# Beyond Film Subtitles: Is YouTube the Best Approximation of Spoken Vocabulary?

**Adam Nohejl** **Frederikus Hudi** **Eunike Andriani Kardinata**
**Shintaro Ozaki** **Maria Angelica Riera Machin** **Hongyu Sun**
**Justin Vasselli** **Taro Watanabe**
Nara Institute of Science and Technology
{nohejl.adam.mt3, frederikus.hudi.fe7, eunike.kardinata.ef9}@is.naist.jp
{ozaki.shintaro.ou6, riera_machin.maria.rn9, sun.hongyu.sg6}@naist.ac.jp
{vasselli.justin_ray.vk4, taro}@is.naist.jp



## Abstract

Word frequency is a key variable in psycholinguistics, useful for modeling human familiarity with words even in the era of large language models (LLMs). Frequency in film subtitles has proved to be a particularly good approximation of everyday language exposure. For many languages, however, film subtitles are not easily available, or are overwhelmingly translated from English. We demonstrate that frequencies extracted from carefully processed YouTube subtitles provide an approximation comparable to, and often better than, the best currently available resources. Moreover, they are available for languages for which a high-quality subtitle or speech corpus does not exist. We use YouTube subtitles to construct frequency norms for five diverse languages, Chinese, English, Indonesian, Japanese, and Spanish, and evaluate their correlation with lexical decision time, word familiarity, and lexical complexity. In addition to being strongly correlated with two psycholinguistic variables, a simple linear regression on the new frequencies achieves a new high score on a lexical complexity prediction task in English and Japanese, surpassing both models trained on film subtitle frequencies and the LLM GPT-4. Our code, the frequency lists, fastText word embeddings, and statistical language models are freely available online.[1]

## 1 Introduction

Word frequency is crucial for psycholinguistic research, as well as for assistive or educational applications involving production or comprehension of words. Traditionally, written corpora have been used for estimates of word frequency, with Kučera and Francis (1967) frequency norms long dominating psycholinguistic research of English.

The size of available written language corpora has grown over time, while speech corpora are still costly to develop and comparably limited in extent. When user-generated text became available on a large scale, it was possible to approximate everyday language exposure by collecting English text from Usenet newsgroups (Burgess and Livesay, 1998), and later French film and TV subtitles (New et al., 2007). Subtitle-based norms for US English, SUBTLEX-US, (Brysbaert and New, 2009) were found more predictive of lexical decision times (LDT) than frequencies based on traditional written corpora or the Usenet-based corpus.

These pioneering studies on subtitle corpora spurred the creation of film and TV subtitle-based frequency norms, dubbed SUBTLEX, for other languages such as Spanish (Cuetos et al., 2011), or British English (van Heuven et al., 2014). SUBTLEX frequencies for two Asian languages, Chinese (Cai and Brysbaert, 2010) and Vietnamese (Pham et al., 2019) were compiled as well. Most of the research, however, has remained focused on languages spoken in WEIRD[2] countries.

Subtitle frequencies are currently being used in a variety of practical tasks which need to model familiarity with words, such as lexical simplification or readability assessment. Despite their practical utility, film subtitle corpora are far from perfect approximations of spoken language. A large part of the non-English SUBTLEX corpora comes from translations of English-language movies. For instance, SUBTLEX-ESP (Cuetos et al., 2011) consists of less than 3% original Spanish subtitles, while more than 92% are translations from English. In Vietnamese, Pham et al. (2019) did not find subtitles more predictive of LDT than a written corpus, citing translation artifacts and cultural differences from predominantly American material as the likely causes. Moreover, the content presented in film dialogue is a very specific subset of spoken language. The speech is almost exclusively scripted and skewed to particular topics and vocabulary (Paetzold and Specia, 2016).

In this work, we build a corpus of untranslated YouTube video subtitles and evaluate the correla-

[1] https://github.com/naist-nlp/tubelex

[2] Western, Educated, Industrial, Rich, and Democratic (WEIRD), an acronym coined by Henrich (2020).

tion of its frequencies with LDT, word familiarity, and lexical complexity, comparing them with frequencies based on available subtitle and speech corpora. We purposely target two languages spoken in WEIRD countries, English and Spanish, with a wealth of previous research to compare with, as well as three languages with diverse characteristics and amounts of resources available, Chinese, Japanese, and Indonesian.

As full corpus data cannot be published due to copyright, we release two basic language models based on the TUBELEX corpus for each language in addition to the frequency lists: a statistical language model (Heafield et al., 2013), which provides smoothed frequencies of word 1-grams to word 5-grams, and fastText word embeddings (Bojanowski et al., 2017) to enable modeling of semantic similarity or analogy, as well as representation of words in downstream application. FastText extends the Word2vec model (Mikolov et al., 2013). Preprocessing details and hyperparameters are provided in Appendix A, model sizes in Appendix B, and evaluation of the embeddings in Appendix C.

## 2 Related Work

### 2.1 Subtitle Corpora

New et al. (2007) collected French film subtitles from the web to create a subtitle corpus. A similar procedure was then used for SUBTLEX-US (Brysbaert and New, 2009), and other SUBTLEX corpora, in some cases adding duplicate removal, e.g. for SUBTLEX-ESP (Cuetos et al., 2011), or various forms of cleaning. While most of the film subtitle corpora are collected from the web (often the OpenSubtitles website[3]), the British SUBTLEX-UK (van Heuven et al., 2014) acquired television subtitles from the BBC broadcasts.

Francom et al. (2014) used film metadata to build a relatively small corpus of untranslated Spanish subtitles, ACTIV-ES, and released lists of its *n*-grams. Paetzold and Specia (2016) restricted movies and series to particular genres to build the SubIMDB corpus.

All of these corpora were built with the intent of approximating spoken language, and most of them were evaluated against psycholinguistic data. Other subtitle corpora were built for different purposes:

OpenSubtitles2016 (Lison and Tiedemann, 2016) and its updated version OpenSubtitles2018 (Lison et al., 2018) are large-scale collections of parallel film and TV subtitles downloaded from the OpenSubtitles website. In addition to parallel text aligned via subtitle timing, word frequencies for individual languages were released as well. For some languages, such as Indonesian, the OpenSubtitles corpus is the only subtitle corpus available.

Takamichi et al. (2021) downloaded audio and subtitles from YouTube to create JTubeSpeech, a Japanese corpus for speech recognition and speaker verification. The corpus or derived data was not published, and the corpus was evaluated only on these two tasks.

### 2.2 Evaluation Methods and Applications

New et al. (2007) evaluated a French subtitle corpus using correlation with LDT to demonstrate that it reflects language exposure better than written corpora. The same approach was subsequently adopted by others for different languages. Paetzold and Specia (2016) additionally evaluated the English SubIMDB on four other psycholinguistic ratings including word familiarity.

Van Paridon and Thompson (2021) used the data from several OpenSubtitles2018 languages to train word embeddings and evaluated them on word analogy and psycholinguistic ratings. The study excluded Chinese, Japanese, and other languages that do not separate words with spaces.

Shardlow (2013) demonstrated that frequency in SUBTLEX-US outperforms frequency in written corpora in ranking lexical simplifications for native speakers. Subtitle frequencies have been widely applied to lexical simplification in various languages for native and non-native speakers, where suitable SUBTLEX corpora were available (e.g. Štajner et al., 2022). Meanwhile, lexical complexity modeling for other languages, such as Japanese (Nishihara and Kajiwara, 2020) or Indonesian (Wibowo et al., 2019), has had to rely on web-scraped corpora instead.

Subtitle frequencies have also been used in a number of other tasks broadly connected to text comprehension, assistive technologies, and language learning, e.g. text readability assessment in English (Chen and Meurers, 2016) and Italian (Okinina et al., 2020), modeling of the orthographic neighborhood effect in English and Dutch (Tulkens et al., 2020), a cross-linguistic study of the mental lexicon in English, German, and Chinese (Tjuka, 2020), construction of a vocabulary list for Finnish language learners (Robertson et al., 2022), or evaluating and improving performance of LLMs in colloquial English (Sun et al., 2024).

[3] http://www.opensubtitles.org/

| Language | Videos | | | Tokens‡ |
|---|---|---|---|---|
| | Found | Cleaned† | Unique† | |
| Chinese | 5,848,257 | 10,172 | 10,146 | 17,865,686 |
| English | 4,748,327 | 105,976 | 105,752 | 170,750,870 |
| Indonesian | 5,265,240 | 34,818 | 34,684 | 34,903,381 |
| Japanese | 4,970,247 | 101,664 | 100,754 | 163,439,781 |
| Spanish | 3,840,068 | 107,166 | 106,676 | 169,188,689 |

Table 1: Corpus construction statistics. †Out of 120,000 downloaded subtitle files. ‡In default tokenization.

## 3 Corpus Construction

We build the corpus using several stages of processing. Table 1 shows statistic of the process.

### 3.1 Subtitle Scraping

As there is no public index of YouTube videos, we use YouTube's search function to search for all Wikipedia article titles in a given language to discover videos, following Takamichi et al. (2021).

To avoid translated or machine-generated subtitles, we restrict videos to those with both audio and manual subtitles explicitly labeled as the target language. For Chinese videos, we did not find enough videos with labeled audio language, so we also accept videos with unlabeled audio. The resulting numbers of videos are listed as Found in Table 1. We sample 120,000 videos for each language, for which we download subtitles.

### 3.2 Cleaning and Duplicate Removal

We identify the language of each subtitle line using the compressed fastText language identification model[4] (Joulin et al., 2016a,b). We discard files containing less than 95% of the target language. From the remaining files, we remove both lines that do not contain any valid characters for the target language (e.g. Latin alphabet for English), and lines that are identified as a different language. Lastly, we discard any files consisting of less than three lines of text. The resulting numbers of files are listed as Cleaned in Table 1.

We consider files duplicate if the cosine similarity between their 1-gram TF-IDF vectors is 0.95 or higher. We remove duplicate files heuristically to achieve a state without any duplicate pair. The final numbers of unique files and tokens in them are listed as Unique and Tokens in Table 1.

[4] https://fasttext.cc/docs/en/language-identification.html

### 3.3 Subtitle Processing

We parse the WebVTT[5] subtitle files, and remove formatting and repetition caused by subtitle scrolling. We preserve words censored by YouTube (replaced with "[ __ ]")[6] and audio descriptions in brackets (e.g. English "[ominous music]", Japanese "【エンジン音】") as special tokens.

### 3.4 Masking Personal Information

We also use special tokens to replace sequences of digits (after tokenization) and anonymize email addresses, web addresses including those without an explicit protocol (e.g. `x.com/username`), and apparent social network handles starting with `@`. Our approach to anonymizing personally identifying information (PII) is informed by the analysis by Subramani et al. (2023) and extends the previous approach of (Soldaini et al., 2024) by also masking web addresses and social network handles.

### 3.5 Tokenization and Frequency Lists

We provide frequency lists in multiple variants:

**default** English, Indonesian, and Spanish segmented using Stanza (Qi et al., 2020) `tokenize,mwt` pipeline ; Japanese segmented using MeCab (Kudo et al., 2004), and the UniDic 2.1.2 dictionary (Den et al., 2007, distributed as unidic-lite[7]); Chinese segmented using the jieba[8] segmenter 0.42.1.

**base** Base form of Japanese tokens, preserving original spelling, obtained from MeCab/UniDic (書字形基本形).

**lemma** English, Indonesian and Spanish lemmatized using Stanza `tokenize,mwt,lemma` pipeline; Japanese lemmatized using MeCab/Unidic (語彙素), i.e. words in the orthographically normalized base form.

**regex** English, Indonesian, and Spanish orthographic words, matching a Python regular expression for sequences of characters belonging to the `\w` (word) class, but not to the `\d` (digit) class.

All tokens are lower-cased and normalized to Unicode NFKC (Whistler, 2023). For each word, the frequency lists provide: `count` – number of occurrences, `videos` – number of videos containing the word, `channels` – number of channels the word occurrs in, `count:`$C$ – number of occurrences of the word in the YouTube video category $C$.

[5] https://www.w3.org/TR/webvtt1/

[6] https://support.google.com/youtube/answer/6373554?hl=en

[7] https://pypi.org/project/unidic-lite/

[8] https://github.com/fxsjy/jieba

| Evaluation Label | Chinese | English | Indonesian | Japanese | Spanish |
|---|---|---|---|---|---|
| Subtitles match speech in the target language | 65% | 91% | 84% | 84% | 89% |
| Subtitles match song in the target language | — | 2% | 1% | 1% | 2% |
| Audio description | — | 1% | 1% | 0% | 0% |
| No speech or song | — | 2% | 0% | 0% | 2% |
| Synthesized speech | 34% | 3% | 13% | 14% | 5% |
| Audio language differs | 1% | 1% | 1% | 1% | 2% |
| Subtitle language differs | — | — | — | — | — |

Table 2: Human evaluation of a sample size 300 for each language, consisting of 100 videos with 3 cues per video.

## 4 Human Evaluation

We performed human evaluation to verify how representative the corpus is of the target languages, and spoken language in particular. We took a sample of size 300 for each language, consisting of 100 videos with 3 random subtitle time stamps for each. The videos were selected using stratified sampling by category and duration[9] for each language. Each sampled timestamp was examined and labeled by a CEFR C2-level non-native speaker for English and by native speakers for the other languages.

The labels and evaluation results are shown in Table 2. Most importantly, among the 1,500 subtitle cues, we have not found a single one whose language would differ from the target language. We have, however, observed different dialects or varieties of each language, as well as apparent non-native speech, sometimes co-occurring in the same video. In the case of Chinese, 2 of the 100 videos were in Cantonese, with traditional Chinese subtitles, while the majority was in Mandarin Chinese. To better understand the composition of the Chinese subtitles, we also analyzed the script used in the whole corpus, and found that 66% videos use simplified Chinese, 33% videos use traditional Chinese, and 1% mix both.[10]

Most proportions of potentially problematic phenomena were relatively low (up to 2%), with the exception of synthesized speech, which ranged from 3% for English to 34% for Chinese. Synthesized speech with subtitles, or subtitles provided for scenes without speech, could effectively be written language, rather than spoken. We further discuss the implications in Section 6.2.

[9]We divided the videos in three similarly large duration classes: [0, 3 min), [3 min, 10 min), and [10 min, ∞).

[10]We used the Hanzi Identifier package (`https://github.com/tsroten/hanzidentifier`). and considered subtitles mixed if they contained the non-majority script variant on at least 2 lines and at least 5% of lines.

## 5 Extrinsic Evaluation

We evaluate multiple corpora on three tasks, LDT, word familiarity, and lexical complexity, comparing them with TUBELEX in default, base, lemma, and regex variants, described in Section 3.5.

For each evaluated corpus, we report correlation measured by Pearson's correlation coefficient (PCC), and the statistical significance of its difference from the correlation with $\text{TUBELEX}_{\text{default}}$ on three levels: $^{***}$ ($p < 0.001$), $^{**}$ ($p < 0.01$), and $^{*}$ ($p < 0.05$). We compute the $p$-values using Steiger's (1980) test for dependent correlations and consider $p \geq 0.05$ not statistically significant.

To demonstrate the practical usefulness of the TUBELEX frequencies, we also predict lexical complexity based on them, and compare our results with the top submissions of the BEA 2024 Multilingual Lexical Simplification Pipeline Shared Task (Shardlow et al., 2024).

### 5.1 Evaluated Corpora and Resources

We evaluate traditional speech corpora, subtitle corpora, and three additional resources:

**Speech corpora:** **BNC-Spoken**, the spoken subset of the British National Corpus (BNC Consortium, 2007); **CREA-Spoken**, the spoken subset of Corpus de Referencia del Español Actual (Real Academia Española, 2004); **CSJ**, the Corpus of Spontaneous Japanese (NINJAL, 2016); **HKUST/MTS** (Liu et al., 2006), a Mandarin telephone speech corpus. We could not find a large enough Indonesian speech corpus.

**Subtitle corpora:** **ACTIV-ES**; **EsPal** (Duchon et al., 2013); **LaboroTV1+2**, the combination of the two releases of LaboroTVSpeech (Ando and Fujihara, 2021); **OpenSubtitles**, the 2018 version; **SubIMDB**; **SUBTLEX** (US, CH, ESP); **SUBTLEX-UK**.

**Other resources:** **GINI**, a Twitter-based metric (Murayama et al., 2018), measuring words' dispersion in frequency of use by different people;

**Wikipedia**; **wordfreq**, a Python library (Speer, 2022) pooling frequency from multiple corpora. Wordfreq combines Wikipedia, Twitter and a subtitle corpus for each of the evaluated languages, as well as 4 more sources for English, Chinese, and Spanish, and 2 more for Japanese. The subtitle data used by wordfreq is OpenSubtitles2018, SUBTLEX-US and SUBTLEX-UK for English, SUBTLEX-CH for Chinese.

For each corpus, we provide technical details in Appendix D, and token and type counts in Appendix E.

### 5.2 Computing Frequency

To deal with words missing in a corpus, we use the formula with Laplace smoothing recommended by Brysbaert and Diependaele (2013) to compute frequency of a token $w$:

$$f(w) = \frac{\text{count}(w) + 1}{\#\text{tokens} + \#\text{types}}, \quad (1)$$

where count($w$) is the number of occurrences of the word $w$, #tokens is the total number of tokens in the corpus, and #types is the number of types in the corpus. As a result, even words missing in the corpus are assigned a non-zero frequency.

For ACTIVE-ES and wordfreq, which do not provide token counts, we instead assign the corpus minimum frequency to missing words. We also directly use GINI values, analogously assigning the corpus maximum value to missing words, as high GINI values indicate high dispersion.

The words featured in our experiments may be tokenized as multiple tokens. We assign them the minimum of the frequencies of the individual tokens, and maximum of the GINI values.

In all experiments we use the logarithm of the above values, except for GINI, where it consistently worsened performance. For a GINI value $g$, we use the additive inverse $-g$ for the purpose of comparison with log-frequencies.

### 5.3 Lexical Decision Time

Lexical decision is one of the basic psycholinguistic tasks, where subjects decide whether a sequence of characters is a valid word or not. The reaction time for each word is its lexical decision time (LDT).

We measure correlation (PCC) with mean LDT from three studies: the English Lexicon Project (Balota et al., 2007), restricted to lower-case words following the approach of Brysbaert and New (2009); the MELD-SCH database (Tsang et al., 2018) of simplified Chinese words; and SPALEX

| | Corpus | Chinese | English | Spanish |
|---|---|---|---|---|
| speech | BNC-Spoken | — | −0.548*** | — |
| | CREA-Spoken | — | — | −0.645*** |
| | HKUST/MTS | −0.465*** | — | — |
| film/TV subtitles | ACTIV-ES | — | — | −0.600*** |
| | EsPal | — | — | −0.807*** |
| | OpenSubtitles | −0.568 | **−0.647**** | −0.811 |
| | SubIMDB | — | −0.646*** | — |
| | SUBTLEX | **−0.587**** | −0.633** | −0.763*** |
| | SUBTLEX-UK | — | −0.625 | — |
| other | GINI | — | −0.420*** | — |
| | Wikipedia | −0.424*** | −0.540*** | −0.705*** |
| | wordfreq | −0.423*** | −0.632** | −0.801*** |
| our | $\text{TUBELEX}_{\text{default}}$ | −0.575 | −0.627 | −0.811 |
| | $\text{TUBELEX}_{\text{regex}}$ | — | −0.627 | **−0.811** |
| | $\text{TUBELEX}_{\text{lemma}}$ | — | −0.624* | −0.808*** |

Table 3: LDT correlation. Strongest (lowest) correlations for each language are in bold.

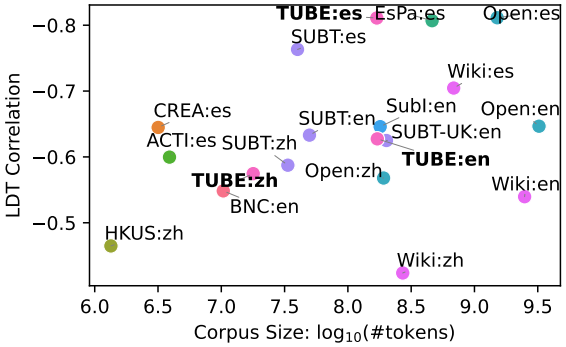


Figure 1: LDT correlation and corpus size. Labeled "*corpus abbr.*:*lang. code*", "TUBE" is $\text{TUBELEX}_{\text{default}}$.

(Aguasvivas et al., 2018) for Spanish. For English and Chinese, we use the published mean LDT. SPALEX only provides raw participant data, which we process by removing times out of the range [200 ms, 2000 ms], as outlined by Aguasvivas et al. (2018), and computing the means.

The results in Table 3 show that in each of the three languages OpenSubtitles and TUBELEX are among the top similarly performing corpora. While OpenSubtitles achieve a stronger correlation for English, $\text{TUBELEX}_{\text{default}}$ achieves a stronger correlation for Chinese.

Other corpora either performed comparably, but only covered a single language (SubIMDB, EsPal) or underperformed noticeably in at least one language (SUBTLEX in Spanish, wordfreq in Chinese, Wikipedia in all languages, and GINI and ACTIV-ES in the one language they cover). Furthermore, as can be seen in Figure 1, TUBELEX and SUBTLEX perform remarkably well relative to their size.

| | Corpus | Chinese | English | Indonesian | Japanese | Spanish |
|---|---|---|---|---|---|---|
| speech | BNC-Spoken | — | 0.741*** | — | — | — |
| | CREA-Spoken | — | — | — | — | 0.535 |
| | CSJ | — | — | — | 0.423*** | — |
| | HKUST/MTS | 0.414*** | — | — | — | — |
| film/TV subtitles | ACTIV-ES | — | — | — | — | 0.526 |
| | EsPal | — | — | — | — | 0.428*** |
| | LaboroTV1+2 | — | — | — | 0.511*** | — |
| | OpenSubtitles | 0.444*** | 0.776 | 0.582*** | 0.296*** | **0.553** |
| | SubIMDB | — | **0.781** | — | — | — |
| | SUBTLEX | 0.505 | 0.773 | — | — | 0.538 |
| | SUBTLEX-UK | — | 0.779 | — | — | — |
| other | GINI | — | 0.664*** | — | **0.593***** | — |
| | Wikipedia | 0.334*** | 0.661*** | 0.455*** | 0.434*** | 0.329*** |
| | wordfreq | 0.242*** | 0.771** | **0.632** | 0.483*** | 0.495*** |
| our | $\text{TUBELEX}_{\text{default}}$ | **0.506** | 0.777 | 0.625 | 0.562 | 0.547 |
| | $\text{TUBELEX}_{\text{regex}}$ | — | 0.777 | 0.617** | — | 0.545 |
| | $\text{TUBELEX}_{\text{base}}$ | — | — | — | 0.576*** | — |
| | $\text{TUBELEX}_{\text{lemma}}$ | — | 0.774 | 0.618 | 0.569*** | 0.551 |

Table 4: Word familiarity correlation. Strongest (highest) correlations for each language are in bold.

### 5.4 Word Familiarity

Word familiarity is a subjective rating of exposure to a given word. Among the subjective variables measured for words in psycholinguistics, it is typically the one most strongly correlated with frequency, and norms for it are available for a wide array of languages.

We measure correlation (PCC) with mean word familiarity from five databases: Chinese familiarity ratings (Su et al., 2023), English MRC lexical database (Coltheart, 1981; Coltheart and Wilson, 1987), Indonesian lexical norms (Sianipar et al., 2016), Japanese word familiarity ratings (Asahara, 2019)[11], and Spanish lexical norms (Guasch et al., 2016). Evaluation on three alternative, smaller databases for English, Spanish, and Japanese can be found in Appendix F.

As shown in Table 4, in each language except Japanese, $\text{TUBELEX}_{\text{default}}$'s correlation is either the strongest one or not significantly weaker. Correlations without any significant difference from $\text{TUBELEX}_{\text{default}}$ are achieved by SUBTLEX in Chinese, by all subtitle corpora and SubIMDB and wordfreq in English, by wordfreq in Indonesian, and by all subtitle corpora except EsPal, and by CREA-Spoken in Spanish. In Japanese, GINI achieves the strongest correlation, followed by $\text{TUBELEX}_{\text{base}}$ and $\text{TUBELEX}_{\text{default}}$.

No corpus achieves results comparable to TUBELEX results across all five languages, but SUBTLEX corpora do not differ significantly on the three languages where they are available. Similarly to LDT, Figure 2 shows that TUBELEX and SUBTLEX perform remarkably well relative to their size, roughly one order of magnitude smaller than the OpenSubtitles corpora.

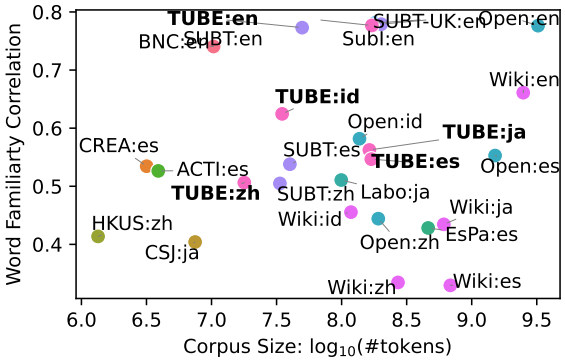


Figure 2: Word familiarity correlation and corpus size. Labeled "*corpus abbr.*:*lang. code*", "TUBE" is $\text{TUBELEX}_{\text{default}}$, not showing outlier "Open:ja".

### 5.5 Lexical Complexity

Lexical complexity is a subjective rating of word comprehension difficulty in a sentence context. Its prediction can be used for the practical NLP task of lexical simplification. The MultiLS dataset (Shardlow et al., 2024), which we use for evaluation, was annotated by non-native speakers (Japanese) or a mix of natives and non-natives (English and Spanish), whereas the two previously evaluated psycholinguistic tasks only use data collected from natives. No lexical complexity dataset is available for Chinese or Indonesian.

As shown in Table 5, the strongest correlation in English and Japanese is achieved by TUBE-

[11]We use the published ratings for reception estimated using a Bayesian linear mixed model.

| | Corpus | English | Japanese | Spanish |
|---|---|---|---|---|
| speech | BNC-Spoken | −0.695*** | — | — |
| | CREA-Spoken | — | — | −0.508*** |
| | CSJ | — | −0.563*** | — |
| film/TV subtitles | ACTIV-ES | — | — | −0.516*** |
| | EsPal | — | — | −0.627 |
| | LaboroTV1+2 | — | −0.610** | — |
| | OpenSubtitles | −0.721*** | −0.191*** | −0.628 |
| | SubIMDB | −0.717*** | — | — |
| | SUBTLEX | −0.696*** | — | −0.618 |
| | SUBTLEX-UK | −0.724** | — | — |
| other | GINI | −0.349*** | −0.379*** | — |
| | Wikipedia | −0.651*** | −0.487*** | −0.454*** |
| | wordfreq | −0.761 | −0.605** | −0.559*** |
| our | $\text{TUBELEX}_{\text{default}}$ | **−0.762** | **−0.661** | −0.604 |
| | $\text{TUBELEX}_{\text{regex}}$ | −0.761** | — | −0.588* |
| | $\text{TUBELEX}_{\text{base}}$ | — | −0.658 | — |
| | $\text{TUBELEX}_{\text{lemma}}$ | −0.749 | −0.622** | **−0.650**** |

Table 5: Lexical complexity correlation. Strongest (lowest) correlations for each language are in bold.

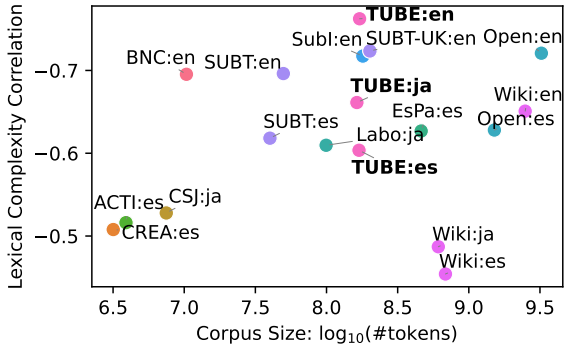


Figure 3: Lexical complexity correlation and corpus size. Labeled "*corpus abbr.*:*lang. code*", "TUBE" is $\text{TUBELEX}_{\text{default}}$, not showing outlier "Open:ja".

$\text{LEX}_{\text{default}}$, and in Spanish by $\text{TUBELEX}_{\text{lemma}}$. Correlations without any significant difference from $\text{TUBELEX}_{\text{default}}$ are achieved by wordfreq in English, and all subtitle corpora except ACTIV-ES for Spanish. Similarly to the previous tasks, Figure 3 shows that TUBELEX and SUBTLEX perform remarkably well relative to their size.

As the dataset was used for evaluation of lexical complexity prediction in a shared task (Shardlow et al., 2024), we also compare predictions based on TUBELEX with top shared task participants. To do so, we fit a linear regression model using a single variable, log-frequency or GINI values to the shared task's trial data (30 instances for each language), and clip the predicted values to the range [0, 1]. We compare our results with the shared task submissions that achieved the highest coefficient of determination $R^2$ (and also highest correlation) in individual languages (TMU-HIT, Enomoto et al., 2024; and GMU, Goswami et al., 2024), and on average across all shared task languages (Archaeology, Cristea and Nisioi, 2024).

| | Corpus / ST System | English | Japanese | Spanish |
|---|---|---|---|---|
| speech | BNC-Spoken | 0.475 | — | — |
| | CREA-Spoken | — | — | 0.186 |
| | CSJ | — | 0.306 | — |
| film/TV subtitles | ACTIV-ES | — | — | −0.253 |
| | EsPal | — | — | 0.170 |
| | LaboroTV1+2 | — | 0.349 | — |
| | OpenSubtitles | 0.445 | 0.019 | 0.332 |
| | SubIMDB | 0.377 | — | — |
| | SUBTLEX | 0.394 | — | −0.254 |
| | SUBTLEX-UK | 0.513 | — | — |
| other | GINI | 0.041 | 0.105 | — |
| | Wikipedia | 0.365 | 0.231 | −0.255 |
| | wordfreq | **0.578** | 0.364 | 0.268 |
| our | $\text{TUBELEX}_{\text{default}}$ | 0.553 | 0.405 | 0.328 |
| | $\text{TUBELEX}_{\text{regex}}$ | 0.552 | — | 0.308 |
| | $\text{TUBELEX}_{\text{base}}$ | — | **0.424** | — |
| | $\text{TUBELEX}_{\text{lemma}}$ | 0.561 | 0.234 | 0.299 |
| top ST | Archaeology (ID=2) | 0.439 | −0.098 | 0.230 |
| | GMU (ID=1) | 0.525 | −0.039 | −0.073 |
| | TMU-HIT (ID=2) | 0.515 | 0.413 | **0.494** |

Table 6: Coefficient of determination $R^2$ achieved in lexical complexity prediction, compared with top shared task systems (top ST), citing their results from Shardlow et al. (2024). Best (highest) results for each language are in bold.

The best results are achieved by $\text{TUBELEX}_{\text{lemma}}$, closely followed by $\text{TUBELEX}_{\text{default}}$, in English; $\text{TUBELEX}_{\text{base}}$, closely followed by TMU-HIT and $\text{TUBELEX}_{\text{default}}$, in Japanese; and by TMU-HIT in Spanish, where it outperformed others by a large margin. As we are using cited $R^2$ values achieved by task participants, we cannot evaluate statistical significance in this case.

A simple linear regression using TUBELEX frequencies has therefore outperformed the top shared task submissions in English and Japanese, namely gradient boosting using multiple features (Archaeology), ensemble of finetuned BERT models (GMU), and GPT-4 few-shot chain-of-thought prompting (TMU-HIT). It also outperformed the first two of them in Spanish.

It should be noted that, in this case, we are evaluating the prediction of lexical complexity, not a mere correlation with it. If we looked only at correlation, thus ignoring misprediction of mean and variance, TMU-HIT's predictions would be more strongly correlated than TUBELEX's in the three languages, and those of the other two systems in English (complete results provided in Appendix H). This may indicate limitations of LLM prompting as a regression method.

## 6 Discussion

### 6.1 Tokenization and Lemmatization

The differences between TUBELEX variants in the evaluation were generally small, but a few observations can be made about each language:

For English, the default variant performs the best across the tasks, but the simpler regex tokenization is never significantly worse. Both always outperform lemmatization.

In the evaluation of Indonesian, limited to familiarity, default tokenization performed the best.

For Japanese the base form performs the best for familiarity, and default tokenization for non-native lexical complexity. Both always outperform the orthographically normalized lemma, which show the importance of the exact written form in Japanese.

For Spanish, lemma performed the best for both familiarity and lexical complexity. Regex and default tokenization performed well in LDT only because the data is already limited to uninflected words. For an inflected language such as Spanish, lemmatization has a clear benefit.

### 6.2 Spoken vs. Written Language

There is a continuum of what we might call spoken and written language in simple terms. During human evaluation we have, for instance, observed that speakers in some videos are reading aloud. On one hand, this would make the subtitles representative of written language, not spoken language. On the other hand, the texts being read cover diverse registers (e.g. the Bible, professionally announced news, or a pre-written speech), and the speakers often shift between reading and commenting. Singing, recitation, scripted acting, and speech rehearsed to various degrees, all appear on YouTube and fall on this written-spoken continuum. Perhaps surprisingly, the same issues apply to corpora of "spontaneous" speech, as they often collect speeches that are prepared (e.g. whole CSJ, news in CREA-Spoken).

In human evaluation (Section 3.5) we have labeled two categories in TUBELEX that we think require attention: songs, which could be over-represented on YouTube compared to everyday exposure, and synthesized speech, which is effectively written language in disguise.

Overall, we believe that the diverse content found on YouTube contributes to the representativeness of the whole spectrum of spoken language at the small expense of including some amount of written language or songs. This contrasts with most speech corpora, as well as and film subtitle corpora. Speech corpora typically restrict the type or topics of speech they contain by design.

For instance, CSJ is limited to prepared monologue in common Japanese (Maekawa et al., 2000), omitting any dialogue and dialect, and HKUST/MTS (Liu et al., 2006) is limited to dialogue about 40 specified topics. Film and TV subtitle corpora, on the other hand, consist predominantly of scripted dialogue.

### 6.3 Corpus Size

Previous studies found that in addition to depending on corpus content, correlation with LDT or familiarity grows approximately logarithmically with corpus size (Tanaka-Ishii and Terada, 2011; Paetzold and Specia, 2016). For corpora over $10^7$ tokens, such growth reflects better frequency estimates for low-frequency words, and is measurable and statistically significant only if such words are sufficiently represented in the evaluation dataset.

As we built TUBELEX using a fixed size (120,000) sample of videos for each language, the final corpus size depends on the number of valid videos after cleaning (see Table 1). The Chinese (18M tokens) and Indonesian (38M tokens) corpora are substantially smaller than the others (163M to 171M tokens). We therefore expect that improvements in correlation could be made by collecting larger corpora, particularly for these two languages, although the effect could be difficult to assess on available data. Increased corpus size also likely benefit language models (see Appendix C).

Sizes of all corpora and datasets used in this study can be found in Appendix E and in Appendix G, respectively.

## 7 Conclusion

We built a YouTube subtitle corpus of untranslated Chinese, English, Indonesian, Japanese, and Spanish. The frequencies showed consistently strong correlation with LDT, word familiarity, and lexical complexity across the languages. In a comparison with film and TV subtitle corpora, speech corpora, and other common frequency resources, only the SUBTLEX corpora were comparable in correlation strength and consistence. TUBELEX, however, covers Japanese and Indonesian, for which a SUBTLEX corpus is not available. TUBELEX also excelled in the practical task of lexical complexity prediction, where a linear regression based on its frequencies not only outperformed all subtitle and speech corpora but also all submissions in a recent shared task on English and Japanese and all but one on Spanish.

## Limitations

We focused on evaluation of our corpus in terms of unigram frequencies as an approximation of language exposure, evaluating them using psycholinguistic data and lexical complexity.

While we also released the higher $n$-grams based on our corpus, we did not evaluate them. We provided only limited evaluation of the word embeddings trained on the corpus (in Appendix C). While our embeddings outperformed those based on Wikipedia in the word similarity task, they achieved lower scores than the much larger OpenSubtitles corpus. We assume this to be an effect of modest corpus size, and expect this to affect the $n$-gram model as well. In this work, we artificially limited the subtitles collected from YouTube to a quantity suitable for modeling unigram frequency. In future work, we plan to explore training more complex models from more extensive YouTube data or joint training from subtitle and written data.

While TUBELEX exceeds traditional speech corpora in size and outperforms them in our evaluation, it has serious limitations for linguistic research. Compared to most specialized speech corpora, it lacks information about types of speech or demographic composition, and suffers from varying quality of transcription. TUBELEX is not limited to any particular language standard and mixes both different language varieties and registers.

We have only collected and evaluated data for five languages. By intentionally selecting a diverse set of languages, however, we demonstrated that our approach is widely applicable to languages with a large enough presence on YouTube. We made our complete source code available for others to reuse and extend.

The data that could be released is limited by copyright, as detailed in the following section.

## Ethical Considerations

The content of YouTube subtitles is copyrighted, which precludes us from distributing the full text of the corpus. In terms of copyright, it is no different from film subtitles, but since YouTube consists of user-generated content, we also had to consider the privacy of the video authors.

We only downloaded subtitles for videos that could be found using the YouTube website search function. The search function is restricted to public videos, excluding any unlisted or private videos.[12]

None of the data that we have released contains identification of individual videos, channels, or video uploaders. The statistical language models we have released contain sequences of at most five consecutive words. The released data does not contain longer excerpts from the original subtitles.

We anonymized multiple kinds of potentially sensitive information before we derived any frequency lists or models from it. In particular, we masked email addresses, HTTP(S) URLs, apparent web URLs without an explicit protocol (e.g. `x.com/username`), apparent social network handles starting with `@`, and all sequences of digits, which are the primary constituent of phone numbers, IP addresses, account numbers, and other personally identifying information.

As we have accessed YouTube without sign-in, our corpus does not contain any subtitles for age-restricted videos, which YouTube defines as not appropriate for viewers under 18.[13] Note that while YouTube's age restriction also applies to "excessive profanity", some subtitles in our corpus still contain vulgar or otherwise inappropriate language, which we did not attempt to remove.

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[12] https://support.google.com/youtube/answer/157177?hl=en

[13] https://support.google.com/youtube/answer/2802167?hl=en

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## A Preprocessing and Hyperparameters for Word Embeddings and Statistical Language Models

| | |
|---|---|
| **Preprocessing** | |
| Sentence Splitting | On subtitle cue boundaries, and rule-based using PySBD 0.3.4 (Sadvilkar and Neumann, 2020), with rules added for Indonesian based on InaNLP (Purwarianti et al., 2016). |
| Tokenization | TUBELEX regex tokenization for English, Japanese, and Spanish, and default tokenization for Japanese and Spanish (details in Section 3.5). |
| Normalization | Lower case, Unicode NFKC (Whistler, 2023). |
| **Hyperparameters** | |
| Word Embeddings | 300-dimensional fastText CBOW model with position weights, 10 negative samples, 10 epochs, character 5-grams, other: default (Grave et al., 2018).<br>– software: `https://github.com/facebookresearch/fastText`<br>– CLI: `fasttext cbow -dim 300 -neg 10 -epoch 10 -minn 5 -maxn 5` |
| Statistical Model | Modified Kneser-Ney language model of order 5 (Heafield et al., 2013).<br>– software: `https://kheafield.com/code/kenlm/`<br>– CLI: `lmplz -o 5` |

Table 7: Preprocessing and hyperparameters used to train word embeddings and statistical language models on TUBELEX. We used the same preprocessing for both.

## B Sizes of Word Embeddings and Statistical Language Models

| Language | Statistical Language Model $n$-Grams | | | | | FastText Vocabulary |
|---|---|---|---|---|---|---|
| | $n=1$ | $n=2$ | $n=3$ | $n=4$ | $n=5$ | |
| Chinese | 432,670 | 5,760,278 | 12,642,939 | 15,320,475 | 15,264,065 | 114,237 |
| English | 420,583 | 12,798,615 | 53,560,054 | 99,046,960 | 126,309,472 | 131,757 |
| Indonesian | 300,647 | 6,746,497 | 20,766,383 | 29,052,968 | 31,555,431 | 81,801 |
| Japanese | 405,676 | 10,898,295 | 45,793,067 | 85,956,149 | 113,644,170 | 145,429 |
| Spanish | 613,056 | 15,482,447 | 62,465,043 | 113,520,573 | 139,641,687 | 197,107 |

Table 8: Numbers of $n$-grams of the statistical language models (KenLM) and vocabulary size of the word embeddings (fastText) trained on TUBELEX. (Minimum frequency for the fastText model is 5.)

## C Evaluation of Word Embeddings

In Tables 9 and 10, we compare the performance of TUBELEX embeddings in word analogy and word similarity with previously published embeddings trained on Wikipedia (Grave et al., 2018), and OpenSubtitles2018 (van Paridon and Thompson, 2021).

The TUBELEX embeddings were trained using the same hyperparameters (see Appendix A) as the Wikipedia embeddings by Grave et al. (2018), while van Paridon and Thompson (2021) used a different setup. All compared embeddings are fastText, but we do not use character $n$-grams to embed out-of-vocabulary words. For fairness, we always evaluate the whole dataset including for out-of-vocabulary words. We only evaluate on English and Spanish, for which comparable evaluation data and pre-trained OpenSubtitles2018 embeddings are available.

In word analogy, TUBELEX embeddings underperform the other embeddings. In word similarity, they outperform Wikipedia, but slightly underperform OpenSubtitles. The overall performance is very close to the OpenSubtitles embeddings, and we hypothesize that the gap between the two is caused by the TUBELEX corpus being an order of magnitude smaller than OpenSubtitles. While we have observed that TUBELEX's size does not affect the quality of unigram frequencies, the word embeddings would likely benefit from a larger corpus.

| Language | Embeddings | Sem.: Geography | Sem.: Family | Semantic | Syntactic | Total |
|---|---|---|---|---|---|---|
| English | Wikipedia | 0.775 | 0.822 | 0.778 | 0.721 | 0.747 |
| | OpenSubtitles | 0.144 | 0.852 | 0.184 | 0.757 | 0.497 |
| | TUBELEX | 0.142 | 0.626 | 0.170 | 0.628 | 0.420 |
| Spanish | Wikipedia | 0.466 | 0.863 | 0.484 | 0.572 | 0.524 |
| | OpenSubtitles | 0.087 | 0.892 | 0.125 | 0.516 | 0.301 |
| | TUBELEX | 0.064 | 0.839 | 0.101 | 0.501 | 0.281 |

Table 9: Accuracy in word analogy evaluated on English data (Mikolov et al., 2013) and Spanish data derived from it (`https://crscardellino.net/SBWCE/`). We list separately accuracy in Geography and Family subcategories of the Semantic category.

| Language | Embeddings | Pearson's $r$ | Spearman's $\rho$ |
|---|---|---|---|
| English | Wikipedia | 0.379 | 0.434 |
| | OpenSubtitles | 0.468 | 0.532 |
| | TUBELEX | 0.385 | 0.457 |
| Spanish | Wikipedia | 0.342 | 0.387 |
| | OpenSubtitles | 0.445 | 0.475 |
| | TUBELEX | 0.415 | 0.450 |

Table 10: Correlation in word similarity evaluated on parallel English and Spanish data from Multi-SimLex (Vulić et al., 2021).

## D Details of the Evaluated Corpora

| | Corpus | Details | Source |
|---|---|---|---|
| speech | **BNC-Spoken** | We construct a frequency list for the spoken subset of BNC by computing a difference of the "all" and "written" unlemmatized BNC frequency lists compiled by Adam Kilgarif. | – https://www.kilgarriff.co.uk/bnc-readme.html |
| | **CREA-Spoken** | We use the frequency list of the spoken subset of CREA. | Alonso et al. (2011) |
| | **CSJ** | We use the published CSJ frequency list lemmatized using MeCab/Unidic. | NINJAL (2018) |
| | **HKUST/MTS** | We construct a frequency list from the corpus transcripts using the jieba tokenization. | – https://catalog.ldc.upenn.edu/LDC2005T32 |
| film/TV subtitles | **ACTIV-ES** | We use the published 1-gram frequency list, version 0.2. | – https://github.com/francojc/activ-es |
| | **EsPal** | We use the public web form, to retrieve frequencies of all tokens for our experiments. | – https://www.bcbl.eu/databases/espal/wordidx.php |
| | **LaboroTV1+2** | LaboroTVSpeech (2020) and LaboroTVSpeech2 (2024): We combine pre-tokenized training and development data of the two releases of to generate a single frequency list. | – https://laboro.ai/activity/column/engineer/eg-laboro-tv-corpus-jp/<br>– https://laboro.ai/activity/column/engineer/laborotvspeech2/ |
| | **OpenSubtitles** | We use the published frequency lists from the updated 2018 version of the collection. For Chinese we use the list identified as "China mainland", which mostly uses simplified Chinese characters. (In the 2018 version, Chinese subtitles are divided into "China mainland" and "Taiwan". Details of the division are not documented. The OpenSubtitles website itself divides Chinese into simplified, traditional, and Cantonese.) | – https://opus.nlpl.eu/OpenSubtitles/&/v2018/OpenSubtitles |
| | **SubIMDB** | We generate a frequency list from the full SubIMDB corpus, which comes in a pre-tokenized form. No frequency list was published for the corpus. | – https://zenodo.org/records/2552407 |
| | **SUBTLEX** | We use the published SUBTLEX raw frequency counts for English (US), Spanish (ESP), and Chinese (CH). | – https://www.ugent.be/pp/experimentele-psychologie/en/research/documents/subtlexus/subtlexus2.zip (US)<br>– http://www.ugent.be/pp/experimentele-psychologie/en/research/documents/subtlexch/subtlexchwf.zip (CH)<br>– https://web.archive.org/web/20220702151524/http://crr.ugent.be/papers/SUBTLEX-ESP.zip (ESP) |
| | **SUBTLEX-UK** | For English, we use raw frequency counts from SUBTLEX-UK as well. | – https://www.psychology.nottingham.ac.uk/subtlex-uk/SUBTLEX-UK.txt.zip |
| other | **GINI** | We use the published WORD GINI lists for English and Japanese. | – https://sociocom.naist.jp/word-gini-en/ |
| | **Wikipedia** | We use frequency lists based on cleaned up Wikipedia text tokenized using a regular expression. | – https://github.com/adno/wikipedia-word-frequency-clean |
| | **wordfreq** | We use the default (large) lists available from the Python library. | – https://pypi.org/project/wordfreq/ |

Table 11: Detailed information and sources for the corpora used for evaluation. Source is the publication, if it contains the frequency lists as supplementary material, or an URL from which the data (corpus or frequency list) is available. The corpora are introduced and cited in Section 2 and Section 5.1.

## E Statistics of the Evaluated Corpora

| Corpus | | Chinese | English | Indonesian | Japanese | Spanish |
|---|---|---|---|---|---|---|
| BNC-Spoken | tokens | — | 10,365,473 | — | — | — |
| | types | — | 669,417 | — | — | — |
| CREA-Spoken | tokens | — | — | — | — | 3,171,903 |
| | types | — | — | — | — | 67,979 |
| CSJ | tokens | — | — | — | 7,479,773 | — |
| | types | — | — | — | 40,630 | — |
| HKUST/MTS | tokens | 1,342,379 | — | — | — | — |
| | types | 42,247 | — | — | — | — |
| ACTIV-ES | tokens | — | — | — | — | 3,897,234 |
| | types | — | — | — | — | 80,787 |
| EsPal | tokens | — | — | — | — | 462,611,693 |
| | types | — | — | — | — | 35,257 |
| LaboroTV1+2 | tokens | — | — | — | 99,367,439 | — |
| | types | — | — | — | 218,762 | — |
| OpenSubtitles | tokens | 191,379,324 | 3,235,391,790 | 137,231,876 | 23,665,222 | 1,512,443,143 |
| | types | 1,009,838 | 2,290,458 | 456,125 | 58,856 | 1,629,907 |
| SubIMDB | tokens | — | 179,967,485 | — | — | — |
| | types | — | 899,603 | — | — | — |
| SUBTLEX | tokens | 33,546,516 | 49,719,560 | — | — | 40,017,237 |
| | types | 99,121 | 74,286 | — | — | 94,261 |
| SUBTLEX-UK | tokens | — | 201,706,753 | — | — | — |
| | types | — | 160,022 | — | — | — |
| GINI | tokens | — | — | — | — | — |
| | types | — | 324,713 | — | 208,275 | — |
| Wikipedia | tokens | 271,230,431 | 2,489,387,103 | 117,956,650 | 610,467,200 | 685,158,870 |
| | types | 1,403,791 | 2,161,820 | 373,461 | 522,210 | 986,947 |
| wordfreq | tokens | — | — | — | — | — |
| | types | 334,609 | 321,180 | 31,188 | 214,960 | 342,072 |
| $\text{TUBELEX}_{\text{default}}$ | tokens | 17,865,686 | 170,750,870 | 34,903,381 | 163,439,781 | 169,188,689 |
| | types | 432,532 | 467,296 | 307,633 | 409,503 | 632,112 |
| $\text{TUBELEX}_{\text{regex}}$ | tokens | — | 170,816,384 | 34,293,878 | — | 166,423,254 |
| | types | — | 420,718 | 300,870 | — | 613,181 |
| $\text{TUBELEX}_{\text{base}}$ | tokens | — | — | — | 163,439,781 | — |
| | types | — | — | — | 378,276 | — |
| $\text{TUBELEX}_{\text{lemma}}$ | tokens | — | 170,764,637 | 34,904,605 | 163,462,537 | 169,188,635 |
| | types | — | 433,545 | 266,827 | 329,303 | 527,060 |

Table 12: Numbers of tokens and types in the corpora evaluated in Section 5.1. Number of types is always based on the actual frequency lists we use (see Appendix D), after lowercasing and combining equivalent words (a few corpora list separately words differing only in case or POS). Number of tokens are either sums of individual token counts or explicit total token counts if available. GINI and wordfreq data do not report numbers of tokens (only index values and relative frequencies, respectively). Wordfreq also removes types with frequency less than $10^{-8}$.

## F Evaluation on Alternative Word Familiarity Norms

| | Corpus | English (Glasgow) | Japanese (Amano+Kondo) | Spanish (Moreno-Martínez) |
|---|---|---|---|---|
| speech | BNC-Spoken | 0.658* | — | — |
| | CREA-Spoken | — | — | 0.510*** |
| | CSJ | — | 0.441*** | — |
| film/TV subtitles | ACTIV-ES | — | — | 0.495*** |
| | EsPal | — | — | 0.557** |
| | LaboroTV1+2 | — | 0.536*** | — |
| | OpenSubtitles | 0.650 | 0.354*** | **0.612** |
| | SubIMDB | **0.675***** | — | — |
| | SUBTLEX | 0.642 | — | 0.585 |
| | SUBTLEX-UK | 0.674*** | — | — |
| other | GINI | 0.482*** | **0.572***** | — |
| | Wikipedia | 0.446*** | 0.423*** | 0.430*** |
| | wordfreq | 0.638** | 0.510*** | 0.557*** |
| our | $\text{TUBELEX}_{\text{default}}$ | 0.646 | 0.544 | 0.610 |
| | $\text{TUBELEX}_{\text{regex}}$ | 0.646 | — | 0.610 |
| | $\text{TUBELEX}_{\text{base}}$ | — | 0.564*** | — |
| | $\text{TUBELEX}_{\text{lemma}}$ | 0.639* | 0.538*** | 0.609 |

Table 13: Word familiarity (alternative norms) correlation (PCC). Strongest (highest) correlations for each language are in bold. Glasgow norms (Scott et al., 2019) for English, norms by Moreno-Martínez et al. (2014) for Spanish, and written word familiarity ratings by Amano and Kondo (1999) for Japanese. All three databases are smaller than the ones presented in Section 5.4.

## G Evaluation Dataset Sizes

| Task | Chinese | English | Indonesian | Japanese | Spanish |
|---|---|---|---|---|---|
| Lexical Decision Time | 12,576 | 38,130 | — | — | 45,190 |
| Lexical Complexity | — | 570 | — | 570 | 593 |
| Word Familiarity | 24,325 | 4,923 | 1,490 | 81,271 | 1,400 |
| Word Familiarity (Alternative) | — | 4,682 | — | 76,883 | 820 |

Table 14: Numbers of instances in the datasets used for evaluation. The individual datasets are introduced in Section 5.3 for lexical decision time, Section 5.5 for lexical complexity, Section 5.4 for word familiarity, and Appendix F for word familiarity – alternative datasets.

## H Correlation with Lexical Complexity Predictions

| | Corpus / ST System | English | Japanese | Spanish |
|---|---|---|---|---|
| speech | BNC-Spoken | 0.701 | — | — |
| | CREA-Spoken | — | — | 0.508 |
| | CSJ | — | 0.565 | — |
| film/TV subtitles | ACTIV-ES | — | — | −0.516 |
| | EsPal | — | — | 0.627 |
| | LaboroTV1+2 | — | 0.610 | — |
| | OpenSubtitles | 0.721 | 0.191 | 0.628 |
| | SubIMDB | 0.717 | — | — |
| | SUBTLEX | 0.696 | — | −0.618 |
| | SUBTLEX-UK | 0.726 | — | — |
| other | GINI | 0.349 | 0.379 | — |
| | Wikipedia | 0.651 | 0.487 | −0.454 |
| | wordfreq | 0.763 | 0.605 | 0.559 |
| our | $\text{TUBELEX}_{\text{default}}$ | 0.766 | 0.661 | 0.604 |
| | $\text{TUBELEX}_{\text{regex}}$ | 0.764 | — | 0.588 |
| | $\text{TUBELEX}_{\text{base}}$ | — | 0.663 | — |
| | $\text{TUBELEX}_{\text{lemma}}$ | 0.758 | 0.622 | 0.650 |
| top ST | Archaelogy (ID=2) | 0.790 | 0.485 | 0.230 |
| | GMU (ID=1) | **0.850** | 0.035 | −0.073 |
| | TMU-HIT (ID=2) | 0.820 | **0.733** | **0.762** |

Table 15: Correlation (PCC) with lexical complexity predictions, discounting misprediction of mean and variance. Best (highest) results for each language are in bold. Values for top shared task submissions (top ST) are cited from Shardlow et al. (2024). See the corresponding $R^2$ results, which measure the goodness of fit, in Table 6, and the discussion at the end of Section 5.5.