A Universal Semantic Space

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Abstract

Multilingual embeddings build on the success of monolingual embeddings and have applications in crosslingual transfer, in machine translation and in the digital humanities. We present the first multilingual embedding space for thousands of languages, a much larger number of languages than in prior work.

1 Introduction

Multilingual embeddings build on the success of monolingual embeddings and have applications in crosslingual transfer (for tasks like sentiment analysis), in machine translation and in the digital humanities. Our goal in this paper is to learn a single embedding space for thousands of languages, a much larger number of languages than in prior work.

As our corpus, we use the New Testament, the only source of high-quality text that provides a reasonable amount of data (about one megabyte) for 1000+ languages. More specifically, we use the New Testament part of Parallel Bible Corpus (PBC). PBC is verse-aligned. We show that embeddings trained based on alignments on the granularity of verse have poor quality and conclude that we need a more fine grained alignment.

Standard alignment algorithms work well if three conditions are met.

1. Large parallel corpora are available.
2. Good tokenizers are available.
3. A sufficient number of the units produced by tokenization have medium to high frequency.

PBC does not meet these three conditions.

1. The amount of data for any given language is small: less than 5 megabytes per language.\(^1\)
2. For many of the 1000+ languages, tokenizers have not been developed.
3. For many languages, default tokenization (segmentation on whitespace and punctuation) contains few medium to high frequency tokens. Examples for languages that have this property are ZUL (a Bantu language) and ESK (an Inuit language), two morphologically rich languages that give rise to few frequent units. See §11.

A standard alignment algorithm attempts to find all correct alignment edges. It can be evaluated using \(F_1\) of correct identification of gold standard alignment edges. For the reasons just given, standard alignment may not be a realistic goal for PBC. We therefore define a new alignment task, specifically for the purpose of learning multilingual embeddings.

High-precision semantic unit alignment. The objective of high-precision semantic unit alignment is to align a sufficient number of semantic units to be able to induce a high-quality semantic space. It is evaluated by means of measures that evaluate the quality of the induced space.

In contrast to standard alignment algorithms, the non-alignment of non-semantic units (e.g., function words) is not penalized. While higher recall is better, a recall at or even lower than 75%

\(^1\)There are a few languages with a “compact” encoding that are a lot smaller than one megabyte. For example, LZH-wenli-high has size .6 megabytes. Most languages are in the range 1-3 megabytes. A few with “lengthy” encodings like MIA are in the range 3-5.
for semantic units can still be sufficient for embedding learning. For example, if the semantic unit “branch” is not aligned, we can conceivably still learn a good embedding for it based on monolingual associations with “tree”, “bough”, “root”, “leaves” as long as these units are aligned correctly.

We propose GREGAL (GREedy Global ALign-ment) to solve the three challenges of aligning PBC: low resource, unavailability of tokenizers and token complexity/infrequency. GREGAL is not designed to do well on the standard alignment task: it does not find many function-word alignments and it has lower recall than standard alignment algorithms. But it has high precision and we will show that its alignments produce a high-quality universal semantic space.

There are no gold standards for many of the 1000+ languages in PBC. We devise TofT (trans-lation of translation), a new evaluation method for multilingual embeddings that can be applied if no resources are available for a language. For an English query \( q \) and a target language \( L_t \), TofT finds the unit \( w_t \) in \( L_t \) that is closest to \( q \) and then the English unit \( w_e \) that is closest to \( w_t \). If the semantics of \( q \) and \( w_e \) are identical (resp. are unrelated), this is deemed evidence for (resp. counter-evidence against) the quality of the embeddings of \( L_t \).

In summary, we make the following contributions in this paper.

- We introduce TofT a new evaluation measure for multilingual embeddings.

The interested reader can look up ISO639-3 codes on this page: en.wikipedia.org/wiki/ISO_639-3

2 Pivot languages

Many of the world’s languages pose difficult problems to NLP researchers. However, some present more challenges than others. While we have encountered many difficulties working with the 1000+ languages of PBC, we also found some languages that have very favorable properties for alignment and embedding learning. Intuitively, we want a language that codes semantic concepts “overtly”. Ideally, the language would have a one-to-one correspondence between semantic concepts and overt units where by a overt unit we mean a unit that can be easily recognized on the surface.

As our working definition of “easily recognizable on the surface”, we adopt “is a token that is found by straightforward tokenization rules”, i.e., whitespace tokenization.

This definition is not a contradiction to our claim that tokenization does not work for many languages. For our approach to work, we stipulate that that there are a few languages that can be easily tokenized. We do not stipulate that all languages can be easily tokenized.

We can apply whitespace tokenization to any language \( L \). How do we know that the result can be interpreted as “\( L \) is a language that encodes semantic concepts overtly”?

Here, we adopt as our proxy measure for “semantic overtness” the number of types. The smaller the number of types, the better. Of course,
Table 2: For each Bible translation, we give the ratio $\rho$ of its size in bytes to the median size in PBC. Hakka Chinese has almost exactly the median size.

| $\rho$ | translation               | language                      |
|-------|---------------------------|-------------------------------|
| 0.42  | LZH-wenli-high            | Classical Chinese             |
| 0.69  | KOR-latinscript           | Korean (Latin)                |
| 0.75  | ENG-kingjames             | English, King James          |
| 0.82  | FRA-despeuples            | French                        |
| 1.00  | HAK                        | Hakka Chinese                 |
| 1.08  | KOR-newworld1999          | Korean (Hangul)               |
| 1.47  | IKE                        | Inuktitut                     |
| 2.56  | TAM-newworld              | Tamil                         |
| 3.44  | MYA-common                | Burmese                       |

Table 1 shows the ten languages in PBC that have the smallest number of types in 5000 randomly selected verses. (These are actually ten of the twelve Bible translations with the fewest number of types. Lahu and Iu Mien occurred twice. We took the instance with the smaller number of types in each case.) Since few verses are non-empty in all 1000+ languages, we take a different random sample in each language. We will refer to these ten languages as **pivot languages** in the rest of the paper.

### 3 Character-level modeling

To overcome tokenization problems, we represent a verse of length $m$ bytes, as a sequence of $m - (n - 1) + 2$ overlapping byte $n$-grams. We pad the verse with an initial and a final space, resulting in two additional $n$-grams (hence “+2”). This representation is in the spirit of earlier byte-level processing, e.g., (Gillick et al., 2016). There are several motivations for this. (i) We can take advantage of byte-level generalizations. (ii) This is robust if there is noise in the byte encoding. (iii) Unicode characters have different properties in different languages, e.g., English characters have properties different from Chinese characters. It is therefore easier to design universal language processing algorithms on the byte level.

One challenge is that the same byte size does not fit all. Table 2 shows the relative size in bytes for nine Bible translations with respect to the median size. HAK is almost exactly at the median size (1.00). The “most compact” language in terms of byte encoding is Classical Chinese (LZH, 0.42). Burmese (MYA) has the longest translation in bytes (3.44): most of the characters in this translation are encoded as three or four bytes. Obviously, the byte size depends on the script, e.g., in Korean (KOR): Latin (0.69) vs. Hangul (1.08). An English (ENG) and a French (FRA) translation are at 0.75 and 0.82. Inuktitut (IKE, 1.47) and Tamil (TAM, 2.56) are at intermediate points between 1.00 and 3.44.

We set the $n$ parameter of $n$-grams to $n = 4$ for Bible translations with $\rho < 2$, $n = 8$ for Bible translations with $2 \leq \rho < 3$ and $n = 12$ for Bible translations with $\rho \geq 3$.

### 4 GREGAL

We compute an alignment between each pivot language and each of the 1000+ PBC languages. We refer to the 1000+ PBC languages as **target languages**. A pivot language verse is represented as a bag of words. A target language verse is represented as a bag of $n$-grams.

GREGAL is a simple greedy algorithm that adds one edge to the bilingual dictionary in each step and then adds edges instantiating the dictionary edge to the alignment. In what follows, edge will refer dictionary edge.

In principle, all relevant statistics are recomputed after each step, but for efficiency reasons we heuristically take several steps at a time during certain phases of the algorithm.

The measures of goodness of a candidate edge are $\chi^2$, frequency and node degree.

The outer loop considers node degree: in the first pass of the algorithm only edges are considered that are the first edge for both nodes connected by the edge. Thus, during this pass, an edge that has been added blocks the two involved nodes for all other alignments during this pass. In the second pass, nodes of degree 2 are permissible and so on.

The “intermediate loop” (between the outer loop and the inner loop) considers frequency, start-
Table 3: Comparison of IBM and GREGAL alignments of pivot language TPI (Tok Pisin) with target languages ENG (ENG-kingjames) and KHM (KHM-newworld). See Table 4 for description of headers.

|       | ENG |       |       |       |       | freq pivot | freq target |
|-------|-----|-------|-------|-------|-------|------------|-------------|
|       | IBM | 7941  | 977615| 104975| 7174  | 125 034    | 051 010     |
|       | GREGAL | 7889 | 985558| 51115 | 1175  | 121 037    | 075 024     |
|       | KHM | 7939  | 2944099| 20173 | 15290 | 017 005    | 001 000     |
|       | GREGAL | 7923 | 2952042| 63287 | 1367  | 162 046    | 077 023     |

Table 4: “t size”: size of median-length type as percentage (in bytes) of average number of bytes per verse. “cov”: coverage of aligned tokens of target language of all bytes of target language. “1, 5, 10, 50”: As an example consider “125” and “051” for eng and fa (first row of Table 3), the two values for the 1% percentile for pivot (125) and target (051). The 1% percentile word of the pivot language occurs in 12.5% of the verses. The 1% percentile word of the target language occurs in 5.1% of the verses.

5 IBM alignments

For brevity, we refer to alignments produced by aligners that are instantiations of the well-known IBM model as IBM alignments. All IBM alignments in this paper are produced by fastalign (Dyer et al., 2013).

We computed intersection IBM alignments for each pivot-target pair.

Table 3 shows IBM and GREGAL alignments for ENG (ENG-kingjames) and KHM (KHM-newworld). Table 4 defines column headers.

A good alignment for universal semantic space induction is a tradeoff between coverage and unit quality. Other things being equal, we want to cover as much of the text as possible with our alignment. The two alignments for KHM are comparable in terms of byte coverage: .556 for IBM and .515 for GREGAL.

Other things being equal, we want “unit quality” to be high. One component of unit quality is frequency. A unit that only occurs once is useless. A unit that occurs a few times is also of little utility. The default frequency threshold is 100 for word2vec because vectors learned for rare words are generally of low quality. If a unit is very frequent, then that is also suspect: most very frequent units are function words and punctuation in English. Again, most function words and punctuation marks are given meaningless vectors by word2vec. However, there are a few very frequent words in the Bible that are content words including names like “Jesus”.

GREGAL results for KHM look better for unit quality: a relatively small number of types (1367) was found, most of which have a frequency in a
reasonable range and are aligned to such units. For example, 5% of GRE-GAL’s n-grams occur in more than 2.3% of the verses and 5% of GRE-GAL’s n-grams are aligned to pivot tokens that occur in more than 4.6% of the verses. The corresponding numbers are 0.0% and 0.5% for IBM.

Our interpretation of the results for KHM in Table 3 is that the tokenization algorithm whose output IBM takes as input failed for KHM. The KHM “tokens” are large chunks: the median-length type has a length of .243 of the average verse. These tokens are too sparse: the 1%-percentile type occurs in only .001 of verses.

In contrast, GRE-GAL is better than IBM on all metrics for KHM. Even though IBM fails for some languages, it works well for many others. An example is ENG in the table: based on the statistics, it is not clear which alignment (IBM or GRE-GAL) is better, but the median token length of 0.049 (IBM) may be more appropriate for English content words than the fixed byte size 0.032 (GRE-GAL).

6 Embedding learning

We use word2vec (Mikolov et al., 2013a) for embedding learning. Vector dimensionality is set to 200 throughout.

6.1 Baseline

For our baseline, we extend Vulic and Moens (2015)’s bilingual method to the multilingual case. The n-grams in each target verse and the words from the corresponding verses of two of the ten pivot languages are collected in a set A. We draw a sample (without replacement) of size \(\alpha|A|\) from A where we set \(\alpha = 0.25\) in this work. There are \(\binom{|A|}{2}\) = 45 combinations of pivot languages, so we perform this sampling 45 times for each verse of each target language. The \(\alpha|A|\) n-grams and words in the sample are shuffled before they are added to the word2vec training corpus.

6.2 Dictionary corpora

For IBM and GRE-GAL, we collect all edges of all alignments. We discard pivot tokens that were aligned to a single target unit on the theory that such a single alignment is unlikely to be correct. For each pivot token \(w_p\) that is aligned to more than one target unit, we collect the \(m\) target units that were aligned to \(w_p\) across languages. We then write ten shuffled lines of length \(m+1\) to the GRE-GAL dictionary corpus. For IBM, we first convert target tokens to target n-grams. We then write ten shuffled lines to the IBM dictionary corpus. The resulting IBM corpus is about twice as large as the GRE-GAL corpus.

6.3 Summary of corpora

- VM. The Vulic&Moens baseline
- IBM. The IBM dictionary corpus
- GRE-GAL. The GRE-GAL dictionary corpus
- VM+IBM. The concatenation of VM and IBM dictionary corpus
- VM+GRE-GAL. The concatenation of VM and GRE-GAL dictionary corpus

7 Evaluation methodology

We use ToT (translation of translation) for evaluation; ToT is based on the common idea of back-and-forth translation. Given a query \(q\) (an n-gram) in a query language (English in our case), we consider the set of \(k^{(T)}\) nearest neighbors of the query in each language \(\{n_{i1}^{(1)}, n_{i2}^{(1)}, \ldots, n_{ik}^{(k)}, n_{ij}^{(1)}\}\). For each intermediate entry we then consider its \(k^{(T)}\) nearest neighbors in English. Overall we get per intermediate Bible translation \(l\) a set \(T_l\) with \(k^{(T)}\) candidate n-grams.

We evaluate the sets \(T_l\) based on tuples consisting of a query \(q\) with a corresponding ground truth set \(G\), which we create manually. We consider a strict and a relaxed ground truth set, denoted by \(G_s\) and \(G_r\), respectively. The strict set contains only n-grams that are exactly or very closely synonymous and that are not “ambiguous”, i.e., cannot occur in two different frequent English words. The relaxed set contains n-grams that are correct, but could also be part of words with completely different meaning. For example for the query “@God” the n-grams “@God” and “God@” are in the strict set (“@” denotes a space). “Aloha” is also in the strict set, as in some English Bible translations “God” is translated as “Aloha”. However, “od’s” is in the relaxed set as it occurs in words different from “God”, e.g., “Herod’s”.

We calculate Bible translation level precision as

\[
p_k := \frac{\sum_{l \in L} \min\{1, |T_l \cap G_i|\}}{|L|} \tag{1}
\]

where \(L\) denotes the set of all Bible translations, \(|L|\) the cardinality of the set \(L\) and \(i \in \{s, r\}\).
Table 5: Precision values for triples of \((i, k^{(I)}, k^{(T)})\). The query is given in the upper left corner of each subtable, e.g., “KJ:@God”. Hyphen indicates that the query was not contained in the dictionary of the corresponding embedding space. The best result in a column is bold. G=GREGAL. I=IBM. VM+G = VM+GREGAL. VM+I = VM+IBM.

8 Experimental setup and results

We use PBC (Mayer and Cysouw, 2014). The version we pulled on 2017-12-11 contains 1777 Bible translations in 1339 languages (ISO639-3 codes). The data is verse aligned; a verse of the New Testament often consists of multiple sentences. We discard Bible translations that only contain the Hebrew Bible because the New Testament has the best coverage across languages. On average, a Bible translation consists of 7575 verses.

Table 5 presents results for nine English queries. PBC is a parallel corpus of Bible translations, not languages. Thus, we must take each of the nine English words from a specific Bible translation: ENG-catholic (CA), ENG-clontz (CL), ENG-common (CO), ENG-kingjames (KJ) and ENG-worldwide (WW).

One can clearly see that GREGAL yields the best performance across queries. One exception is the query “dead”: GREGAL exhibits the worst performance across all methods. Especially for queries with entities, GREGAL seems to work with high accuracy. In contrast, for “@law”, GREGAL shows worse performance while VM+GREGAL even shows increased performance compared to the entities “@God” and “Saul”. VM+IBM yields a small but stable precision gain compared to VM across all queries. IBM works better on entities like “Paul” and “Saul”, but shows low absolute precision values. VM yields low precision across all queries.

To understand the differences in performance more clearly we look at the top 5 predicted n-grams for the setting \((s, 1, 1)\) (based on Bible translation count) for each method in Table 6.

The predictions by VM are quite noisy. Especially the vector of “So@o” is frequently selected, for several of the queries. “Tars” is Tarsus, Saul’s city of origin. For “oliv”, the predictions are of lower quality, but “figs” and “branch”
are semantically related to olive. For “song”, TofT frequently returns “hymn” and “psalm”. Predictions for “dead” include semantically correct n-grams, but with different part of speech: “death” and “die”.

Overall one can see that the count distribution for GREGAL is spikier than for the other methods. This is consistent with the higher precision values reported for GREGAL.

We also examine the actual intermediate tokens (i.e., the nearest neighbors of the query) in German. Top intermediate tokens for “@God” are the correct n-grams “@Got”, “Gott” and “ott”. Interestingly, intermediates for “rain” are mostly “Donn” and “@Don” for German “Donner” (“thunder”). This inconsistency might be due to the word choice in the Bible translations and is also reflected in the top predictions for this query (“rain”, “thun” and “floo”). For “song”, one would expect the German noun “Lied”. However, intermediate tokens also include the verb “singen” (to sing) instead of a noun. For “dead”, GREGAL intermediates mostly entail such entities as “Pontius” or “Antichrist”. This indicates that a poor-quality embedding was learned for the n-gram “dead” in ENG-worldwide.

### 9 Related Work

Methods to evaluate the quality of embeddings can be categorized into *intrinsic* and *extrinsic*. Extrinsic methods include evaluation on tasks like document classification, word similarity and dictionary induction. All of them are not applicable here because for many languages, the Bible is the only existing large corpus and no additional annotated data are available. Intrinsic evaluation methods include QVEC (Ling and Dyer, 2015) and its extension QVEC-CCA (Ammar et al., 2016). However, both methods rely on manually created data as well.

Upadhyay et al. (2016) cluster multilingual embeddings into four approaches. (i) One approach is based on Mikolov et al. (2013b)’s idea that embedding spaces across different languages can be merged into a common space via linear transformations. (ii) The method by Faruqui and Dyer (2014) determine the linear transformation via canonical correlation analysis. (iii) Novel approaches extend Mikolov et al. (2013a)’s skip gram model to a bilingual model by incorporating word alignment data. (iv) The novel approach by Hermann and Blunsom (2014) create multilingual embeddings in 59 languages with monolingual signals and dictionaries. They also propose a method that projects tokens to clusters; clusters are subsequently embedded using one large concatenated corpus. Both methods yield improvements in dependency parsing and document classification tasks. Luong et al. (2017)’s work is similar. Faruqui and Dyer (2014) cluster embeddings across different languages by incorporating word alignment data. However, both methods rely on manually created data as well.

Table 6: Error analysis. Numbers in parentheses indicate the number of Bible translations which point to this 4-gram.
nary induction. Their true multilingual approach (in contrast to aggregating multiple bilingual signals) performs better and they conclude that a multilingual signal is valuable. (iv) Vulic and Moens (2015) create a pseudo bilingual corpus and subsequently run word2vec on this corpus. This is the baseline in our paper.

10 Conclusion

Multilingual embeddings build on the success of monolingual embeddings and have applications in crosslingual transfer, in machine translation and in the digital humanities. We have presented the first multilingual embedding space for thousands of languages, a much larger number of languages than in prior work.

11 Future work

Using the number of types as a criterion for the "pivotness" of a language does not have high precision. We suspect that we selected HAK because the number of HAK types roughly corresponds to the number of Chinese characters, i.e., to units that in many cases occur in historically and semantically weakly related larger phrases, but are not good semantic units for word2vec. A similar case in English would be "tain" in "abstain", "attain", "contain", "entertain", "obtain", "retain", "sustain".

In future work, we will attempt to find better criteria for identifying pivot languages.

We found 24,714 different types in ZUL-newworld and 25,783 different types in ESK based on naive tokenization (white space and punctuation). Compare this to 4192 for ENG-newcentury. TPI “jisas” is IBM-aligned to 15 different ZUL words: “Jesu”, “kaJesu”, “kuJesu”, “kukaJesu”, “kwakunguJesu”, “likaJesu”, “lukaJesu”, “nakuJesu”, “ngoJesu”, “nguJesu”, “noJesu”, “sikaJesu”, “uJesu”, “UJesu”, “zikaJesu”. Similarly, TPI “jisas” is IBM-aligned to 17 different ESK words. This may or may not indicate that IBM alignment for TPI “jisas”, the most frequent name in the New Testament, worked well. But this proliferation of types is likely to harm alignment quality for any word that is less frequent. This is evidence (albeit anecdotal) that there are some languages in PBC that pose great difficulties for IBM.

In future work, we want to investigate this question more rigorously.

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