Abstract

Word frequency is assumed to correlate with word familiarity, but the strength of this correlation has not been thoroughly investigated. In this paper, we report on our analysis of the correlation between a word familiarity rating list obtained through a psycholinguistic experiment and the log-frequency obtained from various corpora of different kinds and sizes (up to the terabyte scale) for English and Japanese. Major findings are threefold: First, for a given corpus, familiarity is necessary for a word to achieve high frequency, but familiar words are not necessarily frequent. Second, correlation increases with the corpus data size. Third, a corpus of spoken language correlates better than one of written language. These findings suggest that cognitive familiarity ratings are correlated to frequency, but more highly to that of spoken rather than written language.

1 Introduction

Word familiarity is the relative ease of perception attributed to every word. For example, the two words “encounter” and “meeting” could be used in a similar way, but “meeting” is cognitively easier than “encounter”. Word familiarity is interesting from a scientific viewpoint to investigate the mental process of word-meaning acquisition. It is also related to language engineering where it is applied in language education and e-learning.

Within the past few decades, attempts have been made to measure word familiarity through human experiments within the psycholinguistic domain. Studies have generated several word familiarity lists such as Wilson’s list (Wilson, 1988) and the MRC database (MRC Psycholinguistic Database, 2006) in English, which consists of several thousand words with familiarity ratings. In Japanese, Amano’s list (Amano and Kondo, 2000) contains about 70,000 pairs of words and corresponding ratings.

Even though such lists have been generated, it is still not entirely clear what processes are involved when readers rate the familiarity of a word. Familiarity ratings have often been interpreted as a measure of the frequency of exposure to a word (MRC Psycholinguistic Database, 2006). Many studies show that a word’s frequency affects its perception (Segui et al., 1982) (Dupoux and Mehler, 1990) (Marslen-Wilson, 1990), while some studies point out that for word perception the familiarity thus acquired through experiment is a better predictor than frequency (Gernsbacher, 1984) (Gordon, 1985) (Kreuz, 1987) (Nusbaum et al., 1984). A psychological study reports the relation between word familiarity and frequency effect in visual and auditory word recognition through experiments (Comine et al., 1990).
All such previous work was done on the psycholinguistic side and there have been only limited attempts on the computational linguistic side to verify the relationship between language statistics and familiarity. This paper reports our investigation of the relation between the word familiarity ratings obtained in a psycholinguistic experiment and the word frequency acquired from various corpora. Our study is limited to investigating the relation through statistical measurements found in corpora, and does not include any psycholinguistic or cognitive experimental results. After showing the basic degree of correlation and its general characteristics, we discuss how the corpus data size and corpus type affect the degree of correlation.

Our study is intended to contribute to a better scientific understanding of word familiarity from a linguistic data viewpoint. The correlation of familiarity with the log frequency of use — information carried by the word — is measured per, in a global sense, Weber-Fechner’s law, which states that the relationship between stimulus and perception is generally logarithmic (Ladd, 2006) (Heidelberger and Klohr, 2004). Familiarity can therefore be a linguistic trace under this law; or, to put it otherwise, Weber-Fechner’s law can be considered a general model underlying familiarity. This article attempts to consider the contours of the nature of familiarity through an empirical approach.

The findings in this article should contribute to language engineering, especially to language education, since an accurate list of word familiarity ratings is the key to reliable reading level assessment. So far, every method we know of measures vocabulary difficulty using either a frequency count or a vocabulary list of easy words. For example, the Dale-Chall method (Chall and Dale, 1995), counts the number of words in a text which are not registered in the Dale-Chall list of 3000 basic words. This list indicates that “easy” words appear in most texts, but the lists are manually constructed without a solid scientific grounding. Familiarity ratings have a great potential to replace such a list, but the experimental workload needed to generate such lists in various languages is a problem. Thus, a statistical measure that can be used as a pseudo-familiarity rating would be valuable. As for the use of frequency in reading level assessment, recent studies have attempted to measure vocabulary difficulty by means of frequency (Collins-Thompsin and Callan, 2004) (Schwarm and Ostendorf, 2005). However, the function of frequency with respect to reading level has not been clarified in these studies. Thus, investigating the nature of frequency with respect to familiarity ratings could provide the key to a better reading level assessment. Our intention in this paper is to show that the log-frequency of a word’s use is a possible measure of such pseudo-familiarity, if it is measured in an adequate corpus. We investigate which corpus conditions lead to higher correlation between a word’s log-frequency and its familiarity.

2 Database

2.1 Word Familiarity Lists

Most readers would probably agree that “meeting” is more familiar than “encounter”. Likewise, coherency is assumed among adults regarding the relative familiarity of words. The exact definition of familiarity remains controversial and the term is not well-defined. Moreover, no psycholinguistic experiment is free from individual variation. Still, familiarity rating attempts to extract such cohesion from human thought through psycholinguistic experiments by taking the view that familiarity lists are a database which partly reveals human perception about language. In general, familiarity ratings are obtained by asking people to subjectively score the familiarity of words on multiple levels, and then post-processing the scores in some standard way defined in psychological experiment methodologies (Coltheart, 1981) (Wilson, 1988) (Amano and Kondo, [5]).
Table 1: Our Database Used to Measure Frequency

| label             | Num. tokens (total words) | Num. types (different words) | spoken/ written text | kind of text     |
|-------------------|---------------------------|-----------------------------|----------------------|------------------|
| WSJ (3-years)     | 42287431                  | 127353                      | written              | newspaper        |
| Wikipedia-E       | 711143194                 | 168533                      | written              | encyclopedia     |
| Web-E             | 88267343947               | 204724587                   | written              | mixture          |
| BNC               | 97098970                  | 364262                      | both                 | mixture          |
| MICASE            | 1279792                   | —                           | spoken               | academic speaking|
| Mainichi (5 years)| 80709011                  | 198767                      | written              | newspaper        |
| Wikipedia-J       | 130418600                 | 619636                      | written              | encyclopedia     |
| Web-J             | 7183558565                | 5474644                     | written              | mixture          |
| Aozora            | 25975560                  | 139961                      | written              | literature       |
| Spoken Corpus-J (SCJ)| 7498763       | 47767                       | spoken               | academic lecture |

The signals were given word based without context.

In English, a list of several thousand words was first reported in [Nusbaum et al., 1984]. A more recent effort has been the MRC project reported in [Cortheart, 1981]. In addition to familiarity, the list contains various scores for each word, such as the acquisition age and the meaningfulness. In total, the MRC list contains 150,837 words for 26 different linguistic properties. However, each score is given for only part of this word set and the familiarity rating is available for only 4894 words through the MRC web-based interface [MRC Psycholinguistic Database, 2006]. This list is used in our study and is called the MRC list in this article. The MRC list was constructed by merging three different sets of familiarity norms: Pavio (unpublished), Toglia and Battig (1978) and Gilhooly and Logie (1980). Each database was constructed separately by asking subjects to rate words by familiarity levels. The three sets of norms were then merged under statistical consideration as described in more detail in Appendix 2 of the MRC Psycholinguistic Database User Manual [Coltheart, 1981]. The historical consequence of this mixture possibly makes the use of this database for this research questionable, but this is the only large familiarity score available in English to date.

For Japanese, Amano and Kondo (1999) generated a word familiarity list of 68,550 words through a large-scale experiment [Amano and Kondo, 2000]. This list, referred to as the Amano list, can be purchased and was used in our study. The values were obtained by asking 40 people to score content words in a standard Japanese dictionary, with a familiarity score of 7 different levels. Each person scored 9000 words, and only statistically plausible judgments were used to generate the final score of familiarity [Amano and Kondo, 1999].

In both of these lists, the familiarity rating ranges from 1.0 to 7.0, with 7.0 being the most familiar and 1.0 being the least familiar. The two lists differ in that the Amano list only contains content words, whereas MRC also has some functional words. Note that functional words can be familiar or unfamiliar. For example, the familiarity of “must” is clearly higher than that of “ought”. The functional words in the MRC list do not necessarily contain most frequently used functional words such as “and” and “to”. The most familiar and unfamiliar words taken from the MRC and Amano lists are listed in the first column of Table 2 for English and Table 3 for Japanese. For Japanese, the word

\[1\text{In MRC, the original ratings ranged from 100 to 700; we divided these by 100 in our experiment so that they would be consistent with the Amano list.} \]
Table 2: Familiar and frequent words (top), unfamiliar and rare words (bottom) in English

|      | MRC  | WSJ  | BNC  | Wikipedia-E | Web-E | MICASE |
|------|------|------|------|-------------|-------|--------|
| Most | breakfast | the  | the  | on          | the   | the    |
| 2nd  | afternoon | be   | be   | as          | and   | that   |
| 3rd  | clothes   | of   | of   | for         | be    | and    |
| 4th  | dad       | to   | and  | to          | of    | you    |
| 5th  | bedroom   | a    | to   | a           | to    | I      |
| 6th  | girl      | in   | a    | in          | a     | of     |
| 7th  | radio     | and  | in   | and         | in    | it     |
| 8th  | book      | say  | have | be          | for   | to     |
| 9th  | water     | that | that | of          | you   | a      |
| 10th | newspaper | have | it   | the         | I     | in     |

|      | MRC  | WSJ  | BNC  | Wikipedia-E | Web-E | MICASE |
|------|------|------|------|-------------|-------|--------|
| Most | metis | zonal | paulet | fatly | sandarach | abatement |
| 2nd  | anele | ziti  | shivery | fading | monopetalous | amuse |
| 3rd  | goral | zestful | decoction | exorable | palatially | angel |
| 4th  | pavis | yodel | folate | edgily | febricity | clown |
| 5th  | witan | yeti  | sural  | bronchitic | coriss | hobby |
| 6th  | jupon | dater | corse  | brassart | acilderts | melon |
| 7th  | kevel | twinbed | armor  | benthonic | sulphurize | oasis |
| 8th  | lagan | daby  | broil  | blushful | amortizement | noodle |
| 9th  | daman | voiron | trey   | bawdily | ruralize | prefix |
| 10th | manus | toxemia | velveteen | alsoran | allotropism | token |

meaning is shown under the word only for content words. Words such as daily and greeting words are among the most familiar words, whereas words which are difficult to find even in dictionaries are among the most unfamiliar. For Japanese, especially, even though the words might not seem difficult from the English translations, the unfamiliarity of words in the lower block of Table 3 is prominent, which is partly noticeable from the excessive complexity of the characters.

2.2 Corpora

Data listed in Table 1 are used to measure frequency. The first block shows corpora for English and the second block shows those for Japanese. Our data includes newspaper corpora, data obtained from Wikipedia, web data, mixed-type corpora, and spoken language corpora.

As the newspaper corpora, we used the three-year WSJ newspaper corpus for English and the five-year Mainichi newspaper corpus for Japanese.

From Wikipedia, we extracted all English and Japanese texts and eliminated tags to acquire plain data. We obtained 1,912,595 pages for English, which amounted to 4.74 gigabytes without tags, whereas we obtained 372,890 pages for Japanese, which amounted to 945 megabytes.

The Web data was crawled and downloaded from the Internet in autumn 2006. Here, too, markup tags were eliminated and texts in English and Japanese were extracted. For English texts, 265,823,502 pages were scanned, which amounted to 1.9 terabytes of text data without tags, and for Japanese 12,751,271 pages were scanned and 69 gigabytes of data obtained.

\[\text{We thank Associate Professor K. Taura, of the University of Tokyo for offering us this data.}\]
Table 3: Familiar and frequent words (top), unfamiliar and rare words (bottom) in Japanese

|        | Amano          | Mainichi       | Aozora         | Wikipedia-J  | Web-J   | SCJ     |
|--------|----------------|----------------|----------------|--------------|---------|---------|
| Most   | ohanayou       | の              | の              | の           | の      | の      |
| 2nd    | thank          | を              | に              | に           | に      | て      |
| 3rd    | car            | に              | は              | は           | を      | だ      |
| 4th    | school         | は              | を              | する         | は      | に      |
| 5th    | money          | が              | が              | を           | する    | が      |
| 6th    | congratulations| する            | と              | が           | する    | が      |
| 7th    | morning        | と              | する            | と           | だ      | も      |
| 8th    | love           | で              | も              | で           | た      | ます    |
| 9th    | father         | いる            | ない            | ある         | ます    | を      |
| 10th   | I              | も              | ある            | いる         | と      | た      |

|        | Amano          | Mainichi       | Aozora         | Wikipedia-J  | Web-J   | SCJ     |
|--------|----------------|----------------|----------------|--------------|---------|---------|
| Most   | cover          | 剥脱            | 絕費           | 火筒         | 面目玉  | 緑取り  |
| 2nd    | sinter         | peeling off    | exfoliation    | gun          | prestige| edge    |
| 3rd    | alumina        | 瓷土            | 煉結           | 肾炎         | 機锋    | 窮迫    |
| 4th    | siskin         | lathe           | waste          | corbel       | brunt   | stranded|
| 5th    | siskin         | 煉結            | 異曲           | 牙癧         | 爆裂    | 更歇    |
| 6th    | familiarity     | mean            | iodine         | change       | depression| late    |
| 7th    | 分葉           | mean            | iodine         | change       | depression| late    |
| 8th    | tiller         | palm            | bulk           | oka          | hand operation| shake |
| 9th    | effort          | bacillus        | urgancy        | lamination   | bulk    | joining |
| 10th   | asphalt        | musk            | annealing      | drought      | gun     | withered branch |
|        | nettle         | 無碍            | 鬃影           | 花活け       | 加え算  | 脈打ち  |
BNC was used as a mixed-type corpus for English, while Aozora, a collection of literature corresponding to the Gutenberg project in Japanese, was used for Japanese. Spoken language corpora transcribed from spoken recordings were also used in our studies. For English we used MICASE (Michigan Corpus of Academic Spoken English)\(^3\), which is available only online. For Japanese, we used the Spoken Corpus of Japanese.

For every corpus except MICASE, frequency was measured after lemmatizing each word into standard forms using Tree-tagger\(^4\) for English and Chasen\(^5\) for Japanese. The standard form was used since every word in the familiarity list is in the standard form. Words of the same form with different senses are not distinguished, since as noted at the beginning of the previous section, a familiarity score was also measured without such disambiguation by context. Note that even after processing words into their standard forms, frequency lists acquired from large corpora can be huge. For example, the list for Web-E was more than 2 gigabytes.

From all corpora, the most frequent words and randomly chosen words which acquired the lowest frequency of \(n\) \((n = 1 \ldots 10)\) are listed in Table 2 and Table 3. In both tables, the most frequent words are common to most corpora in each language, but they do not match the most familiar words. Here, we see an obvious difference between frequency and familiarity: most familiar words are content words, whereas the most frequent words are functional, which is probably due to the lack of functional words in the familiarity list. The same tendency also holds in Japanese. As for the most rare and unfamiliar words, none of the lists share words, which is to be expected since language is characterized by a large number of rare events (LNRE).

3 The basic correlation

When a corpus is large, the frequency of a word will obviously be high. In contrast, the word familiarity rating ranges from 1.0 to 7.0. If a correlation coefficient is calculated directly with the raw frequency count, the calculation will be erroneous. Since log frequency ranges are close to the values of the familiarity ratings, we calculated the correlation coefficients between the log frequency and the familiarity rating. Moreover, from an information theory viewpoint, log-frequency can be interpreted as the information amount carried by a word, so our study can be interpreted as an investigation of the relation between the information amount and the familiarity of a word. In this study, we also assume the Weber-Fechner law applies to familiarity as noted in the Introduction.

Before we look at the correlation coefficients, some preparatory facts need to be established. Figure 1 shows the distribution of MRC and the log-frequency of BNC. The horizontal axis shows the familiarity rating for MRC and the log-frequency for BNC. The vertical axis shows the distribution of words for the corresponding log-frequency or familiarity. The monotonically descending line shows the distribution of BNC, which naturally follows the LNRE tendency of natural language. In contrast, the MRC plot has a peak at about 5 to 6. This shows a sampling bias of the words used for the psycholinguistic experiment when generating the word familiarity list. In fact, this bias is unavoidable, since a human subject can judge familiarity only for known words, and so the cohesion of human judgment regarding rare words is likely to be lower than that for frequently used words.

Bearing this distribution difference in mind, we analyzed the correlation of the familiarity lists and the log-frequency obtained from corpora.

3 http://quod.lib.umich.edu/m/micase/ Since MICASE was only available via a web-based interface, the statistics shown in Table 1 were taken from the MICASE web page.

4 http://www.ims.uni-stuttgart.de/projekte/corplex/TreeTagger/

5 http://chasen-legacy.sourceforge.jp/
The correlation plots of word familiarity and frequency are shown in Figure 2 for English and in Figure 3 for Japanese. Each graph corresponds to a corpus, so there are ten graphs in total, five for each language. The horizontal axes show the familiarity rating, whereas the vertical axes show the log-frequency. Each plot corresponds to a word for which a familiarity rating and a log-frequency were acquired.

The plots in general move from the bottom-left to the upper-right, showing the global trend of correlation. Moreover, the plots form a fat cloud or take a triangular form with the largest angle in the lower right corner. Such a triangular form indicates the inclusion of more rare but familiar words. The triangular tendency is most prominent when the data size is small and the familiarity list is large. For example, the graphs for Japanese, except for Web-J, show this triangular tendency, but the tendency resolves into a cloud without the angle when the corpus size is increased. Taking BNC as an example, five rare and familiar words are listed as follows: spank (familiarity rating=5.36 / frequency=19), pimple (5.57 / 20), dime (5.86 / 39), easygoing (5.25 / 41), quart (5.68 / 50). As shown, these words are familiar, but are unlikely to appear frequently in a corpus depending on the content.

On the other hand, the fact that there are very few plots in the upper left area shows there are few unfamiliar but frequent words. The tendency for plots to exist only in the lower right half of the graph indicates that, for a given corpus, frequent words are always familiar, whereas familiar words are not necessarily frequent. More precisely, for a given corpus, high frequency is a necessary condition for a word to attain a high familiarity rating, but is not a sufficient condition to make the word familiar. A question is then raised: what is a sufficient condition to make a familiar word frequent? Since the investigation was done for a given corpus, the answer to this question depends on the corpus, and thus a more precise question is: what is the corpus condition under which a familiar word is used frequently?

To verify the correlation degree, we calculated the correlation coefficients as shown in Table 4. The table shows three values for each corpus:

Coverage: the number (and percentage) of the words in the familiarity list found in the corpus,
Figure 2: Word familiarity and log-frequency in English
Figure 3: Word familiarity and log-frequency in Japanese.
Table 4: Coverage and Correlation Coefficients

| label                | Coverage of the words in the familiarity list | Pearson’s correlation coefficient | Spearman’s correlation coefficient |
|----------------------|-----------------------------------------------|----------------------------------|-----------------------------------|
| WSJ (3-years)        | 4772 (97.507%)                               | 0.6520                           | 0.7082                            |
| Wikipedia-E          | 4882 (99.755%)                               | 0.6677                           | 0.6801                            |
| Web-E                | 4892 (99.959%)                               | 0.7185                           | 0.7359                            |
| BNC                  | 4869 (99.489%)                               | 0.7438                           | 0.7776                            |
| MICASE               | 3608 (73.722%)                               | 0.5744                           | 0.7127                            |
| Mainichi (5 years)   | 38337 (55.926%)                              | 0.6327                           | 0.5330                            |
| Wikipedia-J          | 44784 (65.330%)                              | 0.5737                           | 0.4452                            |
| Web-J                | 48469 (70.706%)                              | 0.7193                           | 0.4920                            |
| Aozora               | 43430 (63.335%)                              | 0.4484                           | 0.3451                            |
| SCJ                  | 19736 (28.625%)                              | 0.4931                           | 0.5097                            |

Figure 4: Number of ranking reverses and Spearman’s correlation: in English (left) and Japanese (right)

**Pearson:** Pearson’s product-moment correlation coefficient, and  
**Spearman:** Spearman’s rank-order correlation coefficient.

Note that missing values —words which are in the familiarity list but not in the corpus— were not considered when calculating Pearson’s coefficient, whereas they were taken into consideration when calculating Spearman’s coefficient.

The coverage (first column) shows that the larger the corpus size, the greater the coverage. Since the magnitude of MRC is in the thousands, it was well covered: only two words from MRC were missing from the Web-E corpus. In contrast, since the Japanese familiarity list is large, even when using Web-J, the coverage only amounted to about 70%; therefore, the number of missing values is large in the case of Japanese.

The second and third columns show the two correlation coefficients. The general tendency is that a corpus with a high Pearson coefficient has a high Spearman coefficient. For example, the highest correlation coefficients of both types were attained with BNC for English. Still, there are inconsistencies; for example, Web-J had the highest Pearson coefficient for Japanese,
whereas Mainichi had the highest Spearman coefficient.

How significant these differences in the correlation coefficients are can be intuitively understood through simulation as follows. For each English and Japanese familiarity list, a copy of a list is generated (which of course perfectly correlates with the original). For this copy, two successively ranked words are randomly selected, and then their orders are reversed and the correlation with the original list is measured. By repeating this reversing procedure, the correlation will decrease as in Figure 4. The horizontal axes show the number of reversed pairs, and vertical axes show the correlation. In the English case, starting from 4894 ranked words, it required only 93 reverses to attain the BNC correlation, and 124 reverses to reach the Wikipedia-E level. In Japanese, since the Amano list is about ten times larger, more reverses are required to decrease the correlation from Mainichi to Aozora. For the 68,550 words of the Amano list, only 1340 additional reverses are needed to decrease the Mainichi correlation level to that of Aozora. Correlation thus decreases quickly even with slight inconsistencies with the original. Therefore, although the correlation seems different from Table 4, the difference is not as significant as it might seem.

To further reveal differences among the corpora, Table 5 shows the correlation among the corpora for words in the familiarity list. As shown in the first block of Table 5, many of the correlation values are over 0.8, some even near 1.0, showing high correlation in English. For Japanese, where the Amano list has 68,550 words, the values are naturally lower than in the English case, but still consistently above 0.34: this corresponds to almost 4280 reverses (from the Aozora correlation being almost 0.34, which corresponds to the 4280 reverses in Figure 4). Consequently, the difference is not as significant as it might seem from the coefficient values.

Still, the differences among corpora remain a question: what conditions cause one corpus to be more closely correlated with familiarity than another corpora. Therefore, in the remainder of this article we consider what these conditions could be and verify that two corpus criteria affect correlation with the familiarity list.

The correlation scores show that the correlation rises as the amount of data increases. This is natural, since, for a given corpus, high frequency is a necessary condition for high familiarity, and a larger corpus would increase the sampling size. Indeed, Table 4 shows that the correlation
of web data was among the highest if measured by the Pearson coefficient. Moreover, the larger the amount of data, the less triangular the plots are in Figure 2 and Figure 3, which reflects increased correlation. Therefore, the data size seems to account for some of the correlation increase.

The difference is caused not only because of the size counts, though. For example, Table 4 shows that for English, BNC beats Web-E in terms of both correlation coefficients, yet BNC is smaller in magnitude than Web-E. Similarly, for Japanese, Mainichi beats Wikipedia-J for both coefficients, despite Mainichi being much smaller than Wikipedia-J.

Such differences are probably due to differences in the corpus domains. Especially, when we compare the corpora with higher correlation (BNC, web, newspapers) and those with lower correlation (Aozora, Wikipedia), we see that the corpora containing more daily content seem to have higher correlation. BNC includes a spoken part (10%) which consists of orthographic transcriptions of unscripted informal conversations (recorded by volunteers selected from different age, regional and social classes in a demographically balanced way) and spoken language collected in different contexts, ranging from formal business or government meetings to radio shows and phone-ins. Also, MICASE and SCJ —both spoken— have relatively high Spearman coefficients despite their size. In contrast, Aozora and Wikipedia are at the extreme of written form. The highly correlated corpora include texts closer to spoken language, whereas the less correlated ones tend to be formed only of written language.

Consequently, the answer to the question raised in this section appears to consist of two factors:

- corpus size: a larger corpus better correlates with familiarity ratings
- corpus domain: spoken correlates better than written

In the following two sections, we verify the significance of each of these factors.

4 Effect of Data Size

Each corpus was divided into parts with the number of words in each part increasing exponentially (i.e., the number of words was $10^1$, $10^2$, $10^3$ . . . ) until the maximum data size was reached,
where a larger data set included the smaller ones. The relation between data size and correlation is shown in Figure 5. The horizontal axis shows the number of words (in thousands) in log-scale, and the vertical axis shows the correlation. Nine lines are shown, each corresponding to a corpus (except for MICASE, which was available online only). English corpora are represented by solid lines and Japanese corpora by dashed lines. Since the data size differs according to the corpus, the line lengths differ.

For every corpus, the correlation increased with size. The increase shows a log-linear tendency up to about 1 billion words, where a plateau is reached. The effect of data size on correlation is clear from this data.

Such an increase in correlation with data size can be intuitively explained as follows. As shown in Figure 6, consider a graph where the horizontal axis is the log-frequency and the vertical axis is the logarithm of the number of words (in Figure 1, the vertical axis was the distribution, but here it is a histogram). Every corpus follows the power-law with its gradient being almost the same for each natural language text. For a given type of data, an increased amount of data causes a shift of the line towards the upper right. Since the distribution of word familiarity is biased towards the highly frequent range (indicated by the gray zone in the figure), the larger the data, the better sampled the words in the familiarity list are. Thus, for any given data type, increased data size raises the correlation.

5 Effect of Domain

Having seen that a larger amount of data strengthens the correlation, the remaining question is what causes a corpus of a given size to correlate more strongly with the familiarity ratings. This corresponds to finding the reason for the vertical margin among the lines in Figure 5 when the data size was fixed.

In our quest for a statistical explanation for this margin, we examined several statistics for each corpus of the same size. The statistics included the percentage of covered words in the corpus, the percentage of covered tokens in the corpus, the entropy among covered words, the frequency distribution of covered words, and the distribution of bigram and trigram numbers for covered words. None of these statistics were consistent with the degree of correlation. The differences between the corpora lie in the different appearance of individual words depending on the domain.

Thus, for each corpus, we examined words which contributed to low correlation. For a given corpus, we considered common words found in the corpus and the familiarity list. The corpus gives a ranking \( n \) and the familiarity list gives a ranking \( m \) to every word. Words with large absolute values of \( n - m \) are the words which contribute most to lowering the correlation coefficient. Words with the highest \( m - n \) are shown in the first block of Table 6, whereas words of the highest \( n - m \) are shown in the second block. The first block includes more daily usage and spoken words, whereas the second block includes words more often found in written text. For example, clothing and diet words in the first block include words typically used in daily communication, whereas the English words borrowed from French in the second block are more likely to be written. In Japanese, the tendency of typically written words to be among the large \( n - m \) words is even more clear, since the Amano list is larger.

We next compared the correlation coefficients with spoken and written corpora. Since the corpus size will affect the correlation, the same quantity of \( K \) words was taken from each corpus, and the correlation of this sample with the familiarity list was calculated. Since the corpus size differed, \( K \) was defined as the smallest number of words among the corpora in each language (thus, MICASE for English where \( K_{eng}=1,279,792 \), and SCJ for Japanese where \( K_{jap}=7,498,763 \)).
Table 6: Words with the largest ranking difference in the corpus and the familiarity list

| corpus: low, MRC: high | WSJ | Wikipedia-E | Web-E | BNC | MICASE |
|------------------------|-----|-------------|-------|-----|--------|
| pencil                 | mileage | doughnut | sock | bedroom |
| noisy                  | towel | coke | nickel | thirsty |
| oven                   | thoughtful | steady | boring | spoon |
| happiness              | bra | hunger | shrimp | sunshine |

| corpus: high, MRC: low | lire | sonata | dell | essence | hypothesis |
|------------------------|-----|-------|------|---------|------------|
| southland              | hank | portal | fort | lorry | velocity |
| gore                   | aurora | enterprise | debut | rover | precipitate |
| charter                | belle |                         |       |         |            |

words). Since the number of words in the familiarity list also affects the correlation, the top $N$ ranked words were taken from the familiarity list, and the correlation with each corpus of size $K$ was calculated (thus, $K$ is a constant, whereas $N$ is a parameter for each language). Figure 7 shows the results for English and Figure 8 shows those for Japanese. The horizontal axis shows $N$, while the vertical axis shows the correlation.

For English, since we were interested in spoken versus written corpora, BNC was separated into a BNC-spoken part (denoted BNC-s in the figure) and a BNC-written part (BNC-w). The correlation was calculated also for BNC as a mixture of spoken and written with size $K_{eng}$. Thus, there are seven lines in total, two corpora of spoken text (dashed lines) and five corpora of written (solid lines). For Japanese, there are five lines, only one of which is dashed. Note that the ranges of the horizontal axes differ due to the familiarity list size: for MRC the range goes to 4000 and for the Amano list it goes to 30,000.

In general, the dashed lines are above most of the solid lines. This shows the tendency of the spoken corpus to correlate better with the familiarity list than the written corpus does. Still, some solid lines were above the dashed lines in the two graphs. For English, the BNC lines were higher than that of MICASE. The reason for this could not be identified and remains to be determined in our future work, but a possible reason lies in the balanced nature of BNC. BNC is characterized in two ways regarding familiarity: it contains spoken data, and it was constructed to represent the English of daily usage. With regard to the first characteristic of BNC, the MICASE content is academic speech, so even though MICASE consists of spoken language it contains much less familiar content. In contrast, BNC-spoken is more general. Consequently, if a large-scale corpus of daily spoken language is constructed, it should correlate more strongly with MRC.

Regarding the second characteristic of BNC, that it is a representative collection of contemporary language, the fact that BNC-written is more highly correlated than MICASE shows that the content of BNC closely matches the words in the MRC list. Even to the present day, BNC is the only corpus developed with an explicit strategy to create a representative collection of printed English that is available and large in scale. A good contrast is Web-E, which also includes various publications of the day, but is matched less well with MRC. This shows that the familiarity rating is formed of more controlled, meaningful data rather than with noisy, uncontrolled data.

Verification through this approach in Japanese is limited, though, since there is no BNC-

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6 BNC was originally tagged to show whether the text is spoken or written.
like corpus in any language other than English. In Japanese, SCJ, which consists of university lectures, had lower correlation than Web-J. Thus, Web-J might be a fairly good replacement for BNC. Web-E’s correlation line was among those of the corpora based on written texts, so there seems to be a qualitative difference between Web-E and Web-J. This could be due to the fact that Japanese web pages are written and read mostly by native speakers of Japanese, whereas English web pages are often written and read by non-native speakers. Thus, if English web-pages could be filtered to obtain only those written by native speakers of English, a higher correlation with MRC might be attained. However, since web pages are noisy sources of data, the construction of a Japanese corpus that is “representative of the language” still lies in the future.

Comparing Figure 7 and Figure 8 leads to another observation. For Japanese, the correlation levels off when the top familiarity list reaches 5000 words. This suggests that the familiarity rating is only meaningful with respect to the corpus frequency up to about 5000 words. Thus, an MRC list of an order of about 5000 words seems adequate, if there is no language difference. The Dale-Chall list (Chall and Dale, 1995) used in reading level assessment consists of 3000 words, which seems reasonable according to the results of this experiment.

Is frequency correlated with familiarity? Our correlation analysis on corpora suggests that log frequency—as the information amount carried by a word under Weber-Fechner’s law—does correlate with the familiarity rating, if measured on a gigantic corpus of spoken representative language of the day. This is supported by the following observations made so far:

- Log-frequency measured in written corpora correlates fairly well with the familiarity ratings.
- The correlation is higher for spoken language corpora than for written corpora.
- A corpus of academic speech was less correlated than the BNC-written corpus, which comprises representative language of the day.

Unfortunately, such corpora do not exist in any language, although the closest is BNC. Therefore, a final conclusion must wait until such a corpus becomes available. Further investigation to verify the relationship between frequency and familiarity remains as our future work.
6 Conclusion

Even though it has been assumed that word frequency correlates with word familiarity, how strong this correlation is has not been thoroughly investigated. In this paper, we report on our analysis of various corpora in English and Japanese.

The correlation coefficient of corpus log-frequency with a word familiarity list was 0.57 to 0.74 for English using the MRC familiarity list, and 0.45 to 0.72 for Japanese with the Amano list. For a given corpus, frequent words always had high familiarity, but familiar words did not necessarily have high frequency.

To explain why the log-frequency of some corpora was better correlated with the familiarity rating than was the case for other corpora, we investigated two conditions. The first was the corpus size. The log-frequency of larger corpora was more strongly correlated with familiarity ratings than that of smaller corpora. By changing the corpus size, we found that increasing the amount of data will increase the correlation in a log-linear manner up to 1 billion corpus words. The second condition was the type of corpus. The log-frequency was more strongly correlated with the familiarity ratings when the corpus consisted of spoken rather than written data. Even when the corpus content was academic speech, the log-frequency of the corpus was more highly correlated with the familiarity ratings than that of most written corpora. Such findings partly show the nature of familiarity as the information amount carried by the word, under a more general model of Weber-Fechner’s law that the relationship between stimulus and perception is in general logarithmic.

From the language engineering viewpoint, a log-frequency list —if obtained from a large-scale corpus— could be used for a pseudo-measurement of familiarity scores. The approximation will be better if collected from spoken language and daily content. Since most current corpora are collections of written text, our work also suggests that the construction of corpora consisting of typical spoken text (e.g., not university lectures) will be useful, as will the collection of texts for BNC-type corpora in various languages. How such pseudo-scores can be applied to reading level assessment will be part of our future work.

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