognates. Because of this, cognates differ more than non-cognates do and thus it is harder for the model to fit well on cognates.

The length effects found in Multilink are in line with the length effects found in Pruijn's study (2015), except for English to Dutch translation in cognates. In this category, Multilink shows a significant negative correlation between RT and word length (both for input and output length) instead of a positive correlation as the empirical data does. The reason for this discrepancy is the fact that smaller cognates are more likely to have lower perceptual overlap to their translation equivalent. Since identical cognates were not included, the highest possible overlap a cognate with three letters can have is 2/3 = 66.66…%. For longer words, one letter does have less impact on similarity and thus slows RT less. In Dutch to English cognate translation, all correlations between RT and word length were negative, but the ML correlations were higher and showed significance (as opposed to the correlations of the empirical RT data with word length).

10. Exploration of interlingual homographs

In addition to cognates, I also mentioned above the phenomenon of interlingual homographs, better known as false friends. These false friends are difficult for the model to translate, since the model is not told that it receives a Dutch or an English word. It only knows what the output should be. The translation simulation tasks we have used provide phonological output in the other language. However, if a false friend is presented, it is not clear to the model what language this word is in.

So, if for example the word ROOM is presented and Dutch phonological output is asked, we probably meant to present the English word. The output in this case is based on the similarity of (all word pairs, including) “CREAM-ROOM”, and “ROOM-KAMER” with the input string “ROOM”. In this case, the added similarity value of CREAM with “ROOM”, and ROOM with “ROOM” (0,4 + 1), is larger than the added similarity values of KAMER with “ROOM” (0 + 1), and ROOM with “ROOM”. The best match will be with “CREAM-ROOM” and since Dutch phonological output was asked, the phonological output of the Dutch word “ROOM” will be given, although we wanted the model to output the Dutch phonological representation of the English word “ROOM”.

Because of this inability of the model to understand false friends, the model will probably make mistakes half of the time, and, when it does not make a mistake, its performance will be no better than on control words.

10.1. Lexical decision with interlingual homographs and cognates

In this section, I will discuss a paper by Dijkstra, Van Jaarsveld, and Ten Brinke (1998) that examined cognates and false friends. This paper describes three experiments, of which I will cover the first one only.

The experiment was a typical lexical decision task and was carried out with forty-one highly proficient yet unbalanced bilinguals with Dutch as their L1 and English as their L2. The participants were presented four blocks of 112 English words each on a computer monitor. The participants had two buttons to press: they would press one button if they thought the text presented to them was a valid word, and they would press the other button if they thought a non-word was shown (pseudo words were included in this experiment). The results of this experiment were clear: "While cognates were responded to significantly faster than their matched purely monolingual control items, no significant difference in RTs was obtained between homographs and their controls" (Dijkstra et al., 1998, p.55). The lower RTs for cognates are explained by the overlap in semantics. This could result in extra confirmation that the cognate is a valid word and thus the faster RT. The fact that homographs do not differ significantly from their controls could indicate that in such a task, people are at least not distracted by the fact that the item shown also has meaning in a different lexicon.

10.2. Interlingual homographs in Multilink

In ML simulation with false friends, we expect to find the same results as Dijkstra et al. (1998) found; RT on cognates < RT on non-cognates = RT on false friends. To test this, I have used the relatively small dataset of the words Vanlangendonck (2014) used in her experiment (38 words). I will present the words to the model and request Dutch phonological output.

The correct response rate was very low; only 10 words were translated correctly. The other words were either translated incorrectly or the English phonological representation of the input word was given. For the averages of cognates and non-cognates, I will use the dataset of Pruijn (2015). The results are visible in table 12.

Amongst the words that were correctly translated, were 2 near-cognates, so this sped up the translation process for these two words. Overall, we can say that false friends are translated very poorly by the model: only 10 of the 39 were translated correctly. The false friends that are translated correctly are translated slower than cognates, but a little bit faster than non-cognates. These findings – apart from the difference between non-cognates and false friends, which probably is caused by the 2 near-cognates included in the false friends – are in line with the findings of Dijkstra et al. (1998).

	Cognates	Non-Cognates	False Friends
Average ML cycle time	22.51	24.62	23.87

Table 12: Average Multilink cycle time on different word categories

11. Discussion and Conclusion

During this project, which was a group project, a lot of people have come up with ideas to further improve Multilink. At the start of the project, we were given access to Multilink as it was developed by Rekké and Dijkstra (2012). A lot of ideas to change and improve the model arose and were tried. After we decided to freeze the model and start running the simulations, it has been changed further, resulting in the implementations mentioned in section 3.3.

According to my simulations, the Multilink model is successful in both word recognition and in word translation. Although Multilink is built to serve as a word translation model, it is appealing to notice that it performs well on word recognition too, since word recognition is a crucial step in word translation. On word recognition, the model outperforms the IA model and the BIA model on their lexicons and reaches high correlations with the empirical data gathered by Dijkstra (2010) and Vanlangendonck (2014).

In the translation simulations, no effect of translation direction was found. An effect of cognate status was found, however. Furthermore, the model-to-data fit was much better on the non-cognate data than it was on the cognate data. The reason for this is the poor definition of cognate by Pruijn (2015) in combination with the non-binary definition of cognate of Multilink; some words defined as cognates barely receive a boost in activation, because the similarity percentage is not large enough. People, however, would see the similarity between those words (e.g. SEA - ZEE). This discrepancy causes the relatively poor fit of Multilink on the cognate groups.

False friends are still difficult to translate correctly for Multilink; there currently is no way to specify the input language to Multilink and the output is only based on which semantic node receives most activation. This makes it possible for the model to return the input as output.

12. Future Research

During the work on my thesis, I have discovered how Multilink works. It is a powerful model and performs well in simulating human-like reaction times. Some aspects of it need further development, however.

1. The Levenshtein Distance measure could be replaced or adjusted. Currently all transformations have the same cost. I think it would be more realistic if some translations would have lower costs (replacing Z with S, or B with P) than other transformations.
2. For the model to handle the translation of false friends correctly, the model needs some kind of indication in what language the input is. In normal Lexical Decision and word translation tasks, the input language is provided as well. Therefore it would be reasonable to include this feature in Multilink in some way.
3. In my simulations, I have also looked at the effect of input word length on reaction times. Many studies support the idea that longer word lengths increase reaction time. In Multilink, word length is not considered at all. It would be desirable for Multilink to include a parameter that takes into account word length.

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14. Appendices

For the simulations in my thesis, I needed different lexicons and different input files. I will include all of them here as appendices. In section 14.1 and 14.2, I will present the lexicons I used for my simulations with the IA and BIA data. In section 14.3, I will present the lexicon I used for the simulation of word translation, and in 14.4 and 14.5, I will present the parts of the lexicon that were added to the lexicon of 14.3 to include all the words in the Dijkstra et al. (2010) study and the Vanlangendonck (2014) study.

In 14.6 and 14.7, I will present the inputs that were used in the simulations of the word recognition experiments of Dijkstra et al. (2010) and Vanlangendonck (2014), and in 14.8 and 14.9, I will present the inputs I used to simulate word translation. Section 14.10 consists of the input words used in section 10; the simulation with interlingual homographs.

14.1. IA Lexicon

```
Dutch:O--Dutch:P--English:O--English:P
DAT,22077.22--dAt,22077.22--THAT,9999.99--D{t,9999.99
WAT,10991.46--wAt,10991.46--WHAT,9842.45--wQt,9842.45
DEZE,1716.92--dez@,1716.92--THIS,7978.73--DIs,7978.73
JOUW,733.21--jMw,733.21--YOUR,6445.39--j$R,6445.39
HEBBEN,3433.66--hEb@,3433.66--HAVE,6161.41--h{v,6161.41
WETEN,977.26--wet@,977.26--KNOW,5721.18--n5,5721.18
MET,6812.14--mEt,6812.14--WITH,5048.33--wID,5048.33
GEWOON,1007.99--x@won,1007.99--JUST,4749.14--_Vst,4749.14
HIER,4516.62--hir,4516.62--HERE,4525.25--h7R,4525.25
ZE,9310.51--z@,9310.51--THEY,4102.94--D1,4102.94
ALS,6343.35--Als,6343.35--LIKE,3998.96--l2k,3998.96
KOMEN,1143.88--kom@,1143.88--COME,3140.98--kVm,3140.98
GOED,3488.11--xut,3488.11--WELL,2990.65--wEl,2990.65
WILLEN,754.27--wIl@,754.27--WANT,2759.18--wQnt,2759.18
GOED,3488.11--xut,3488.11--GOOD,2610.14--gUd,2610.14
ZAL,2198.25--zAl,2198.25--WILL,2123.65--wIl,2123.65
VAN,10410.25--vAn,10410.25--FROM,2039.06--frQm,2039.06
WANNEER,458.82--wAner,458.82--WHEN,2034.1--wEn,2034.1
TERUG,1336.35--t@r}x,1336.35--BACK,2009.16--b{k,2009.16
OKE,52.44--oke,52.44--OKAY,2006.27--5k1,2006.27
```

TIJD,898.46--tKt,898.46--TIME,1958.63--t2m,1958.63
KIJKEN,495.23--kKk@,495.23--LOOK,1947.27--lUk,1947.27
NEMEN,391.29--nem@,391.29--TAKE,1891.04--t1k,1891.04
HEN,328.98--hEn,328.98--THEM,1778.82--DEm,1778.82
GEWEEST,520.02--x@west,520.02--BEEN,1736.73--bin,1736.73
SOMMIGE,93.74--sOm@G@,93.74--SOME,1727.24--sVm,1727.24
VERTELLEN,466.94--v@rtEl@,466.94--TELL,1724.49--tEl,1724.49
WAREN,648.69--war@,648.69--WERE,1662.82--w3R,1662.82
BENEDEN,187.97--b@ned@,187.97--DOWN,1490.27--d6n,1490.27
DAN,4297.95--dAn,4297.95--THEN,1489.53--DEn,1489.53
MAKEN,957.27--mak@,957.27--MAKE,1387.75--m1k,1387.75
OVER,2702.21--ov@r,2702.21--OVER,1323.29--5v@R,1323.29
MEER,2035.88--mer,2035.88--MORE,1298.59--m$R,1298.59
NOODZAAK,3.38--notsak,3.38--NEED,1294.9--nid,1294.9
GEMIDDELDE,7.39--x@mId@ld@,7.39--MEAN,1243.98--min,1243.98
HEEL,1038.77--hel,1038.77--VERY,1241.25--vErI,1241.25
GEVEN,475.61--xev@,475.61--GIVE,1167.82--gIv,1167.82
LIEFDE,208.9--livd@,208.9--LOVE,1114.98--lVv,1114.98
ZEI,1283.69--zK,1283.69--SAID,1108.45--sEd,1108.45
ZEKER,854.89--zek@r,854.89--SURE,1099.82--S$R,1099.82
ALLEEN,1469.24--Alen,1469.24--ONLY,1083.71--5nlI,1083.71
VEEL,1155.79--vel,1155.79--MUCH,973.25--mVJ,973.25
HULP,239.77--h}lp,239.77--HELP,921.12--hElp,921.12
ZELFS,387.15--zElfs,387.15--EVEN,875.92--ivH,875.92
ROEP,48.53--rup,48.53--CALL,861.39--k$l,861.39
PRATEN,642.27--prat@,642.27--TALK,855--t$k,855
IN,8822.64--In,8822.64--INTO,844.59--Intu,844.59
VIND,690.91--vInt,690.91--FIND,830.96--f2nd,830.96
WACHT,834.29--wAxt,834.29--WAIT,830.25--w1t,830.25
WERKEN,306.82--wErk@,306.82--WORK,798.02--w3k,798.02
LEVEN,1045.27--lev@,1045.27--LIFE,796.65--l2f,796.65
HUIS,818.9--hLs,818.9--HOME,774.33--h5m,774.33
DAN,4297.95--dAn,4297.95--THAN,738.8--D{n,738.8
WEG,1481.66--wEx,1481.66--AWAY,730.9--@w1,730.9
LAATSTE,398.82--latst@,398.82--LAST,723.1--l#st,723.1
OOIT,465.25--ojt,465.25--EVER,709.22--Ev@R,709.22
STOP,301.97--stOp,301.97--STOP,707.27--stQp,707.27
HOUDEN,502.75--hMd@,502.75--KEEP,702.86--kip,702.86
VERTELDE,119.94--v@rtEld@,119.94--TOLD,699.59--t5ld,699.59
MOET,3928.29--mut,3928.29--MUST,699.24--mVst,699.24
LANG,596.85--lAN,596.85--LONG,675.16--lQN,675.16
DOET,835.25--dut,835.25--DOES,666.71--dVz,666.71
MOOI,616.06--moj,616.06--NICE,649.51--n2s,649.51
NAAM,470.6--nam,470.6--NAME,641.86--n1m,641.86
VOELEN,117.86--vul@,117.86--FEEL,627.24--fil,627.24
FIJN,198.06--fKn,198.06--FINE,598.08--f2n,598.08
SOORT,222.02--sort,222.02--KIND,590.69--k2nd,590.69
GEMAAKT,277.73--x@makt,277.73--MADE,561.29--m1d,561.29
MEISJE,382.74--mKsj@,382.74--GIRL,557.12--g3l,557.12
HOREN,352.28--hor@,352.28--HEAR,555.35--h7R,555.35
VERBLIJF,11.8--v@rblKf,11.8--STAY,515.65--st1,515.65
BABY,151.8--bebi,151.8--BABY,509.37--b1bI,509.37
TONEN,37.05--ton@,37.05--SHOW,488.35--S5,488.35
ZORG,218.82--zOrx,218.82--CARE,485.25--k8R,485.25
GEDAAN,883.04--x@dan,883.04--DONE,485.04--dVn,485.04
GEEST,94.97--xest,94.97--MIND,484.61--m2nd,484.61
LINKS,68.56--lINks,68.56--LEFT,484.45--lEft,484.45
HEL,84.04--hEl,84.04--HELL,470.82--hEl,470.82
MISSEN,85.39--mIs@,85.39--MISS,467.65--mIs,467.65
KWAM,478.85--kwAm,478.85--CAME,463.73--k1m,463.73
VOLGENDE,286.37--vOlG@nd@,286.37--NEXT,452.75--nEkst,452.75

DODEN,217.98--dod@,217.98--KILL,452.57--kIl,452.57
ANDERS,772.57--And@rs,772.57--ELSE,449.16--Els,449.16
DOOD,992.15--dot,992.15--DEAD,448.98--dEd,448.98
ECHT,1594.99--Ext,1594.99--REAL,442.8--r7l,442.8
KAMER,275.24--kam@r,275.24--ROOM,439.51--rum,439.51
GREEP,15.64--xrep,15.64--HOLD,436.73--h5ld,436.73
BEWEGING,45.3--b@weGIN,45.3--MOVE,418.14--muv,418.14
DEZELFDE,151.02--d@zElvd@,151.02--SAME,417.18--s1m,417.18
GEGAAN,122.75--x@Gan,122.75--WENT,411.51--wEnt,411.51
BESTE,305.2--bEst@,305.2--BEST,404.37--bEst,404.37
GEZIEN,691.59--x@zin,691.59--SEEN,384.96--sin,384.96
HOOFD,274.05--hoft,274.05--HEAD,371.51--hEd,371.51
WIST,594.47--wIst,594.47--KNEW,368.96--nju,368.96
VEEL,1155.79--vel,1155.79--MANY,359.43--mEnI,359.43
IDEE,482.99--ide,482.99--IDEA,359.04--2d7,359.04
SPELEN,247.77--spel@,247.77--PLAY,354.53--pl1,354.53
ONTMOETEN,127.97--Ontmut@,127.97--MEET,352.27--mit,352.27
MEEST,58.95--mest,58.95--MOST,350.76--m5st,350.76
VROUW,821.67--vrMw,821.67--WIFE,348.92--w2f,348.92
EENMAAL,36.2--enmal,36.2--ONCE,344.88--wVns,344.88
LEVEN,1045.27--lev@,1045.27--LIVE,344.59--lIv,344.59
GEBRUIKT,128.22--x@brLkt,128.22--USED,344.14--juzd,344.14
NAM,116.08--nAm,116.08--TOOK,342.24--tUk,342.24
HOOP,367.83--hop,367.83--HOPE,320.63--h5p,320.63
OPEN,337.64--op@,337.64--OPEN,320.41--5p@n,320.41
HARD,159.46--hArt,159.46--HARD,307.84--h#d,307.84
BEURT,41.89--b|rt,41.89--TURN,306.47--t3n,306.47
DAGEN,290.15--daG@,290.15--DAYS,305.73--d1z,305.73
KINDEREN,474.49--kInd@r@,474.49--KIDS,301.1--kIdz,301.1
WEG,1481.66--wEx,1481.66--GONE,296.76--gQn,296.76
BEIDE,65.27--bKd@,65.27--BOTH,295.33--b5T,295.33
DEUR,247.48--d|r,247.48--DOOR,292.06--d$R,292.06
ZODANIG,2.56--zodan@x,2.56--SUCH,291.22--sVJ,291.22
GEZICHT,183.63--x@zIxt,183.63--FACE,289.16--f1s,289.16
VIJF,281.57--vKf,281.57--FIVE,285.45--f2v,285.45
VLOEK,18.77--vluk,18.77--DAMN,283.53--d{m,283.53
GEVAL,137.21--x@vAl,137.21--CASE,282.41--k1s,282.41
HAND,199.91--hAnt,199.91--HAND,279.65--h{nd,279.65
JAAR,762.67--jar,762.67--YEAR,277.92--j7R,277.92
VERLOREN,128.08--v@rlor@,128.08--LOST,274--lQst,274
LAAT,2032.73--lat,2032.73--LATE,269.73--l1t,269.73
GEMAKKELIJK,37.37--x@mAk@l@k,37.37--EASY,265.71--izI,265.71
GESLOTEN,52.32--x@slot@,52.32--SHUT,263.82--SVt,263.82
DEEL,142.35--del,142.35--PART,261.51--p#t,261.51
TRANSACTIE,3.82--trAnsAksi,3.82--DEAL,261.37--dil,261.37
SPOEDIG,14.34--spud@x,14.34--SOON,257.65--sun,257.65
VIER,242.08--vir,242.08--FOUR,255.78--f$R,255.78
WAAR,3198.67--war,3198.67--TRUE,253.35--tru,253.35
ELK,142.49--Elk,142.49--EACH,253.25--iJ,253.25
KRIK,1.1--krIk,1.1--JACK,251.59--_{k,251.59
MIJN,4412.02--mKn,4412.02--MINE,250.98--m2n,250.98
STAD,272.61--stAt,272.61--TOWN,247.92--t6n,247.92
PIJN,266.16--pKn,266.16--HURT,246.35--h3t,246.35
GAF,191.52--xAf,191.52--GAVE,243.69--g1v,243.69
LEZEN,107.8--lez@,107.8--READ,241.22--rid,241.22
WEEK,235.61--wek,235.61--WEEK,238.51--wik,238.51
WOORD,129.09--wort,129.09--WORD,235.55--w3d,235.55
WENS,59.39--wEns,59.39--WISH,235.12--wIS,235.12
SPEL,95.11--spEl,95.11--GAME,233.84--g1m,233.84
SCHOT,33.04--sxOt,33.04--SHOT,227.43--SQt,227.43
LIEF,113.95--lif,113.95--DEAR,223.43--d7R,223.43

DAME,82.74--dam@,82.74--LADY,217.08--l1dI,217.08
LOPEN,221.57--lop@,221.57--WALK,215.86--w$k,215.86
BRAND,44.39--brAnt,44.39--FIRE,215.49--f2@R,215.49
HAAT,151.32--hat,151.32--HATE,214.59--h1t,214.59
REST,175.03--rEst,175.03--REST,212.96--rEst,212.96
OOK,2762.1--ok,2762.1--ALSO,206.43--$ls5,206.43
LIJN,68.72--lKn,68.72--LINE,206.18--l2n,206.18
KANT,312.67--kAnt,312.67--SIDE,200.92--s2d,200.92
HELFT,65.68--hElft,65.68--HALF,199.14--h#f,199.14
PLUKKEN,6.49--pl}k@,6.49--PICK,198.39--pIk,198.39
KOEL,8.76--kul,8.76--COOL,195.88--kul,195.88
LICHAAM,147.54--lIxam,147.54--BODY,195.53--bQdI,195.53
HOOG,63.23--hox,63.23--HIGH,195--h2,195
STUREN,92.66--styr@,92.66--SEND,179.78--sEnd,179.78
GRATIS,45.37--xrat@s,45.37--FREE,177.53--fri,177.53
BOEK,150.93--buk,150.93--BOOK,176.98--bUk,176.98
FEIT,43.04--fKt,43.04--FACT,172.57--f{kt,172.57
BLIJ,277.3--blK,277.3--GLAD,171.37--gl{d,171.37
STAD,272.61--stAt,272.61--CITY,169.1--sItI,169.1
VOL,207.21--vOl,207.21--FULL,166.9--fUl,166.9
TOT,1131.5--tOt,1131.5--TILL,166.73--tIl,166.73
ZIEK,129.2--zik,129.2--SICK,165.43--sIk,165.43
NIEUWS,178.42--niws,178.42--NEWS,164.69--njuz,164.69
VERLIEZEN,96.78--v@rliz@,96.78--LOSE,164.35--luz,164.35
BESPAREN,9.72--b@spar@,9.72--SAVE,162.31--s1v,162.31
UUR,348.69--yr,348.69--HOUR,162.29--6@R,162.29
GESTORVEN,58.82--x@stOrv@,58.82--DIED,157.22--d2d,157.22
ETEN,445.92--et@,445.92--FOOD,154.43--fud,154.43
GELUK,166.02--x@l}k,166.02--LUCK,153.73--lVk,153.73
HAAR,2975.87--har,2975.87--HAIR,153.55--h8R,153.55
SOORT,222.02--sort,222.02--SORT,148.71--s$t,148.71
HANGEN,55.39--hAN@,55.39--HANG,147.75--h{N,147.75
TEAM,114.29--tim,114.29--TEAM,147.61--tim,147.61
TREKKEN,82.05--trEk@,82.05--PULL,146.45--pUl,146.45
PLAN,143.34--plEn,143.34--PLAN,145.73--pl{n,145.73
VEILIG,174.92--vKl@x,174.92--SAFE,143.2--s1f,143.2
DATUM,13.84--dat}m,13.84--DATE,141.53--d1t,141.53
LIJKEN,95.93--lKk@,95.93--SEEM,139.82--sim,139.82
HEER,104.14--her,104.14--LORD,138.16--l$d,138.16
VERZONDEN,2.33--v@rzOnd@,2.33--SENT,138--sEnt,138
SNEL,463.6--snEl,463.6--FAST,137.45--f#st,137.45
RIJDEN,150.04--rKd@,150.04--RIDE,135.37--r2d,135.37
TEKEN,76.36--tek@,76.36--SIGN,133.27--s2n,133.27
OVERTREFFEN,2.29--ov@rtrEf@,2.29--BEAT,131.69--bit,131.69
KOUDE,19.85--kMd@,19.85--COLD,130.16--k5ld,130.16
KONING,138.53--konIN,138.53--KING,129.25--kIN,129.25
ARM,79.26--Arm,79.26--POOR,129.08--p$R,129.08
BAAS,167.21--bas,167.21--BOSS,124.29--bQs,124.29
VERLEDEN,68.54--v@rled@,68.54--PAST,123.76--p#st,123.76
KUS,51.89--k}s,51.89--KISS,121.16--kIs,121.16
VOETEN,58.08--vut@,58.08--FEET,120.73--fit,120.73
VOELDE,93.37--vuld@,93.37--FELT,119.82--fElt,119.82
STAP,126.53--stAp,126.53--STEP,118.67--stEp,118.67
VALLEN,180.98--vAl@,180.98--FALL,118.51--f$l,118.51
REKENING,56.3--rek@nIN,56.3--BILL,118.45--bIl,118.45
WEG,1481.66--wEx,1481.66--ROAD,111.94--r5d,111.94
MINDER,121.27--mInd@r,121.27--LESS,111.1--lEs,111.1
GEEN,3956.92--xen,3956.92--NONE,110.61--nVn,110.61
SLIJTAGE,0.34--slKtaZ@,0.34--WEAR,109.33--w8R,109.33
PASSEREN,6.13--pAser@,6.13--PASS,108.12--p#sVp,108.12
BEZIG,196.41--bez@x,196.41--BUSY,106.53--bIzI,106.53

WEKKEN,9.83--wEk@,9.83--WAKE,105.22--w1k,105.22
BAL,80.63--bAl,80.63--BALL,104.96--b$l,104.96
MAMA,206.45--mAma,206.45--MAMA,103.71--m#m@,103.71
BLAUW,32.91--blMw,32.91--BLUE,102.39--blu,102.39
SCHIP,115.28--sxIp,115.28--SHIP,98.88--SIp,98.88
CLUB,52.34--kl}p,52.34--CLUB,98.78--klVb,98.78
PIJN,266.16--pKn,266.16--PAIN,97.94--p1n,97.94
ZINGEN,65.52--zIN@,65.52--SING,97.59--sINVp,97.59
BLAZEN,17.65--blaz@,17.65--BLOW,97.57--bl5,97.57
BOOT,95.93--bot,95.93--BOAT,95.78--b5t,95.78
EERLIJK,172.38--erl@k,172.38--FAIR,94.75--f8R,94.75
LIED,21.27--lit,21.27--SONG,93.69--sQN,93.69
RING,52.34--rIN,52.34--RING,92.75--rIN,92.75
VERKOPEN,90.56--v@rkop@,90.56--SELL,92.25--sEl,92.25
OPHOUDEN,63.69--OphMd@,63.69--QUIT,90.1--kwIt,90.1
BEWAARD,12.58--b@wart,12.58--KEPT,89.39--kEpt,89.39
DWAAS,22.75--dwas,22.75--FOOL,89.33--ful,89.33
KALMTE,2.54--kAlmt@,2.54--CALM,89.04--k#m,89.04
DONKER,64.44--dONk@r,64.44--DARK,88.61--d#k,88.61
LAND,244--lAnt,244--LAND,88.12--l{nd,88.12
SCHATTIG,28.68--sxAt@x,28.68--CUTE,87.75--kjut,87.75
ROTS,14.66--rOts,14.66--ROCK,86.16--rQk,86.16
LEGER,107.98--leG@r,107.98--ARMY,85.69--#mI,85.69
BETAALD,88.16--b@talt,88.16--PAID,85.67--p1d,85.67
KAART,79.67--kart,79.67--CARD,85.43--k#d,85.43
BANK,91.91--bANk,91.91--BANK,84.98--b{Nk,84.98
PROEF,20.44--pruf,20.44--TEST,84.08--tEst,84.08
GEBOREN,85.46--x@bor@,85.46--BORN,83.69--b$n,83.69
VIS,50.08--vIs,50.08--FISH,83.49--fIS,83.49
TOETREDEN,0.39--tutred@,0.39--JOIN,83.43--_4n,83.43
LOOD,5.03--lot,5.03--LEAD,83.25--lid,83.25
REIS,90.37--rKs,90.37--TRIP,82.39--trIp,82.39
MARKERING,0.53--mArkerIN,0.53--MARK,82.02--m#k,82.02
STER,43.77--stEr,43.77--STAR,81.35--st#R,81.35
LIJST,66.77--lKst,66.77--LIST,80.59--lIst,80.59
RIJK,79.15--rKk,79.15--RICH,80.39--rIJ,80.39
GOUD,61.99--xMt,61.99--GOLD,78.94--g5ld,78.94
ZITPLAATS,0.75--zItplats,0.75--SEAT,78.78--sit,78.78
KNOEIEN,2.26--knuj@,2.26--MESS,78.14--mEs,78.14
ZIEL,82.67--zil,82.67--SOUL,76.96--s5l,76.96
DIEP,68.4--dip,68.4--DEEP,76.39--dip,76.39
LANGZAAM,50.97--lANzam,50.97--SLOW,76.02--sl5,76.02
BIER,53.35--bir,53.35--BEER,75.49--b7R,75.49
GEBIED,58.29--x@bit,58.29--AREA,74.92--8r7,74.92
TRAP,52.28--trAp,52.28--KICK,73.41--kIk,73.41
ONHEIL,1.9--OnhKl,1.9--EVIL,73.16--ivP,73.16
GRAP,51.02--xrAp,51.02--JOKE,73.02--_5k,73.02
VIEL,85.87--vil,85.87--FELL,73--fEl,73
GELD,793.61--xElt,793.61--CASH,72.43--k{S,72.43
PARK,30.87--pArk,30.87--PARK,72.12--p#k,72.12
GRIJPEN,16.65--xrKp@,16.65--GRAB,70.86--gr{b,70.86
MUUR,66.89--myr,66.89--WALL,70.69--w$l,70.69
GEVANGENIS,104.9--x@vAN@nIs,104.9--JAIL,70.63--_1l,70.63
DUW,15.32--dyw,15.32--PUSH,70.55--pUS,70.55
SPRINGEN,46.86--sprIN@,46.86--JUMP,69.82--_Vmp,69.82
NEUS,70.04--n|s,70.04--NOSE,69.75--n5z,69.75
VERBERGEN,34.69--v@rbErG@,34.69--HIDE,69.69--h2d,69.69
ANGST,69.34--ANst,69.34--FEAR,69.08--f7R,69.08
BAND,79.28--bEnt,79.28--TAPE,68.84--t1p,68.84
PAK,313.2--pAk,313.2--SUIT,68.61--sut,68.61
HEILIG,12.21--hKl@x,12.21--HOLY,68.14--h5lI,68.14

NEGEN,64.28--neG@,64.28--NINE,67.47--n2n,67.47
FILM,174.28--fIlm,174.28--FILM,65.25--fIlm,65.25
BOOM,52.25--bom,52.25--TREE,65--tri,65
VOET,50.81--vut,50.81--FOOT,64.92--fUt,64.92
GIFT,4.92--xIft,4.92--GIFT,64.51--gIft,64.51
SAKE,1.65--sake,1.65--SAKE,64.16--s1k,64.16
ROLLEN,16.85--rOl@,16.85--ROLL,63.27--r5l,63.27
OP,8068.8--Op,8068.8--UPON,62.73--@pQn,62.73
RACE,26.32--res,26.32--RACE,61.9--r1s,61.9
ONZIN,111.23--OnzIn,111.23--CRAP,61.78--kr{p,61.78
PLEK,177.41--plEk,177.41--SPOT,61.57--spQt,61.57
TYPE,38.08--tip@,38.08--TYPE,60.65--t2p,60.65
WESTEN,29.66--wEst@,29.66--WEST,60.55--wEst,60.55
WIJN,60.44--wKn,60.44--WINE,60.35--w2n,60.35
NEK,57.72--nEk,57.72--NECK,59.51--nEk,59.51
GROEIEN,25.68--xruj@,25.68--GROW,59.49--gr5,59.49
WIND,50.58--wInt,50.58--WIND,59.37--wInd,59.37
GAT,49.97--xAt,49.97--HOLE,58.22--h5l,58.22
BEER,25.45--ber,25.45--BEAR,57.41--b8R,57.41
WILD,25.41--wIlt,25.41--WILD,57.31--w2ld,57.31
SLOT,52.46--slOt,52.46--LOCK,56.57--lQk,56.57
DURVEN,16.6--d}rv@,16.6--DARE,55.41--d8R,55.41
BRANDWOND,0.89--brAndwOnt,0.89--BURN,55.22--b3n,55.22
TANTE,62.34--tAnt@,62.34--AUNT,55.2--#nt,55.2
KOSTEN,43.84--kOst@,43.84--COST,54.92--kQst,54.92
CEL,49.97--sEl,49.97--CELL,54.35--sEl,54.35
BOM,51.32--bOm,51.32--BOMB,53.65--bQm,53.65
NOTITIE,1.58--notitsi,1.58--NOTE,53.55--n5t,53.55
WINKEL,65.13--wINk@l,65.13--SHOP,53.55--SQp,53.55
NOTEN,8.14--not@,8.14--NUTS,53.51--nVts,53.51
BAND,79.28--bEnt,79.28--BAND,53.41--b{nd,53.41
CODE,46.7--kod@,46.7--CODE,53.12--k5d,53.12
ROOS,11.71--ros,11.71--ROSE,53.02--r5z,53.02
KOPI�REN,3.75--kopijIr@n,3.75--COPY,52.27--kQpI,52.27
WARM,70.91--wArm,70.91--WARM,52.14--w$m,52.14
VERKOCHT,56.6--v@rkOxt,56.6--SOLD,52.06--s5ld,52.06
HAL,20.38--hAl,20.38--HALL,51.94--h$l,51.94
KAMP,41.73--kAmp,41.73--CAMP,51.22--k{mp,51.22
PLICHT,28.1--plIxt,28.1--DUTY,50.96--djutI,50.96
MAAN,42.1--man,42.1--MOON,49.96--mun,49.96
HELD,59.64--hElt,59.64--HERO,49.84--h7r5,49.84
OOST,7.45--ost,7.45--EAST,49.55--ist,49.55
RISICO,44.23--riziko,44.23--RISK,49.04--rIsk,49.04
REGEN,26.48--reG@,26.48--RAIN,48.9--r1n,48.9
REUSACHTIG,1.97--r|sAxt@x,1.97--HUGE,48.37--hju_,48.37
REGEL,77.32--reG@l,77.32--RULE,48.14--rul,48.14
BEMANNING,20.35--b@mAnIN,20.35--CREW,47.53--kru,47.53
PLUS,24.54--pl}s,24.54--PLUS,47.04--plVs,47.04
ZWEMBAD,23.17--zwEmbAt,23.17--POOL,46.98--pul,46.98
STOM,103.91--stOm,103.91--DUMB,46.96--dVm,46.96
GROOTTE,7.71--xrot@,7.71--SIZE,46.14--s2z,46.14
KOKEN,33.8--kok@,33.8--COOK,45.57--kUk,45.57
VOGEL,32.27--voG@l,32.27--BIRD,45.45--b3d,45.45
DRUG,6.4--dr}k,6.4--DRUG,45.22--drVg,45.22
CAKE,9.86--kek,9.86--CAKE,45.06--k1k,45.06
FILE,4.94--fAjl,4.94--FILE,44.04--f2l,44.04
HUID,39.56--hLt,39.56--SKIN,44.04--skIn,44.04
VULLEN,14.73--v}l@,14.73--FILL,43.94--fIl,43.94
BUREAU,66.93--byro,66.93--DESK,43.9--dEsk,43.9
PAK,313.2--pAk,313.2--PACK,43.82--p{k,43.82
GELOGEN,41.53--x@loG@,41.53--LIED,43.8--lid,43.8

VLEES,61.67--vles,61.67--MEAT,43.65--mit,43.65
JURY,31.17--Zyri,31.17--JURY,42.76--_9rI,42.76
FORMULIER,6.68--fOrmylir,6.68--FORM,42.75--f$m,42.75
HOOFD,274.05--hoft,274.05--MAIN,42.73--m1n,42.73
PAPA,223.28--pApa,223.28--PAPA,42.59--p@p#,42.59
MELK,39.7--mElk,39.7--MILK,42.53--mIlk,42.53
HELD,59.64--hElt,59.64--HELD,42.45--hEld,42.45
VOEDEN,14.75--vud@,14.75--FEED,42.39--fid,42.39
LELIJK,29.23--lel@k,29.23--UGLY,42.16--VglI,42.16
JAS,48.11--jAs,48.11--COAT,42.08--k5t,42.08
BEET,18.5--bet,18.5--BITE,40.78--b2t,40.78
WASSEN,27.97--wAs@,27.97--WASH,40.73--wQS,40.73
TREK,125.73--trEk,125.73--DRAW,40.41--dr$,40.41
WARMTE,10.5--wArmt@,10.5--HEAT,40.08--hit,40.08
LUID,9.08--lLt,9.08--LOUD,39.82--l6d,39.82
KLOK,23.9--klOk,23.9--BELL,39.33--bEl,39.33
DECAAN,4.53--dekan,4.53--DEAN,38.71--din,38.71
STOTEN,6.38--stot@,6.38--BUTT,38.57--bVt,38.57
UITZICHT,19.21--LtsIxt,19.21--VIEW,38.53--vju,38.53
HAAK,12.65--hak,12.65--HOOK,38--hUk,38
HEUVEL,15.71--h|v@l,15.71--HILL,37.55--hIl,37.55
PAGINA,12.69--paGina,12.69--PAGE,37.49--p1_,37.49
PAAR,434.44--par,434.44--PAIR,37.25--p8R,37.25
ZIET,569.16--zit,569.16--SEES,37.24--siz,37.24
MAIL,3.36--mel,3.36--MAIL,36.84--m1l,36.84
NAAR,4447.55--nar,4447.55--ONTO,36.69--Qntu,36.69
NEP,18.09--nEp,18.09--FAKE,36.33--f1k,36.33
BIDDEN,36.82--bId@,36.82--PRAY,36.22--pr1,36.22
EENHEID,24.72--enhKt,24.72--UNIT,36.18--junIt,36.18
MEER,2035.88--mer,2035.88--LAKE,36--l1k,36
DAK,54.84--dAk,54.84--ROOF,35.65--ruf,35.65
ZUIGELING,0.34--zLG@lIN,0.34--BABE,35.57--b1b,35.57
BASEREN,0.69--bazer@,0.69--BASE,35.37--b1s,35.37
FIRMA,8.78--fIrma,8.78--FIRM,35.27--f3m,35.27
WIE,1829.45--wi,1829.45--WHOM,35.2--hum,35.2
LEUGENAAR,35.72--l|G@nar,35.72--LIAR,35.14--l2@R,35.14
ZUIGEN,9.7--zLG@,9.7--SUCK,34.88--sVk,34.88
HUUR,28.88--hyr,28.88--RENT,34.55--rEnt,34.55
STEMMEN,40.02--stEm@,40.02--VOTE,34.33--v5t,34.33
LIFT,65.47--lIft,65.47--LIFT,34.14--lIft,34.14
HUMEUR,4.92--hym|r,4.92--MOOD,34.04--mud,34.04
MANNETJE,21.36--mAn@tj@,21.36--MALE,33.94--m1l,33.94
REEBOK,0.62--rebOk,0.62--BUCK,33.75--bVk,33.75
RIJBAAN,0.39--rKban,0.39--LANE,33.41--l1n,33.41
RUK,7.41--r}k,7.41--JERK,33.14--_3k,33.14
BONDGENOOT,4.02--bOntx@not,4.02--ALLY,32.67--{l2,32.67
POST,37--pOst,37--POST,32.43--p5st,32.43
LANG,596.85--lAN,596.85--TALL,32.33--t$l,32.33
KLEIN,195.66--klKn,195.66--TINY,32.22--t2nI,32.22
RUNS,0.48--r}ns,0.48--RUNS,32.1--rVnz,32.1
POORT,25.06--port,25.06--GATE,32.04--g1t,32.04
ZACHT,22.85--zAxt,22.85--SOFT,32.02--sQft,32.02
ZWEMMEN,39.47--zwEm@,39.47--SWIM,31.8--swIm,31.8
SCHADEN,3.32--sxad@,3.32--HARM,31.78--h#m,31.78
BLIES,3.93--blis,3.93--BLEW,31.57--blu,31.57
ZWAK,35.4--zwAk,35.4--WEAK,31.51--wik,31.51
STORMLOOP,0.37--stOrmlop,0.37--RUSH,31.41--rVS,31.41
SNEEUW,24.31--snew,24.31--SNOW,31.35--sn5,31.35
OBLIGATIE,0.39--obliGatsi,0.39--BOND,31.27--bQnd,31.27
BAD,42.58--bAt,42.58--BATH,31.12--b#T,31.12
TOUR,3.77--tur,3.77--TOUR,30.8--t9R,30.8

SCHOEN,13.45--sxun,13.45--SHOE,30.39--Su,30.39
BENDE,32.24--bEnd@,32.24--GANG,30.14--g{N,30.14
BOERDERIJ,29.57--burd@rK,29.57--FARM,30.04--f#m,30.04
SEXY,36.34--sEksi,36.34--SEXY,29.98--sEksI,29.98
GOSH,0.32--gOS,0.32--GOSH,29.9--gQS,29.9
GROEIDE,8.12--xrujd@,8.12--GREW,29.27--gru,29.27
STUURMAN,3.32--styrmAn,3.32--MATE,29.24--m1t,29.24
LADEN,10.7--lad@,10.7--LOAD,29.22--l5d,29.22
VERLIES,49.07--v@rlis,49.07--LOSS,29.12--lQs,29.12
MAALTIJD,15.37--maltKt,15.37--MEAL,28.86--mil,28.86
STORTPLAATS,1.07--stOrtplats,1.07--DUMP,28.82--dVmp,28.82
RU�NE,1.05--ryin@,1.05--RUIN,28.53--rUIn,28.53
WIJS,36.25--wKs,36.25--WISE,28.47--w2z,28.47
ROZE,19.09--r<z@,19.09--PINK,28.47--pINk,28.47
GEHANGEN,2.1--x@hAN@,2.1--HUNG,28.16--hVN,28.16
BUSTE,0.48--byst@,0.48--BUST,27.57--bVst,27.57
STIER,9.6--stir,9.6--BULL,27.51--bUl,27.51
DRAAD,13.31--drat,13.31--WIRE,27.51--w2@R,27.51
STIJGEN,8.71--stKG@,8.71--RISE,27.43--r2z,27.43
SCHEUR,6.38--sx|r,6.38--TEAR,27--t8R,27
HOUT,23.58--hMt,23.58--WOOD,27--wUd,27
LOT,60.14--lOt,60.14--FATE,26.96--f1t,26.96
GEBONDEN,6.79--x@bOnd@,6.79--TIED,26.75--t2d,26.75
SLEPEN,8.94--slep@,8.94--DRAG,26.45--dr{g,26.45
WAKKER,201.37--wAk@r,201.37--WOKE,26.35--w5k,26.35
VLAK,47.73--vlAk,47.73--FLAT,26.22--fl{t,26.22
BOT,14.52--bOt,14.52--BONE,26.06--b5n,26.06
AMEN,24.72--am@,24.72--AMEN,25.98--#mEn,25.98
UITGLIJDEN,0.37--LtxlKd@,0.37--SLIP,25.88--slIp,25.88
JACHT,23.99--jAxt,23.99--HUNT,25.86--hVnt,25.86
TAXI,50.84--tAksi,50.84--TAXI,25.84--t{ksI,25.84
VUIL,24.06--vLl,24.06--DIRT,25.69--d3t,25.69
MARINE,21.75--marin@,21.75--NAVY,25.69--n1vI,25.69
GEGEVENS,27.81--x@Gev@ns,27.81--DATA,25.61--d1t@,25.61
TANK,19.25--tENk,19.25--TANK,25.61--t{Nk,25.61
HUREN,15.23--hyr@,15.23--HIRE,25.53--h2@R,25.53
GOLF,17.54--xOlf,17.54--GOLF,25.53--gQlf,25.53
DAGERAAD,3.96--daG@rat,3.96--DAWN,25.51--d$n,25.51
VERKOOP,37.96--v@rkop,37.96--SALE,25.39--s1l,25.39
WAARSCHUWEN,27.42--warsxyw@,27.42--WARN,25.35--w$n,25.35
STRENG,13.47--strEN,13.47--HANK,25.31--h{Nk,25.31
SOEP,17.84--sup,17.84--SOUP,25.2--supVp,25.2
WERF,1.42--wErf,1.42--YARD,25.06--j#d,25.06
DREW,5.24--drew,5.24--DREW,25.04--dru,25.04
HERTOG,9.81--hErtOx,9.81--DUKE,25.04--djuk,25.04
ZUIVER,10.63--zLv@r,10.63--PURE,24.92--pj9R,24.92
TARIEF,1.88--tarif,1.88--RATE,24.92--r1t,24.92
EEND,8.99--ent,8.99--DUCK,24.76--dVk,24.76
POP,23.9--pOp,23.9--DOLL,24.76--dQl,24.76
MISLUKKEN,3.48--mIsl}k@,3.48--FAIL,24.59--f1l,24.59
PAD,41.99--pAt,41.99--PATH,24.55--p#T,24.55
RIEM,14.16--rim,14.16--BELT,24.35--bElt,24.35
STAART,17.95--start,17.95--TAIL,23.9--t1l,23.9
STOF,29.25--stOf,29.25--DUST,23.84--dVst,23.84
VAL,115.46--vAl,115.46--TRAP,23.84--tr{p,23.84
BREED,6.22--bret,6.22--WIDE,23.8--w2d,23.8
DEK,21.88--dEk,21.88--DECK,23.76--dEk,23.76
RAND,19.12--rAnt,19.12--EDGE,23.51--E_,23.51
JAMMER,92.2--jAm@r,92.2--PITY,23.51--pItI,23.51
GEGOTEN,1.49--x@Got@,1.49--CAST,23.14--k#st,23.14
MEID,114.52--mKt,114.52--MAID,22.82--m1d,22.82

TOUW,26.25--tMw,26.25--ROPE,22.71--r5p,22.71
ONBELEEFD,12.17--Omb@left,12.17--RUDE,22.06--rud,22.06
PUNK,1.01--p}Nk,1.01--PUNK,21.98--pVNk,21.98
KNAL,14.82--knAl,14.82--BOOM,21.8--bum,21.8
KOM,2612.54--kOm,2612.54--BOWL,21.45--b5l,21.45
NUL,17.61--n}l,17.61--ZERO,21.45--z7r5,21.45
ONTKENNEN,12.9--OntkEn@,12.9--DENY,21.39--dIn2,21.39
ZELDZAAM,10.02--zEltsam,10.02--RARE,21.31--r8R,21.31
GOLF,17.54--xOlf,17.54--WAVE,21.25--w1v,21.25
DROEG,31.21--drux,31.21--WORE,21.2--w$R,21.2
GRIJS,8.53--xrKs,8.53--GRAY,21.12--gr1,21.12
OVERSPRINGEN,0.02--ov@rsprIN@,0.02--SKIP,21.1--skIp,21.1
HOORN,8--hOrn,8--HORN,21.08--h$n,21.08
MIJL,15.32--mKl,15.32--MILE,21--m2l,21
GENEZEN,30.3--x@nez@,30.3--CURE,20.84--kj9R,20.84
BEGRAVEN,51.96--b@Grav@,51.96--BURY,20.67--bErI,20.67
GRAAF,19.55--xraf,19.55--EARL,20.43--3l,20.43
ZAND,19.99--zAnt,19.99--SAND,20.29--s{nd,20.29
KOOI,13.81--koj,13.81--CAGE,20.27--k1_,20.27
WOLF,20.26--wOlf,20.26--WOLF,20.27--wUlf,20.27
VLEUGEL,8.83--vl|G@l,8.83--WING,20.24--wIN,20.24
DUN,9.1--d}n,9.1--THIN,20.18--TIn,20.18
ZONE,13.08--z<n@,13.08--ZONE,20.12--z5n,20.12
KNAL,14.82--knAl,14.82--BANG,19.98--b{N,19.98
LENING,10.27--lenIN,10.27--LOAN,19.86--l5n,19.86
FRISDRANK,3.75--frIzdrANk,3.75--SODA,19.84--s5d@,19.84
MASKER,19.23--mAsk@r,19.23--MASK,19.8--m#sk,19.8
RUNDVLEES,3.02--r}ntfles,3.02--BEEF,19.71--bif,19.71
ZOUT,15.5--zMt,15.5--SALT,19.51--s$lt,19.51
PIJP,13.81--pKp,13.81--PIPE,19.39--p2p,19.39
SPIT,1.33--spIt,1.33--SPIT,19.35--spIt,19.35
PLAATS,213.38--plats,213.38--SITE,19.22--s2t,19.22
GEMAK,18.04--x@mAk,18.04--EASE,19.1--iz,19.1
AANVAL,47.59--anvAl,47.59--BOUT,19.1--b6t,19.1
WINKELCENTRUM,10.59--wINk@lsEntr}m,10.59--MALL,18.9--m$l,18.9
NAGEL,4.05--naG@l,4.05--NAIL,18.65--n1l,18.65
ONDEUGD,1.12--Ond|xt,1.12--VICE,18.63--v2sI,18.63
GIL,9.99--gIl,9.99--YELL,18.41--jEl,18.41
ZOEKEN,273.23--zuk@,273.23--SEEK,18.31--sik,18.31
ROL,54.01--rOl,54.01--ROLE,18.22--r5l,18.22
MIDDAG,22.64--mIdAx,22.64--NOON,18.12--nun,18.12
IJZER,7.11--Kz@r,7.11--IRON,17.94--2@n,17.94
INPAKKEN,14.29--ImpAk@,14.29--WRAP,17.8--r{p,17.8
GEBREK,14.02--x@brEk,14.02--LACK,17.75--l{k,17.75
JEAN,12.46--_in,12.46--JEAN,17.73--_1n,17.73
CLUE,0.11--klu,0.11--CLUE,17.61--klu,17.61
VLAG,17.79--vlAx,17.79--FLAG,17.49--fl{g,17.49
TENT,40.93--tEnt,40.93--TENT,17.49--tEnt,17.49
TERMIJN,6.29--tErmKn,6.29--TERM,17.45--t3m,17.45
BREUK,5.47--br|k,5.47--SNAP,17.39--sn{p,17.39
BORGTOCHT,5.83--bOrxtOxt,5.83--BAIL,17.35--b1l,17.35
MASSA,9.17--mAsa,9.17--MASS,17.25--m{s,17.25
BRANDSTOF,14.5--brAntstOf,14.5--FUEL,17.18--fj9l,17.18
WETTEN,18.07--wEt@,18.07--LAWS,17.02--l$z,17.02
WASTAFEL,0.89--wAstaf@l,0.89--SINK,16.92--sINk,16.92
VEGEN,6.04--veG@,6.04--WIPE,16.88--w2p,16.88
TOON,34.67--ton,34.67--TONE,16.86--t5n,16.86
DOEL,77.45--dul,77.45--GOAL,16.75--g5l,16.75
VRAAGT,103.2--vraxt,103.2--ASKS,16.71--#sks,16.71
WADEN,0.3--wad@,0.3--WADE,16.47--w1d,16.47
BUIS,6.08--bLs,6.08--TUBE,16.43--tjub,16.43

WISKUNDE,11.66--wIsk}nd@,11.66--MATH,16.39--m{T,16.39
BABBELEN,4.73--bAb@l@,4.73--CHAT,16.27--J{t,16.27
DRUG,6.4--dr}k,6.4--DOPE,16.08--d5p,16.08
VERSNELLING,3--v@rsnElIN,3--GEAR,16--g7R,16
VERKRACHTING,13.1--v@rkrAxtIN,13.1--RAPE,16--r1p,16
GEZOEM,0.5--x@zum,0.5--BUZZ,15.96--bVz,15.96
TOON,34.67--ton,34.67--TUNE,15.61--tjun,15.61
UITGANG,14.68--LtxAN,14.68--EXIT,15.57--EksIt,15.57
FORT,9.38--fOrt,9.38--FORT,15.43--f$t,15.43
VLOGEN,4.94--vloG@,4.94--FLEW,15.39--flu,15.39
KAP,12.28--kAp,12.28--HOOD,15.39--hUd,15.39
ROMMEL,19.09--rOm@l,19.09--JUNK,15.37--_VNk,15.37
DIEET,9.24--dijet,9.24--DIET,15.37--d2@t,15.37
VERDIENEN,64.14--v@rdin@,64.14--EARN,15.35--3n,15.35
LEEUW,14.7--lew,14.7--LION,15.35--l2@n,15.35
ZEEP,14.22--zep,14.22--SOAP,15.2--s5p,15.2
GIETEN,1.94--xit@,1.94--POUR,15.12--p$R,15.12
RIJST,9.17--rKst,9.17--RICE,15.08--r2s,15.08
BOCHT,8.37--bOxt,8.37--BEND,15.06--bEnd,15.06
GASTHEER,7.55--xAsther,7.55--HOST,15.02--h5st,15.02
ZEER,149.85--zer,149.85--SORE,15--s$R,15
ZEEHOND,0.57--zehOnt,0.57--SEAL,14.75--sil,14.75
KNIE,10.24--kni,10.24--KNEE,14.69--ni,14.69
SPINNEN,6.31--spIn@,6.31--SPIN,14.63--spIn,14.63
GEN,1.97--xEn,1.97--GENE,14.57--_in,14.57
DOOF,18.59--dof,18.59--DEAF,14.53--dEf,14.53
HAVEN,17.08--hav@,17.08--PORT,14.53--p$t,14.53
VALS,26.6--vAls,26.6--FOUL,14.47--f6l,14.47
OMDRAAIEN,15.28--Omdraj@,15.28--FLIP,14.27--flIp,14.27
AFDELING,32.77--AvdelIN,32.77--WARD,14.25--w$d,14.25
SCHULD,178.1--sx}lt,178.1--DEBT,14.22--dEt,14.22
MAIS,5.46--mAjs,5.46--CORN,14.22--k$n,14.22
ZELF,437.46--zElf,437.46--SELF,14.16--sElf,14.16
STRUIK,2.7--strLk,2.7--BUSH,14.12--bUS,14.12
GROT,17.45--xrOt,17.45--CAVE,13.98--k1v,13.98
FANS,10.84--fEns,10.84--FANS,13.94--f{nz,13.94
STOPPEN,194.24--stOp@,194.24--DARN,13.9--d#n,13.9
LADY,16.28--ledi,16.28--DAME,13.76--d1m,13.76
STROOM,29.87--strom,29.87--FLOW,13.75--fl5,13.75
ZEIL,6.91--zKl,6.91--SAIL,13.75--s1l,13.75
KRIJGEN,496.9--krKG@,496.9--GAIN,13.73--g1n,13.73
GEDICHT,14.73--x@dIxt,14.73--POEM,13.65--p5Im,13.65
KARBONADE,0.43--kArbonad@,0.43--CHOP,13.61--JQp,13.61
SCHUUR,15.94--sxyr,15.94--BARN,13.59--b#n,13.59
PALM,2.47--pAlm,2.47--PALM,13.24--p#m,13.24
STAPEL,10.22--stap@l,10.22--PILE,13.18--p2l,13.18
ZWEEP,4.87--zwep,4.87--WHIP,13.16--wIp,13.16
ZAK,96.87--zAk,96.87--SACK,12.92--s{k,12.92
LAMP,13.88--lAmp,13.88--LAMP,12.88--l{mp,12.88
DUIKEN,16.05--dLk@,16.05--DIVE,12.82--d2v,12.82
HAVIK,2.36--havIk,2.36--HAWK,12.75--h$k,12.75
TAAK,42.63--tak,42.63--TASK,12.73--t#sk,12.73
KIN,7.8--kIn,7.8--CHIN,12.69--JIn,12.69
POMP,6.63--pOmp,6.63--PUMP,12.65--pVmp,12.65
POOL,3.54--pul,3.54--POLE,12.59--p5l,12.59
KLAP,29.27--klAp,29.27--SLAP,12.47--sl{p,12.47
NETJES,30.05--nEtj@s,30.05--NEAT,12.45--nit,12.45
TOSS,0.3--tOs,0.3--TOSS,12.39--tQs,12.39
DUIM,10.79--dLm,10.79--INCH,12.37--InJ,12.37
BAND,79.28--bEnt,79.28--TIRE,12.37--t2@R,12.37
BUIL,0.91--bLl,0.91--BUMP,12.35--bVmp,12.35

GAZON,3.09--xazOn,3.09--LAWN,12.35--l$n,12.35
FOND,0.23--fOnt,0.23--FOND,12.33--fQnd,12.33
ITEM,1.83--it@m,1.83--ITEM,12.31--2t@m,12.31
DUS,1407.45--d}s,1407.45--THUS,12.31--DVs,12.31
NEIGING,3.54--nKGIN,3.54--TEND,12.27--tEnd,12.27
SAAI,31.47--saj,31.47--DULL,12.08--dVl,12.08
DUBBELTJE,1.88--d}b@ltj@,1.88--DIME,12.06--d2m,12.06
HAGEL,1.35--haG@l,1.35--HAIL,12.02--h1l,12.02
KLEI,2.7--klK,2.7--CLAY,12--kl1,12
VERHAAL,202.98--v@rhal,202.98--TALE,12--t1l,12
LINK,12.87--lINk,12.87--LINK,11.94--lINk,11.94
JAZZ,6.97--_Es,6.97--JAZZ,11.92--_{z,11.92
CHEF,31.05--SEf,31.05--CHEF,11.88--SEf,11.88
SLANK,3.16--slANk,3.16--SLIM,11.86--slIm,11.86
PIL,9.4--pIl,9.4--PILL,11.82--pIl,11.82
HERT,6.13--hErt,6.13--HART,11.76--h#t,11.76
LENEN,35.33--len@,35.33--LEND,11.67--lEnd,11.67
LUI,47.68--lL,47.68--LAZY,11.59--l1zI,11.59
PLOT,2.33--plOt,2.33--PLOT,11.59--plQt,11.59
SCHOTEL,5.51--sxot@l,5.51--DISH,11.45--dIS,11.45
PIK,36.5--pIk,36.5--COCK,11.37--kQk,11.37
GENEZEN,30.3--x@nez@,30.3--HEAL,11.33--hil,11.33
WOEDE,24.95--wud@,24.95--RAGE,11.31--r1_,11.31
HALTE,5.01--hAlt@,5.01--HALT,11.27--h$lt,11.27
BAGAGERUIMTE,0.53--bAGaZ@rLmt@,0.53--BOOT,11.14--but,11.14
LEEFTIJDEN,1.12--leftKd@,1.12--AGES,11.12--1_Iz,11.12
NEST,11.27--nEst,11.27--NEST,11.1--nEst,11.1
SCHUUR,15.94--sxyr,15.94--SHED,10.98--SEd,10.98
LIKKEN,7.5--lIk@,7.5--LICK,10.96--lIk,10.96
KREUPEL,2.93--kr|p@l,2.93--LAME,10.92--l1m,10.92
GESCHEURD,5.81--x@sx|rt,5.81--TORN,10.84--t$n,10.84
GEREEDSCHAP,13.15--x@retsxAp,13.15--TOOL,10.75--tul,10.75
PAUS,12.62--pMs,12.62--POPE,10.71--p5p,10.71
LAM,7.34--lAm,7.34--LAMB,10.63--l{m,10.63
FONDS,3.82--fOnts,3.82--FUND,10.61--fVnd,10.61
GEIT,8.07--xKt,8.07--GOAT,10.53--g5t,10.53
VARKENSVLEES,3.36--vArk@sfles,3.36--PORK,10.53--p$k,10.53
WORTEL,6.11--wOrt@l,6.11--ROOT,10.47--rut,10.47
DOBBELEN,1.92--dOb@l@,1.92--DICE,10.45--d2s,10.45
TWEELING,15.8--twelIN,15.8--TWIN,10.43--twIn,10.43
PLUG,1.1--pl}x,1.1--PLUG,10.41--plVg,10.41
REED,40.75--ret,40.75--RODE,10.39--r5d,10.39
MAGER,8.64--maG@r,8.64--LEAN,10.37--lin,10.37
KIPPENREN,0.34--kIp@rEn,0.34--COOP,10.35--kupVp,10.35
JEEP,7.71--_ip,7.71--JEEP,10.27--_ip,10.27
LEK,10.45--lEk,10.45--LEAK,10.14--lik,10.14
WORM,9.1--wOrm,9.1--WORM,10.12--w3m,10.12
VERSLETEN,3.66--v@rslet@,3.66--WORN,10.08--w$n,10.08
ZUUR,10.18--zyr,10.18--ACID,9.96--{sId,9.96
MENU,6.63--meny,6.63--MENU,9.96--mEnju,9.96
EED,10.79--et,10.79--OATH,9.88--5T,9.88
KERN,9.26--kErn,9.26--CORE,9.82--k$R,9.82
ZIJDE,18.8--zKd@,18.8--SILK,9.78--sIlk,9.78
DOK,7.66--dOk,7.66--DOCK,9.75--dQk,9.75
MUNT,10.89--m}nt,10.89--COIN,9.75--k4n,9.75
AAS,9.06--as,9.06--BAIT,9.73--b1t,9.73
KAAL,8.23--kal,8.23--BALD,9.73--b$ld,9.73
GREEP,15.64--xrep,15.64--GRIP,9.69--grIp,9.69
TEMPO,11.78--tEmpo,11.78--PACE,9.57--p1sI,9.57
AFGUNST,1.56--Afx}nst,1.56--ENVY,9.55--EnvI,9.55
MOLEN,4.53--mol@,4.53--MILL,9.53--mIl,9.53

CENT,36.93--sEnt,36.93--CENT,9.47--sEnt,9.47
SCANNEN,3.11--skEn@,3.11--SCAN,9.41--sk{n,9.41
DAAD,16.65--dat,16.65--DEED,9.31--did,9.31
DICHTER,27.24--dIxt@r,27.24--POET,9.22--p5It,9.22
WENK,0.39--wENk,0.39--HINT,9.2--hInt,9.2
GRIJS,8.53--xrKs,8.53--GREY,9.2--gr1,9.2
DAL,3.89--dAl,3.89--DALE,9.08--d1l,9.08
KAUWEN,4.69--kMw@,4.69--CHEW,9.06--Ju,9.06
KAR,6.75--kAr,6.75--CART,9.04--k#t,9.04
SOK,3.11--sOk,3.11--SOCK,8.98--sQk,8.98
GEHOORZAMEN,9.1--x@horzam@,9.1--OBEY,8.94--@b1,8.94
OVEN,9.9--ov@,9.9--OVEN,8.88--VvH,8.88
VORK,5.19--vOrk,5.19--FORK,8.82--f$k,8.82
STEKEN,35.83--stek@,35.83--STAB,8.76--st{b,8.76
STRAAL,7.27--stral,7.27--BEAM,8.73--bim,8.73
HERT,6.13--hErt,6.13--DEER,8.71--d7R,8.71
ROEM,7.98--rum,7.98--FAME,8.65--f1m,8.65
VOUWEN,1.17--vMw@,1.17--FOLD,8.63--f5ld,8.63
SOUTENEUR,0.25--sut@n|r,0.25--PIMP,8.63--pImp,8.63
HOUWEN,0.21--hMw@,0.21--HACK,8.55--h{k,8.55
SOLO,4--solo,4--SOLO,8.55--s5l5,8.55
INVAL,5.81--InvAl,5.81--RAID,8.55--r1d,8.55
RANG,9.19--rAN,9.19--RANK,8.49--r{Nk,8.49
GEWAAD,2.13--x@wat,2.13--ROBE,8.49--r5b,8.49
TROMMEL,1.85--trOm@l,1.85--DRUM,8.47--drVm,8.47
LITTEKEN,9.81--lItek@,9.81--SCAR,8.47--sk#R,8.47
KAAL,8.23--kal,8.23--BARE,8.33--b8R,8.33
RIET,0.87--rit,0.87--CANE,8.33--k1n,8.33
SCHEURDE,1.99--sx|rd@,1.99--TORE,8.29--t$R,8.29
KAAP,1.1--kap,1.1--CAPE,8.24--k1p,8.24
LONG,9.47--lON,9.47--LUNG,8.24--lVN,8.24
ZONG,10.47--zON,10.47--SANG,8.22--s{N,8.22
PONY,4.92--pOni,4.92--PONY,8.1--p5nI,8.1
SLANG,21.59--slAN,21.59--HOSE,8.06--h5z,8.06
MOL,7.55--mOl,7.55--MOLE,8.06--m5l,8.06
DIENBLAD,1.23--dimblAt,1.23--TRAY,8.04--tr1,8.04
VERBLEKEN,1.12--v@rblek@,1.12--PALE,8.02--p1l,8.02
PLOOI,0.57--ploj,0.57--TUCK,7.96--tVk,7.96
LOUTER,2.33--lMt@r,2.33--MERE,7.86--m7R,7.86
REK,2.38--rEk,2.38--RACK,7.78--r{k,7.78
BODEM,15.3--bod@m,15.3--SOIL,7.78--s4l,7.78
VERVELEN,7.25--v@rvel@,7.25--BORE,7.75--b$R,7.75
AUTO,458--Mto,458--AUTO,7.67--$t5,7.67
TOT,1131.5--tOt,1131.5--UNTO,7.63--VntU,7.63
STILTE,37.87--stIlt@,37.87--HUSH,7.61--hVS,7.61
ZAAD,6.33--zat,6.33--SEED,7.57--sid,7.57
STOUTMOEDIG,0.32--stMtmud@x,0.32--BOLD,7.55--b5ld,7.55
BAS,1.92--bAs,1.92--BASS,7.55--b1s,7.55
HIEL,0.85--hil,0.85--HEEL,7.39--hil,7.39
MONNIK,5.95--mOn@k,5.95--MONK,7.37--mVNk,7.37
VUIST,6.77--vLst,6.77--FIST,7.35--fIst,7.35
TIJ,3.09--tK,3.09--TIDE,7.35--t2d,7.35
SMELTEN,5.79--smElt@,5.79--MELT,7.31--mElt,7.31
TEEK,0.87--tek,0.87--TICK,7.25--tIk,7.25
KROM,2.84--krOm,2.84--BENT,7.22--bEnt,7.22
GLEN,4.09--glen,4.09--GLEN,7.18--glEn,7.18
VERTROUWEN,141.74--v@rtrMw@,141.74--RELY,7.18--rIl2,7.18
MENSEN,1089.4--mEns@,1089.4--FOLK,7.16--f5k,7.16
OPHEF,2.9--OphEf,2.9--FUSS,7.14--fVs,7.14
TREK,125.73--trEk,125.73--HAUL,7.08--h$l,7.08
KUDDE,12.42--k}d@,12.42--HERD,7.06--h3d,7.06

KOORD,2.26--kort,2.26--CORD,7.02--k$d,7.02
MUILDIER,0.73--mLldir,0.73--MULE,7.02--mjul,7.02
STOETERIJ,0.07--stut@rK,0.07--STUD,6.94--stVd,6.94
MYTHE,6.2--mite,6.2--MYTH,6.9--mIT,6.9
BOUT,0.94--bMt,0.94--BOLT,6.88--b5lt,6.88
LUNCH,42.42--l}nS,42.42--CHOW,6.86--J6,6.86
ECHO,8.92--Exo,8.92--ECHO,6.86--Ek5,6.86
NAZI,5.69--natsi,5.69--NAZI,6.86--n#tsI,6.86
BOON,1.42--bon,1.42--BEAN,6.84--bin,6.84
PLEITEN,3.32--plKt@,3.32--PLEA,6.84--pli,6.84
ZWAAN,1.99--zwan,1.99--SWAN,6.82--swQn,6.82
POSE,1.12--poz@,1.12--POSE,6.8--p5z,6.8
LUS,1.37--l}s,1.37--LOOP,6.76--lup,6.76
SPRONG,24.17--sprON,24.17--LEAP,6.67--lip,6.67
DRANG,4.71--drAN,4.71--URGE,6.65--3_,6.65
SCHIJF,4.55--sxKf,4.55--DISK,6.63--dIsk,6.63
STEENKOOL,1.3--steNkol,1.3--COAL,6.57--k5l,6.57
MUIZEN,5.6--mLz@,5.6--MICE,6.57--m2s,6.57
JAPON,0.73--japOn,0.73--GOWN,6.55--g6n,6.55
PIER,7.36--pir,7.36--PIER,6.55--p7R,6.55
HIKE,0.14--hAjk,0.14--HIKE,6.53--h2k,6.53
SIGNAAL,29.13--sInjal,29.13--BEEP,6.51--bip,6.51
IJDEL,2.79--Kd@l,2.79--VAIN,6.51--v1n,6.51
HERRIE,13.97--hEri,13.97--RIOT,6.49--r2@t,6.49
STOVEN,0.21--stov@,0.21--STEW,6.43--stju,6.43
CUPS,0.18--k}ps,0.18--CUPS,6.39--kVps,6.39
KEREL,139.68--ker@l,139.68--CHAP,6.35--J{p,6.35
BAKKEN,11.85--bAk@,11.85--BAKE,6.33--b1k,6.33
VIJVER,4.32--vKv@r,4.32--POND,6.33--pQnd,6.33
SLAAPBANK,0.48--slabANk,0.48--BUNK,6.27--bVNk,6.27
KINDERBEDJE,0.05--kInd@rbEtj@,0.05--CRIB,6.2--krIb,6.2
PIJNBOOM,0.18--pKmbom,0.18--PINE,6.2--p2n,6.2
TARIEF,1.88--tarif,1.88--FARE,6.16--f8R,6.16
GROOT,237.51--xrot,237.51--VAST,6.1--v#st,6.1
KAM,5.28--kAm,5.28--COMB,6.06--k5m6t,6.06
SCHEUTJE,0.59--sx|tj@,0.59--DASH,6.04--d{S,6.04
KOKEN,33.8--kok@,33.8--BOIL,5.94--b4l,5.94
HOOGTEPUNT,6.84--hoxt@p}nt,6.84--PEAK,5.94--pik,5.94
ROEREN,2.17--rur@,2.17--STIR,5.9--st3R,5.9
NAAKT,30.55--nakt,30.55--NUDE,5.9--njud,5.9
LIJM,3.98--lKm,3.98--GLUE,5.88--glu,5.88
BANK,91.91--bANk,91.91--SOFA,5.86--s5f@,5.86
GALANT,1.19--xalAnt,1.19--BEAU,5.84--b5,5.84
ZUUR,10.18--zyr,10.18--SOUR,5.82--s6@R,5.82
DICHTSLAAN,0.5--dIxtslan,0.5--SLAM,5.8--sl{m,5.8
ALMA,2.56--Alma,2.56--ALMA,5.76--{lm@,5.76
GLOED,2.08--xlut,2.08--GLOW,5.75--gl5,5.75
KLEM,10.47--klEm,10.47--CLIP,5.69--klIp,5.69
PAD,41.99--pAt,41.99--TOAD,5.69--t5d,5.69
GRAF,34.53--xrAf,34.53--TOMB,5.63--tum,5.63
VERVAGEN,2.38--v@rvaG@,2.38--FADE,5.61--f1d,5.61
NOODLOT,5.53--nodlOt,5.53--DOOM,5.61--dum,5.61
DUIF,5.35--dLf,5.35--DOVE,5.57--dVv,5.57
LUST,18.41--l}st,18.41--LUST,5.57--lVst,5.57
VEST,8.07--vEst,8.07--VEST,5.57--vEst,5.57
GEZOND,31.83--x@zOnt,31.83--SANE,5.51--s1n,5.51
PROOI,7.82--proj,7.82--PREY,5.51--pr1,5.51
SCHORS,1.14--sxOrs,1.14--BARK,5.49--b#k,5.49
SLEUF,0.09--sl|f,0.09--SLOT,5.49--slQt,5.49
HUILEN,54.52--hLl@,54.52--WEEP,5.49--wip,5.49
SCHERING,0.09--sxerIN,0.09--WARP,5.49--w$p,5.49

RANG,9.19--rAN,9.19--RANG,5.43--r{N,5.43
MUNT,10.89--m}nt,10.89--MINT,5.43--mInt,5.43
BESPOTTEN,1.46--b@spOt@,1.46--MOCK,5.37--mQk,5.37
ROER,7.8--rur,7.8--HELM,5.35--hElm,5.35
SCHIL,1.12--sxIl,1.12--PEEL,5.35--pil,5.35
DOSIS,7.82--doz@s,7.82--DOSE,5.29--d5s,5.29
ZOOL,0.91--zol,0.91--SOLE,5.25--s5l,5.25
EENZAAM,31.56--enzam,31.56--LONE,5.25--l5n,5.25
COLT,2.72--kolt,2.72--COLT,5.24--k5lt,5.24
TEKST,19.94--tEkst,19.94--TEXT,5.24--tEkst,5.24
ERFGENAAM,5.79--Erfx@nam,5.79--HEIR,5.22--8R,5.22
BLAD,11.14--blAt,11.14--LEAF,5.2--lif,5.2
HOMP,0.27--hOmp,0.27--HUNK,5.16--hVNk,5.16
MODE,11.02--mod@,11.02--MODE,5.16--m5d,5.16
KRUID,2.15--krLt,2.15--HERB,4.98--h3b,4.98
NAAKTSLAK,0.09--naktslAk,0.09--SLUG,4.96--slVg,4.96
QUIZ,2.36--kwIs,2.36--QUIZ,4.94--kwIz,4.94
YANG,1.26--jAN,1.26--YANG,4.94--j{N,4.94
STORM,29.61--stOrm,29.61--GALE,4.9--g1l,4.9
HOOP,367.83--hop,367.83--HEAP,4.88--hip,4.88
VERDOVEN,3.54--v@rdov@,3.54--NUMB,4.88--nVm,4.88
ZEKERING,1.01--zek@rIN,1.01--FUSE,4.86--fjuz,4.86
GEWAS,0.66--x@wAs,0.66--CROP,4.86--krQp,4.86
MILD,2.47--mIlt,2.47--MILD,4.8--m2ld,4.8
ONVERBIDDELIJK,0.3--Onv@rbId@l@k,0.3--GRIM,4.78--grIm,4.78
GOLF,17.54--xOlf,17.54--GULF,4.73--gVlf,4.73
RUKKEN,7.66--r}k@,7.66--YANK,4.71--j{Nk,4.71
VLOT,6.43--vlOt,6.43--RAFT,4.71--r#ft,4.71
LIDMAAT,0.09--lIdmat,0.09--LIMB,4.67--lIm,4.67
LENS,4.14--lEns,4.14--LENS,4.67--lEnz,4.67
GEZONKEN,4.71--x@zONk@,4.71--SUNK,4.65--sVNk,4.65
BING,0.91--bIN,0.91--BING,4.57--bIN,4.57
SPOOR,43.72--spor,43.72--RAIL,4.57--r1l,4.57
TOCHT,9.54--tOxt,9.54--TREK,4.49--trEk,4.49
SCHERP,20.83--sxErp,20.83--KEEN,4.47--kin,4.47
BROOD,33.59--brot,33.59--LOAF,4.47--l5f,4.47
CULTUS,1.05--k}lt}s,1.05--CULT,4.45--kVlt,4.45
KRAAI,2.63--kraj,2.63--CROW,4.45--kr5,4.45
GLUREN,4.64--xlyr@,4.64--PEEP,4.43--pip,4.43
VERACHTELIJK,1.78--v@rAxt@l@k,1.78--VILE,4.43--v2l,4.43
BULT,3.41--b}lt,3.41--HUMP,4.41--hVmp,4.41
LUCHTEN,3.34--l}xt@,3.34--VENT,4.41--vEnt,4.41
VLUCHTTEN,1.81--vl}xt@,1.81--FLED,4.39--flEd,4.39
PION,3.18--pijOn,3.18--PAWN,4.33--p$n,4.33
MONDELING,0.69--mOnd@lIN,0.69--ORAL,4.31--$r@l,4.31
DINEREN,7.8--diner@,7.8--DINE,4.29--d2n,4.29
SCHIMMEL,2.95--sxIm@l,2.95--MOLD,4.29--m5lt,4.29
TRIMMEN,0.3--trIm@,0.3--TRIM,4.27--trIm,4.27
GRAS,18.75--xrAs,18.75--TURF,4.27--t3f,4.27
LOKKEN,11.69--lOk@,11.69--LURE,4.25--l9R,4.25
ROMP,6.47--rOmp,6.47--HULL,4.22--hVl,4.22
JEUK,2.58--j|k,2.58--ITCH,4.18--IJ,4.18
RIJP,8.1--rKp,8.1--RIPE,4.18--r2p,4.18
BETEUGELEN,0.46--b@t|G@l@,0.46--CURB,4.1--k3b,4.1
STAM,12.46--stAm,12.46--CLAN,4.1--kl{n,4.1
NIETIG,2.77--nit@x,2.77--VOID,4.1--v4d,4.1
TIENER,8.42--tin@r,8.42--TEEN,4.1--tin,4.1
SCHUIT,1.33--sxLt,1.33--HULK,4.08--hVlk,4.08
VERKLIKKER,4.83--v@rklIk@r,4.83--FINK,4.04--fINk,4.04
BRULLEN,1.37--br}l@,1.37--ROAR,4.02--r$R,4.02
RIF,2.56--rIf,2.56--REEF,4--rif,4

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BLOEDDE,3.27--blud@,3.27--BLED,3.94--blEd,3.94
CLAM,0.11--klEm,0.11--CLAM,3.92--kl{m,3.92
LAMP,13.88--lAmp,13.88--BULB,3.92--bVlb,3.92
SUIZEN,0.48--sLz@,0.48--WHIZ,3.9--wIz,3.9
KHAN,3.38--k#n,3.38--KHAN,3.88--k#n,3.88
VAAS,4.57--vas,4.57--VASE,3.84--v#z,3.84
HELAAS,69.34--helas,69.34--ALAS,3.82--@l{s,3.82
WOEDE,24.95--wud@,24.95--FURY,3.82--fj9rI,3.82
SPLEET,1.78--splet,1.78--SLIT,3.8--slIt,3.8
VERBOND,7.16--v@rbOnt,7.16--PACT,3.76--p{kt,3.76
VASTEN,1.51--vAst@,1.51--LENT,3.73--lEnt,3.73
KANT,312.67--kAnt,312.67--LACE,3.71--l1s,3.71
NERTS,0.71--nErts,0.71--MINK,3.71--mINk,3.71
KNOOP,9.51--knop,9.51--KNOT,3.69--nQt,3.69
BOOG,8.55--box,8.55--ARCH,3.69--#J,3.69
STUTTEN,0.39--st}t@,0.39--PROP,3.69--prQp,3.69
SLAP,7.11--slAp,7.11--LIMP,3.67--lImp,3.67
ZOLDER,8.19--zOld@r,8.19--LOFT,3.65--lQft,3.65
RUIL,15.39--rLl,15.39--SWAP,3.63--swQp,3.63
DRAAIKOLK,0.62--drajkOlk,0.62--EDDY,3.61--EdI,3.61
OUD,183.26--Mt,183.26--AGED,3.59--1_Id,3.59
ADER,3.27--ad@r,3.27--VEIN,3.59--v1n,3.59
BROK,1.65--brOk,1.65--LUMP,3.55--lVmp,3.55
BUIT,10.4--bLt,10.4--LOOT,3.55--lut,3.55
MIST,45.6--mIst,45.6--MIST,3.55--mIst,3.55
DEUK,2.65--d|k,2.65--DENT,3.53--dEnt,3.53
WENK,0.39--wENk,0.39--WINK,3.53--wINk,3.53
PIKKEN,16.44--pIk@,16.44--PECK,3.53--pEk,3.53
OPSCHEPPEN,3.86--OpsxEp@,3.86--BRAG,3.51--br{g,3.51
SCHUIM,3.54--sxLm,3.54--FOAM,3.51--f5m,3.51
SUNG,0.62--s}N,0.62--SUNG,3.49--sVN,3.49
POLO,2.22--polo,2.22--POLO,3.49--p5l5,3.49
WEKEN,148.3--wek@,148.3--SOAK,3.45--s5k,3.45
BETA,2.83--bEta,2.83--BETA,3.43--bit@,3.43
ARABISCH,2.97--arabis,2.97--ARAB,3.41--{r@b,3.41
ZUCHT,2.61--z}xt,2.61--SIGH,3.39--s2,3.39
ZWERVEN,2.54--zwErv@,2.54--ROAM,3.39--r5m,3.39
BINDEN,8.99--bInd@,8.99--BIND,3.35--b2nd,3.35
TOL,3.75--tOl,3.75--TOLL,3.35--t5l,3.35
NORM,3.04--nOrm,3.04--NORM,3.33--n$m,3.33
VLO,0.78--vlo,0.78--FLEA,3.31--fli,3.31
ROOSKLEURIG,0.59--roskl|r@x,0.59--ROSY,3.31--r5zI,3.31
LIMOEN,1.53--limun,1.53--LIME,3.29--l2m,3.29
PINT,1.49--pInt,1.49--PINT,3.27--p2nt,3.27
OPLOSSEN,32.84--OplOs@,32.84--COPE,3.25--k5p,3.25
INHAM,0.39--InhAm,0.39--COVE,3.25--k5v,3.25
HASPEL,0.32--hAsp@l,0.32--REEL,3.25--ril,3.25
FUNK,0.73--f}Nk,0.73--FUNK,3.16--fVNk,3.16
WOL,3.75--wOl,3.75--WOOL,3.16--wUl,3.16
VOEREN,36.29--vur@,36.29--WAGE,3.12--w1_,3.12
TROTSEREN,2.36--trOtser@,2.36--DEFY,3.1--dIf2,3.1
SCHEENBEEN,0.55--sxemben,0.55--SHIN,3.08--SIn,3.08
FOUT,165.27--fMt,165.27--FLAW,3.04--fl$,3.04
BRIK,0.75--brIk,0.75--BRIG,3.04--brIg,3.04
HARK,1.51--hArk,1.51--RAKE,2.98--r1k,2.98
KALF,3.06--kAlf,3.06--CALF,2.96--k#f,2.96
SLUIER,3.13--slLj@r,3.13--VEIL,2.96--v1l,2.96
VOCHTIG,3.25--vOxt@x,3.25--DAMP,2.92--d{mp,2.92
KEGEL,0.43--keG@l,0.43--CONE,2.92--k5n,2.92
MERRIE,2.72--mEri,2.72--MARE,2.9--m8R,2.9
HELLING,2.38--hElIN,2.38--RAMP,2.88--r{mp,2.88
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KURK,1.62--k}rk,1.62--CORK,2.86--k$k,2.86
PLAAG,8.42--plax,8.42--PEST,2.86--pEst,2.86
NEON,0.48--nejOn,0.48--NEON,2.86--niQn,2.86
MOS,1.14--mOs,1.14--MOSS,2.84--mQs,2.84
BONS,3.13--bOns,3.13--BONG,2.78--bQN,2.78
NUTTELOOS,8.71--n}t@los,8.71--IDLE,2.76--2dP,2.76
IDOOL,1.97--idol,1.97--IDOL,2.76--2dP,2.76
ATOOM,1.14--atom,1.14--ATOM,2.75--{t@m,2.75
ROOIEN,1.69--roj@,1.69--GRUB,2.73--grVb,2.73
TEMMEN,2.38--tEm@,2.38--TAME,2.73--t1m,2.73
GRIJNS,3.16--xrKns,3.16--GRIN,2.71--grIn,2.71
HOEPEL,7.36--hup@l,7.36--HOOP,2.69--hup,2.69
MEISJE,382.74--mKsj@,382.74--LASS,2.67--l{s,2.67
VOOR,6709.9--vor,6709.9--FORE,2.65--f$R,2.65
TOETEREN,1.19--tut@r@,1.19--HOOT,2.61--hut,2.61
STAATSGREEP,1.46--statsxrep,1.46--COUP,2.61--kup,2.61
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14.2. BIA Lexicon

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Dutch:O--Dutch:P--English:O--English:P
OVER,9.9--ov@r,9.9--ABOUT,3631.49--@b6t,3631.49
ZUUR,10.18--zyr,10.18--ACID,9.96--{sId,9.96
BANG,477.21--bAN,477.21--AFRAID,247.67--@fr1d,247.67
WEER,1136.95--wer,1136.95--AGAIN,792.71--@gEn,792.71
ALFA,3.73--Alfa,3.73--ALPHA,8.12--{lf@,8.12
BOZE,14.89--boz@,14.89--ANGRY,58.98--{NgrI,58.98
DIER,28.1--dir,28.1--ANIMAL,45.49--{nImP,45.49
MIER,2.54--mir,2.54--ANT,5.35--{nt,5.35
ENIG,51.75--en@x,51.75--ANY,1099.37--EnI,1099.37
ROND,172.65--rOnt,172.65--AROUND,736.73--@r6nd,736.73
PAKT,35.01--pAkt,35.01--ARRESTED,34.92--@rEstId,34.92
PIJL,7.11--pKl,7.11--ARROW,7.84--{r5,7.84
KONT,73.57--kOnt,73.57--ASS,226.37--{s,226.37
LAAN,1.23--lan,1.23--AVENUE,16.88--{v@nju,16.88
HEEN,396.09--hen,396.09--AWAY,730.9--@w1,730.9
BIJL,9.26--bKl,9.26--AX,4.33--{ks,4.33
BABY,151.8--bebi,151.8--BABY,509.37--b1bI,509.37
SPEK,5.35--spEk,5.35--BACON,11.86--b1k@n,11.86
KAAL,8.23--kal,8.23--BALD,9.73--b$ld,9.73
BAND,79.28--bEnt,79.28--BAND,53.41--b{nd,53.41
BERM,0.69--bErm,0.69--BANK,84.98--b{Nk,84.98
BAST,0.41--bAst,0.41--BARK,5.49--b#k,5.49
FUST,0.11--f}st,0.11--BARREL,10.63--b{r@l,10.63
BARS,2.7--bArs,2.7--BARS,17.96--b#z,17.96
BASE,0.41--baz@,0.41--BASE,35.37--b1s,35.37
MAND,4.3--mAnt,4.3--BASKET,13.18--b#skIt,13.18
BAAI,4.51--baj,4.51--BAY,24.24--b1,24.24
BALK,1.81--bAlk,1.81--BEAM,8.73--bim,8.73
BOON,1.42--bon,1.42--BEAN,6.84--bin,6.84
BEER,25.45--ber,25.45--BEAR,57.41--b8R,57.41
MOOI,616.06--moj,616.06--BEAUTIFUL,279.73--bjut@fUl,279.73
WENK,0.39--wENk,0.39--BECK,3.82--bEk,3.82
PERK,0.09--pErk,0.09--BED,187.12--bEd,187.12
BIER,53.35--bir,53.35--BEER,75.49--b7R,75.49
BUIK,26.09--bLk,26.09--BELLY,15.57--bElI,15.57
RIEM,14.16--rim,14.16--BELT,24.35--bElt,24.35
BAAT,2.47--bat,2.47--BENEFIT,14.35--bEnIfIt,14.35
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BEST,306.52--bEst,306.52--BEST,404.37--bEst,404.37
KOEK,3.27--kuk,3.27--BISCUIT,3.75--bIskIt,3.75
BITS,0.82--bIts,0.82--BIT,235.04--bIt,235.04
TRUT,40.11--tr}t,40.11--BITCH,168.8--bIJ,168.8
BEET,18.5--bet,18.5--BITE,40.78--b2t,40.78
BLOK,11.62--blOk,11.62--BLOCK,40.53--blQk,40.53
SLAG,63.94--slAx,63.94--BLOW,97.57--bl5,97.57
SLAG,63.94--slAx,63.94--BLOW,97.57--bl5,97.57
BOOT,95.93--bot,95.93--BOAT,95.78--b5t,95.78
LIJF,23.65--lKf,23.65--BODY,195.53--bQdI,195.53
KOOK,7.52--kok,7.52--BOILING,4.22--b4lIN,4.22
BOUT,0.94--bMt,0.94--BOLT,6.88--b5lt,6.88
BOEK,150.93--buk,150.93--BOOK,176.98--bUk,176.98
BUIT,10.4--bLt,10.4--BOOTY,6.14--butI,6.14
SAAI,31.47--saj,31.47--BORING,27.41--b$rIN,27.41
BAAS,167.21--bas,167.21--BOSS,124.29--bQs,124.29
FLES,45.71--flEs,45.71--BOTTLE,50.75--bQtP,50.75
BOOG,8.55--box,8.55--BOW,20.27--b6,20.27
TEIL,0.14--tKl,0.14--BOWL,21.45--b5l,21.45
ETUI,0.07--etwi,0.07--BOX,89.75--bQks,89.75
BEHA,4.12--beha,4.12--BRA,10.92--br#,10.92
MERK,19.12--mErk,19.12--BRAND,13.96--br{nd,13.96
BRES,0.69--brEs,0.69--BREACH,6.22--briJ,6.22
ADEM,53.15--ad@m,53.15--BREATH,44.92--brET,44.92
BRUG,44.07--br}x,44.07--BRIDGE,45.71--brI_,45.71
GESP,0.96--xEsp,0.96--BUCKLE,5.04--bVkP,5.04
BUIL,0.91--bLl,0.91--BUMP,12.35--bVmp,12.35
TROS,0.34--trOs,0.34--BUNCH,58.88--bVnJ,58.88
DRUK,207.11--dr}k,207.11--BUSY,106.53--bIzI,106.53
MAAR,8385.73--mar,8385.73--BUT,4417.47--bVt,4417.47
KNOP,16.46--knOp,16.46--BUTTON,28.25--bVtH,28.25
KOOP,48.34--kop,48.34--BUY,192.43--b2,192.43
DOOR,1455.7--dor,1455.7--BY,1340.47--b2,1340.47
KOOL,4.73--kol,4.73--CABBAGE,2.9--k{bI_,2.9
KAST,30.05--kAst,30.05--CABINET,8.33--k{bInIt,8.33
KOOI,13.81--koj,13.81--CAGE,20.27--k1_,20.27
CAKE,9.86--kek,9.86--CAKE,45.06--k1k,45.06
KUIT,0.5--kLt,0.5--CALF,2.96--k#f,2.96
ROEP,48.53--rup,48.53--CALL,861.39--k$l,861.39
KALM,69.43--kAlm,69.43--CALM,89.04--k#m,89.04
KAMP,41.73--kAmp,41.73--CAMP,51.22--k{mp,51.22
KANO,2.24--kano,2.24--CANOE,3.57--k@nu,3.57
MUTS,4.46--m}ts,4.46--CAP,18.75--k{p,18.75
KAAP,1.1--kap,1.1--CAPE,8.24--k1p,8.24
AUTO,458--Mto,458--CAR,483.06--k#R,483.06
KAAR,0.21--kar,0.21--CARD,85.43--k#d,85.43
ZORG,218.82--zOrx,218.82--CARE,485.25--k8R,485.25
ZAAK,239.34--zak,239.34--CASE,282.41--k1s,282.41
GROT,17.45--xrOt,17.45--CAVE,13.98--k1v,13.98
CENT,36.93--sEnt,36.93--CENT,9.47--sEnt,9.47
EEUW,25.15--ew,25.15--CENTURY,20.84--sEnJUrI,20.84
AKTE,4.18--Akt@,4.18--CERTIFICATE,8.98--s@tIfIk1t,8.98
KALK,1.01--kAlk,1.01--CHALK,3.59--J$k,3.59
WANG,7.89--wAN,7.89--CHEEK,7.16--Jik,7.16
KAAS,22.85--kas,22.85--CHEESE,39.04--Jiz,39.04
CHEF,31.05--SEf,31.05--CHEF,11.88--SEf,11.88
KERS,1.62--kErs,1.62--CHERRY,13.59--JErI,13.59
KIST,27.67--kIst,27.67--CHEST,40.98--JEst,40.98
KIND,333.3--kInt,333.3--CHILD,157.65--J2ld,157.65
CHIP,14.52--tSIp,14.52--CHIP,20.61--JIp,20.61
KEUS,61.61--k|s,61.61--CHOICE,97.55--J4s,97.55
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KOOR,6.88--kor,6.88--CHOIR,5.31--kw2@R,5.31
KIES,35.35--kis,35.35--CHOOSE,48.06--Juz,48.06
BROK,1.65--brOk,1.65--CHUNK,4.14--JVNk,4.14
KERK,79.49--kErk,79.49--CHURCH,69.67--J3J,69.67
STAD,272.61--stAt,272.61--CITY,169.1--sItI,169.1
CLAN,3.16--klEn,3.16--CLAN,4.1--kl{n,4.1
KLAS,48.98--klAs,48.98--CLASS,117.35--kl#s,117.35
LEEM,0.27--lem,0.27--CLAY,12--kl1,12
REIN,1.99--rKn,1.99--CLEAN,121.24--klin,121.24
KNAP,68.05--knAp,68.05--CLEVER,27.27--klEv@R,27.27
KLIK,3.04--klIk,3.04--CLICK,6.41--klIk,6.41
KLIP,0.64--klIp,0.64--CLIFF,21.57--klIf,21.57
KLIM,10.79--klIm,10.79--CLIMB,19.75--kl2m,19.75
KLEM,10.47--klEm,10.47--CLIP,5.69--klIp,5.69
KLOK,23.9--klOk,23.9--CLOCK,58.63--klQk,58.63
DOEK,8.83--duk,8.83--CLOTH,6.1--klQT,6.1
WOLK,5.44--wOlk,5.44--CLOUD,11.75--kl6d,11.75
CLUB,52.34--kl}p,52.34--CLUB,98.78--klVb,98.78
KUST,31.88--k}st,31.88--COAST,26.69--k5st,26.69
MUNT,10.89--m}nt,10.89--COIN,9.75--k4n,9.75
COLA,11.46--kola,11.46--COKE,18.59--k5k,18.59
KOUD,95.95--kMt,95.95--COLD,130.16--k5ld,130.16
COLT,2.72--kOlt,2.72--COLT,5.24--k5lt,5.24
ZUIL,0.55--zLl,0.55--COLUMN,10.96--kQl@m,10.96
COMA,2.72--koma,2.72--COMA,12.27--k5m@,12.27
BOUW,12.33--bMw,12.33--CONSTRUCTION,13.84--k@nstrVkSH,13.84
KOEL,8.76--kul,8.76--COOL,195.88--kul,195.88
KERN,9.26--kErn,9.26--CORE,9.82--k$R,9.82
MAIS,5.55--mAjs,5.55--CORN,14.22--k$n,14.22
HOEK,49.92--huk,49.92--CORNER,52.53--k$n@R,52.53
LIJK,74.46--lKk,74.46--CORPSE,10.1--k$ps,10.1
GANG,110.8--xAN,110.8--CORRIDOR,5.57--kQrId$R,5.57
KOST,80.4--kOst,80.4--COSTS,15.78--kQsts,15.78
RAAD,83.01--rat,83.01--COUNSEL,14.24--k6nsP,14.24
LAND,244--lAnt,244--COUNTRY,161.84--kVntrI,161.84
PAAR,434.44--par,434.44--COUPLE,223.41--kVpP,223.41
MOED,41.05--mut,41.05--COURAGE,23.67--kVrI_,23.67
LOOP,118.2--lop,118.2--COURSE,487.22--k$s,487.22
NEEF,48.48--nef,48.48--COUSIN,48.84--kVzH,48.84
KRAB,3.86--krAp,3.86--CRAB,6.9--kr{b,6.9
REET,53.21--ret,53.21--CRACK,32.84--kr{k,32.84
REET,53.21--ret,53.21--CRACK,32.84--kr{k,32.84
KRAT,3.82--krAt,3.82--CRATE,4.1--kr1t,4.1
ROOM,7.59--rom,7.59--CREAM,48.71--krim,48.71
BOEF,6.2--buf,6.2--CROOK,5.67--krUk,5.67
KROM,2.84--krOm,2.84--CROOKED,5.69--krUkt,5.69
SNIT,0.3--snIt,0.3--CUT,229.76--kVt,229.76
STEK,1.3--stEk,1.3--CUTTING,22.08--kVtIN,22.08
DANS,37.82--dAns,37.82--DANCE,148.04--d#ns,148.04
DURF,47.41--d}rf,47.41--DARE,55.41--d8R,55.41
DATA,12.6--data,12.6--DATES,18.25--d1ts,18.25
DODE,59.85--dod@,59.85--DEAD,448.98--dEd,448.98
DOVE,2.52--dov@,2.52--DEAF,14.53--dEf,14.53
LIEF,113.95--lif,113.95--DEAR,223.43--d7R,223.43
DOOD,992.15--dot,992.15--DEATH,216.69--dET,216.69
PUIN,2.38--pLn,2.38--DEBRIS,3.12--d1bri,3.12
DAAD,16.65--dat,16.65--DEED,9.31--did,9.31
DIEP,68.4--dip,68.4--DEEP,76.39--dip,76.39
DEUK,2.65--d|k,2.65--DENT,3.53--dEnt,3.53
BORG,11.23--bOrx,11.23--DEPOSIT,10.8--dIpQzIt,10.8
VUIL,24.06--vLl,24.06--DIRT,25.69--d3t,25.69

VIES,19.8--vis,19.8--DIRTY,66.45--d3tI,66.45
RAMP,25.89--rAmp,25.89--DISASTER,17.27--dIz#st@R,17.27
VAAT,1.42--vat,1.42--DISH,11.45--dIS,11.45
NOOD,15.48--not,15.48--DISTRESS,7.27--dIstrEs,7.27
WIJK,9.58--wKk,9.58--DISTRICT,20.94--dIstrIkt,20.94
DUIK,8.69--dLk,8.69--DIVE,12.82--d2v,12.82
DOEN,2677.85--dun,2677.85--DO,6135.59--du,6135.59
ARTS,32.79--Arts,32.79--DOCTOR,263.94--dQkt@R,263.94
DOES,0.07--dus,0.07--DOES,666.71--dVz,666.71
HOND,168.65--hOnt,168.65--DOG,192.84--dQg,192.84
GAAR,2.77--xar,2.77--DONE,485.04--dVn,485.04
EZEL,11.41--ez@l,11.41--DONKEY,5.35--dQNkI,5.35
DEUR,247.48--d|r,247.48--DOOR,292.06--d$R,292.06
DOPE,4.69--dop,4.69--DOPE,16.08--d5p,16.08
STIP,1.56--stIp,1.56--DOT,6.63--dQt,6.63
DEEG,1.85--dex,1.85--DOUGH,15.88--d5,15.88
DUIF,5.35--dLf,5.35--DOVE,5.57--dVv,5.57
WAAS,0.91--was,0.91--DOWN,1490.27--d6n,1490.27
TEUG,0.87--t|x,0.87--DRAFT,7.27--dr#ft,7.27
LEEP,0.05--lep,0.05--DRAG,26.45--dr{g,26.45
LADE,2.26--lad@,2.26--DRAWER,13--dr$@R,13
JURK,55.75--j}rk,55.75--DRESS,87.2--drEs,87.2
BOOR,3.45--bor,3.45--DRILL,13.75--drIl,13.75
DROP,1.83--drOp,1.83--DROP,130.61--drQp,130.61
DRUG,6.4--dr}k,6.4--DRUG,45.22--drVg,45.22
TROM,0.5--trOm,0.5--DRUM,8.47--drVm,8.47
EEND,8.99--ent,8.99--DUCK,24.76--dVk,24.76
STOF,29.25--stOf,29.25--DUST,23.84--dVst,23.84
PRIL,0.25--prIl,0.25--EARLY,108.04--3lI,108.04
ETEN,445.92--et@,445.92--EAT,251.88--it,251.88
ECHO,8.92--Exo,8.92--ECHO,6.86--Ek5,6.86
RAND,19.12--rAnt,19.12--EDGE,23.51--E_,23.51
LIFT,65.47--lIft,65.47--ELEVATOR,24.41--ElIv1t@R,24.41
LEEG,61.74--lex,61.74--EMPTY,47.24--EmptI,47.24
EIND,83.17--Knt,83.17--END,265.86--End,265.86
NIJD,0.34--nKt,0.34--ENVY,9.55--EnvI,9.55
EVEN,1396.52--ev@,1396.52--EQUALLY,5.37--ikw@lI,5.37
FOUT,165.27--fMt,165.27--ERROR,9.27--Er@R,9.27
OOIT,465.25--ojt,465.25--EVER,709.22--Ev@R,709.22
ALOM,1.39--AlOm,1.39--EVERYWHERE,51.78--EvrIw8R,51.78
RUIL,15.39--rLl,15.39--EXCHANGE,20.22--IksJ1n_,20.22
DUUR,34.53--dyr,34.53--EXPENSIVE,27.94--IkspEnsIv,27.94
MATE,3.84--mat@,3.84--EXTENT,4.06--IkstEnt,4.06
OGEN,260.85--oG@,260.85--EYES,221.55--2z,221.55
FEIT,43.04--fKt,43.04--FACT,172.57--f{kt,172.57
FAIR,2.36--f)r,2.36--FAIR,94.75--f8R,94.75
VALK,2.58--vAlk,2.58--FALCON,3.31--f$lk@n,3.31
ROEM,7.98--rum,7.98--FAME,8.65--f1m,8.65
ROEM,7.98--rum,7.98--FAME,8.65--f1m,8.65
FARM,1.85--fArm,1.85--FARM,30.04--f#m,30.04
BOER,14.77--bur,14.77--FARMER,11.84--f#m@R,11.84
MODE,11.02--mod@,11.02--FASHION,18.76--f{SH,18.76
BOND,13.47--bOnt,13.47--FEDERATION,3.86--fEd@r1SH,3.86
PONT,0.66--pOnt,0.66--FERRY,5.35--fErI,5.35
VELD,15.96--vElt,15.96--FIELD,70.2--fild,70.2
FILM,174.28--fIlm,174.28--FILM,65.25--fIlm,65.25
VUUR,100.57--vyr,100.57--FIRE,215.49--f2@R,215.49
FERM,0.18--fErm,0.18--FIRM,35.27--f3m,35.27
VIJF,281.57--vKf,281.57--FIVE,285.45--f2v,285.45
VAST,662.03--vAst,662.03--FIXED,32.29--fIkst,32.29
VLAG,17.79--vlAx,17.79--FLAG,17.49--fl{g,17.49

VLAM,7.94--vlAm,7.94--FLAME,9.04--fl1m,9.04
VLAK,47.73--vlAk,47.73--FLAT,26.22--fl{t,26.22
VLAK,47.73--vlAk,47.73--FLAT,26.22--fl{t,26.22
MEEL,1.69--mel,1.69--FLOUR,3.16--fl6@R,3.16
MIST,45.6--mIst,45.6--FOG,9.45--fQg,9.45
VOUW,1.72--vMw,1.72--FOLD,8.63--f5ld,8.63
VOET,50.81--vut,50.81--FOOT,64.92--fUt,64.92
FORD,7.36--fOrt,7.36--FORD,11.51--f$d,11.51
WOUD,5.19--wMt,5.19--FOREST,18.88--fQrIst,18.88
VORK,5.19--vOrk,5.19--FORK,8.82--f$k,8.82
VORM,39.47--vOrm,39.47--FORM,42.75--f$m,42.75
FORT,9.38--fOrt,9.38--FORT,15.43--f$t,15.43
VIER,242.08--vir,242.08--FOUR,255.78--f$R,255.78
VRIJ,232.91--vrK,232.91--FREE,177.53--fri,177.53
VERS,17.86--vErs,17.86--FRESH,54.51--frES,54.51
VERS,17.86--vErs,17.86--FRESH,54.51--frES,54.51
PRET,9.03--prEt,9.03--FUN,235.49--fVn,235.49
PELS,0.78--pEls,0.78--FUR,8.27--f3R,8.27
PROP,2.38--prOp,2.38--GAG,7.06--g{g,7.06
SPEL,95.11--spEl,95.11--GAME,233.84--g1m,233.84
TUIN,36.66--tLn,36.66--GARDEN,26.55--g#dH,26.55
HOMO,36.91--homo,36.91--GAY,59.08--g1,59.08
HAAL,302.29--hal,302.29--GET,4583.76--gEt,4583.76
REUS,7.45--r|s,7.45--GIANT,27.06--_2@nt,27.06
GIFT,4.92--xIft,4.92--GIFT,64.51--gIft,64.51
MEID,114.52--mKt,114.52--GIRL,557.12--g3l,557.12
GLAS,57.15--xlAs,57.15--GLASS,60.71--gl#s,60.71
BRIL,24.49--brIl,24.49--GLASSES,33.12--gl#sIz,33.12
LIJM,3.98--lKm,3.98--GLUE,5.88--glu,5.88
GAAN,2650.41--xan,2650.41--GO,3793.04--g5,3793.04
GOAL,3.2--gol,3.2--GOAL,16.75--g5l,16.75
GEIT,8.07--xKt,8.07--GOAT,10.53--g5t,10.53
GOUD,61.99--xMt,61.99--GOLD,78.94--g5ld,78.94
GOLF,17.54--xOlf,17.54--GOLF,25.53--gQlf,25.53
GOED,3488.11--xut,3488.11--GOOD,2610.14--gUd,2610.14
HAVE,1.21--hav@,1.21--GOODS,12.31--gUdz,12.31
GANS,5.88--xAns,5.88--GOOSE,13.04--gus,13.04
TOGA,1.46--toGa,1.46--GOWN,6.55--g6n,6.55
OPOE,0.62--opu,0.62--GRANNY,8.43--gr{nI,8.43
GRAS,18.75--xrAs,18.75--GRASS,16.78--gr#s,16.78
GRAF,34.53--xrAf,34.53--GRAVE,26.27--gr1v,26.27
GROS,0.34--xrOs,0.34--GROSS,15.27--gr5s,15.27
GAST,56.26--xAst,56.26--GUEST,39.94--gEst,39.94
GIDS,11.39--xIts,11.39--GUIDE,17.84--g2d,17.84
GOOT,6.06--xot,6.06--GUTTER,5.24--gVt@R,5.24
VENT,189.99--vEnt,189.99--GUY,762.61--g2,762.61
VENT,189.99--vEnt,189.99--GUY,762.61--g2,762.61
HAAR,2975.87--har,2975.87--HAIR,153.55--h8R,153.55
HALF,104.76--hAlf,104.76--HALF,199.14--h#f,199.14
HAND,199.91--hAnt,199.91--HAND,279.65--h{nd,279.65
HANG,28.26--hAN,28.26--HANGING,53.63--h{NIN,53.63
BLIJ,277.3--blK,277.3--HAPPY,333.2--h{pI,333.2
HARD,159.46--hArt,159.46--HARD,307.84--h#d,307.84
HAAS,2.17--has,2.17--HARE,3.82--h8R,3.82
HERT,6.13--hErt,6.13--HART,11.76--h#t,11.76
HOED,35.95--hut,35.95--HAT,64.18--h{t,64.18
LUIK,6.68--lLk,6.68--HATCH,12.82--h{J,12.82
HAAT,151.32--hat,151.32--HATE,214.59--h1t,214.59
HOOI,2.88--hoj,2.88--HAY,6.37--h1,6.37
KROP,2.84--krOp,2.84--HEAD,371.51--hEd,371.51
HART,196.37--hArt,196.37--HEART,244.18--h#t,244.18

HIEL,0.85--hil,0.85--HEEL,7.39--hil,7.39
ROER,7.8--rur,7.8--HELM,5.35--hElm,5.35
HELM,11.09--hElm,11.09--HELMET,9.47--hElmIt,9.47
HULP,239.77--h}lp,239.77--HELP,921.12--hElp,921.12
HIER,4516.62--hir,4516.62--HERE,4525.25--h7R,4525.25
HELD,59.64--hElt,59.64--HERO,49.84--h7r5,49.84
HOOG,63.23--hox,63.23--HIGH,195--h2,195
HEUP,4.09--h|p,4.09--HIP,15.41--hIp,15.41
ZIJN,7968.23--zKn,7968.23--HIS,2124.78--hIz,2124.78
HOME,1.94--hom,1.94--HOME,774.33--h5m,774.33
EREN,7.57--er@,7.57--HONOR,96.31--Qn@R,96.31
HAAK,12.65--hak,12.65--HOOK,38--hUk,38
HOPE,4.28--hop@,4.28--HOPE,320.63--h5p,320.63
GEIL,11.8--xKl,11.8--HORNY,8.39--h$nI,8.39
WARM,70.91--wArm,70.91--HOT,189.84--hQt,189.84
WARM,70.91--wArm,70.91--HOT,189.84--hQt,189.84
PAND,5.85--pAnt,5.85--HOUSE,514--h6z,514
ROMP,6.47--rOmp,6.47--HULL,4.22--hVl,4.22
BULT,3.41--b}lt,3.41--HUMP,4.41--hVmp,4.41
HOMP,0.27--hOmp,0.27--HUNK,5.16--hVNk,5.16
IDEE,482.99--ide,482.99--IDEA,359.04--2d7,359.04
ZIEK,129.2--zik,129.2--ILL,21.27--Il,21.27
INKT,5.17--INkt,5.17--INK,7.49--INk,7.49
IRIS,5.88--ir@s,5.88--IRIS,5.29--2@rIs,5.29
ERIN,7.57--ErIn,7.57--IT,9999.99--It,9999.99
JEUK,2.58--j|k,2.58--ITCH,4.18--IJ,4.18
KAFT,0.71--kAft,0.71--JACKET,33.41--_{kIt,33.41
JADE,3.86--jad@,3.86--JADE,5.08--_1d,5.08
KAAK,5.12--kak,5.12--JAW,7.14--_$,7.14
GAAI,0.32--xaj,0.32--JAY,16.1--_1,16.1
JAZZ,6.97--_Es,6.97--JAZZ,11.92--_{z,11.92
JEEP,7.71--_ip,7.71--JEEP,10.27--_ip,10.27
JOOD,14.34--jot,14.34--JEW,10.76--_u,10.76
KLUS,37.78--kl}s,37.78--JOB,413--_Qb,413
VOEG,5.03--vux,5.03--JOINT,27.55--_4nt,27.55
GRAP,51.02--xrAp,51.02--JOKE,73.02--_5k,73.02
REIS,90.37--rKs,90.37--JOURNEY,19.94--_3nI,19.94
JULI,11.8--jyli,11.8--JULY,12.08--_ul2,12.08
JUNI,12.94--jyni,12.94--JUNE,18.86--_un,18.86
JUNK,4.71--_}Nk,4.71--JUNK,15.37--_VNk,15.37
JURY,31.17--Zyri,31.17--JURY,42.76--_9rI,42.76
KHAN,3.38--k#n,3.38--KHAN,3.88--k#n,3.88
JOCH,18.77--jOx,18.77--KID,339.2--kId,339.2
NIER,3.91--nir,3.91--KIDNEY,9.69--kIdnI,9.69
ZOEN,9.99--zun,9.99--KISS,121.16--kIs,121.16
KNIE,10.24--kni,10.24--KNEE,14.69--ni,14.69
LADY,16.28--ledi,16.28--LADY,217.08--l1dI,217.08
MEER,2035.88--mer,2035.88--LAKE,36--l1k,36
MANK,2.58--mANk,2.58--LAME,10.92--l1m,10.92
LAMP,13.88--lAmp,13.88--LAMP,12.88--l{mp,12.88
LANS,1.9--lAns,1.9--LANCE,10.86--l#ns,10.86
TAAL,36.29--tal,36.29--LANGUAGE,35.1--l{NgwI_,35.1
LAAT,2032.73--lat,2032.73--LATE,269.73--l1t,269.73
LACH,46.72--lAx,46.72--LAUGH,62.86--l#f,62.86
LAVA,2.77--lava,2.77--LAVA,3.45--l#v@,3.45
LOOD,5.03--lot,5.03--LEAD,83.25--lid,83.25
BLAD,11.14--blAt,11.14--LEAF,5.2--lif,5.2
LIGA,0.57--liGa,0.57--LEAGUE,18.63--lig,18.63
LEER,50.63--ler,50.63--LEATHER,13.59--lED@R,13.59
POOT,6.95--pot,6.95--LEG,56.51--lEg,56.51
POOT,6.95--pot,6.95--LEG,56.51--lEg,56.51

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LOEP,0.21--lup,0.21--LENS,4.67--lEnz,4.67
PEIL,1.72--pKl,1.72--LEVEL,51.63--lEvP,51.63
SLAP,7.11--slAp,7.11--LIMP,3.67--lImp,3.67
LIJN,68.72--lKn,68.72--LINE,206.18--l2n,206.18
LINK,12.87--lINk,12.87--LINK,11.94--lINk,11.94
LAST,53.49--lAst,53.49--LOAD,29.22--l5d,29.22
SLOT,52.46--slOt,52.46--LOCK,56.57--lQk,56.57
LOGE,1.74--l<z@,1.74--LODGE,6.69--lQ_,6.69
LANG,596.85--lAN,596.85--LONG,675.16--lQN,675.16
KIJK,1049.77--kKk,1049.77--LOOK,1947.27--lUk,1947.27
HEER,104.14--her,104.14--LORD,138.16--l$d,138.16
BOEL,52.37--bul,52.37--LOT,569.92--lQt,569.92
LUID,9.08--lLt,9.08--LOUD,39.82--l6d,39.82
LAAG,31.1--lax,31.1--LOW,59.14--l5,59.14
BONK,0.57--bONk,0.57--LUMP,3.55--lVmp,3.55
LONG,9.47--lON,9.47--LUNG,8.24--lVN,8.24
LUST,18.41--l}st,18.41--LUST,5.57--lVst,5.57
LUXE,10.11--lyks@,10.11--LUXURY,6.02--lVkS@rI,6.02
MAAK,648.19--mak,648.19--MAKING,222.53--m1kIN,222.53
MENS,144.66--mEns,144.66--MAN,1845.75--m{n,1845.75
MERG,0.69--mErx,0.69--MARROW,2.96--m{r5,2.96
MARS,20.67--mArs,20.67--MARS,10.49--m#z,10.49
MAAL,17.29--mal,17.29--MEAL,28.86--mil,28.86
MURW,0.48--m}rw,0.48--MELLOW,3--mEl5,3
DEUN,0.07--d|n,0.07--MELODY,6.61--mEl@dI,6.61
MENU,6.63--meny,6.63--MENU,9.96--mEnju,9.96
KWIK,1.67--kwIk,1.67--MERCURY,3.82--m3kjUrI,3.82
BODE,1.67--bod@,1.67--MESSENGER,8.06--mEsIn_@R,8.06
MILD,2.47--mIlt,2.47--MILD,4.8--m2ld,4.8
MIJL,15.32--mKl,15.32--MILE,21--m2l,21
MELK,39.7--mElk,39.7--MILK,42.53--mIlk,42.53
MINI,1.97--mini,1.97--MINI,3.61--mInI,3.61
MISS,16.33--mIs,16.33--MISS,467.65--mIs,467.65
MAMA,206.45--mAma,206.45--MOM,430.39--mQm,430.39
GELD,793.61--xElt,793.61--MONEY,640.76--mVnI,640.76
MAAN,42.1--man,42.1--MOON,49.96--mun,49.96
BERG,34.3--bErx,34.3--MOUNTAIN,35.39--m6ntIn,35.39
ROUW,3.96--rMw,3.96--MOURNING,3.43--m$nIN,3.43
MUIS,11.14--mLs,11.14--MOUSE,19.12--m6z,19.12
MUIL,1.88--mLl,1.88--MOUTH,104.41--m6T,104.41
DREK,0.62--drEk,0.62--MUD,14.82--mVd,14.82
MUST,0.32--m}st,0.32--MUST,699.24--mVst,699.24
SNOR,9.95--snOr,9.95--MUSTACHE,4.94--m@st#S,4.94
MIJN,4412.02--mKn,4412.02--MY,6762.73--m2,6762.73
NAAM,470.6--nam,470.6--NAME,641.86--n1m,641.86
SMAL,2.08--smAl,2.08--NARROW,7.02--n{r5,7.02
SMAL,2.08--smAl,2.08--NARROW,7.02--n{r5,7.02
AARD,15.32--art,15.32--NATURE,45.16--n1J@R,45.16
NAZI,5.69--natsi,5.69--NAZI,6.86--n#tsI,6.86
HALS,7.5--hAls,7.5--NECK,59.51--nEk,59.51
BUUR,3.06--byr,3.06--NEIGHBOR,16.94--n1b@R,16.94
NEST,11.27--nEst,11.27--NEST,11.1--nEst,11.1
TOCH,1693.53--tOx,1693.53--NEVERTHELESS,5.9--nEv@D@lEs,5.9
LEUK,595.57--l|k,595.57--NICE,649.51--n2s,649.51
NEEN,20.76--nen,20.76--NO,5971.55--n5w1,5971.55
EDEL,1.14--ed@l,1.14--NOBLE,14.59--n5bP,14.59
KNIK,1.81--knIk,1.81--NOD,3.98--nQd,3.98
RUIS,1.3--rLs,1.3--NOISE,34.88--n4z,34.88
NORM,3.04--nOrm,3.04--NORM,3.33--n$m,3.33
NEUS,70.04--n|s,70.04--NOSE,69.75--n5z,69.75
NIET,18323.98--nit,18323.98--NOT,5424.96--nQt,5424.96
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NOTA,1.1--nota,1.1--NOTE,53.55--n5t,53.55
NIKS,831.61--nIks,831.61--NOTHING,853.61--nVTIN,853.61
ERAF,63.44--ErAf,63.44--OFF,1179.51--Qf,1179.51
AMBT,2.36--Amt,2.36--OFFICE,203.9--QfIs,203.9
VAAK,180.02--vak,180.02--OFTEN,57.35--QfH,57.35
OLIE,25.25--oli,25.25--OIL,41.08--4l,41.08
OUWE,75.26--Mw@,75.26--OLD,608.94--5ld,608.94
EROP,158.18--ErOp,158.18--ON,6955.73--Qn,6955.73
EENS,1392.11--ens,1392.11--ONCE,344.88--wVns,344.88
OPEN,337.64--op@,337.64--OPEN,320.41--5p@n,320.41
DUNK,2.38--d}Nk,2.38--OPINION,42--@pInj@n,42
KANS,264.38--kAns,264.38--OPPORTUNITY,41--Qp@tjun@tI,41
ORDE,50.49--Ord@,50.49--ORDER,156.57--$d@R,156.57
WEES,233.69--wes,233.69--ORPHAN,5.75--$fH,5.75
OVEN,9.9--ov@,9.9--OVEN,8.88--VvH,8.88
RUND,3.54--r}nt,3.54--OX,7.78--Qks,7.78
TRED,0.57--trEt,0.57--PACE,9.57--p1sI,9.57
PACT,2.49--pAkt,2.49--PACT,3.76--p{kt,3.76
VERF,14.48--vErf,14.48--PAINT,36.8--p1nt,36.8
PALM,2.47--pAlm,2.47--PALM,13.24--p#m,13.24
PAPA,223.28--pApa,223.28--PAPA,42.59--p@p#,42.59
PARK,30.87--pArk,30.87--PARK,72.12--p#k,72.12
PART,4.07--pArt,4.07--PART,261.51--p#t,261.51
PASS,4.21--pAs,4.21--PASS,108.12--p#s,108.12
PION,3.18--pijOn,3.18--PAWN,4.33--p$n,4.33
ERWT,0.55--Ert,0.55--PEA,3.9--pi,3.9
RUST,75.4--r}st,75.4--PEACE,69.61--pis,69.61
PAUW,0.96--pMw,0.96--PEACOCK,5.12--pikQk,5.12
PIEK,4.94--pik,4.94--PEAK,5.94--pik,5.94
VOLK,71.55--vOlk,71.55--PEOPLE,1102.98--pipP,1102.98
BEDE,0.3--bed@,0.3--PETITION,4.22--p@tISH,4.22
FASE,15.55--faz@,15.55--PHASE,12.33--f1z,12.33
FOTO,119.16--foto,119.16--PHOTO,22.84--f5t5,22.84
PLUK,2.84--pl}k,2.84--PICKING,32.51--pIkIN,32.51
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TUBE,0.89--tyb@,0.89--TUBE,16.43--tjub,16.43
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14.3. Lexicon used for word translation (Pruijn, 2015) simulation

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AUTO,458--Mto,458--CAR,483.06--k#R,483.06
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AVOND,180.61--avOnt,180.61--EVENING,120.69--ivHIN,120.69
BAAI,4.51--baj,4.51--BAY,24.24--b1,24.24
BAAL,3.96--bal,3.96--SACK,12.92--s{k,12.92
BAAN,158.45--ban,158.45--JOB,413--_Qb,413
BAARD,11.64--bart,11.64--BEARD,12.61--b7d,12.61
BAAS,167.21--bas,167.21--BOSS,124.29--bQs,124.29
BAAT,2.47--bat,2.47--BENEFIT,14.35--bEnIfIt,14.35
BABY,151.8--bebi,151.8--BABY,509.37--b1bI,509.37
BAKKER,4--bAk@r,4--BAKER,13.69--b1k@R,13.69
BAL,80.63--bAl,80.63--BALL,104.96--b$l,104.96
BALKON,6.63--bAlkOn,6.63--BALCONY,7.31--b{lk@nI,7.31
BALLON,5.28--bAlOn,5.28--BALLOON,8.67--b@lun,8.67
BANAAN,5.33--banan,5.33--BANANA,10.73--b@n#n@,10.73
BAND,79.28--bAnt,79.28--TIRE,12.37--t2@R,12.37
BANK,91.91--bANk,91.91--COUCH,23.47--k6J,23.47
BASIS,34.71--baz@s,34.71--BASE,35.37--b1s,35.37
BEDRAG,14.73--b@drAx,14.73--AMOUNT,24.75--@m6nt,24.75
BEDRIJF,73.38--b@drKf,73.38--COMPANY,147.2--kVmp@nI,147.2
BEEK,3.43--bek,3.43--BROOK,2.04--brUk,2.04
BEELD,40.06--belt,40.06--STATUE,10.59--st{Ju,10.59
BEHAARD,0.73--b@hart,0.73--HAIRY,6.31--h8rI,6.31
BEKEND,89.8--b@kEnt,89.8--KNOWN,123.53--n5n,123.53
BEKER,8.78--bek@r,8.78--CUP,51.65--kVp,51.65
BEL,311.67--bEl,311.67--BUBBLE,8--bVbP,8
BELANG,32.27--b@lAN,32.27--INTEREST,50.94--Intr@st,50.94
BELEEFD,17.49--b@left,17.49--POLITE,13.94--p@l2t,13.94
BELEID,9.99--b@lKt,9.99--POLICY,27.02--pQl@sI,27.02
BERICHT,59.78--b@rIxt,59.78--MESSAGE,91.51--mEsI_,91.51
BEROEMD,24.49--b@rumt,24.49--FAMOUS,45.02--f1m@s,45.02
BES,0.62--bEs,0.62--BERRY,3.49--bErI,3.49
BESLUIT,28.26--b@slLt,28.26--DECISION,55.06--dIsIZH,55.06
BETON,4.34--b@tOn,4.34--CONCRETE,7.43--kQNkrit,7.43
BEWIJS,101.92--b@wKs,101.92--PROOF,34.39--pruf,34.39
BIEFSTUK,7.36--bifst}k,7.36--STEAK,16.24--st1k,16.24
BIER,53.35--bir,53.35--BEER,75.49--b7R,75.49
BIJBEL,23.05--bKb@l,23.05--BIBLE,18.33--b2bP,18.33
BIJL,9.26--bKl,9.26--AXE,4.88--{ks,4.88
BIJSTAAN,4.07--bKstan,4.07--ASSIST,7.84--@sIst,7.84
BIJVAL,0.25--bKvAl,0.25--APPROVAL,8.39--@pruvP,8.39
BISSCHOP,9.88--bIsxOp,9.88--BISHOP,16.76--bIS@p,16.76
BLAD,11.14--blAt,11.14--LEAF,5.2--lif,5.2
BLEEK,24.17--blek,24.17--PALE,8.02--p1l,8.02
BLIJVEN,517.57--blKv@,517.57--REMAIN,33.22--rIm1n,33.22
BLOED,185.32--blut,185.32--BLOOD,186.12--blVd,186.12
BLOEM,13.49--blum,13.49--FLOWER,22.76--fl6@R,22.76
BLOESEM,0.66--blus@m,0.66--BLOSSOM,3.61--blQs@m,3.61
BOCHT,8.37--bOxt,8.37--BEND,15.06--bEnd,15.06
BODEM,15.3--bod@m,15.3--SOIL,7.78--s4l,7.78
BOEK,150.93--buk,150.93--BOOK,176.98--bUk,176.98
BOEKEN,66.91--buk@,66.91--ACHIEVE,7.33--@Jiv,7.33
BOEKET,2.06--bukEt,2.06--BOUQUET,3.22--bUk1,3.22
BOEKJE,11.02--bukj@,11.02--NOTEBOOK,4.61--n5tbUk,4.61
BOER,14.77--bur,14.77--FARMER,11.84--f#m@R,11.84
BOK,2.17--bOk,2.17--BUCK,33.75--bVk,33.75
BOKSER,6.45--bOks@r,6.45--BOXER,3.84--bQks@R,3.84
BOON,1.42--bon,1.42--BEAN,6.84--bin,6.84
BOOR,3.45--bor,3.45--DRILL,13.75--drIl,13.75
BOOS,105.79--bos,105.79--ANGRY,58.98--{NgrI,58.98
BOOT,95.93--bot,95.93--BOAT,95.78--b5t,95.78
BORD,27.3--bOrt,27.3--PLATE,25.65--pl1t,25.65
BORG,11.23--bOrx,11.23--SECURITY,94.31--sIkj9r@tI,94.31

BORSTEL,2.1--bOrst@l,2.1--BRUSH,14.16--brVS,14.16
BOT,14.52--bOt,14.52--BONE,26.06--b5n,26.06
BOTER,10.52--bot@r,10.52--BUTTER,20.43--bVt@R,20.43
BOUILLON,1.28--buljOn,1.28--BROTH,0.88--brQT,0.88
BOUT,0.94--bMt,0.94--BOLT,6.88--b5lt,6.88
BROEK,67.28--bruk,67.28--TROUSERS,5.16--tr6z@z,5.16
BROOD,33.59--brot,33.59--LOAF,4.47--l5f,4.47
BROODJE,12.76--brotj@,12.76--BUN,2.88--bVn,2.88
BRUID,21.13--brLt,21.13--BRIDE,24.22--br2d,24.22
BRUIN,13.68--brLn,13.68--BROWN,60.12--br6n,60.12
BUFFEL,1.12--b}f@l,1.12--BUFFALO,11.9--bVf@l5,11.9
BUIDEL,0.73--bLd@l,0.73--POUCH,1.71--p6J,1.71
BUIS,6.08--bLs,6.08--TUBE,16.43--tjub,16.43
BULT,3.41--b}lt,3.41--BUMP,12.35--bVmp,12.35
BUREAU,66.93--byro,66.93--DESK,43.9--dEsk,43.9
BURGER,19.19--b}rG@r,19.19--CITIZEN,13.33--sItIzH,13.33
BUS,64.83--b}s,64.83--MAILBOX,4.16--m1lbQks,4.16
CADEAU,29.29--kado,29.29--PRESENT,89.45--prIzEnt,89.45
CEL,49.97--sEl,49.97--CELL,54.35--sEl,54.35
CENTRAAL,2.68--sEntral,2.68--CENTRAL,24.75--sEntr@l,24.75
CHEMISCH,3.09--xemis,3.09--CHEMICAL,11.35--kEmIkP,11.35
CHIRURG,8.85--Sir}rx,8.85--SURGEON,16.43--s3_@n,16.43
CHLOOR,0.98--xlor,0.98--CHLORINE,0.75--kl$rin,0.75
CIRKEL,12.44--sIrk@l,12.44--CIRCLE,21.51--s3kP,21.51
COCON,1.42--kokOn,1.42--COCOON,1.12--k@kun,1.12
CONGRES,12.28--kONGrEs,12.28--CONGRESS,8.22--kQNgrEs,8.22
CRU,0.57--kry,0.57--CRUDE,3.04--krud,3.04
CULTUUR,11.62--k}ltyr,11.62--CULTURE,13.94--kVlJ@R,13.94
CURSUS,8.78--k}rz}s,8.78--COURSE,487.22--k$s,487.22
DAGBOEK,16.99--dAGbuk,16.99--DIARY,8.98--d2@rI,8.98
DAK,54.84--dAk,54.84--ROOF,35.65--ruf,35.65
DALING,1.19--dalIN,1.19--DECLINE,2.98--dIkl2n,2.98
DAME,82.74--dam@,82.74--LADY,217.08--l1dI,217.08
DAMP,0.41--dAmp,0.41--FUMES,2.86--fjumz,2.86
DANS,37.82--dAns,37.82--DANCE,148.04--d#ns,148.04
DAS,13.38--dAs,13.38--TIE,44.43--t2,44.43
DATUM,13.84--dat}m,13.84--DATE,141.53--d1t,141.53
DECOR,1.62--dekOr,1.62--SCENERY,3.78--sin@rI,3.78
DEEG,1.85--dex,1.85--DOUGH,15.88--d5,15.88
DEEL,142.35--del,142.35--PART,261.51--p#t,261.51
DERDE,76.49--dErd@,76.49--THIRD,74.53--T3d,74.53
DEUGD,6.43--d|xt,6.43--VIRTUE,5.16--v3tju,5.16
DEUK,2.65--d|k,2.65--DENT,3.53--dEnt,3.53
DEUR,247.48--d|r,247.48--DOOR,292.06--d$R,292.06
DICHT,182.3--dIxt,182.3--SHUT,263.82--SVt,263.82
DICHTER,27.24--dIxt@r,27.24--POET,9.22--p5It,9.22
DIEET,9.24--dijet,9.24--DIET,15.37--d2@t,15.37
DIEF,29.96--dif,29.96--THIEF,24.27--Tif,24.27
DIEFSTAL,13.51--difstAl,13.51--THEFT,6.75--TEft,6.75
DIENBLAD,1.23--dimblAt,1.23--TRAY,8.04--tr1,8.04
DIEP,68.4--dip,68.4--DEEP,76.39--dip,76.39
DIER,28.1--dir,28.1--ANIMAL,45.49--{nImP,45.49
DIK,42.6--dIk,42.6--THICK,13.98--TIk,13.98
DILLE,0.25--dIl@,0.25--DILL,1.76--dIl,1.76
DINER,24.08--dine,24.08--DINNER,202.67--dIn@R,202.67
DINGEN,510.78--dIN@,510.78--THINGS,692.88--TINz,692.88
DOCHTER,219.3--dOxt@r,219.3--DAUGHTER,171.35--d$t@R,171.35
DODEN,217.98--dod@,217.98--KILL,452.57--kIl,452.57
DOEK,8.83--duk,8.83--CLOTH,6.1--klQT,6.1
DOEL,77.45--dul,77.45--TARGET,37.96--t#gIt,37.96
DOK,7.66--dOk,7.66--DOCK,9.75--dQk,9.75

DOM,77.82--dOm,77.82--SILLY,57.1--sIlI,57.1
DOMEIN,3.11--domKn,3.11--DOMAIN,2.59--d5m1n,2.59
DONKER,64.44--dONk@r,64.44--DARK,88.61--d#k,88.61
DOOD,992.15--dot,992.15--DEATH,216.69--dET,216.69
DOOF,18.59--dof,18.59--DEAF,14.53--dEf,14.53
DOOLHOF,2.63--dolhOf,2.63--MAZE,2.55--m1z,2.55
DORP,53.99--dOrp,53.99--VILLAGE,33.57--vIlI_,33.57
DORSTIG,2.42--dOrst@x,2.42--THIRSTY,12.29--T3stI,12.29
DOUCHE,22.25--duS,22.25--SHOWER,41.12--S6@R,41.12
DOZIJN,7.91--dozKn,7.91--DOZEN,24.14--dVzH,24.14
DRACHT,0.14--drAxt,0.14--COSTUME,14.14--kQstjUm,14.14
DREIGING,5.81--drKGIN,5.81--THREAT,20.76--TrEt,20.76
DRINGEND,23.19--drIN@nt,23.19--URGENT,14.86--3_@nt,14.86
DROOG,19.64--drox,19.64--DRY,42.82--dr2,42.82
DRUK,207.11--dr}k,207.11--PRESSURE,53.12--prES@R,53.12
DUBBEL,17.08--d}b@l,17.08--DOUBLE,62.71--dVbP,62.71
DUIF,5.35--dLf,5.35--PIGEON,5.9--pI_In,5.9
DUIM,10.79--dLm,10.79--THUMB,11.82--TVm,11.82
DUIN,0.39--dLn,0.39--DUNE,1--djun,1
DUIVEL,45.12--dLv@l,45.12--DEVIL,41.33--dEvP,41.33
DUN,9.1--d}n,9.1--THIN,20.18--TIn,20.18
DWAAS,22.75--dwas,22.75--FOOLISH,17.51--fulIS,17.51
DWALING,0.62--dwalIN,0.62--ERROR,9.27--Er@R,9.27
EEND,8.99--ent,8.99--DUCK,24.76--dVk,24.76
EENHEID,24.72--enhKt,24.72--UNIT,36.18--junIt,36.18
EERLIJK,172.38--erl@k,172.38--HONEST,72.33--QnIst,72.33
EEUWIG,43.88--ew@x,43.88--ETERNAL,10.73--It3nP,10.73
EIGEN,355.96--KG@,355.96--OWN,459.2--5n,459.2
EIK,1.53--Kk,1.53--OAK,5.61--5k,5.61
EILAND,51.59--KlAnt,51.59--ISLAND,39.57--2l@nd,39.57
EINDE,112.94--Knd@,112.94--END,265.86--End,265.86
ENGEL,32.63--EN@l,32.63--ANGEL,78.27--1n_@l,78.27
ERG,749.2--Erx,749.2--TERRIBLE,94.02--tEr@bP,94.02
ERTS,0.71--Erts,0.71--ORE,1.65--$R,1.65
EZEL,11.41--ez@l,11.41--DONKEY,5.35--dQNkI,5.35
FABEL,0.53--fab@l,0.53--FABLE,0.39--f1bP,0.39
FASE,15.55--faz@,15.55--PHASE,12.33--f1z,12.33
FEE,5.67--fe,5.67--FAIRY,16.69--f8rI,16.69
FEL,6.27--fEl,6.27--FIERCE,4.78--f7s,4.78
FIGUUR,12.19--fiGyr,12.19--FIGURE,129.37--fIg@R,129.37
FILM,174.37--fIlm,174.37--MOVIE,122.96--muvI,122.96
FIRMA,8.78--fIrma,8.78--FIRM,35.27--f3m,35.27
FLAUW,21.5--flMw,21.5--FAINT,9.27--f1nt,9.27
FLITS,3.32--flIts,3.32--FLASH,15.35--fl{S,15.35
FLUIT,7.39--flLt,7.39--WHISTLE,15.45--wIsP,15.45
FLUWEEL,1.12--flywel,1.12--VELVET,6.27--vElvIt,6.27
FOLIE,1.03--foli,1.03--FOIL,1.22--f4l,1.22
FONTEIN,3.96--fOntKn,3.96--FOUNTAIN,6.9--f6ntIn,6.9
FOREL,1.9--forEl,1.9--TROUT,4.02--tr6t,4.02
FORTUIN,14.27--fOrtLn,14.27--FORTUNE,29.76--f$Jun,29.76
FRASE,0.09--fraz@,0.09--PHRASE,9.1--fr1z,9.1
FUNCTIE,10.15--f}Nksi,10.15--FUNCTION,11.08--fVNkSH,11.08
GASTHEER,7.55--xAsther,7.55--HOST,15.02--h5st,15.02
GAT,49.97--xAt,49.97--HOLE,58.22--h5l,58.22
GAZON,3.09--xazOn,3.09--LAWN,12.35--l$n,12.35
GEBED,10.59--x@bEt,10.59--PRAYER,15.78--pr1@R,15.78
GEBOUW,68.26--x@bMw,68.26--BUILDING,99.57--bIldIN,99.57
GEBREK,14.02--x@brEk,14.02--LACK,17.75--l{k,17.75
GEDURFD,1.39--x@d}rft,1.39--DARING,4.2--d8rIN,4.2
GEEL,9.56--xel,9.56--YELLOW,33.8--jEl5,33.8
GEEST,94.97--xest,94.97--SPIRIT,49.35--spIrIt,49.35

GEEUW,0.25--xew,0.25--YAWN,1--j$n,1
GEHEIM,101.76--x@hKm,101.76--SECRET,109.51--sikrIt,109.51
GEHOOR,5.95--x@hor,5.95--HEARING,44.73--h7rIN,44.73
GEIT,8.07--xKt,8.07--GOAT,10.53--g5t,10.53
GELD,793.61--xElt,793.61--MONEY,640.76--mVnI,640.76
GELDEND,3--xEld@nt,3--GOING,404--g5IN,404
GELEI,0.71--Z@lK,0.71--JELLY,7.12--_ElI,7.12
GELOOF,395.2--x@lof,395.2--FAITH,46.33--f1T,46.33
GEMENGD,3.11--Z@ni,3.11--MIXED,21.37--mIkst,21.37
GENIE,25.22--Z@ni,25.22--GENIUS,34.76--_inj@s,34.76
GERING,0.96--x@rIN,0.96--MINOR,12.82--m2n@R,12.82
GERST,0.5--xErst,0.5--BARLEY,0.9--b#lI,0.9
GESCHENK,18.75--x@sxENk,18.75--GIFT,64.51--gIft,64.51
GESLACHT,8.1--x@slAxt,8.1--GENDER,2.8--_End@R,2.8
GESP,0.96--xEsp,0.96--BUCKLE,5.04--bVkP,5.04
GETIJ,1.35--x@tK,1.35--TIDE,7.35--t2d,7.35
GEUL,1.21--x|l,1.21--TRENCH,3.08--trEnJ,3.08
GEVAAR,91.54--x@var,91.54--DANGER,43.67--d1n_@R,43.67
GEVAL,137.21--x@vAl,137.21--CASE,282.41--k1s,282.41
GEVANG,1.14--x@vAN,1.14--PRISON,66.04--prIzH,66.04
GEVECHT,48.98--x@vExt,48.98--FIGHT,201.08--f2t,201.08
GEVOEL,128.27--x@vul,128.27--FEELING,51.79--filIN,51.79
GEVOLG,7.18--x@vOlx,7.18--RESULT,19.76--rIzVlt,19.76
GEWEER,55.39--x@wer,55.39--RIFLE,14.57--r2fP,14.57
GEWELF,0.27--x@wElf,0.27--VAULT,12.04--v$lt,12.04
GEWICHT,17.29--x@wIxt,17.29--WEIGHT,36.27--w1t,36.27
GEWIN,0.87--x@wIn,0.87--GAIN,13.73--g1n,13.73
GEZICHT,183.63--x@zIxt,183.63--FACE,289.16--f1s,289.16
GEZOEM,0.5--x@zum,0.5--BUZZ,15.96--bVz,15.96
GEZOND,31.83--x@zOnt,31.83--HEALTHY,24.75--hElTI,24.75
GIDS,11.39--xIts,11.39--GUIDE,17.84--g2d,17.84
GIF,13.56--xIf,13.56--POISON,24.55--p4zH,24.55
GIPS,2.36--xIps,2.36--PLASTER,2.63--pl#st@R,2.63
GLAD,8--xlAt,8--SMOOTH,18.27--smuD,18.27
GLAS,57.15--xlAs,57.15--GLASS,60.71--gl#s,60.71
GLAZUUR,1.42--xlazyr,1.42--ICING,1.39--2sIN,1.39
GLETSJER,1.44--glEtS@r,1.44--GLACIER,0.75--gl{sj@R,0.75
GLIMLACH,14.43--xlImlAx,14.43--SMILE,58--sm2l,58
GLOED,2.08--xlut,2.08--GLOW,5.75--gl5,5.75
GOLF,17.54--xOlf,17.54--WAVE,21.25--w1v,21.25
GOUD,61.99--xMt,61.99--GOLD,78.94--g5ld,78.94
GRAAD,4.02--xrat,4.02--DEGREE,14.88--dIgri,14.88
GRAF,34.53--xrAf,34.53--GRAVE,26.27--gr1v,26.27
GRAFIEK,0.98--xrafik,0.98--GRAPH,0.75--gr#f,0.75
GRAP,51.02--xrAp,51.02--JOKE,73.02--_5k,73.02
GRAPPIG,128.45--xrAp@x,128.45--FUNNY,218.18--fVnI,218.18
GRAS,18.75--xrAs,18.75--GRASS,16.78--gr#s,16.78
GRATIS,45.37--xrat@s,45.37--FREE,177.53--fri,177.53
GRENS,37.96--xrEns,37.96--FRONTIER,3.27--frVnt7R,3.27
GRETIG,1.99--xret@x,1.99--EAGER,6.86--ig@R,6.86
GROEN,28.06--xrun,28.06--GREEN,72.47--grin,72.47
GROND,110.25--xrOnt,110.25--GROUND,72.47--gr6nd,72.47
GROOT,237.51--xrot,237.51--LARGE,41.45--l#_,41.45
GROOTTE,7.71--xrot@,7.71--SIZE,46.14--s2z,46.14
GULDEN,1.92--x}ld@,1.92--GOLDEN,23.27--g5ld@n,23.27
HAAI,9.44--haj,9.44--SHARK,14.98--S#k,14.98
HAAN,4.28--han,4.28--ROOSTER,3.86--rust@R,3.86
HAAR,43.3--har,43.3--HAIR,43.3--h8R,43.3
HAAS,2.17--has,2.17--HARE,3.82--h8R,3.82
HAGEL,1.35--haG@l,1.35--HAIL,12.02--h1l,12.02
HALS,7.5--hAls,7.5--NECK,59.51--nEk,59.51

HAMER,8.55--ham@r,8.55--HAMMER,12.47--h{m@R,12.47
HANDEL,26.05--hAnd@l,26.05--TRADE,35.2--tr1d,35.2
HANDSCHOEN,6.68--hAntsxun,6.68--GLOVE,10.1--glVv,10.1
HANDTAS,4.32--hAntAs,4.32--HANDBAG,2.63--h{ndb{g,2.63
HANDVAT,2.01--hAntfAt,2.01--HANDLE,108.41--h{ndP,108.41
HAUTAIN,0.18--hot),0.18--HAUGHTY,0.41--h$tI,0.41
HAVER,0.89--hav@r,0.89--OATS,2.06--5ts,2.06
HAVIK,2.36--havIk,2.36--HAWK,12.75--h$k,12.75
HEELAL,11.05--helAl,11.05--UNIVERSE,25.27--junIv3s,25.27
HEET,338.51--het,338.51--HOT,189.84--hQt,189.84
HEILIG,12.21--hKl@x,12.21--HOLY,68.14--h5lI,68.14
HEK,22.78--hEk,22.78--FENCE,16.06--fEns,16.06
HELD,59.64--hElt,59.64--HERO,49.84--h7r5,49.84
HEMEL,116.86--hem@l,116.86--HEAVEN,56.61--hEvH,56.61
HENDEL,3.68--hEnd@l,3.68--LEVER,3.2--liv@R,3.2
HENGST,4.78--hENst,4.78--STALLION,3.2--st{lj@n,3.2
HERFST,9.08--hErfst,9.08--AUTUMN,3.78--$t@m,3.78
HEVIG,4.02--hev@x,4.02--VIOLENT,16.67--v2@l@nt,16.67
HIEL,0.85--hil,0.85--HEEL,7.39--hil,7.39
HOED,35.95--hut,35.95--HAT,64.18--h{t,64.18
HOEK,49.92--huk,49.92--CORNER,52.53--k$n@R,52.53
HOEPEL,7.36--hup@l,7.36--HOOP,2.69--hup,2.69
HOEST,2.88--hust,2.88--COUGH,8.78--kQf,8.78
HOEVE,0.73--huv@,0.73--FARM,30.04--f#m,30.04
HOF,23.19--hOf,23.19--YARD,25.06--j#d,25.06
HOMP,0.27--hOmp,0.27--CHUNK,4.14--JVNk,4.14
HOND,168.65--hOnt,168.65--DOG,192.84--dQg,192.84
HONING,7.16--honIN,7.16--HONEY,300.49--hVnI,300.49
HOOFD,274.05--hoft,274.05--HEAD,371.51--hEd,371.51
HOOG,63.23--hox,63.23--TALL,32.33--t$l,32.33
HOOIBERG,1.76--hojbErx,1.76--HAYSTACK,1.37--h1st{k,1.37
HOORN,8--horn,8--HORN,21.08--h$n,21.08
HOUDING,20.08--hMdIN,20.08--ATTITUDE,26.08--{tItjud,26.08
HUID,39.56--hLt,39.56--SKIN,44.04--skIn,44.04
HUIS,818.9--hLs,818.9--HOUSE,514--h6s,514
HUISDIER,5.83--hLzdir,5.83--PET,20.18--pEt,20.18
HYMNE,0.39--hImn@,0.39--HYMN,1.63--hIm,1.63
IDOOL,1.97--idol,1.97--IDOL,2.76--2dP,2.76
IEP,0.27--ip,0.27--ELM,1.43--Elm,1.43
IJZER,7.11--Kz@r,7.11--IRON,17.94--2@n,17.94
IMPULS,2.4--Imp}ls,2.4--IMPULSE,5.27--ImpVls,5.27
INGANG,16.35--INGAN,16.35--ENTRY,12.16--EntrI,12.16
INHOUD,7.71--InhMt,7.71--CONTENT,7.63--kQntEnt,7.63
INSEKT,0.14--InsEkt,0.14--INSECT,3.16--InsEkt,3.16
IVOOR,1.33--ivor,1.33--IVORY,1.39--2v@rI,1.39
JAAR,762.67--jar,762.67--YEAR,277.92--j7R,277.92
JACHT,23.99--jAxt,23.99--YACHT,8.22--jQt,8.22
JAGER,11.18--jaG@r,11.18--HUNTER,18.35--hVnt@R,18.35
JONG,91.61--jON,91.61--YOUNG,243.18--jVN,243.18
JONGEN,435.7--jON@,435.7--BOY,529.82--b4,529.82
JURK,55.75--j}rk,55.75--DRESS,87.2--drEs,87.2
KAARS,5.88--kars,5.88--CANDLE,8.02--k{ndP,8.02
KAART,79.67--kart,79.67--MAP,31.82--m{p,31.82
KAAS,22.85--kas,22.85--CHEESE,39.04--Jiz,39.04
KABEL,9.76--kab@l,9.76--CABLE,21.73--k1bP,21.73
KACHEL,2.86--kAx@l,2.86--STOVE,7.59--st5v,7.59
KALK,1.01--kAlk,1.01--LIME,3.29--l2m,3.29
KALKOEN,10.4--kAlkun,10.4--TURKEY,22.61--t3kI,22.61
KAM,5.28--kAm,5.28--COMB,6.06--k5m,6.06
KANAAL,13.95--kanal,13.95--CHANNEL,24.41--J{nP,24.41
KANON,6.17--kanOn,6.17--CANNON,8.71--k{n@n,8.71

KANS,264.38--kans,264.38--CHANCE,241.24--J#ns,241.24
KANTOOR,124.42--kAntor,124.42--OFFICE,203.9--QfIs,203.9
KAP,12.28--kAp,12.28--HOOD,15.39--hUd,15.39
KAR,6.75--kAr,6.75--CART,9.04--k#t,9.04
KAST,30.05--kAst,30.05--HIVE,0.98--h2v,0.98
KAT,52.85--kAt,52.85--CAT,66.33--k{t,66.33
KATOEN,5.05--katun,5.05--COTTON,14.18--kQtH,14.18
KAUWGOM,5.85--kMwGOm,5.85--GUM,13.39--gVm,13.39
KEEL,27.28--kel,27.28--THROAT,36.02--Tr5t,36.02
KEIZER,27.33--kKz@r,27.33--EMPEROR,13.53--Emp@r@R,13.53
KERN,9.26--kErn,9.26--NUCLEUS,0.88--njukl7s,0.88
KETTING,19.14--kEtIN,19.14--NECKLACE,9.75--nEklIs,9.75
KEU,1.65--k|,1.65--CUE,7.78--kju,7.78
KIND,333.3--kInt,333.3--CHILD,157.65--J2ld,157.65
KIP,37.89--kIp,37.89--CHICKEN,61.73--JIkIn,61.73
KLAAR,556.28--klar,556.28--READY,387.8--rEdI,387.8
KLANT,35.33--klAnt,35.33--CUSTOMER,15.2--kVst@m@R,15.2
KLAP,29.27--klAp,29.27--SLAP,12.47--sl{p,12.47
KLAUW,3.27--klMw,3.27--CLAW,4.37--kl$,4.37
KLERK,1.62--klErk,1.62--CLERK,12.9--kl#k,12.9
KLIK,3.04--klIk,3.04--CLICK,6.41--klIk,6.41
KLIMAAT,4.12--klimat,4.12--CLIMATE,3.53--kl2mIt,3.53
KLINK,6.72--klINk,6.72--LATCH,1.92--l{J,1.92
KLOK,23.9--klOk,23.9--CLOCK,58.63--klQk,58.63
KNAL,14.82--knAl,14.82--BANG,19.98--b{N,19.98
KNECHT,2.79--knExt,2.79--SERVANT,12.14--s3v@nt,12.14
KNIE,10.24--kni,10.24--KNEE,14.69--ni,14.69
KNOFLOOK,4.39--knOflok,4.39--GARLIC,6--g#lIk,6
KNOOP,9.51--knop,9.51--KNOT,3.69--nQt,3.69
KNOP,16.46--knOp,16.46--BUTTON,28.25--bVtH,28.25
KNUPPEL,7.32--kn}p@l,7.32--BAT,20.63--b{t,20.63
KOE,18.55--ku,18.55--COW,25.51--k6,25.51
KOFFER,33.87--kOf@r,33.87--SUITCASE,13.39--sutk1s,13.39
KOFFIE,133.41--kOfi,133.41--COFFEE,144.53--kQfI,144.53
KOKEN,33.8--kok@,33.8--COOK,45.57--kUk,45.57
KOM,2612.54--kOm,2612.54--SOCKET,1.61--sQkIt,1.61
KOMPAS,4.55--kOmpAs,4.55--COMPASS,4.06--kVmp@s,4.06
KONIJN,18.87--konKn,18.87--RABBIT,20.94--r{bIt,20.94
KONING,138.53--konIN,138.53--KING,129.25--kIN,129.25
KOOPJE,3.38--kopj@,3.38--BARGAIN,12--b#gIn,12
KOOPWAAR,1.42--kopwar,1.42--GOODS,12.31--gUdz,12.31
KOOR,6.88--kor,6.88--CHOIR,5.31--kw2@R,5.31
KOORD,2.26--kort,2.26--CORD,7.02--k$d,7.02
KOORTS,14.77--korts,14.77--FEVER,19.94--fiv@R,19.94
KOPEN,130.64--kop@,130.64--BUY,192.43--b2,192.43
KOPIE,16.85--kopi,16.85--COPY,52.27--kQpI,52.27
KOPPEL,6.95--kOp@l,6.95--COUPLE,223.41--kVpP,223.41
KOPPIG,10.75--kOp@x,10.75--STUBBORN,10.86--stVb@n,10.86
KORAAL,0.82--koral,0.82--CORAL,2.37--kQr@l,2.37
KORREL,0.73--kOr@l,0.73--GRAIN,4.76--gr1n,4.76
KORT,47.52--kOrt,47.52--SHORT,85.63--S$t,85.63
KOST,80.4--kOst,80.4--LIVING,156.53--lIvIN,156.53
KOSTBAAR,5.88--kOzdbar,5.88--VALUABLE,15.59--v{lj9bP',15.59
KOUD,95.95--kMt,95.95--COLD,130.16--k5ld,130.16
KRAAL,1.12--kral,1.12--BEAD,1.12--bid,1.12
KRAAN,6.4--kran,6.4--FAUCET,1.43--f$sIt,1.43
KRACHTIG,10.31--krAxt@x,10.31--POWERFUL,35.12--p6@fUl,35.12
KRAMP,3.27--krAmp,3.27--CRAMP,2.8--kr{mp,2.8
KREEFT,5.53--kreft,5.53--LOBSTER,7.33--lQbst@R,7.33
KREEK,0.96--krek,0.96--CREEK,8.9--krik,8.9
KRIJGER,8.1--krKG@r,8.1--WARRIOR,10.12--wQr7R,10.12

KRIJT,11.82--krKt,11.82--CHALK,3.59--J$k,3.59
KRIK,1.1--krIk,1.1--JACK,251.59--_{k,251.59
KRISTAL,4.87--krIstAl,4.87--CRYSTAL,16.14--krIstP,16.14
KRUISING,4.41--krLsIN,4.41--CROSSING,8.71--krQsIN,8.71
KRUK,2.56--kr}k,2.56--STOOL,3.51--stul,3.51
KRUL,0.3--kr}l,0.3--CURL,2.35--k3l,2.35
KUDDE,12.42--k}d@,12.42--HERD,7.06--h3d,7.06
KUIL,3--kLl,3--PIT,13.22--pIt,13.22
KUIP,0.85--kLp,0.85--TUB,12.69--tVb,12.69
KUNST,37.09--k}nst,37.09--ART,70.8--#t,70.8
KURK,1.62--k}rk,1.62--CORK,2.86--k$k,2.86
KUST,31.88--k}st,31.88--COAST,26.69--k5st,26.69
KWARTAAL,1.51--kwArtal,1.51--QUARTER,26.02--kw$t@R,26.02
LAAG,31.1--lax,31.1--LOW,59.14--l5,59.14
LAARS,4.18--lars,4.18--BOOT,11.14--but,11.14
LAATST,60.49--latst,60.49--LAST,723.1--l#st,723.1
LAFAARD,20.56--lAfart,20.56--COWARD,14.39--k6@d,14.39
LANG,596.85--lAN,596.85--LONG,675.16--lQN,675.16
LAST,53.49--lAst,53.49--BURDEN,9.82--b3dH,9.82
LASTIG,67.69--lAst@x,67.69--ANNOYING,11.12--@n4IN,11.12
LAWAAI,17.08--lawaj,17.08--NOISE,34.88--n4z,34.88
LEEFTIJD,44.98--leftKt,44.98--AGE,79.2--1_,79.2
LEEG,61.74--lex,61.74--EMPTY,47.24--EmptI,47.24
LEERLING,12.99--lerlIN,12.99--PUPIL,3.14--pjupP,3.14
LEGAAL,11.75--leGal,11.75--LEGAL,35.71--ligP,35.71
LEGER,107.98--leG@r,107.98--ARMY,85.69--#mI,85.69
LEK,10.45--lEk,10.45--LEAK,10.14--lik,10.14
LELIE,0.85--leli,0.85--LILY,26.86--lIlI,26.86
LEPEL,5.01--lep@l,5.01--SPOON,7.61--spun,7.61
LERAAR,29.66--lerar,29.66--TEACHER,55.73--tiJ@R,55.73
LETSEL,3.11--lEts@l,3.11--INJURY,10.2--In_@rI,10.2
LEVEND,55.61--lev@nt,55.61--ALIVE,154.47--@l2v,154.47
LEZER,1.53--lez@r,1.53--READER,5.45--rid@R,5.45
LICHAAM,147.54--lIxam,147.54--BODY,195.53--bQdI,195.53
LICHTER,4.41--lIxt@r,4.41--LIGHTER,8.96--l2t@R,8.96
LID,33.18--lIt,33.18--MEMBER,28.78--mEmb@R,28.78
LIED,21.27--lit,21.27--SONG,93.69--sQN,93.69
LINKS,68.56--lINks,68.56--LEFT,484.45--lEft,484.45
LINT,7.98--lInt,7.98--RIBBON,5.06--rIb@n,5.06
LITTEKEN,9.81--lItek@,9.81--SCAR,8.47--sk#R,8.47
LOGE,2.04--l<z@,2.04--LODGE,6.69--lQ_,6.69
LOOPBAAN,2.74--loban,2.74--CAREER,45.2--k@r7R,45.2
LOPER,4.34--lop@r,4.34--RUNNER,4.96--rVn@R,4.96
LUCHT,89--l}xt,89--SKY,44.8--sk2,44.8
LUS,1.37--l}s,1.37--TAB,5.76--t{b,5.76
MAAG,23.55--max,23.55--STOMACH,33.82--stVm@k,33.82
MAALTIJD,15.37--maltKt,15.37--MEAL,28.86--mil,28.86
MAAN,42.1--man,42.1--MOON,49.96--mun,49.96
MAAT,69.18--mat,69.18--PAL,57.59--p{l,57.59
MAJOOR,52.8--major,52.8--MAJOR,104.76--m1_@R,104.76
MAMA,206.45--mAma,206.45--MOM,430.39--mQm,430.39
MAND,4.3--mAnt,4.3--BASKET,13.18--b#skIt,13.18
MANIER,257.4--manir,257.4--WAY,1424.73--w1,1424.73
MAP,4.53--mAp,4.53--FOLDER,1.63--f5ld@R,1.63
MARKER,0.23--mArk@r,0.23--MARKER,5.24--m#k@R,5.24
MARMER,1.97--mArm@r,1.97--MARBLE,5.22--m#bP,5.22
MATROOS,3.98--mAtros,3.98--SAILOR,12.39--s1l@R,12.39
MEDISCH,12.23--medis,12.23--MEDICAL,54.39--mEdIkP,54.39
MEEUW,0.64--mew,0.64--GULL,1.1--gVl,1.1
MEID,114.52--mKt,114.52--MAID,22.82--m1d,22.82
MEISJE,382.74--mKsj@,382.74--GIRL,557.12--g3l,557.12

MENEER,518.44--m@ner,518.44--MISTER,45.61--mIst@R,45.61
MENING,34.48--menIN,34.48--OPINION,42--@pInj@n,42
MENS,144.66--mEns,144.66--HUMAN,124.76--hjum@n,124.76
MENTAAL,3.84--mEntal,3.84--MENTAL,19.65--mEntP,19.65
MERG,0.69--mErx,0.69--MARROW,2.96--m{r5,2.96
MERK,19.12--mErk,19.12--MARK,82.02--m#k,82.02
MERRIE,2.72--mEri,2.72--MARE,2.9--m8R,2.9
MES,46.24--mEs,46.24--KNIFE,46.8--n2f,46.8
METAAL,9.54--metal,9.54--METAL,19.45--mEtP,19.45
METHODE,8.48--metod@,8.48--METHOD,7.88--mit@R,7.88
METRO,13.1--metro,13.1--SUBWAY,10.71--sVbw1,10.71
MIDDEL,14.5--mId@l,14.5--MEANS,218.35--minz,218.35
MIDDEN,47.29--mId@,47.29--MIDDLE,89.2--mIdP,89.2
MIER,2.54--mir,2.54--ANT,5.35--{nt,5.35
MIJT,0.07--mKt,0.07--STACK,6.1--st{k,6.1
MINNAAR,12.87--mInar,12.87--LOVER,26.63--lVv@R,26.63
MINUUT,42.69--minyt,42.69--MINUTE,377.49--mInIt,377.49
MIS,219.69--mIs,219.69--MASS,17.25--m{s,17.25
MISDAAD,43.22--mIzdat,43.22--CRIME,71.24--kr2m,71.24
MISSIE,53.4--mIsi,53.4--MISSION,47.06--mISH,47.06
MIST,45.6--mIst,45.6--FOG,9.45--fQg,9.45
MODDER,12.81--mOd@r,12.81--MUD,14.82--mVd,14.82
MOE,89.94--mu,89.94--TIRED,112.65--t2@d,112.65
MOEDER,652.49--mud@r,652.49--MOTHER,479.92--mVD@R,479.92
MOEDIG,18.84--mud@x,18.84--BRAVE,31.71--br1v,31.71
MOEITE,68.6--mujt@,68.6--TROUBLE,223.55--trVbP,223.55
MOER,9.22--mur,9.22--NUT,15.63--nVt,15.63
MOL,7.55--mOl,7.55--MOLE,8.06--m5l,8.06
MOLEN,4.53--mol@,4.53--MILL,9.53--mIl,9.53
MOND,165.93--mOnt,165.93--MOUTH,104.41--m6T,104.41
MONNIK,5.95--mOn@k,5.95--MONK,7.37--mVNk,7.37
MONSTER,49.97--mOnst@r,49.97--SAMPLE,14.59--s#mpP,14.59
MORAAL,6.88--moral,6.88--MORAL,13.51--mQr@l,13.51
MORGEN,423.61--mOrG@,423.61--TOMORROW,335.96--t@mQr5,335.96
MOS,1.14--mOs,1.14--MOSS,2.84--mQs,2.84
MOSTERD,4.99--mOst@rt,4.99--MUSTARD,6.45--mVst@d,6.45
MOTIEF,15.5--motif,15.5--MOTIVE,13.24--m5tIv,13.24
MOUT,0.11--mMt,0.11--MALT,1.65--m$lt,1.65
MOUW,4.18--mMw,4.18--SLEEVE,5.61--sliv,5.61
MUF,0.57--m}f,0.57--STALE,2.92--st1l,2.92
MUIS,11.14--mLs,11.14--MOUSE,19.12--m6s,19.12
MUNT,10.89--m}nt,10.89--MINT,5.43--mInt,5.43
MUUR,66.89--myr,66.89--WALL,70.69--w$l,70.69
MUZIEK,107.46--myzik,107.46--MUSIC,151.65--mjuzIk,151.65
NAAD,1.78--nat,1.78--SEAM,0.65--sim,0.65
NAAM,470.6--nam,470.6--NAME,641.86--n1m,641.86
NACHT,204.44--nAxt,204.44--NIGHT,866.04--n2t,866.04
NAGEL,4.05--naG@l,4.05--NAIL,18.65--n1l,18.65
NATUUR,26.96--natyr,26.96--NATURE,45.16--n1J@R,45.16
NEEF,48.48--nef,48.48--NEPHEW,16.59--nEvju,16.59
NEGEN,64.28--neG@,64.28--NINE,67.47--n2n,67.47
NERVEUS,42.9--nErv|s,42.9--NERVOUS,67.16--n3v@s,67.16
NETTO,0.64--nEto,0.64--NET,15.55--nEt,15.55
NEUTRAAL,4.18--n|tral,4.18--NEUTRAL,4.22--njutr@l,4.22
NICHT,22.96--nIxt,22.96--NIECE,9.53--nis,9.53
NIER,3.91--nir,3.91--KIDNEY,9.69--kIdnI,9.69
NIETIG,2.77--nit@x,2.77--VOID,4.1--v4d,4.1
NIEUWS,178.42--niws,178.42--NEWS,164.69--njuz,164.69
NIKKEL,0.39--nIk@l,0.39--NICKEL,8.45--nIkP,8.45
NOORD,5.76--nort,5.76--NORTH,63.88--n$T,63.88
NUL,17.61--n}l,17.61--ZERO,21.45--z7r5,21.45

OCHTEND,39.54--Oxt@nt,39.54--MORNING,439--m$nIN,439
OMA,72.86--oma,72.86--GRANDMA,45.59--gr{nm#,45.59
ONDEUGD,1.12--Ond|xt,1.12--VICE,18.63--v2s,18.63
ONDIEP,1.23--Ondip,1.23--SHALLOW,5.9--S{l5,5.9
ONKRUID,3.18--ONkrLt,3.18--WEED,11.76--wid,11.76
ONTZET,1.33--OntsEt,1.33--RELIEF,14.59--rIlif,14.59
ONZIN,111.23--OnzIn,111.23--NONSENSE,28.47--nQns@ns,28.47
OOG,68.4--ox,68.4--EYE,111.78--2,111.78
OOM,108.78--om,108.78--UNCLE,124.06--VNkP,124.06
OOR,25.02--or,25.02--EAR,32--7R,32
OORLOG,178.96--orlOx,178.96--WAR,174.75--w$R,174.75
OPRIT,3.93--OprIt,3.93--DRIVEWAY,6.73--dr2vw1,6.73
OPROEP,11.07--Oprup,11.07--CALL,861.39--k$l,861.39
OPSLAG,8.44--OpslAx,8.44--STORAGE,8.86--st$rI_,8.86
OPTIE,11.21--Opsi,11.21--OPTION,14.43--QpSH,14.43
OUD,183.26--Mt,183.26--OLD,608.94--5ld,608.94
PAARD,83.63--part,83.63--HORSE,92.88--h$s,92.88
PAD,41.99--pAt,41.99--TOAD,5.69--t5d,5.69
PAK,313.2--pAk,313.2--SUIT,68.61--sut,68.61
PANEEL,2.01--panel,2.01--PANEL,7.29--p{nP,7.29
PANIEK,39.86--panik,39.86--PANIC,21.84--p{nIk,21.84
PANISCH,0.3--panis,0.3--FRANTIC,2.27--fr{ntIk,2.27
PANTER,1.53--pAnt@r,1.53--PANTHER,2.57--p{nT@R,2.57
PAPIER,31.05--papir,31.05--PAPER,103.35--p1p@R,103.35
PAREL,3.02--par@l,3.02--PEARL,15.67--p3l,15.67
PARFUM,10.89--pArf}m,10.89--PERFUME,11.43--p3fjum,11.43
PARTIJ,22.62--pArtK,22.62--PARTY,233.14--p#tI,233.14
PASSIEF,1.14--pAsif,1.14--PASSIVE,2.18--p{sIv,2.18
PASTA,5.92--pAsta,5.92--PASTE,1.71--p1st,1.71
PAUS,12.62--pMs,12.62--POPE,10.71--p5p,10.71
PAUZE,27.19--pMz@,27.19--PAUSE,5.39--p$z,5.39
PEPER,3.8--pep@r,3.8--PEPPER,8.8--pEp@R,8.8
PERZIK,2.29--pErzIk,2.29--PEACH,6.35--piJ,6.35
PIJN,266.16--pKn,266.16--PAIN,97.94--p1n,97.94
PIJP,13.81--pKp,13.81--PIPE,19.39--p2p,19.39
PINDA,2.13--pInda,2.13--PEANUT,12.35--pinVt,12.35
PIRAAT,6.4--pirat,6.4--PIRATE,7.35--p2@r@t,7.35
PISTOOL,102.63--pistol,102.63--PISTOL,10.06--pIstP,10.06
PIT,5.53--pIt,5.53--WICK,2.51--wIk,2.51
PITTIG,3.75--pIt@x,3.75--SPICY,3.31--sp2sI,3.31
PLAFOND,8.58--plafOnt,8.58--CEILING,8.35--silIN,8.35
PLAK,3.13--plAk,3.13--SLICE,8.53--sl2s,8.53
PLANEET,46.33--planet,46.33--PLANET,38.73--pl{nIt,38.73
PLANK,11.21--plANk,11.21--SHELF,6.96--SElf,6.96
PLEK,177.41--plEk,177.41--SPOT,61.57--spQt,61.57
PLICHT,28.1--plIxt,28.1--DUTY,50.96--djutI,50.96
PLOEG,9.81--plux,9.81--SHIFT,22.82--SIft,22.82
PLONS,0.48--plOns,0.48--SPLASH,4.22--spl{S,4.22
PLUCHE,0.32--plyS,0.32--PLUSH,0.55--plVS,0.55
POEDER,6.15--pud@r,6.15--POWDER,16.04--p6d@R,16.04
POEF,1.01--puf,1.01--CUSHION,2.16--kUSH,2.16
POGING,22.57--poGIN,22.57--ATTEMPT,19.12--@tEmpt,19.12
POLITIE,346.17--politsi,346.17--POLICE,236.16--p@lis,236.16
POMPOEN,2.49--pOmpun,2.49--PUMPKIN,10.84--pVmpkIn,10.84
POORT,25.06--port,25.06--GATE,32.04--g1t,32.04
POOT,6.95--pot,6.95--PAW,3.12--p$,3.12
PORTIE,4.62--pOrsi,4.62--PORTION,4.33--p$SH,4.33
POT,30.62--pOt,30.62--JAR,8.31--_#R,8.31
POTLOOD,5.44--pOtlot,5.44--PENCIL,9.86--pEnsP,9.86
PRIJS,86.6--prKs,86.6--PRICE,53.37--pr2s,53.37
PRIK,4.6--prIk,4.6--PRICK,14.12--prIk,14.12

PRIMAAT,0.3--primat,0.3--PRIMATE,0.69--pr2m1t,0.69
PRINS,45.26--prIns,45.26--PRINCE,45.08--prIns,45.08
PROBLEEM,341.78--problem,341.78--PROBLEM,330.06--prQbl@m,330.06
PROCENT,44.52--prosEnt,44.52--PERCENT,25.75--p@sEnt,25.75
PRODUKT,0.55--prod}kt,0.55--PRODUCT,14.75--prQdVkt,14.75
PROOI,7.82--proj,7.82--PREY,5.51--pr1,5.51
PROZA,0.39--proza,0.39--PROSE,0.94--pr5z,0.94
PRUIM,1.12--prLm,1.12--PLUM,3.41--plVm,3.41
PUBLIEK,41.87--pyblik,41.87--PUBLIC,71.08--pVblIk,71.08
PUZZEL,5.26--p}z@l,5.26--PUZZLE,7.33--pVzP,7.33
RAAM,70.84--ram,70.84--WINDOW,86--wInd5,86
RADIJS,0.41--radKs,0.41--RADISH,0.61--r{dIS,0.61
RAIL,0.46--rel,0.46--RAIL,4.57--r1l,4.57
RAKET,14.82--rakEt,14.82--ROCKET,11.84--rQkIt,11.84
RAMP,25.89--rAmp,25.89--DISASTER,17.27--dIz#st@R,17.27
RAND,19.12--rAnt,19.12--EDGE,23.51--E_,23.51
RAUW,4.67--rMw,4.67--RAW,10.18--r$,10.18
RECHTER,63.28--rExt@r,63.28--JUDGE,79.67--_V_,79.67
REDEN,163.67--red@,163.67--REASON,193.29--rizH,193.29
REFREIN,1.14--r@frKn,1.14--CHORUS,6.08--k$r@s,6.08
REGEN,26.48--reG@,26.48--RAIN,48.9--r1n,48.9
REIKEN,2.74--rKk@,2.74--RANGE,22.76--r1n_,22.76
REIS,90.37--rKs,90.37--TRIP,82.39--trIp,82.39
REK,2.38--rEk,2.38--RACK,7.78--r{k,7.78
REL,2.7--rEl,2.7--RIOT,6.49--r2@t,6.49
RESPONS,0.94--rEspOns,0.94--RESPONSE,16.1--rIspQns,16.1
RIEM,14.16--rim,14.16--BELT,24.35--bElt,24.35
RIJ,84.84--rK,84.84--ROW,26.33--r5,26.33
RIJK,79.15--rKk,79.15--RICH,80.39--rIJ,80.39
RIJP,8.1--rKp,8.1--MATURE,8.22--m@tj9R,8.22
RIJST,9.17--rKst,9.17--RICE,15.08--r2s,15.08
RIJWIEL,1--rKwil,1--BICYCLE,6--b2sIkP,6
RIMBOE,1.33--rImbu,1.33--BUSH,14.12--bUS,14.12
RIMPEL,0.8--rImp@l,0.8--WRINKLE,1.88--rINkP,1.88
RIT,14.77--rIt,14.77--RIDE,135.37--r2d,135.37
RITME,8.85--rItm@,8.85--RHYTHM,10.9--rID@m,10.9
RIVIER,52.87--rivir,52.87--RIVER,55.47--rIv@R,55.47
ROEST,2.31--rust,2.31--RUST,2.49--rVst,2.49
ROET,1.46--rut,1.46--SOOT,1.08--sUt,1.08
ROG,1.39--rOx,1.39--RAY,97.37--r1,97.37
ROK,7.23--rOk,7.23--SKIRT,9.96--sk3t,9.96
ROMP,6.47--rOmp,6.47--HULL,4.22--hVl,4.22
RONDE,21.82--rOnd@,21.82--ROUND,66.53--r6nd,66.53
ROOK,46.63--rok,46.63--SMOKE,65.43--sm5k,65.43
ROOM,7.59--rom,7.59--CREAM,48.71--krim,48.71
ROT,87.15--rOt,87.15--ROTTEN,17.47--rQtH,17.47
ROZIJN,0.3--rozKn,0.3--RAISIN,1.63--r1zH,1.63
RUIL,15.39--rLl,15.39--EXCHANGE,20.22--IksJ1n_,20.22
RUIMTE,77.25--rLmt@,77.25--SPACE,66.06--sp1s,66.06
SAAI,31.47--saj,31.47--DULL,12.08--dVl,12.08
SAMEN,370.64--sam@,370.64--TOGETHER,383.39--t@gED@R,383.39
SAP,7.09--sAp,7.09--JUICE,9.9--_us,9.9
SATIJN,0.78--satKn,0.78--SATIN,2.61--s{tIn,2.61
SAUS,9.56--sMs,9.56--SAUCE,15.59--s$s,15.59
SCALP,0.94--skAlp,0.94--SCALP,3.69--sk{lp,3.69
SCHAAP,6.54--sxap,6.54--SHEEP,13.43--Sip,13.43
SCHAAR,6.36--sxar,6.36--SCISSORS,6.69--sIz@z,6.69
SCHAARS,2.22--schaars,2.22--SCARCE,1.71--sk8s,1.71
SCHADE,31.83--sxad@,31.83--HARM,31.78--h#m,31.78
SCHADUW,20.92--sxadyw,20.92--SHADOW,21.18--S{d5,21.18
SCHAKEL,14.64--sxak@l,14.64--LINK,11.94--lINk,11.94

SCHAKEN,4--sxak@,4--CHESS,7.45--JEs,7.45
SCHAT,264.03--sxAt,264.03--TREASURE,19.06--trEZ@R,19.06
SCHATTIG,28.68--sxAt@x,28.68--CUTE,87.75--kjut,87.75
SCHEIDEN,25.29--sxKd@,25.29--SEPARATE,21.71--sEp@r1t,21.71
SCHEMER,0.37--sxem@r,0.37--TWILIGHT,3.06--tw2l2t,3.06
SCHEP,4.62--sxEp,4.62--SHOVEL,6.84--SVvP,6.84
SCHEPSEL,4.41--sxEps@l,4.41--CREATURE,21.41--kriJ@R,21.41
SCHERP,20.83--sxErp,20.83--SHARP,23.78--S#p,23.78
SCHIL,1.12--sxIl,1.12--PEEL,5.35--pil,5.35
SCHILDER,10.5--sxIld@r,10.5--PAINTER,6.75--p1nt@R,6.75
SCHOK,11.66--sxOk,11.66--SHOCK,28.78--SQk,28.78
SCHOON,49.28--sxon,49.28--CLEAN,121.24--klin,121.24
SCHOOT,49.35--sxot,49.35--LAP,13.47--l{p,13.47
SCHOP,16.19--sxOp,16.19--KICK,73.41--kIk,73.41
SCHOUDER,18.57--sxMd@r,18.57--SHOULDER,26.2--S5ld@R,26.2
SCHRIJN,0.16--sxrKn,0.16--SHRINE,2.96--Sr2n,2.96
SCHROEF,1.97--sxruf,1.97--SCREW,37.49--skru,37.49
SCHUIM,3.54--sxLm,3.54--FOAM,3.51--f5m,3.51
SCHULD,178.1--sx}lt,178.1--GUILT,14.9--gIlt,14.9
SCHULDIG,85.91--sx}ld@x,85.91--GUILTY,62.29--gIltI,62.29
SEKS,100.14--sEks,100.14--SEX,152.18--sEks,152.18
SEREEN,0.69--seren,0.69--SERENE,1.24--sIrin,1.24
SERVET,1.78--sErvEt,1.78--NAPKIN,3.61--n{pkIn,3.61
SESSIE,6.15--sEsi,6.15--SESSION,13.29--sESH,13.29
SFINX,0.91--sfINks,0.91--SPHINX,1.02--sfINks,1.02
SHORTS,0.8--SOrts,0.8--SHORTS,9.41--S$ts,9.41
SIGAAR,9.83--siGar,9.83--CIGAR,12.94--sIg#R,12.94
SIMPEL,52.92--sImp@l,52.92--SIMPLE,89.31--sImpP,89.31
SJAAL,5.31--Sal,5.31--SCARF,4.69--sk#f,4.69
SKELET,2.84--sk@lEt,2.84--SKELETON,5.12--skElItH,5.12
SLAAF,17.75--slaf,17.75--SLAVE,18.43--sl1v,18.43
SLAGER,6.63--slaG@r,6.63--BUTCHER,8.51--bUJ@R,8.51
SLAK,2.38--slAk,2.38--SNAIL,1.76--sn1l,1.76
SLANG,21.59--slAN,21.59--SNAKE,22.35--sn1k,22.35
SLANK,3.16--slANk,3.16--SLIM,11.86--slIm,11.86
SLECHT,267.81--slExt,267.81--BAD,545.18--b{d,545.18
SLET,28.58--slEt,28.58--TART,2.39--t#t,2.39
SLEUTEL,80.7--sl|t@l,80.7--KEY,86.86--ki,86.86
SLINGER,1.46--slIN@r,1.46--SLING,2.29--slIN,2.29
SLUW,3.2--slyw,3.2--SLY,2.67--sl2,2.67
SMAAK,29.18--smak,29.18--TASTE,51.31--t1st,51.31
SMARAGD,1.92--smarAxt,1.92--EMERALD,2.57--Em@r@ld,2.57
SMERIG,24.35--smer@x,24.35--FILTHY,16.43--fIlTI,16.43
SMERIS,22.91--smer@s,22.91--COP,86.14--kQp,86.14
SNEL,463.6--snEl,463.6--SWIFT,3.86--swIft,3.86
SNELHEID,24.22--snElhKt,24.22--SPEED,41.25--spid,41.25
SOCIAAL,7.94--soSal,7.94--SOCIAL,33.39--s5SP,33.39
SODA,2.61--soda,2.61--SODA,19.84--s5d@,19.84
SOEP,17.84--sup,17.84--SOUP,25.2--sup,25.2
SOK,3.11--sOk,3.11--SOCK,8.98--sQk,8.98
SOLDAAT,53.03--sOldat,53.03--SOLDIER,38.92--s5l_@R,38.92
SOM,3.89--sOm,3.89--SUM,10.25--sVm,10.25
SOMBER,6.88--sort,6.88--GLOOMY,2.41--glumI,2.41
SOORT,222.02--sort,222.02--KIND,590.69--k2nd,590.69
SOP,0.62--sOp,0.62--SUDS,0.47--sVdz,0.47
SPANNEND,20.76--spAn@nt,20.76--EXCITING,34.82--Iks2tIN,34.82
SPANNING,16.17--spAnIN,16.17--TENSION,8.55--tEnSH,8.55
SPECIAAL,50.63--speSal,50.63--SPECIAL,148.57--spESP,148.57
SPEEKSEL,2.95--speks@l,2.95--SALIVA,2.65--s@l2v@,2.65
SPELEN,247.77--spel@,247.77--PLAY,354.53--pl1,354.53
SPIEGEL,27.44--spiG@l,27.44--MIRROR,24.18--mIr@R,24.18

SPIER,2.7--spir,2.7--MUSCLE,13.61--mVsP,13.61
SPION,18.5--spijOn,18.5--SPY,20.06--sp2,20.06
SPLEET,1.78--splet,1.78--CRACK,32.84--kr{k,32.84
SPOED,2.77--sput,2.77--HURRY,173.65--hVrI,173.65
SPONS,2.49--spOns,2.49--SPONGE,6.71--spVn_,6.71
SPOOK,12.76--spok,12.76--PHANTOM,4.08--f{nt@m,4.08
SPORT,20.12--spOrt,20.12--SPORTS,27.59--sp$ts,27.59
SPUIT,9.79--spLt,9.79--SYRINGE,1.94--sIrIn_,1.94
STAART,17.95--start,17.95--TAIL,23.9--t1l,23.9
STAD,272.61--stAt,272.61--CITY,169.1--sItI,169.1
STAF,11.62--stAf,11.62--STAFF,32--st#f,32
STAKING,3.25--stakIN,3.25--STRIKE,45.57--str2k,45.57
STAM,12.46--stAm,12.46--TRUNK,19.8--trVNk,19.8
STANK,11.14--stANk,11.14--STENCH,2.22--stEnJ,2.22
STAPEL,10.22--stap@l,10.22--PILE,13.18--p2l,13.18
STAR,8.03--stAr,8.03--RIGID,1.86--rI_Id,1.86
STAREN,13.08--star@,13.08--STARE,9.96--st8R,9.96
STEIL,1.76--stKl,1.76--STEEP,2.45--stip,2.45
STEM,86.53--stEm,86.53--VOICE,86.16--v4s,86.16
STER,43.77--stEr,43.77--STAR,81.35--st#R,81.35
STERKTE,8.32--stErkt@,8.32--STRENGTH,36.92--strENT,36.92
STEUN,32.68--st|n,32.68--SUPPORT,0.73--s@p$t,0.73
STIEKEM,11.69--stik@m,11.69--SNEAKY,4.24--snikI,4.24
STIER,9.6--stir,9.6--BULL,27.51--bUl,27.51
STIJF,7.96--stKf,7.96--STIFF,10.25--stIf,10.25
STIJGING,0.82--stKGIN,0.82--RISE,27.43--r2z,27.43
STILTE,37.87--stIlt@,37.87--SILENCE,25.37--s2l@ns,25.37
STOF,29.25--stOf,29.25--MATERIAL,22.14--m@t7r7l,22.14
STOK,14.48--stOk,14.48--STICK,97.12--stIk,97.12
STOM,103.91--stOm,103.91--STUPID,184.41--stjupId,184.41
STOMP,2.33--stOmp,2.33--STUMP,2.45--stVmp,2.45
STOOM,5.88--stom,5.88--STEAM,13.45--stim,13.45
STOPPEL,0.05--stOp@l,0.05--BRISTLE,0.22--brIsP,0.22
STRAAT,100.34--strat,100.34--STREET,148.18--strit,148.18
STRAK,16.76--strAk,16.76--TIGHT,50.92--t2t,50.92
STRENG,13.47--strEN,13.47--STRAND,1.84--str{nd,1.84
STRIJD,44.73--strKt,44.73--STRUGGLE,13.37--strVgP,13.37
STRO,1.78--stro,1.78--STRAW,6.24--str$,6.24
STROOM,29.87--strom,29.87--STREAM,8.04--strim,8.04
STROP,4.37--strOp,4.37--NOOSE,2.18--nus,2.18
STRUIK,2.7--strLk,2.7--SHRUB,0.27--SrVb,0.27
STUK,175.67--st}k,175.67--PIECE,124.49--pis,124.49
SUBTIEL,5.69--s}ptil,5.69--SUBTLE,6.94--sVtP,6.94
SUCCES,103.64--syksEs,103.64--SUCCESS,27.25--s@ksEs,27.25
SUF,4.57--s}f,4.57--DROWSY,0.73--dr6zI,0.73
SYMBOOL,13.84--sImbol,13.84--SYMBOL,8.59--sImbP,8.59
SYSTEEM,45.83--sistem,45.83--SYSTEM,91.51--sIst@m,91.51
TAAI,9.03--taj,9.03--TOUGH,90.51--tVf,90.51
TAAK,42.63--tak,42.63--TASK,12.73--t#sk,12.73
TACTVOL,1.28--tAktfOl,1.28--TACTFUL,0.57--t{ktfUl,0.57
TAFEL,83.4--taf@l,83.4--TABLE,105.63--t1bP,105.63
TALRIJK,0.82--tAlrKk,0.82--NUMEROUS,3.59--njum@r@s,3.59
TAND,8.07--tAnt,8.07--TOOTH,13.57--tuT,13.57
TANG,4.3--tAN,4.3--PLIERS,1.16--pl2@z,1.16
TANTE,62.34--tAnt@,62.34--AUNT,55.2--#nt,55.2
TAPIJT,10.77--tapKt,10.77--CARPET,11.65--k#pIt,11.65
TAS,58.36--tAs,58.36--BAG,94.04--b{g,94.04
TEDER,2.77--ted@r,2.77--TENDER,8.88--tEnd@R,8.88
TEEK,0.87--tek,0.87--TICK,7.25--tIk,7.25
TEER,3.34--ter,3.34--TAR,3.14--t#R,3.14
TEMPEL,14.66--tEmp@l,14.66--TEMPLE,17.55--tEmpP,17.55

TERMIJN,6.29--tErmKn,6.29--TERM,17.45--t3m,17.45
TERREUR,3.11--tEr|r,3.11--TERROR,9--tEr@R,9
THEE,58.79--te,58.79--TEA,58.63--ti,58.63
TIENER,8.42--tin@r,8.42--TEENAGER,6.88--tin1_@R,6.88
TIJDPERK,8.67--tKtpErk,8.67--ERA,5.71--7r@,5.71
TIJGER,11.69--tKG@r,11.69--TIGER,18.53--t2g@R,18.53
TIK,6.81--tIk,6.81--TAP,14.75--t{p,14.75
TITEL,18.23--tit@l,18.23--TITLE,18.57--t2tP,18.57
TOEKOMST,103.45--tukOmst,103.45--FUTURE,103.49--fjuJ@R,103.49
TOERIST,3.91--turIst,3.91--TOURIST,4.65--t9rIst,4.65
TOGA,1.46--toGa,1.46--GOWN,6.55--g6n,6.55
TOMAAT,2.97--tomat,2.97--TOMATO,5.9--t@m#t5,5.9
TONG,31.9--tON,31.9--TONGUE,31.16--tVN,31.16
TOOST,5.79--tost,5.79--TOAST,33.47--t5st,33.47
TOREN,19.21--tor@,19.21--TOWER,22.84--t6@R,22.84
TOUW,26.25--tMw,26.25--ROPE,22.71--r5p,22.71
TRAAG,9.79--trax,9.79--SLOW,76.02--sl5,76.02
TRAAN,2.63--tran,2.63--TEAR,27--t7R,27
TRANT,0.53--trAnt,0.53--MANNER,11.53--m{n@R,11.53
TRAP,52.28--trAp,52.28--STAIRS,23.76--st8z,23.76
TRIEST,17.66--trist,17.66--SAD,63.37--s{d,63.37
TRIOMF,3.45--trijOmf,3.45--TRIUMPH,4.65--tr2@mf,4.65
TROFEE,4.37--trofe,4.37--TROPHY,7.55--tr5fI,7.55
TROMMEL,1.85--trOm@l,1.85--DRUM,8.47--drVm,8.47
TROPISCH,1.1--tropis,1.1--TROPICAL,3.2--trQpIkP,3.2
TROTS,111.46--trOts,111.46--PROUD,83.63--pr6d,83.63
TROTTOIR,1.28--trOtwar,1.28--SIDEWALK,5.47--s2dw$k,5.47
TROUW,52.34--trMw,52.34--LOYALTY,11.67--l4@ltI,11.67
TRUC,19.62--tryk,19.62--TRICK,47.27--trIk,47.27
TRUI,11.62--trL,11.62--SWEATER,13.8--swEt@R,13.8
TUIN,36.66--tLn,36.66--GARDEN,26.55--g#dH,26.55
TULP,0.48--t}lp,0.48--TULIP,0.78--tjulIp,0.78
TWAALF,46.49--twalf,46.49--TWELVE,18.82--twElv,18.82
TWEE,1007.83--twe,1007.83--TWO,1066.35--tu,1066.35
TYFOON,0.41--tifon,0.41--TYPHOON,1.47--t2fun,1.47
UITEEN,6.4--Lten,6.4--APART,47.02--@p#t,47.02
UITGANG,14.68--LtxAN,14.68--ENDING,15.92--EndIN,15.92
UNIE,2.08--yni,2.08--UNION,21.78--junj@n,21.78
UUR,348.69--yr,348.69--HOUR,162.29--6@R,162.29
VAAG,8.99--vax,8.99--VAGUE,4.53--v1g,4.53
VAANDEL,0.91--vand@l,0.91--BANNER,5.92--b{n@R,5.92
VAART,9.95--vart,9.95--VOYAGE,6--v4I_,6
VAARTUIG,1.56--vartLx,1.56--VESSEL,9.35--vEsP,9.35
VAATJE,0.59--vatj@,0.59--KEG,3.43--kEg,3.43
VADER,795.62--vad@r,795.62--FATHER,554.49--f#D@R,554.49
VANDAAG,369.61--vAndax,369.61--TODAY,433.8--t@d1,433.8
VARKEN,24.74--vArk@,24.74--PIG,39.14--pIg,39.14
VAT,19.05--vAt,19.05--BARREL,10.63--b{r@l,10.63
VEE,13.63--ve,13.63--CATTLE,13.22--k{tP,13.22
VEER,3.43--ver,3.43--QUILL,2.73--kwIl,2.73
VELD,15.96--vElt,15.96--FIELD,70.2--fild,70.2
VERDERF,2.38--v@rdErf,2.38--RUIN,28.53--rUIn,28.53
VERDRIET,26.48--v@rdrit,26.48--GRIEF,10.82--grif,10.82
VERF,14.48--vErf,14.48--PAINT,36.8--p1nt,36.8
VERHAAL,202.98--v@rhal,202.98--STORY,220.78--st$rI,220.78
VERKEER,15.28--v@rker,15.28--TRAFFIC,28.51--tr{fIk,28.51
VERKEERD,115.51--v@rkert,115.51--WRONG,523.1--rQN,523.1
VERKOOP,37.96--vErkop,37.96--SALES,12.71--s1lz,12.71
VERLIES,49.07--v@rlis,49.07--LOSS,29.12--lQs,29.12
VERSLAG,24.15--v@rslAx,24.15--REPORT,108--rIp$t,108
VET,18.52--vEt,18.52--GREASE,6.94--gris,6.94

VETE,1.12--vet@,1.12--FEUD,1.29--fjud,1.29
VETER,1.33--vet@r,1.33--SHOELACE,0.75--Sul1s,0.75
VIES,19.8--vis,19.8--DIRTY,24.56--d3tI,24.56
VIJF,281.57--vKf,281.57--FIVE,285.45--f2v,285.45
VIJVER,4.32--vKv@r,4.32--POND,6.33--pQnd,6.33
VINGER,28.91--vIN@r,28.91--FINGER,36.67--fINg@R,36.67
VIOOL,4.3--vijol,4.3--VIOLIN,4.75--v2@lIn,4.75
VIS,50.08--vIs,50.08--FISH,83.49--fIS,83.49
VISIE,8.23--vizi,8.23--VISION,23.88--vIZH,23.88
VLAG,17.79--vlAx,17.79--FLAG,17.49--fl{g,17.49
VLAK,47.73--vlAk,47.73--PLANE,95.53--pl1n,95.53
VLAM,7.94--vlAm,7.94--FLAME,9.04--fl1m,9.04
VLEES,61.67--vles,61.67--MEAT,43.65--mit,43.65
VLIEGER,3.8--vliG@r,3.8--KITE,2.29--k2t,2.29
VLOED,2.2--vlut,2.2--FLOOD,5.71--flVd,5.71
VLOEK,18.77--vluk,18.77--CURSE,18.22--k3s,18.22
VLUCHTIG,1.58--vl}xt@x,1.58--FUGITIVE,5.18--fju_@tIv,5.18
VOCHT,16.19--vOxt,16.19--LIQUID,7.75--lIkwId,7.75
VOD,1.51--vOt,1.51--RAG,4.78--r{g,4.78
VOERTUIG,12.1--vurtLx,12.1--VEHICLE,22.61--v7kP,22.61
VOET,50.81--vut,50.81--FOOT,64.92--fUt,64.92
VOLK,71.55--vOlk,71.55--PEOPLE,1102.98--pipP,1102.98
VONNIS,7.48--vOn@s,7.48--VERDICT,10.94--v3dIkt,10.94
VOORJAAR,2.38--vorjar,2.38--SPRING,31.31--sprIN,31.31
VORM,39.47--vOrm,39.47--SHAPE,30.24--S1p,30.24
VOS,7.59--vOs,7.59--FOX,21.61--fQks,21.61
VRAAG,436.76--vrax,436.76--QUESTION,198.35--kwEsJ@n,198.35
VREDE,65.01--vred@,65.01--PEACE,69.61--pis,69.61
VREEMD,126.67--vremt,126.67--STRANGE,86.43--str1n_,86.43
VRIEND,491.43--vrint,491.43--FRIEND,419.29--frEnd,419.29
VROUW,821.67--vrMw,821.67--WOMAN,434.63--wUm@n,434.63
VUIL,24.06--vLl,24.06--FOUL,14.47--f6l,14.47
VUILNIS,8.94--vLlnIs,8.94--GARBAGE,26.1--g#bI_,26.1
VUIST,6.77--vLst,6.77--FIST,7.35--fIst,7.35
WAARDE,25.63--ward@,25.63--WORTH,109.2--w3T,109.2
WAARHEID,189.39--warhKt,189.39--TRUTH,192.18--truT,192.18
WAGEN,77.82--waG@,77.82--WAGON,17.76--w{g@n,17.76
WALGING,1.12--wAlGIN,1.12--DISGUST,2.76--dIsgVst,2.76
WALNOOT,0.71--wAlnot,0.71--WALNUT,1.96--w$lnVt,1.96
WANG,7.89--wAN,7.89--CHEEK,7.16--Jik,7.16
WAPEN,140.59--wap@,140.59--WEAPON,46.65--wEp@n,46.65
WARMTE,10.5--wArmt@,10.5--WARMTH,4.45--w$mT,4.45
WASBEER,1.58--wAzber,1.58--RACCOON,1.43--r@kun,1.43
WEIDE,1.26--wKd@,1.26--PASTURE,1.53--p#sJ@R,1.53
WEINIG,110.45--wKn@x,110.45--LITTLE,1446.39--lItP,1446.39
WEKEN,148.3--wek@,148.3--SOAK,3.45--s5k,3.45
WELZIJN,5.83--wElzKn,5.83--WELFARE,7.88--wElf8R,7.88
WENK,0.39--wENk,0.39--HINT,9.2--hInt,9.2
WENS,59.39--wEns,59.39--WISH,235.12--wIS,235.12
WERELD,394.01--wer@lt,394.01--WORLD,455.22--w3ld,455.22
WERK,680.23--wErk,680.23--WORK,798.02--w3k,798.02
WERPER,1.42--wErp@r,1.42--PITCHER,3.24--pIJ@R,3.24
WET,80.45--wEt,80.45--LAW,116.31--l$,116.31
WETENSCHAP,23.3--wet@sxAp,23.3--SCIENCE,37.25--s2@ns,37.25
WEZEL,2.06--wez@l,2.06--WEASEL,4.9--wizP,4.9
WIEG,4.12--wix,4.12--CRADLE,2.84--kr1dP,2.84
WIEL,7.04--wil,7.04--WHEEL,27.06--wil,27.06
WIJN,60.44--wKn,60.44--WINE,60.35--w2n,60.35
WIJNSTOK,0.55--wKnstOk,0.55--VINE,2.1--v2n,2.1
WIJSHEID,11.09--wKshKt,11.09--WISDOM,11.08--wIzd@m,11.08
WIJZE,25.18--wKz@,25.18--SAGE,1.75--s1_,1.75

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WINNAAR,23.6--wInar,23.6--WINNER,31.22--wIn@R,31.22
WISSEL,2.74--wIs@l,2.74--SWITCH,28.12--swIJ,28.12
WIT,33.48--wIt,33.48--WHITE,171.45--w2t,171.45
WOESTIJN,27.74--wustKn,27.74--DESERT,27.98--dEz@t,27.98
WOL,3.75--wOl,3.75--WOOL,3.16--wUl,3.16
WOLK,5.44--wOlk,5.44--CLOUD,11.75--kl6d,11.75
WOORD,129.09--wort,129.09--WORD,235.55--w3d,235.55
WORST,8.78--wOrst,8.78--SAUSAGE,7.78--sQsI_,7.78
WORTEL,6.11--wOrt@l,6.11--ROOT,10.47--rut,10.47
WRAAK,44.02--wrak,44.02--REVENGE,19.04--rIvEn_,19.04
ZAAL,15.41--zal,15.41--HALL,51.94--h$l,51.94
ZACHT,22.85--zAxt,22.85--SOFT,32.02--sQft,32.02
ZAK,96.87--zAk,96.87--POCKET,35.71--pQkIt,35.71
ZALF,1.69--zAlf,1.69--OINTMENT,1.63--4ntm@nt,1.63
ZALIG,9.15--zal@x,9.15--GORGEOUS,24.06--g$_@s,24.06
ZAND,19.99--zAnt,19.99--SAND,20.29--s{nd,20.29
ZEDIG,0.23--zed@x,0.23--MODEST,5.88--mQdIst,5.88
ZEE,67.8--ze,67.8--SEA,59.84--si,59.84
ZELDZAAM,10.02--zEltsam,10.02--RARE,21.31--r8R,21.31
ZETEL,3.06--zet@l,3.06--SEAT,78.78--sit,78.78
ZEVEN,103.52--zev@,103.52--SEVEN,104.45--sEvH,104.45
ZIEKTE,37.14--zikt@,37.14--SICKNESS,7.94--sIknIs,7.94
ZIEL,82.67--zil,82.67--SOUL,76.96--s5l,76.96
ZIJDE,18.8--zKd@,18.8--SILK,9.78--sIlk,9.78
ZILVER,9.95--zIlv@r,9.95--SILVER,31.75--sIlv@R,31.75
ZIN,172.65--zIn,172.65--SENTENCE,20.53--sEnt@ns,20.53
ZINLOOS,13.74--zInlos,13.74--USELESS,19.94--juslIs,19.94
ZITTEND,2.15--zIt@nt,2.15--SITTING,94.39--sItIN,94.39
ZOET,10.98--zut,10.98--SWEET,145.2--swit,145.2
ZOLDER,8.19--zOld@r,8.19--ATTIC,7.84--{tIk,7.84
ZOMER,42.9--zom@r,42.9--SUMMER,78.67--sVm@R,78.67
ZON,68.81--zOn,68.81--SUN,69.67--sVn,69.67
ZOOM,4.18--zom,4.18--HEM,0.82--hEm,0.82
ZOON,348.19--zon,348.19--SON,410.76--sVn,410.76
ZORG,218.82--zOrx,218.82--CARE,485.25--k8R,485.25
ZUID,5.12--zLt,5.12--SOUTH,64.47--s6T,64.47
ZUIVEL,0.64--zLv@l,0.64--DAIRY,2.78--d8rI,2.78
ZUIVER,10.63--zLv@r,10.63--PURE,24.92--pj9R,24.92
ZUS,131.03--z}s,131.03--SISTER,180.53--sIst@R,180.53
ZUSTER,71.51--z}st@r,71.51--NURSE,44.98--n3s,44.98
ZUURSTOF,13.13--zyrstOf,13.13--OXYGEN,13.88--QksI_@n,13.88
ZWAAN,1.99--zwan,1.99--SWAN,6.82--swQn,6.82
ZWAARTE,0.34--zwart@,0.34--GRAVITY,6.88--gr{v@tI,6.88
ZWAKTE,5.9--zwAkt@,5.9--WEAKNESS,8.9--wiknIs,8.9
ZWALUW,0.85--zwalyw,0.85--SWALLOW,12.73--swQl5,12.73
ZWART,57.31--zwArt,57.31--BLACK,167.94--bl{k,167.94
ZWEER,79.42--zwer,79.42--ULCER,2.57--Vls@R,2.57
ZWEET,12.87--zwet,12.87--SWEAT,21.86--swEt,21.86
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14.4. Additional words for Dijkstra et al. (2010) simulation

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AAP,28.56--ap,28.56--MONKEY,33.51--mVNkI,33.51
BAMBOE,0.69--bAmbu,0.69--BAMBOO,1.57--b{mbu,1.57
BOOM,52.25--bom,52.25--TREE,65--tri,65
BRIES,1.33--bris,1.33--BREEZE,8.04--briz,8.04
CHAOS,15.8--xaOs,15.8--CHAOS,9.39--k1Qs,9.39
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CIRCUS,13.77--sIrk}s,13.77--CIRCUS,17.06--s3k@s,17.06
CRISIS,11.89--krisEs,11.89--CRISIS,16.65--kr2sIs,16.65
DAK,54.84--dAk,54.84--ROOF,35.65--ruf,35.65
DEBAT,5.74--d@bAt,5.74--DEBATE,9.29--dIb1t,9.29
DETAIL,9.26--detAj,9.26--DETAIL,19.39--dit1l,19.39
DOKTER,244.07--dOkt@r,244.07--DOCTOR,263.94--dQkt@R,263.94
DOORN,1.99--dorn,1.99--THORN,5.1--T$n,5.1
DORST,19.14--dOrst,19.14--THIRST,3.73--T3st,3.73
EIS,12.07--Ks,12.07--DEMAND,17.12--dIm#nd,17.12
FLES,45.71--flEs,45.71--BOTTLE,50.75--bQtP,50.75
GEDICHT,14.73--x@dIxt,14.73--POEM,13.65--p5Im,13.65
GEK,542.88--xEk,542.88--CRAZY,272.27--kr1zI,272.27
GEMAK,18.04--x@mAk,18.04--EASE,19.1--iz,19.1
GENADE,31.92--x@nad@,31.92--MERCY,25.31--m3sI,25.31
GERUCHT,11.96--x@r}xt,11.96--RUMOR,10.41--,10.41
GRIJS,8.53--xrKs,8.53--GREY,9.2--gr1,9.2
GROT,17.45--xrOt,17.45--CAVE,13.98--k1v,13.98
GUNST,20.49--x}nst,20.49--FAVOUR,18.59--f1v@R,18.59
HAVEN,17.08--hav@,17.08--PORT,14.53--,14.53
HEKS,26.76--hEks,26.76--WITCH,27.65--wIJ,27.65
HELDER,20.19--hEld@r,20.19--BRIGHT,44.41--br2t,44.41
HERTOG,9.81--hErtOx,9.81--DUKE,25.04--djuk,25.04
HOEK,49.92--huk,49.92--ANGLE,14.92--{NgP,14.92
HONGER,92.45--hON@r,92.45--HUNGER,5.88--hVNg@R,5.88
HOTEL,88.73--hotEl,88.73--HOTEL,103.22--h5tEl,103.22
HUUR,28.88--hyr,28.88--RENT,34.55--rEnt,34.55
IDIOOT,117.29--idijot,117.29--IDIOT,66.22--Id7t,66.22
JEUGD,27.88--j|xt,27.88--YOUTH,16.82--juT,16.82
JUWEEL,3.41--jywel,3.41--JEWEL,7.24--_u@l,7.24
KAART,79.67--kart,79.67--CARD,85.43--k#d,85.43
KERN,9.26--kErn,9.26--CORE,9.82--k$R,9.82
KEUZE,66.45--k|z@,66.45--CHOICE,97.55--J4s,97.55
KLEUR,39.68--kl|r,39.68--COLOUR,8.71--kVl@R,8.71
KOEL,8.76--kul,8.76--COOL,195.88--kul,195.88
KOGEL,43.72--koG@l,43.72--BULLET,38.24--bUlIt,38.24
KUSSEN,45.62--k}s@,45.62--PILLOW,11.39--pIl5,11.39
LAWAAI,17.08--lawaj,17.08--NOISE,34.88--n4z,34.88
LELIJK,29.23--lel@k,29.23--UGLY,42.16--VglI,42.16
LENGTE,8.74--lENt@,8.74--LENGTH,7.02--lENT,7.02
LUI,47.68--lL,47.68--BUCKET,10.02--bVkIt,10.02
MAAGD,22.43--maxt,22.43--VIRGIN,18.84--v3_In,18.84
MELOEN,2.01--m@lun,2.01--MELON,4.27--mEl@n,4.27
MENIGTE,12.12--men@xt@,12.12--CROWD,37.37--kr6d,37.37
MENU,6.63--meny,6.63--MENU,9.96--mEnju,9.96
MILD,2.47--mIlt,2.47--MILD,4.8--m2ld,4.8
MODEL,20.24--modEl,20.24--MODEL,32.06--mQdP,32.06
MOERAS,9.74--murAs,9.74--SWAMP,8.98--swQmp,8.98
MOTOR,42.63--motOr,42.63--ENGINE,31.88--En_In,31.88
MUNT,10.89--m}nt,10.89--COIN,9.75--k4n,9.75
NAALD,8.51--nalt,8.51--NEEDLE,11.92--nidP,11.92
NEST,11.27--nEst,11.27--NEST,11.1--nEst,11.1
ONTWERP,8.99--OntwErp,8.99--DESIGN,16.2--dIz2n,16.2
OORZAAK,13.35--orzak,13.35--CAUSE,310.04--k$z,310.04
OOST,7.45--ost,7.45--EAST,49.55--ist,49.55
PIJL,7.11--pKl,7.11--ARROW,7.84--{r5,7.84
POST,37--pOst,37--MAIL,36.84--m1l,36.84
PUNT,73.77--p}nt,73.77--POINT,236.53--p4nt,236.53
RIDDER,13.58--rId@r,13.58--KNIGHT,26.76--n2t,26.76
RING,52.34--rIN,52.34--RING,92.75--rIN,92.75
SCHERM,13.68--sxErm,13.68--SCREEN,23.39--skrin,23.39
SCHULD,178.1--sx}lt,178.1--DEBT,14.22--dEt,14.22

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SNEEUW,24.31--snew,24.31--SNOW,31.35--sn5,31.35
SNEL,463.6--snEl,463.6--FAST,137.45--f#st,137.45
SNOEP,12.55--snup,12.55--CANDY,35.78--k{ndI,35.78
SPIJT,665.78--spKt,665.78--REGRET,27.14--rIgrEt,27.14
SPORT,20.12--spOrt,20.12--SPORT,19.9--sp$t,19.9
STEM,86.53--stEm,86.53--VOTE,34.33--v5t,34.33
STERK,95.22--stErk,95.22--STRONG,86.86--strQN,86.86
STORM,29.61--stOrm,29.61--STORM,30.86--st$m,30.86
SUIKER,21.82--sLk@r,21.82--SUGAR,37.76--SUg@R,37.76
TEKEN,76.36--tek@,76.36--SIGN,133.27--s2n,133.27
TENNIS,4.64--tEn@s,4.64--TENNIS,13.63--tEnIs,13.63
TWIJFEL,34.03--twKf@l,34.03--DOUBT,62.84--d6t,62.84
VERHAAL,202.98--v@rhal,202.98--TALE,12--t1l,12
VIJAND,60.69--vKjAnt,60.69--ENEMY,48.51--En@mI,48.51
VONK,2.22--vONk,2.22--SPARK,6.27--sp#k,6.27
VUIL,24.06--vLl,24.06--DIRT,25.69--d3t,25.69
WEES,233.69--wes,233.69--ORPHAN,5.75--$fH,5.75
WIND,50.58--wInt,50.58--WIND,59.37--w2nd,59.37
WINTER,22.36--wInt@r,22.36--WINTER,26.22--wInt@R,26.22
WORTEL,6.11--wOrt@l,6.11--CARROT,3.82--k{r@t,3.82
ZAAD,6.33--zat,6.33--SEED,7.57--sid,7.57
ZEEP,14.22--zep,14.22--SOAP,15.2--s5p,15.2
ZOUT,15.5--zMt,15.5--SALT,19.51--s$lt,19.51
ZUUR,10.18--zyr,10.18--ACID,9.96--{sId,9.96
ZWAAR,80.84--zwar,80.84--HEAVY,47.29--hEvI,47.29
PLAN,143.34--plAn,143.34--PLAN,145.73--pl{n,145.73
KUS,51.89--k@s,51.89--KISS,121.16--kIs,121.16
TYPE,38.08--tip@,38.08--TYPE,60.65--t2p,60.65
WILD,25.41--WIlt,25.41--WILD,57.31--w2ld,57.31
TREIN,73.15--trKn,73.15--TRAIN,95.06--tr1n,95.06
WINKEL,65.13--wINk@l,65.13--SHOP,53.55--SQp,53.55
CODE,46.7--kod@,46.7--CODE,53.12--k5d,53.12
MELK,39.7--mElk,39.7--MILK,42.53--mIlk,42.53
SCHOEN,13.45--sxun,13.45--SHOE,30.39--Su,30.39
MASKER,19.23--mAsk@r,19.23--MASK,19.8--m#sk,19.8
KROON,14.32--kron,14.32--CROWN,13.69--kr6n,13.69
OVEN,9.9--ov@n,9.9--OVEN,8.88--VvH,8.88
LAM,7.34--lAm,7.34--LAMB,10.63--l{m,10.63
MYTHE,6.2--mit@,6.2--MYTH,6.9--mIT,6.9
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14.5. Additional words for Vanlangendonck (2014) simulation

```
ALARM,34.78--alArm,34.78--ALARM,29.84--@l#m,29.84
ATLAS,1.1--AtlAs,1.1--ATLAS,1.02--{tl@s,1.02
BABY,151.8--bebi,151.8--BABY,509.37--b1bI,509.37
CAKE,9.86--kek,9.86--CAKE,45.06--k1k,45.06
CLOWN,11.66--klMn,11.66--CLOWN,15.82--kl6n,15.82
COACH,31.81--kotS,31.81--COACH,47.63--k5J,47.63
CODE,46.7--kod@,46.7--CODE,53.12--k5d,53.12
DRAMA,11.16--drama,11.16--DRAMA,20.16--dr#m@,20.16
EXTRA,60.58--Ekstra,60.58--EXTRA,59.16--Ekstr@,59.16
FILM,174.37--fIlm,174.37--FILM,65.25--fIlm,65.25
FORT,9.38--fOrt,9.38--FORT,15.43--f$t,15.43
FRUIT,12.94--frLt,12.94--FRUIT,21.73--frut,21.73
HARD,159.46--hArt,159.46--HARD,307.84--h#d,307.84
HELP,279.95--hElp,279.95--HELP,921.12--hElp,921.12
HOBBY,8.67--hObi,8.67--HOBBY,6.94--hQbI,6.94
```

LAMP,13.88--lAmp,13.88--LAMP,12.88--l{mp,12.88
LAVA,2.77--lava,2.77--LAVA,3.45--l#v@,3.45
OVEN,9.9--ov@,9.9--OVEN,8.88--VvH,8.88
PARK,30.87--pArk,30.87--PARK,72.12--p#k,72.12
PLAN,143.34--plAn,143.34--PLAN,145.73--pl{n,145.73
PLANT,11.69--plAnt,11.69--PLANT,27.61--pl#nt,27.61
POKER,6.54--pok@r,6.54--POKER,16.06--p5k@R,16.06
PONY,4.92--pOni,4.92--PONY,8.1--p5nIz,8.1
POST,37--pOst,37--POST,32.43--p5st,32.43
PURE,14.7--,14.7--PURE,24.92--pj9R,24.92
SNACK,2.33--snEk,2.33--SNACK,9.14--sn{k,9.14
SOFA,3.13--sofa,3.13--SOFA,5.86--s5f@,5.86
SOLO,4--solo,4--SOLO,8.55--s5l5,8.55
TAXI,50.84--tAksi,50.84--TAXI,25.84--t{ksI,25.84
TENT,40.93--tEnt,40.93--TENT,17.49--tEnt,17.49
TEST,43.15--tEst,43.15--TEST,84.08--tEst,84.08
TOILET,39.49--twAlEt,39.49--TOILET,28.9--t4lIt,28.9
TYPE,38.08--tip@,38.08--TYPE,60.65--t2p,60.65
WARM,70.91--wArm,70.91--WARM,52.14--w$m,52.14
WILD,25.41--wIlt,25.41--WILD,57.31--w2ld,57.31
WOLF,20.26--wOlf,20.26--WOLF,20.27--wUlf,20.27
WORM,9.1--wOrm,9.1--WORM,10.12--w3m,10.12
ZONE,13.08--zzonen,13.08--ZONE,20.12--z5nd,20.12
ARTIEST,10.08--Artist,10.08--ARTIST,28.63--#tIst,28.63
BAD,42.58--bAt,42.58--BATH,31.12--b#T,31.12
BEEST,52.55--best,52.55--BEAST,24.55--bist,24.55
BLOK,11.62--blOk,11.62--BLOCK,40.53--blQk,40.53
BOM,51.32--bOm,51.32--BOMB,53.65--bQm,53.65
BORST,26.64--bOrst,26.64--CHEST,40.98--JEst,40.98
FRONS,0.37--frOns,0.37--FROWN,2.04--fr6n,2.04
GAST,56.26--xAst,56.26--GUEST,39.94--gEst,39.94
HEL,84.04--hEl,84.04--HELL,470.82--hEl,470.82
HOOP,367.83--hop,367.83--HOPE,320.63--h5p,320.63
HOUT,23.58--hMt,23.58--WOOD,27--wUd,27
HUIS,818.9--hLs,818.9--HOME,774.33--h5m,774.33
IDEE,482.99--ide,482.99--IDEA,359.04--2d7,359.04
KALF,3.06--kAlf,3.06--CALF,2.96--k#f,2.96
KAMP,41.73--kAmp,41.73--CAMP,51.22--k{mp,51.22
KEGEL,0.43--keG@l,0.43--CONE,2.92--k5n,2.92
KIKKER,8.23--kIk@r,8.23--FROG,11.82--frQg,11.82
KOMMA,2.15--kOma,2.15--COMMA,0.98--kQm@,0.98
KOOI,13.81--koj,13.81--CAGE,20.27--k1_,20.27
KROON,14.32--kron@,14.32--CROWN,13.69--kr6n,13.69
KUS,51.89--k}s,51.89--KISS,121.16--kIs,121.16
LAM,7.34--lAm,7.34--LAMB,10.63--l{m,10.63
LIJM,3.98--lKm,3.98--GLUE,5.88--glu,5.88
LONG,9.47--lON,9.47--LUNG,8.24--lVN,8.24
MAGIE,32.98--maGi,32.98--MAGIC,52.69--m{_Ik,52.69
MA�S,5.21--,5.21--CORN,14.22--k$n,14.22
MASKER,19.23--mAsk@r,19.23--MASK,19.8--m#sk,19.8
MELK,39.7--mElk,39.7--MILK,42.53--mIlk,42.53
MYTHE,6.2--mite,6.2--MYTH,6.9--mIT,6.9
OLIJF,0.75--olKf,0.75--OLIVE,7.35--QlIv,7.35
PAD,41.99--pAt,41.99--PATH,24.55--p#T,24.55
PIEK,4.94--pik,4.94--PEAK,5.94--pik,5.94
PIL,9.4--pIl,9.4--PILL,11.82--pIl,11.82
PILOOT,30.12--pilot,30.12--PILOT,26.67--p2l@t,26.67
ROOS,11.71--ros,11.71--ROSE,53.02--r5z,53.02
SCHOEN,13.45--sxun,13.45--SHOE,30.39--SQd,30.39
SLOT,52.46--slOt,52.46--LOCK,56.57--lQk,56.57
SPOOR,43.72--spor,43.72--TRAIL,19.2--tr1l,19.2

STOUTMOEDIG,0.32--stMtmud@x,0.32--BOLD,7.55--b5ld,7.55
STRAND,40.16--strAnt,40.16--BEACH,56.63--biJ,56.63
TEKST,19.94--tEkst,19.94--TEXT,5.24--tEkst,5.24
TREIN,73.15--trKn,73.15--TRAIN,95.06--tr1n,95.06
TROTS,111.46--trOts,111.46--PRIDE,27.67--pr2d,27.67
VORK,5.19--vOrk,5.19--FORK,8.82--f$k,8.82
VROUW,821.67--vrMw,821.67--FEMALE,31.61--fim1l,31.61
WINKEL,65.13--wINk@l,65.13--SHOP,53.55--SQp,53.55
WOND,14.02--wOnt,14.02--WOUND,26.53--wund,26.53
ZICHT,23.44--zIxt,23.44--SIGHT,45.31--s2t,45.31
KUNST,37.09--k}nst,37.09--ARTS,9.22--#ts,9.22
KNAL,14.82--knAl,14.82--BANG,19.98--b{N,19.98
RUNDVLEES,3.02--r}ntfles,3.02--BEEF,19.71--bif,19.71
BLANCO,1.85--blANko,1.85--BLANK,9.71--bl{Nk,9.71
TREE,1.17--tre,1.17--BOOM,21.8--bum,21.8
SAAI,31.47--saj,31.47--BORING,27.41--b$rIN,27.41
MERK,19.12--mErk,19.12--BRAND,13.96--br{nd,13.96
RAS,16.46--rAs,16.46--BREED,6.33--brid,6.33
DUIF,5.35--dLf,5.35--DOVE,5.57--dVv,5.57
MAP,4.53--mAp,4.53--FOLDER,1.63--f5ld@R,1.63
BENDE,32.24--bEnd@,32.24--GANG,30.14--g{N,30.14
KERN,9.26--kErn,9.26--GIST,1.1--_Ist,1.1
BLIJ,277.3--blK,277.3--GLAD,171.37--gl{d,171.37
SOORT,222.02--sort,222.02--KIND,590.69--k2nd,590.69
LUS,1.37--l}s,1.37--LOOP,6.76--lup,6.76
AANBOD,26.85--ambOt,26.85--OFFER,74.71--Qf@R,74.71
VIJVER,4.32--vKv@r,4.32--POND,6.33--pQnd,6.33
ZWEMBAD,23.17--zwEmbAt,23.17--POOL,46.98--pul,46.98
GEPAST,7.16--x@pAst,7.16--PROPER,25.27--prQp@R,25.27
HELLING,2.38--hElIN,2.38--RAMP,2.88--r{mp,2.88
ZELDZAAM,10.02--zEltsam,10.02--RARE,21.31--r8R,21.31
DAK,54.84--dAk,54.84--ROOF,35.65--ruf,35.65
KAMER,275.24--kam@r,275.24--ROOM,439.51--rum,439.51
JARGON,0.64--jArGOn,0.64--SLANG,1.39--sl{N,1.39
KLAP,29.27--klAp,29.27--SLAP,12.47--sl{p,12.47
SLANK,3.16--slANk,3.16--SLIM,11.86--slIm,11.86
DRAAI,65.93--draj,65.93--SPIN,14.63--spIn,14.63
PLEK,177.41--plEk,177.41--SPOT,61.57--spQt,61.57
LENTE,16.3--lEnt@,16.3--SPRING,31.31--sprIN,31.31
PODIUM,19.55--podij}m,19.55--STAGE,45.57--st1_,45.57
STAAL,10.18--stal,10.18--STEEL,18.45--stil,18.45
STRAND,40.16--strAnt,40.16--STRAND,1.84--str{nd,1.84
VAL,115.46--vAl,115.46--TRAP,23.84--tr{p,23.84
BOOM,52.25--bom,52.25--TREE,65--tri,65
GROOT,237.51--xrot,237.51--VAST,6.1--v#st,6.1
SLECHTST,0.48--slExtst,0.48--WORST,56.35--w3st,56.35
BANG,477.21--bAN,477.21--AFRAID,247.67--@fr1d,247.67
STRAND,40.16--strAnt,40.16--BEACH,56.63--biJ,56.63
TRIL,2.06--trIl,2.06--BEEF,19.71--bif,19.71
BORING,0.07--borIN,0.07--BORE,7.75--b$R,7.75
KIND,333.3--kInt,333.3--CHILD,157.65--J2ld,157.65
GANG,110.8--xAN,110.8--CORRIDOR,5.57--kQrId$R,5.57
LOOP,118.2--lop,118.2--COURSE,487.22--k$s,487.22
ROOM,7.59--rom,7.59--CREAM,48.71--krim,48.71
DOVE,2.52--dov@,2.52--DEAF,14.53--dEf,14.53
RAMP,25.89--rAmp,25.89--DISASTER,17.27--dIz#st@R,17.27
ARTS,32.79--Arts,32.79--DOCTOR,263.94--dQkt@R,263.94
BRAND,44.39--brAnt,44.39--FIRE,215.49--f2@R,215.49
VAST,662.03--vAst,662.03--FIXED,32.29--fIkst,32.29
FOLDER,1.81--fOld@r,1.81--FLYER,3.39--,3.39
STAGE,2.93--staZ@,2.93--INTERNSHIP,2.98--,2.98

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SPRING,25.61--sprIN,25.61--JUMP,69.82--_Vmp,69.82
BRIEF,73.84--brif,73.84--LETTER,82.61--lEt@R,82.61
SLAP,7.11--slAp,7.11--LIMP,3.67--lImp,3.67
SPOT,7.57--spOt,7.57--MOCKERY,1.84--mQk@rI,1.84
POOL,3.54--pol,3.54--POLE,12.59--p5l,12.59
POND,37.07--pOnt,37.07--POUND,13.88--p6nd,13.88
ROOF,2.26--rof,2.26--ROBBER,4.69--rQb@R,4.69
OFFER,12.37--Of@r,12.37--SACRIFICE,17.9--s{krIf2s,17.9
WORST,8.78--wOrst,8.78--SAUSAGE,7.78--sQsI_,7.78
GLAD,8--xlAt,8--SLIPPERY,4.41--slIp@rI,4.41
SLIM,111.55--slIm,111.55--SMART,96.25--sm#t,96.25
SLANG,21.59--slAN,21.59--SNAKE,22.35--sn1k,22.35
SPIN,7.8--spIn,7.8--SPIDER,10.1--sp2d@R,10.1
TRAP,52.28--trAp,52.28--STAIRWAY,1.59--st8w1,1.59
STEEL,8.62--stel,8.62--STEM,2.24--stEm,2.24
TREE,1.17--tre,1.17--STEP,118.67--stEp,118.67
PROPER,2.93--prop@r,2.93--TIDY,3.71--t2dI,3.71
BOOM,52.25--bom,52.25--TREE,65--tri,65
RARE,43.98--rar,43.98--WEIRD,101.1--w7d,101.1
BLANK,16.81--blANk,16.81--WHITE,171.45--w2t,171.45
BREED,6.22--bret,6.22--WIDE,23.8--w2d,23.8
GIST,0.62--xIst,0.62--YEAST,0.86--jist,0.86
```

14.6. Input Dijkstra et al. (2010) simulation

```
0:ACID
0:ANGEL
0:ANGLE
0:ANGRY
0:ANIMAL
0:ARMY
0:ARROW
0:BAKER
0:BAMBOO
0:BANANA
0:BEARD
0:BOTTLE
0:BREEZE
0:BRIDE
0:BRIGHT
0:BUCKET
0:BUCKET
0:BULL
0:BULLET
0:CANDY
0:CARD
0:CARROT
0:CAUSE
0:CAVE
0:CHAOS
0:CHOICE
0:CIRCLE
0:CIRCUS
0:CODE
0:COFFEE
0:COIN
0:COLOUR
0:COOL
0:CORD
0:CORE
0:CRAZY
0:CRIME
0:CRISIS
0:CROWD
0:CROWN
0:DANGER
0:DEAF
0:DEBATE
0:DEBT
0:DEMAND
0:DESIGN
0:DESK
0:DETAIL
0:DIRT
0:DOCTOR
0:DOMAIN
0:DONKEY
0:DOUBT
0:DUCK
0:DUKE
0:DUTY
0:EAGLE
0:EASE
0:EAST
0:EMPTY
0:ENEMY
0:ENGINE
0:ERROR
0:FAITH
0:FAST
0:FAVOUR
0:FEAR
0:FEVER
0:FIST
0:FOOT
0:GARDEN
0:GOLD
0:GRAVE
0:GREEN
0:GREY
0:GUIDE
0:HEAVY
0:HOLE
0:HONEY
0:HORSE
0:HOTEL
0:HOUR
0:HUNGER
0:IDIOT
0:JEWEL
0:JOKE
0:JUDGE
0:JUICE
0:KING
0:KISS
0:KNIFE
0:KNIGHT
0:LAMB
0:LARGE
0:LENGTH
0:LOSS
0:MAIL
0:MASK
0:MASS
0:MELON
0:MEMBER
0:MENU
0:MERCY
0:MILD
0:MILK
0:MODEL
0:MONKEY
0:MOON
0:MYTH
0:NEEDLE
0:NEST
0:NOISE
0:NOISE
0:ORPHAN
0:OVEN
0:PAIN
0:PEACE
0:PEARL
0:PIGEON
0:PILLOW
0:PLAN
0:POCKET
0:POEM
0:POET
```

0:POINT
0:PORT
0:PRICE
0:PRINCE
0:PROOF
0:PURE
0:RABBIT
0:RAIL
0:REGRET
0:RENT
0:RHYTHM
0:RICH
0:RING
0:ROOF
0:RUMOR
0:SALT
0:SCREEN
0:SEED
0:SHAPE
0:SHOE
0:SHOP
0:SIGN
0:SKIRT
0:SLEEVE
0:SMOOTH
0:SNOW
0:SOAP
0:SOCK
0:SONG
0:SOUP
0:SOUTH
0:SPARK
0:SPOON
0:SPORT
0:STORM
0:STORY
0:STRONG
0:SUGAR
0:SUMMER
0:SWAMP
0:TALE
0:TARGET
0:TENNIS
0:THIEF
0:THIN
0:THIRST
0:THORN
0:THUMB
0:TOMATO
0:TONGUE
0:TOOTH
0:TOWER
0:TRAIN
0:TREE
0:TYPE
0:UGLY
0:VIRGIN
0:VOTE
0:VOYAGE
0:WALL
0:WAVE
0:WHEEL
0:WILD
0:WIND
0:WINTER
0:WITCH
0:YOUTH

14.7. Input Vanlangendonck (2014) simulation

0:RAISIN
0:SHARK
0:FROG
0:FAIRY
0:MAZE
0:GLUE
0:CAGE
0:RABBIT
0:LAWN
0:LEAF
0:CONE
0:NURSE
0:FEVER
0:BOLD
0:LOCK
0:CLOUD
0:TRAIL
0:CORN
0:FOAM
0:PRIDE
0:SNAKE
0:FEMALE
0:WAVE
0:IRON
0:CHEST
0:ROOF
0:WOOD
0:BEACH
0:SHOP
0:DRESS
0:RAIN
0:SONG
0:FEAR
0:ARMY
0:GIRL
0:CITY
0:HOME
0:LAVA
0:CLOWN
0:HOBBY
0:WORM
0:POKER
0:SNACK
0:SOFA
0:WOLF
0:SOLO
0:OVEN
0:PONY
0:ZONE
0:ATLAS
0:CAKE
0:TOILET
0:ALARM
0:TAXI
0:LAMP
0:TENT
0:COACH
0:FRUIT
0:CODE
0:DRAMA
0:EXTRA
0:FORT
0:PURE
0:WILD
0:BABY
0:WARM
0:PARK
0:FILM
0:POST
0:TEST
0:PLANT
0:PLAN
0:HARD
0:TYPE
0:HELP
0:COMMA
0:MOLE
0:SOCK
0:SATIN
0:BEAST
0:LAMB
0:TIGER
0:IDOL
0:DOCK
0:WOOL
0:CALF
0:FORK
0:PILL
0:LUNG
0:FLAG
0:DIET
0:STIFF
0:SAND
0:MAID
0:SILVER
0:BAKER
0:ATOM
0:MYTH
0:BOMB
0:MAGIC
0:KNEE
0:PILOT
0:MILK
0:GOLD
0:ARTIST
0:TASK
0:METAL
0:BLOCK
0:BOAT
0:CAMP
0:TRAIN
0:NECK
0:ROUND
0:HELL
0:MASS
0:RIVER
0:IDEA
0:BOOK
0:WORK
0:CLAW
0:DUNE
0:FROWN
0:PLUM
0:SWAN
0:BEAN
0:CORD
0:GOAT
0:NAIL
0:OLIVE
0:THIEF
0:CORK
0:MASK
0:WINNER
0:CIGAR
0:DEAF
0:TOWER
0:MONK
0:PEAK
0:SHOE
0:KISS
0:CROWN
0:SAUCE
0:FLOOD
0:PANIC

0:BATH
0:BUTTER
0:FIST
0:WOUND
0:GUIDE
0:GUEST
0:TONGUE
0:PATH
0:HERO
0:WHEEL
0:TEXT
0:WINE
0:TITLE
0:ROSE
0:SIGHT
0:PAIN
0:FOOT
0:PRICE
0:HOPE
0:HOUR
0:FIELD
0:NAME

14.8. Input English to Dutch Pruijn (2015) simulation

0:BOAT
0:BOOK
0:BOSS
0:COFFEE
0:DAUGHTER
0:FATHER
0:FIELD
0:FIGURE
0:FOOT
0:FRIEND
0:GROUND
0:HAIR
0:HONEY
0:HOUSE
0:MIDDLE
0:MINUTE
0:MOTHER
0:MOUTH
0:MUSIC
0:NAME
0:NIGHT
0:PAIN
0:POLICE
0:RICH
0:STREET
0:SUN
0:TABLE
0:TEA
0:WORD
0:WORK
0:WORLD
0:YEAR
0:BAKER
0:BIBLE
0:BRIDE
0:BROWN
0:CORAL
0:CULTURE
0:CURL
0:DOMAIN
0:EAR
0:FLAME
0:FOX
0:METHOD
0:MOTIVE
0:MOUSE
0:PANIC
0:PEARL
0:PEPPER
0:PIPE
0:PIRATE
0:RAW
0:RICE
0:SAUCE
0:SILVER
0:SLAVE
0:SWEAT
0:TASK
0:THIEF
0:TIGER
0:TROPHY
0:VAGUE
0:VISION
0:WARMTH
0:ANGRY
0:ART
0:BLACK
0:BODY
0:BOY
0:BUILDING
0:CAR
0:CLEAN
0:DARK
0:DIRTY
0:DOG
0:EYE
0:FACE
0:FEELING
0:GIRL
0:HORSE
0:KEY
0:LOW
0:MONEY
0:MORNING
0:OFFICE
0:QUESTION
0:SHOWER
0:SONG
0:SPACE
0:STORY
0:TIRED
0:UNCLE
0:VOICE
0:WALL
0:WINDOW
0:WOMAN
0:ANT
0:AUTUMN
0:AXE
0:BULL
0:CLOUD
0:COWARD
0:CURSE
0:EAGLE
0:FARMER
0:FEVER
0:GARDEN
0:GARLIC
0:GLOVE
0:HEALTHY
0:HUNTER
0:JUICE
0:KIDNEY
0:LACK
0:MIRROR
0:MUSCLE
0:PEACH
0:PENCIL
0:PLATE
0:RABBIT
0:SCAR
0:SCIENCE
0:SHARK
0:SLEEVE
0:SOFT
0:SPICY
0:SPOON
0:YELLOW

14.9. Input Dutch to English Pruijn (2015) simulation

0:BIER
0:BOEK
0:DOCHTER
0:EINDE
0:GOUD
0:GROND
0:HOOFD
0:HUIS
0:KAT
0:KOFFIE
0:MAAN
0:MOEDER
0:MOND
0:MUZIEK
0:NAAM
0:NACHT
0:PIJN
0:PRIJS
0:RIJK
0:RIVIER
0:STRAAT
0:TAFEL
0:THEE
0:VADER
0:VOET
0:VRIEND
0:WERELD
0:WERK

0:WIJN
0:WOORD
0:ZEE
0:ZOON
0:BAKKER
0:BALKON
0:BIJBEL
0:BOT
0:BRUID
0:BRUIN
0:DIEF
0:DOMEIN
0:DROOG
0:GEIT
0:HONING
0:KLIMAAT
0:MUIS
0:NATUUR
0:OOR
0:PAREL
0:PEPER
0:PIJP
0:PIRAAT
0:RAUW
0:REGEN
0:SAUS
0:SOK
0:SOM
0:TROFEE
0:VELD
0:VLAM
0:VOS
0:WARMTE
0:WEZEL
0:ZILVER
0:ZWEET
0:AUTO
0:AVOND
0:BEDRIJF
0:BOOS
0:BUREAU
0:DAK
0:DONKER
0:DORP
0:GEBOUW
0:GELD
0:GEVAAR
0:GEVOEL
0:GEZICHT
0:HOND
0:JONGEN
0:KANTOOR
0:LICHAAM
0:MES
0:MOE
0:MUUR
0:OORLOG
0:PAARD
0:RUIMTE
0:SCHOON
0:SLEUTEL
0:STAD
0:TANTE
0:VERHAAL
0:VRAAG
0:VROUW
0:ZORG
0:ZWART
0:AREND
0:BEKER
0:BIJL
0:BOER
0:DUIF
0:GEEL
0:GEZOND
0:HAAI
0:HERFST
0:IJZER
0:JAGER
0:KNOP
0:KOORTS
0:LAWAAI
0:LEPEL
0:LIED
0:MAAG
0:MEISJE
0:MIER
0:MOUW
0:NIER
0:PERZIK
0:PITTIG
0:SLAGER
0:SPIER
0:STIER
0:VERF
0:VERKEER
0:VIES
0:VLOEK
0:WOLK
0:ZACHT

14.10. Input false friends simulation

0:ARTS
0:BANG
0:BLANK
0:BOOM
0:BORING
0:BRAND
0:BRAVE
0:BREED
0:BRIEF
0:DOVE
0:FOLDER
0:GANG
0:GIST
0:GLAD
0:KIND
0:LOOP
0:OFFER
0:POND
0:POOL
0:PROPER
0:RAMP
0:RARE
0:ROOF
0:ROOM
0:SLANG
0:SLAP
0:SLIM
0:SPIN
0:SPOT
0:SPRING
0:STAGE
0:STEEL
0:STRAND
0:TERM
0:TRAP
0:TREE
0:VAST
0:WORST