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The Construction and Evaluation of the LEAFTOP Dataset of Automatically Extracted Nouns in 1480 Languages

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Abstract

The LEAFTOP (language extracted automatically from thousands of passages) dataset consists of nouns that appear in multiple places in the four gospels of the New Testament. We use a naive approach — probabilistic inference — to identify likely translations in 1480 other languages. We evaluate this process and find that it provides lexiconaries with accuracy from 42% (Korafe) to 99% (Runyankole), averaging 72% correct across evaluated languages. The process translates up to 161 distinct lemmas from Koine Greek (average 159). We identify nouns which appear to be easy and hard to translate, language families where this technique works, and future possible improvements and extensions. The claims to novelty are: the use of a Koine Greek New Testament as the source language; using a fully-annotated manually-created grammatically parse of the source text; a custom scraper for texts in the target languages; a new metric for language similarity; a novel strategy for evaluation on low-resource languages.

Keywords: leaftop, bible, corpus, Koine Greek, lexicon, low-resource languages

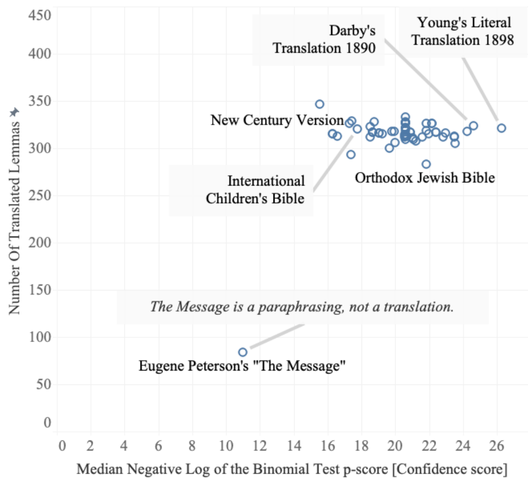


Figure 1: Paraphrased vs literal translations of the New Testament into English

Language Family	Languages Evaluated
Niger-Congo	Fon; Guinea Kpelle; Igbo; Samia; Luganda; Mano; Runyankole; Swahili; Twi; Soga; Yoruba
Afro-Asiatic	Tunisian Arabic; Modern Standard Arabic; Moroccan Arabic; Chadian Arabic
Dravidian	Telugu
Artificial	Esperanto
Arnhem	Gunwinggu
Austronesian	Cebuano; Dobu; Hiligaynon; Hiri Motu; Kilivila; Nyindrou; Takia; Tagalog
Trans-New Guinea	Korafe; Melpa
Indo-European	Bengali; German; French; Hindi; Marathi; Sinhala; Urdu
Nilo-Saharan	Teso

Table 1: The subset of the 1480 languages in the LEAFTOP dataset which have been evaluated, and the language families they are part of.

1. Introduction

This paper discusses a large new dataset designed to be useful for tasks involving part-of-speech identification, grammar morphology and language similarity measures which was created by extracting vocabulary from Bible translations. It establishes a baseline of accuracy for target language noun extraction using sensible naive techniques at scale, for the languages spoken by the majority of the world's population.

The resulting LEAFTOP dataset is both wide (1480 languages) and deep (160 nouns). For inflected languages it contains forms for number (singular vs plural) for all nouns; for some nouns it can also supply gender and case variations.

The Ethnologue (Eberhard et al., 2021) reports the existence of 7,139 living languages. There are surprisingly few data sets which cover a large proportion of the world's population that also have sufficient depth for machine learning techniques. There are only 82 nouns listed in the extended Swadesh 207 list; the ASJP database (Wichmann and Brown, 2020) covers only the Swadesh 100 and is therefore even smaller with only 46 nouns. This is a vocabulary that is too small for many machine learning techniques. Panlex (Kamholz et al., 2014) has sufficient depth and structure for many tasks,

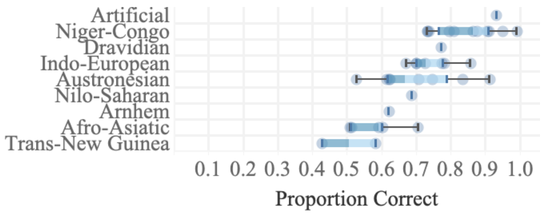


Figure 2: The LEAFTOP extraction approach works surprisingly well for languages in the Niger-Congo family and for some Austronesian languages, and less well for Trans-New Guinea languages.

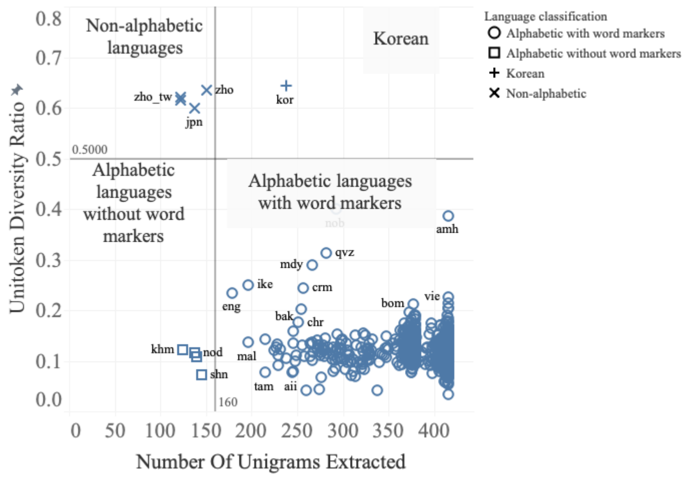


Figure 3: Identifying the written structure of the language. Korean is included as an alphabetic language with word break markers by algorithm 2 but is — as would be expected — an outlier. All other languages in the dataset are handled correctly.

but unfortunately has surprising gaps for the grammar morphology task we were pursuing[1].

Bible translations exist for the native languages of 80% of the world's population (Wycliffe, 2020). As of the end of December 2020, the Bible has been fully translated into 717 languages. A further 1,582 languages have a New Testament translation. As discussed in section 4, the four gospels alone are sufficient to generate singular and plural forms for 160 nouns in most (but not all) of these 2,299 languages.

2. Extensions of past work

Compared to past work in lemma extraction and massively parallel language corpora, a number of small incremental changes have been made:

- More successful scraping by writing site-specific parsers.
- An algorithm (algorithm 2) for identifying whether a language uses word markers and whether it has an alphabet.
- Automated identification of whether the translation attempted to be literal or used paraphrasing extensively.
- Used Koine Greek as the source language and leveraging existing manually-created part-of-speech annotations.

McCarthy et al. (2020) presented their work collating the Bible in 1600 languages at LREC in 2020, which re-used the CMU Wilderness Corpus (Black, 2019). They encountered limitations with this — verse alignment was challenging because the verse numbers are in-line in the text. Our improvement over this approach was to scrape from Bible gateways where the verse information is encoded in the metadata of the HTML[2].

In addition, where McCarthy et al. could only handle languages that have word-marker boundaries, the LEAFTOP dataset is able to distinguish between languages that have word marker boundaries, languages that don't have word marker boundaries that are nonetheless alphabetic (e.g. Thai, Khmer), and languages that don't have word marker boundaries that are non-alphabetic (e.g. Chinese characters, which LEAFTOP calls "uni-token" extractions) using the method in algorithm 2 (discussed in section 3.3. For alphabetic languages without word markers, the LEAFTOP dataset defaults to using quad-tokens, which is incorrect, and serves as a placeholder for future improvements.

Christodouloupoulos and Steedman (2015) assembled a corpus of translations into 100 different languages, preferring the oldest common translation where multiple translations exist. Their hope was that this would not be too archaic in language and also be the most literal translation. This led to them choosing the King James Version[3] (or Authorized Version) for English which sadly fails on both criteria[4]. Our reservations on this choice led us to want to use statistical methods to identify the translations which are likely to be literal, using the consistency of the translations of each source lemma. If two translations into the same lan-

[1]For example, as of the time of writing, Panlex correctly offers "mfuasi" as a translation for the English word "disciple", but without a direct English-to-Swahili translation, it offers "chama" (which is incorrect) as a two-step translation for "disciples".

[2]Prior to the 9th Circuit's decision on hiQ Labs, Inc. v. LinkedIn Corp in April 2022 scraping of this nature was of dubious legality.

[3]Which, uniquely among documents from the 17th century is not in the public domain. It is protected (still) by royal charter, but is allowed to be used for research purposes.

[4]Even at the time of publishing, "you" was displacing "thee" in spoken English for example. The many mistranslations of the KJV are well known, see (Tsoraklidis, 2001) for a small sample.

Algorithm 1 Vocabulary extraction algorithm

```
L ← the set of Greek lemmas that appear twice or more in the Gospels maintaining the same case, number and gender
B ← the Bible versions in the target language
for all l ∈ L do
    for all b ∈ B do
        C ← { verses present in translation b}
        V ← C ∩ { verses where lemma l appears }
        U ← C ∩ { verses where lemma l does not appear and neither does l in any other case, number or gender }
        for k ←unigram, unitoken, quadtoken do
            T ← {}
            for v ←V do
                s ← TokenizeVerse(b, v, k)
                T ← T ∪ s
            end for
            m ← ∞
            n ← {}
            for t ← T do
                Q ← the verses where t is present
                R ← the verses where t is not present
                X ← |V ∩ Q|
                Y ← |V ∩ R|
                Z ← |U ∩ Q|
                W ← |U ∩ R|
                p ← BinomTest(X,Y,Z,W,greater)
                if p = m then
                    n ← n ∪ {t}
                else if p ≤ m then
                    n ← {t}
                    m ← p
                end if
            end for
            if |n| = 1 then
                Trans(b, l, k) ← t
            end if
        end for
    end for
end for
```

guage have substantially different confidence scores[5] in lemma identification, and also substantially different numbers of lemmas that can be translated, then it is clear which version is a paraphrase. The results of this for English language translations is shown in Figure 1. These less literal translations are still included in LEAFTOP anyway.

With the exception of translations for the benefit of the Assyrian Church of the East[6], New Testament translations are supposed to be translations from Koine Greek. In practice, Bible translators use a variety of language sources; but when a word has ambiguous meanings, best practice is to refer to the Greek form.

This may not completely resolve the matter if the Greek itself covers multiple meanings in the target language. But we would expect — in general — word alignment from Greek should outperform word alignment from English[7]. Previous attempts to generate vocabulary from New Testament translations (such as the University of North Texas' submission to (McCarthy et al., 2019) and (Nicolai and Yarowsky, 2019)) have used English language sources to recover target language lemmas. And indeed, these have suffered from low accuracy, with the latter reference reporting 57.6% accuracy in their task. This falls far short of proving the superiority of aligning with Koine Greek in general for all languages, but it was sufficient evidence to support the authors' choice for LEAFTOP.

Finally, there is a loss of accuracy derived from automated tagging of parts of speech. An extensive search of the literature has failed to find any research on how accurate automated POS tagging of English language Bible translations is beyond what was in (Agić et al., 2015) which includes the unquantified sentence "Bible translations typically have fewer POS-unambiguous words than newswire." It is unlikely, though, that an automated tagger will be able to compete with the centuries of analysis that grammarians and translators have done on the New Testament source documents.

3. Data sources and Extraction

The source code is available[8]. This section explains the code and the choices made in developing it. Most of the works that were scraped are held under copyright and cannot be shared as part of this dataset.

3.1. Koine Greek Parsing

We chose to extract vocabulary from only the four Gospels in the hope that they would be using less abstract vocabulary and — written for an agrarian society — have terms that were mostly universal. This is unfortunately not true, as we discovered when the translations were evaluated in Gunwinggu[9] where words like "governor" and "prison" were untranslatable.

The history of the OpenText.org website is given in (Land and Pang, 2017); it is a manually-annotated copy of the Codex Sinaiticus performed by experienced linguists and theologians. As discussed in (Metzger, 1991), the Codex Sinaiticus is the second-best text we

[5]As discussed in section 3.3.3, the confidence score is the ratio of the negative log p-value of the best candidate word to the second best candidate word.

[6]Who hold that the correct source for New Testament translations is the Peshitta.

[7]Given how translation is done in low-resource languages, word alignment for low resource languages will probably work best when the source is the dominant language in the local region.

[8]`https://github.com/solresol/thousand-language-morphology`

[9]Also known as Bininj Gun-Wok and Kunwinjkuan, it is a language spoken by the Bininj people of West Arnhem Land in northern Australia, who have been mostly nomadic.

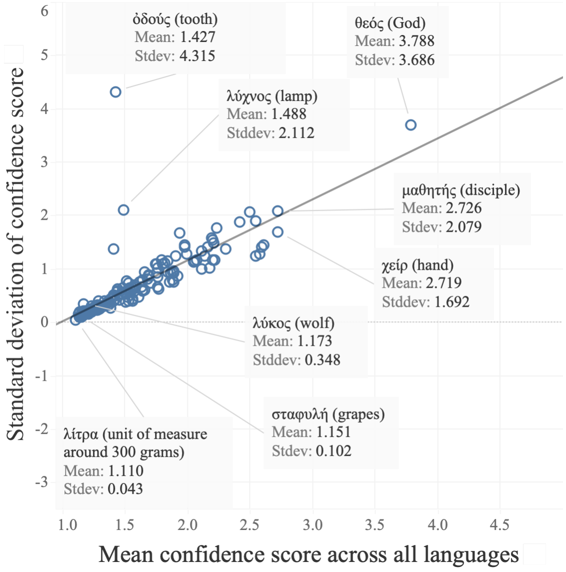


Figure 4: Scatterplot of mean and standard deviation (across all languages) of the confidence of the vocabulary extraction for each Koine Greek lemma (with English translation)

have of the 4 Gospels of the New Testament, but the grammatical annotations of the Codex Sinaiticus (and the Codex Sinaiticus itself) are the most accessible to researchers — they are available on github (Porter et al., 2018). Our review of the annotations found few mistakes: συκῆ (fig tree) is marked as neuter in Mark 11:13 instead of feminine; ἀλάβαστρον (jar for alabaster) is marked as feminine in Mark 14:3 instead of neuter. On no occasions was a noun marked as any other part of speech, nor any other part of speech marked as a noun. This is far from a perfect evaluation, but if these are the only problems, then the accuracy of these annotations is above 99.9%. The OpenText.org annotations also include Louw-Nida domains (Louw and Nida, 1998), which could be used in future projects for establishing p-adic word embeddings.

The XML sources were imported and all nouns whose annotated lemma did not begin with a capital letter (979 distinct lemmas) were identified and grouped based on gender (masculine, feminine, neuter), number and case (nominative, accusative, dative and genitive). Koine Greek (by the time of the New Testament) had lost the dual as a number, and only had singular and plural. Nouns that appeared only once in a given gender, number and case were dropped (leaving 567 lemmas, in 1185 forms).

We made the decision to limit the extraction to pairs of nouns that appear in both singular and plural forms, of which there are only 188. They appear in 666[10] different forms. On the one hand, this does allow for interesting grammar morphology tasks and substantially reduced the computation time required, but on the other

Algorithm 2 Algorithm for identifying the written structure of the language and choosing the correct tokenisation method

$u \leftarrow max(|\{$ Trans$(b, l,$unigram$)$ $\forall l \in L\}| \forall b \in B)$
$v \leftarrow max(|\{$ Trans$(b, l,$unitoken$)$ $\forall l \in L\}| \forall b \in B)$
$w \leftarrow$ the number of tokens in Trans$(b, l,$unitoken$)$ counting duplicates
if $u \geq 160$ **then**
  return `alphabet,word markers,unigram`
else if $v \geq \frac{w}{2}$ **then**
  return `non-alphabetic, unitoken`
else
  return `alphabetic, no word markers, quadtoken`
end if

L and B are from algorithm 1. 160 was found empirically from the clustering shown in Figure 3.

hand, it is an arbitrary constraint that could be dropped in a future version of the dataset.

In practice, Algorithm 1 was never able to extract more than 161 lemmas. On average, it extracted 159.2 terms (standard devation = 4.87).

3.2. Scraping

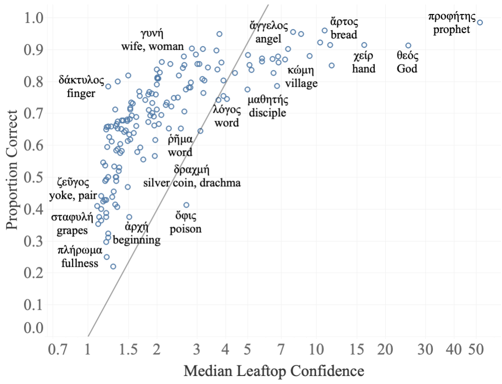
There are 3370 verses in the Gospels that contain nouns; only 2724 of them contain one of the 188 lemmas, so a small optimisation is not to fetch verses that will not be useful. This also helped establish that the purpose of the scraping is for research and not to create a complete copy. The scraper was written to use Selenium (Software Freedom Conservancy, 2021) to control a web browser to fetch the data; allowing for the inefficiency of this, and long delays to avoid triggering CAPTCHAs, the process of scraping the 6,008,134 verses from `www.bible.com` took several weeks.

The scraper rejected 217 of the 2,356 Bible versions because of some fundamental problem — a required book of the Bible being not present being the most common. Disputed verses (such as the passage from John 7:51 – 8:11, which was merged into the gospels later and therefore not present in all Bible translations) were captured as empty strings. This does not appear to reduce the accuracy of the lemma identification of the 10 nouns that appear in that passage that are also found in the repeated nouns list, since even the least common lemma δάκτυλος (finger) appears another 8 times in the Gospels.

Manual corrections were made for the Armenian Catholic Bible (which has many out-by-one misnumbered verses), and also for the Vulgate where some verses are coalesced.

Each Bible scrape collected the language code for the translation, which is a near match to ISO639-3, except that languages can have variants based on geography or orthography. For example, there are separate translations for `por` and `por_pt` (Portugese in different countries); and `shu` and `shu_rom` (Chadian Arabic in

[10]Which is an amusing coincidence.



Proportion Correct = 0.572*ln(Median Leaftop Confidence). P-value < 0.0001, R^2 = 0.732

Figure 5: Relationship between confidence and accuracy with forced linear regression

traditional script or Roman script). These are stored as separate languages within LEAFTOP. Each ISO639-3 code (and variant) is connected to a language name and geography using a Wikidata extract.

3.3. Vocabulary Extraction

The vocabulary extraction took 26,000 CPU hours, which was parallel-processed on a 64-cpu ARM processor in Amazon Web Services[11].

The vocabulary extraction algorithm is given in Algorithm 1. Note that it inefficiently calculates results for all tokenisation methods — unigrams (single words), unitokens (single unicode points) and quadgrams. On completion, algorithm 2 was run to identify which tokenisation method is the most appropriate for the language, and other results are discarded.

In essence Algorithm 1 runs a one-sided binomial test asking whether a word or token in the target language appears improbably often in the same verses as a Koine Greek lemma; the word or token that is found most improbably often (having the lowest p-value from the binomial test) is declared to be the best translation. If there is a tie for least-likely-to-be-a-chance result, no word is chosen.

3.3.1. Example

Consider how μνημεῖον (tomb, grave) is translated in the World English Bible. μνημεῖον appears in 35 distinct verses in the gospels in various forms; it appears in the nominative singular in only two verses: John 19:41 and John 19:42[12].

The scraping process successfully captured 2862 verses, but missed two of these 35 μνημεῖον verses. Setting aside the other 31 verses because they have the lemma μνημεῖον in some other case or number leaves 2831 verses from which we can calculate a baseline probability-of-appearance for an English unigram.

Focussing on the two verses with the nominative singular of μνημεῖον, the World English Bible translation shows 52 unigrams (including punctuation) of which 38 are distinct: unigrams such as "tomb", "laid", "garden" and "the".

The unigram "tomb" appears 6 times in the 2831 verses, giving it a baseline probability of $2.2 * 10^{-3}$ of appearing in a random gospel verse; "garden" appears 4 times, giving it a baseline probability of $1.4 * 10^{-3}$; "laid" appears 29 times (baseline probability $1.0 * 10^{-2}$). At the other extreme, the unigram "the" appears 1,916 times, for a baseline probability of 0.68. It is unsurprising when "the" appears in a verse, and very surprising when "garden" does.

The unigram "tomb" appears in both John 19:41 and John 19:42, as do the unigrams "the" and "laid", but "garden" only appears in the first of these verses. We can then perform a one-sided binomial test for each unigram. For "tomb", $B(2, 2, 2.2 * 10^{-3}) = 4.5 * 10^{-6}$; "laid" $B(2, 2, 1.4 * 10^{-3}) = 1.04 * 10^{-4}$; "garden" $B(1, 2, 1.4 * 10^{-3}) = 2.8 * 10^{-3}$; "the" $B(2, 2, 0.68) = 0.46$. From this we can conclude that a valid translation for μνημεῖον into English is "tomb".

3.3.2. Short-comings and failures

An obvious problem with this approach is that languages that inflect nouns with a case system that is substantially different to Koine Greek's — such as Arabic — are handled quite poorly, since there will be many distinct forms in the target language "competing" to be the best translation for each Koine Greek lemma.

A more subtle problem arises when more than one lemma translates into the same word in a target language (such as "fish" in English being a translation for ἰχθύς and ὀψάριον), since this alters the baseline appearance probability. The binomial test is very sensitive to changes in this baseline, and where there are mistakes in the LEAFTOP dataset, this is often the root cause.

3.3.3. Confidence score

These p-values from the binomial tests can be remarkably small – the median p-value across all languages for translating θεός (God) is $4.46 * 10^{-17}$, so it is more convenient to work in terms of the negative base-10 log of the p-value.

The ratio of this negative log p-value of the best word to the second best word is recorded in the LEAFTOP database as the confidence score. In the μνημεῖον example, the next nearest alternative to "tomb" is "laid"; the ratio between their log p-values is 1.3.

As discussed in section 4.2, the confidence score is a useful (but not sufficient) predictor of whether the vocabulary is correct.

[11] A `c6g.16xlarge` spot instance.

[12] *[41] Now in the place where he was crucified there was a garden. In the garden was a new tomb in which no man had ever yet been laid. [42] Then because of the Jews' Preparation Day (for the tomb was near at hand) they laid Jesus there.* — World English Bible

Lemma	*English*	*correct%*	*Rank*
προφήτης	prophet	98.4	161
ὕδωρ	water	95.9	160
ἔτος	year	95.5	159
ἄνεμος	wind	94.9	157
πρόβατον	sheep	94.9	157
παραβολή	parable	92.2	156
χείρ	hand	91.4	155
ἄρτος	bread	91.3	154
θεός	God	91.3	153
ἱμάτιον	coat	90.3	152

Table 2: Top 10 lemmas most likely to be extracted correctly

Figure 4 shows the mean and standard deviations of the confidence scores for each lemma. Words like θεός (God), μαθητής (disciple) and χείρ (hand) are usually easy to identify in most target languages, which is unsurprising as they are very commonly used in the gospels and are unlikely to be paraphrased. These have very high confidence scores.

Conversely, words like λίτρα (a unit of measure), σταφυλή (grapes) and λύκος (wolf) are usually the hardest to identify, suggesting that translators were either unable to be consistent in the way that they translate these terms or that these terms regularly appear as part of a repeated multi-term phrase.

ὀδούς (tooth) is either easy to extract if the translators translated Matthew 5:38[13] very literally or nearly impossible to extract otherwise. Similarly the confidence in extracting λύχνος (lamp) is heavily influenced by the translators' choices in Luke 12:35[14].

245 language codes have more than one translation available. For these languages, a consensus-by-vote for each lemma is taken based on the results from the Bible versions in that language. The confidence scores are multiplied[15] and stored as `cumulative_confidence` in the LEAFTOP extracts for each language. Where there is a tie for the best word, nothing is chosen. For languages without a second translation, a pseudo-consensus (the answer derived from the sole translation) is used.

4. Results

The LEAFTOP dataset has 625,351 distinct words in 1502 different languages. 22 of those languages are variant forms of some other language (e.g. `zho_tw`, `urd_dv`). Taking each language and considering each Koine Greek lemma as a concept, there are 239,156 distinct records.

[13] *You have heard that it was said, "An eye for an eye, and a tooth for a tooth."* — World English Bible

[14] *Let your waist be dressed and your lamps burning.* — World English Bible

[15] An additive model is also being investigated.

Lemma	*English*	*correct%*	*Rank*
τροφή	food	37.5	8
κλῆρος	lots (casting of lots), inheritance	37.5	8
τράπεζα	table	37.5	8
κοιλία	womb, stomach, source of feelings and emotions	36.4	7
σταφυλή	grapes	35.3	6
ἀρχή	beginning	32.4	5
βρέφος	babies	31.1	4
ὀφειλέτης	debtor	29.6	3
πλήρωμα	fullness	25.0	2
στάχυς	head of grain	21.9	1

Table 3: Bottom 10 lemmas least likely to be extracted correctly

4.1. Evaluations of correctness

The numbers in Section 4 include words that are incorrect. The error count is hard to obtain. Randomly sampling from 1,480 languages would have been impractical, since there would be a high probability of landing on a language that has a very small number of speakers, or is extinct.

Instead, the approach taken was to group by language geography, find freelancers in the appropriate part of the world, and pay for them either to check the extracted vocabulary themeselves, or to find speakers of regional languages who could do this. This was only partly successful; we were unable to find freelance translators for any South American or North American indigenous language. Only one Australian Aboriginal language has been checked, and that wasn't even from one of the larger language families. The list of languages (and the language family associated with them) is shown in Table 1.

The evaluations themselves have errors, which are preserved as-is in the LEAFTOP evaluations data. Examples that we noticed include French *pains* being marked as incorrect for ἄρτος (bread), and Swahili *Mungu* being marked as incorrect for θεός (God). There are likely to be more.

A chart summarising the evaluations done by the translators is shown in Figure 2. In total they checked 10,464 distinct words, corresponding to 5,120 (language, lemma) combinations; respectively approximately 1.7% and 2.1% of the total vocabulary.

An interesting accident happened with Chadian Arabic. Due to a miscommunication by the first author, the evaluator checked the translations for both `shu` (60.4% correct) and `shu_rom` (59.2% correct) — the latter being Chadian Arabic written in Romanized letters. While it is premature to assume that LEAFTOP works equally well across different writing systems, this result does hint at that.

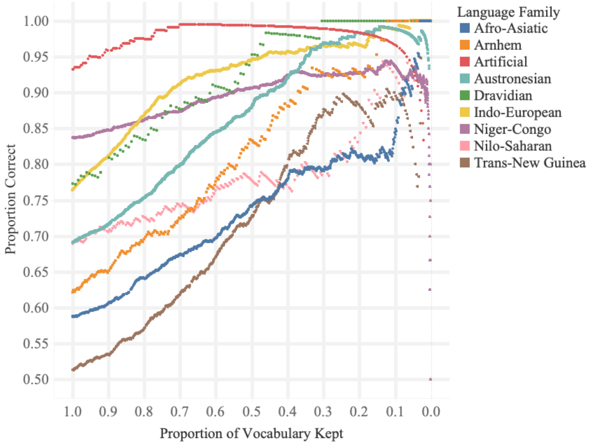


Figure 6: Trade-off curve of correctness vs size — altering the confidence threshold cut-off generally increases the probability of having correct vocabulary

4.2. Approaches for improving vocabulary accuracy

Linguists working with the LEAFTOP data may be willing to trade off a smaller vocabulary for higher accuracy.

As shown by the trend line in Figure 5, confidence doesn't fully explain accuracy. Even when the regression is against the rank of the proportion correct, the R^2 is still only 0.83; so even a non-linear monotonic relationship is not fully explanatory. But in general, higher confidence scores are predictive of the higher accuracy. By setting a minimum confidence cut-off threshold, it is possible to have a smaller data set that has higher accuracy. Figure 6 shows the trade-offs that are possible.

Considering Figure 5 again, words like *wind*, *disease* and *finger* are disproportionately likely to be extracted correctly, and conversely, religious terms such as *prophet*, *God* and *parable* are much harder to extract correctly given how often these words appear in the Gospels — it is common for the LEAFTOP algorithm to mistake the word for God (for example) in an usual case or number.

This offers an alternative approach, which is to filter out by vocabulary. Table 2 lists the lemmas that are the most likely to be correct, and Table 3 lists the lemmas that are most likely to be incorrect.

Finally, it is rare for the singular and plural of a word to differ substantially, but there are many lemmas in the LEAFTOP database where the extracted singulars and plurals differ. χρόνος (time) is translated into German as `Zeit` in the singular (which is correct), and as `längere` ("longer") in the plural. An obvious filter that could be implemented for alphabetic languages is to count the number of letter sequences in common and find a threshold below which it is unlikely to be a correct translation; a Levenshtein distance (or equivalent) could also be used. A more sophisticated filter could be created by building a machine learning model to predict the plural from the singular and to discard lemmas where there is a mismatch. We are working on this latter approach.

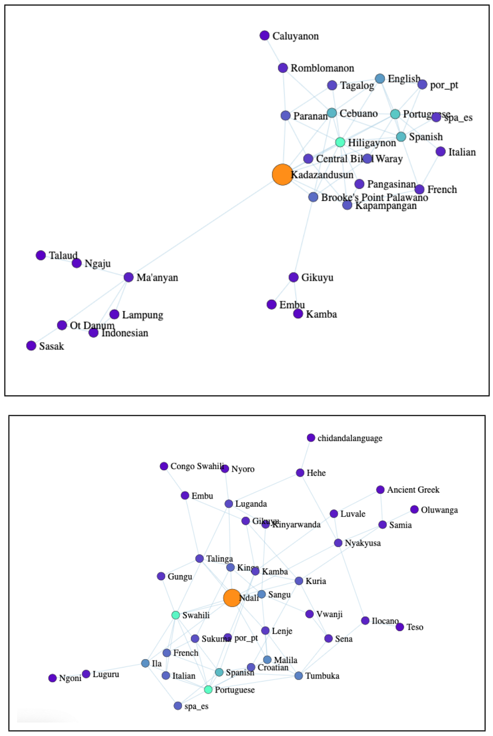


Figure 7: Screenshots of the LEAFTOP explorer

5. Exploratory Tools

The last component of the LEAFTOP database is the explorer. This is an interactive set of web pages for showing the relationships between different languages. The idea behind it is that if two languages are related, then the challenges faced by translators should have been similar — words and concepts that do not map nicely from Koine Greek to one language should also be hard to map into a related language. Likewise, concepts that have straightforward mappings, should also be straightforward in a related language.

This is of course a vast simplification of a much more complex system and the goal is to explore the limitations of this toy model.

This relatedness of two languages is quantified in the LEAFTOP dataset by the Spearman correlation statistic between the confidence scores of the two languages — for each lemma the confidence score from language 1 is the x value and the confidence score for language 2 is the y axis. The approximately-160 data points can then be correlated.

To visualise these correlation statistics and make an interesting interactive demonstration of this data, the first author created a D3.js (Bostok, 2018) force simulation model. Each language is modelled as a ball connected to other languages by a spring. The strength of the spring is proportional to the correlation. To simplify the user interface, only the languages with the closest and strongest springs are shown to the user. Sample outputs are shown in Figure 7.

The results are simultaneously disappointing and exciting. Many languages are connected to each other correctly. Unfortunately, the languages spoken by European missionaries and translators correlate very strongly with many target languages in completely different language families — e.g. the confidence scores of Spanish and Hiligaynon are highly correlated across lemmas. Possible causes for this could be an implicit bias by translators; or could be related to the introduction of new vocabulary from the missionary's native language substituting for vocabulary that didn't exist previously; or it could simply be random noise.

6. Conclusion

The LEAFTOP dataset is an extremely large collection of nouns across many different languages, with a measured accuracy across a variety of language families. It has been used for building multilingual pluralization models and for language exploration. There are straightforward extensions that could be done to improve its accuracy and coverage.

The source code for creating the dataset is `https://github.com/solresol/thousand-language-morphology`, and the final outputs (the dataset itself) are in `https://github.com/solresol/leaftop`.

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