Active Learning for Massively Parallel Translation of Constrained Text into Low Resource Languages

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Abstract
We translate a closed text that is known in advance and available in many languages into a new and severely low resource language. Most human translation efforts adopt a portion-based approach to translate consecutive pages/chapters in order, which may not suit machine translation. We compare the portion-based approach that optimizes coherence of the text locally with the random sampling approach that increases coverage of the text globally. Our results show that the random sampling approach performs better. When training on a seed corpus of ~1,000 lines from the Bible and testing on the rest of the Bible (~30,000 lines), random sampling gives a performance gain of +8.5 BLEU using English as a simulated low resource language, and +1.9 BLEU using Eastern Pokomchi, a Mayan language. Furthermore, we compare three ways of updating machine translation models with increasing amount of human post-edited data through iterations. We find that adding newly post-edited data to training after vocabulary update without self-supervision performs the best. We propose an algorithm for human and machine to work together seamlessly to translate a closed text into a severely low resource language.

1 Introduction
Machine translation has flourished ever since the first computer was made (Hirschberg and Manning, 2015; Popel et al., 2020). Over the years, human translation is assisted by machine translation to remove human bias and translation capacity limitations (Koehn and Haddow, 2009; Li et al., 2014; Savoldi et al., 2021; Bowker, 2002; Bowker and Fisher, 2010; Koehn, 2009). By learning human translation taxonomy and post-editing styles, machine translation borrows many ideas from human translation to improve performance through active learning (Settles, 2012; Carl et al., 2011; Denkowski, 2015). We propose a workflow to bring human translation and machine translation to work together seamlessly in translation of a closed text into a severely low resource language as shown in Figure 1 and Algorithm 1.

Given a closed text that has many existing translations in different languages, we are interested in translating it into a severely low resource language well. Researchers recently have shown achievements in translation using very small seed parallel corpora in low resource languages (Lin et al., 2020; Qi et al., 2018; Zhou et al., 2018a). Construction methods of such seed corpora are therefore pivotal in translation performance. Historically, this is mostly determined by field linguists’ experiential and intuitive discretion. Many human translators employ a portion-based strategy when translating large texts. For example, translation of the book “The Little Prince” may be divided into smaller tasks of translating 27 chapters, or even smaller translation units like a few consecutive pages. Each translation unit contains consecutive
sentences. Consequently, machine translation often uses seed corpora that are chosen based on human translators’ preferences, but may not be optimal for machine translation.

We propose to use a random sampling approach to build seed corpora when resources are extremely limited. In other words, when field linguists have limited time and resources, which lines would be given priority? Given a closed text, we propose that it would beneficial if field linguists translate randomly sampled $\sim 1,000$ lines first, getting the first machine translated draft of the whole text, and then post-edit to obtain final translation of each portion iteratively as shown in Algorithm [1]. We recognize that the portion-based translation is very helpful in producing quality translation with formality, cohesion and contextual relevance. Thus, our proposed way is not to replace the portion-based approach, but instead, to get the best of both worlds and to expedite the translation process as shown in Figure [1].

The main difference of the two approaches is that the portion-based approach focuses on preserving coherence of the text locally, while the random-sampling approach focuses on increasing coverage of the text globally. Our results show that the random sampling approach performs better. When training on a seed corpus of $\sim 1,000$ lines from the Bible and testing on the rest of the Bible ($\sim 30,000$ lines), random sampling beats the portion-based approach by $+8.5$ BLEU using English as a simulated low resource language training on a family of languages built on the distortion measure, and by $+1.9$ using a Mayan language, Eastern Pokomchi, training on a family of languages based on the linguistic definition. Using random sampling, machine translation is able to produce a high-quality first draft of the whole text that expedites the subsequent iterations of translation efforts.

Moreover, we compare three different ways of incorporating incremental post-edited data during the translation process. We find that self-supervision using the whole translation draft affects performance adversely, and is best to be avoided. We also show that adding the newly post-edited text to training with vocabulary update performs the best.
Algorithm 1: Proposed joint human machine translation sequence for a given closed text.

**Input:** A text of \(N\) lines consisting multiple books/portions, parallel in \(L\) source languages

**Output:** A full translation in the target low resource language, \(l'\)

0. Initialize translation size, \(n = 0\), vocabulary size, \(v = 0\), vocabulary update size, \(\Delta v = 0\);
1. Randomly sample \(S (\sim 1,000)\) sentences with vocabulary size \(v_S\) for human translators to produce the seed corpus, update \(n = S, v = v_S\);
2. Rank and pick a family of close-by languages by linguistic, distortion or performance metric;
   while \(n < N\) do
     if \(\Delta v > 0\) then
       3. Pretrain on the full texts of neighboring languages;
       4. Train on the \(n\) sentences of all languages in multi-source multi-target configuration;
       5. Train on the \(n\) sentences of all languages in multi-source single-target configuration;
       6. Combine translations from all source languages using the centeredness measure;
       7. Review all books/portions of the translation draft;
       8. Pick a book/portion with \(n'\) lines and \(v'\) more vocabulary;
     9. Complete human post-editing of the portion chosen, \(v = v + v', n = n + n', \Delta v = v'\);

return full translation co-produced by human (Step 1, 7-9) and machine (Step 0, 2-6) translation;

2 Related Works

2.1 Human Translation and Machine Translation

Machine translation began about the same time as the first computer (Hirschberg and Manning, 2015; Popel et al., 2020). Over the years, human translators have different reactions to machine translation advances, mixed with doubt or fear (Hutchins, 2001). Some researchers study human translation taxonomy for machine to better assist human translation and post-editing efforts (Carl et al., 2011; Denkowski, 2015). Human translators benefit from machine assistance as human individual bias and translation capacity limitations are compensated for by large-scale machine translation (Koehn and Haddow, 2009; Li et al., 2014; Savoldi et al., 2021; Bowker 2002; Bowker and Fisher, 2010; Koehn, 2009). On the other hand, machine translation benefits from professional human translators’ context-relevant and culturally-appropriate translation and post-editing efforts (Hutchins, 2001). Severely low resource translation is a fitting ground for close human machine collaboration (Zong, 2018; Carl et al., 2011; Martínez, 2003).

2.2 Severely Low Resource Text-based Translation

Many use multiple rich-resource languages to translate to a low resource language using multilingual methods (Johnson et al., 2017; Ha et al., 2016; Firat et al., 2016; Zoph and Knight 2016; Zoph et al., 2016; Adams et al., 2017; Gillick et al., 2016; Zhou et al., 2018a,b). Some use data selection for active learning (Eck et al., 2005). Some use as few as \(\sim 4,000\) lines (Lin et al., 2020; Qi et al., 2018) and \(\sim 1,000\) lines (Zhou and Waibel, 2021) of data. Some do not use low resource data (Neubig and Hu, 2018; Karakanta et al., 2018).

2.3 Active Learning and Random Sampling

Active learning has long been used in machine translation (Settles, 2012; Ambati, 2012; Eck et al., 2005; Haffari and Sarkar, 2009; González-Rubio et al., 2012; Miura et al., 2016; Gangadharaiah et al., 2009). Random sampling and data selection has been successful (Kendall and Smith, 1938; Knuth, 1991; Clarkson and Shor, 1989; Sennrich et al., 2015; Hoang et al., 2018; He et al., 2016; Gu et al., 2018). The mathematician Donald Knuth uses the population of Menlo Park to illustrate the value of random sampling (Knuth, 1991).
Table 1: Examples of different texts with the number of languages translated to date (UNESCO, 1932; Mayer and Cysouw, 2014; de Saint-Exupéry, 2019; Laozi, 2019; Fung et al., 2020; Coelho, 2015; Rowling, 2019; Tolkien, 2012; Lee, 2013; Thampi et al., 2020; Xueqin, 2016; Hugo, 1863).

| Book                     | Author                        | Books | Chapters | Pages | Languages |
|--------------------------|-------------------------------|-------|----------|-------|-----------|
| The Bible                | Multiple                      | 66    | 1,189    | 1,281 | 689       |
| The Little Prince        | Antoine de Saint Exupéry      | 1     | 27       | 96    | 382       |
| Dao De Jing              | Laozi                         | 1     | 81       | ~10   | >250      |
| COVID-19 Wiki Page       | Multiple                      | 1     | 1        | ~50   | 155       |
| The Alchemist            | Paulo Coelho                  | 1     | 2        | 163   | 70        |
| Harry Potter             | J. K. Rowling                 | 7     | 199      | 3,407 | 60        |
| The Lord of the Rings    | J. R. R. Tolkien              | 6     | 62       | 1,037 | 57        |
| Frozen Movie Script      | Jennifer Lee                  | 1     | 112      | ~40   | 41        |
| The Hand Washing Song    | Multiple                      | 1     | 1        | 1     | 28        |
| Dream of the Red Chamber | Xueqin Cao                    | 2     | 120      | 2500  | 23        |
| Les Misérables           | Victor Hugo                   | 68    | 365      | 1,462 | 21        |

3 Methodology

We train our models using a state-of-the-art multilingual transformer by adding language labels to each source sentence (Johnson et al., 2017; Ha et al., 2016; Zhou et al., 2018a,b). We borrow the order-preserving named entity translation method by replacing each named entity with \( \text{__NE} \) (Zhou et al., 2018b) using a multilingual lexicon table that covers 124 source languages and 2,939 named entities (Zhou and Waibel, 2021). For example, the sentence “Somchai calls Juan” is transformed to “\( \text{__opt_src_en __opt_tgt_ca __NE0 calls __NE1} \)” to translate to Chuj. We use families of close-by languages constructed by ranking 124 source languages by distortion measure \((FAMD)\), performance measure \((FAMP)\) and linguistic family \((FAMO)\); the distortion measure ranks languages by decreasing probability of zero distortion, while the performance measure incorporates an additional probability of fertility equalling one (Zhou and Waibel, 2021). Using families constructed, we pretrain our model first on the whole text of nearby languages, then we train on the \( \sim 1,000 \) lines of low resource data and the corresponding lines in other languages in a multi-source multi-target fashion. We finally train on the \( \sim 1,000 \) lines in a multi-source single-target fashion (Zhou and Waibel, 2021).

We combine translations of all source languages into one. Let all \( N \) translations be \( t_i, i = 1, \ldots, N \) and let similarity between translations \( t_i \) and \( t_j \) be \( S_{ij} \). We rank all translations according to how centered it is with respect to other sentences by summing all its similarities to the rest through \( \sum_j S_{ij} \) for \( i = 1, \ldots, N \). We take the most centered translation for every sentence, \( \max_i \sum_j S_{ij} \), to build the combined translation output. The expectation of the combined score is higher than that of any of the source languages (Zhou and Waibel, 2021).

Our work differs from the past research in that we put low resource translation into the broad collaborative scheme of human machine translation. We compare the portion-based approach with the random sampling approach in building seed corpora. We also compare three methods of updating models with increasing amount of human post-edited data. We add the newly post-edited data to training in three ways: with vocabulary update, without vocabulary update, or incorporating the whole translation draft in a self-supervised fashion additionally. For best performance, we build the seed corpus by random sampling, update vocabulary iteratively, and add newly post-edited data to training without self-supervision. We also have a larger test set, we test on \( \sim 30,000 \) lines rather than \( \sim 678 \) lines from existing research.

We propose a joint human machine translation workflow in Algorithm 1. After pretraining
Table 2: Performance training on 1,093 lines of Eastern Pokomchi data on FAMO$$^+$$, FAMD and FAMP. We train using the portion-based approach in Luke, and using random sampling in Rand. During testing, Best is the book with highest BLEU score, and All is the performance on ∼29,000 lines of test data.

| Language      | Luke | Rand | Luke | Rand | Luke | Rand |
|---------------|------|------|------|------|------|------|
| German        | 35.6 | 20.0 | 37.0 | 20.8 | 37.3 | 19.6 |
| Danish        | 36.7 | 19.0 | 38.2 | 25.9 | 37.3 | 19.6 |
| Dutch         | 36.4 | 20.4 | 39.7 | 27.2 | 36.4 | 21.1 |
| Norwegian     | 36.5 | 20.2 | 40.0 | 26.9 | 37.2 | 20.8 |
| Swedish       | 34.9 | 19.7 | 39.9 | 26.2 | 38.3 | 22.2 |
| Spanish       | 36.8 | 21.5 | 39.8 | 27.6 | 35.1 | 21.6 |
| French        | 36.0 | 19.7 | 39.6 | 26.1 | 36.2 | 20.3 |
| Italian       | 36.7 | 20.6 | 38.4 | 26.9 | 37.3 | 21.0 |
| Portuguese    | 32.4 | 15.8 | 30.1 | 21.3 | 33.2 | 16.5 |
| Romanian      | 34.9 | 19.3 | 37.1 | 26.0 | 36.4 | 21.6 |

4 Data

We work on the Bible in 124 source languages (Mayer and Cysouw, 2014), and have experiments for English, a simulated language, and Eastern Pokomchi, a Mayan language. We train on ∼1,000 lines of low resource data and on full texts for all the other languages. We aim to translate the rest of the text (∼30,000 lines) into the low resource language. In pretraining, we use 80%, 10%, 10% split for training, validation and testing. In training, we use 3.3%, 0.2%, 96.5% split for training, validation and testing. Our test size is >29 times of the training size. We use the book “Luke” for the portion-based approach as suggested by many human translators.

Training on ∼100 million parameters with GeForce RTX 2080 Ti, we employ a 6-layer encoder and a 6-layer decoder with 512 hidden states, 8 attention heads, 512 word vector size, 2,048 hidden units, 6,000 batch size, 0.1 label smoothing, 2.5 learning rate, 0.1 dropout and attention dropout, an early stopping patience of 5 after 190,000 steps, “BLEU” validation metric, “adam” optimizer and “noam” decay method (Klein et al., 2017; Papineni et al., 2002). We increase patience to 25 for larger data in the second stage of training in Figure 2a and 2b.
Table 3: Performance training on 1,086 lines of Eastern Pokomchi data on FAMO⁺, FAMD and FAMP. We train using the portion-based approach in Luke, and using random sampling in Rand. During testing, Best is the book with highest BLEU score, and All is the performance on ∼29,000 lines of test data.

| Input Language Family | By Linguistics | By Distortion | By Performance |
|-----------------------|----------------|---------------|----------------|
|                       | FAMO⁺          | FAMD          | FAMP           |
| Training              | Luke           | Rand          | Training       | Luke           | Rand          | Training       | Luke           | Rand          |
| Testing               | 23.1 8.6       | 19.7 10.5     | Combined       | 23.3 8.5       | 17.7 9.5      | Combined       | 22.4 7.2       | 15.8 7.8      
| Chuj                  | 21.8 7.9       | 16.5 9.8      | Chuj           | 21.8 7.0       | 13.2 7.3      | Chuj           | 21.8 7.0       | 13.2 7.3      
| Cakchiquel            | 22.3 7.9       | 18.2 9.9      | Cakchiquel     | 22.4 7.9       | 17.3 9.1      | Cakchiquel     | 21.2 6.9       | 14.8 7.4      
| Guajajara             | 19.9 7.1       | 14.7 8.9      | Guajajara      | 19.2 6.9       | 14.2 8.2      | Guajajara      | 18.9 5.9       | 10.6 6.6      
| Mam                   | 22.2 8.6       | 19.7 10.6     | Russian        | 22.2 7.3       | 13.7 8.5      | Mam            | 21.9 7.5       | 17.1 8.0      
| Kanjobal              | 21.8 8.1       | 17.5 10.0     | Toba           | 22.0 8.3       | 16.8 9.4      | Kanjobal       | 21.6 7.1       | 13.8 7.6      
| Cuzco                 | 22.4 7.8       | 17.7 9.8      | Myanmar        | 19.2 5.3       | 10.7 6.5      | Thai           | 21.9 6.3       | 10.5 7.0      
| Ayacucho              | 21.6 7.6       | 18.5 9.7      | Slovenský      | 22.2 7.5       | 13.5 8.7      | Daddi          | 19.9 6.2       | 15.3 6.9      
| Bolivian              | 22.3 7.8       | 17.4 9.8      | Latin          | 22.0 7.8       | 14.8 9.0      | Gumatj         | 19.2 3.8       | 8.9 3.3       
| Huallaga              | 22.2 7.7       | 18.0 9.7      | Bokano         | 22.6 8.4       | 17.8 9.4      | Navajo         | 21.4 6.5       | 13.5 7.3      
| Aymara                | 21.5 7.5       | 18.6 9.6      | Norwegian      | 22.6 8.3       | 16.7 9.4      | Kim            | 21.6 7.0       | 13.9 7.5      

Table 3: Performance training on 1,086 lines of Eastern Pokomchi data on FAMO⁺, FAMD and FAMP. We train using the portion-based approach in Luke, and using random sampling in Rand. During testing, Best is the book with highest BLEU score, and All is the performance on ∼29,000 lines of test data.

5 Results

We observe that random sampling performs better than the portion-based approach. In Table 2 and 3, random sampling gives a performance gain of +8.5 for English on FAMD and +1.9 for Eastern Pokomchi on FAMO⁺. The performance gain for Eastern Pokomchi may be lower because Mayan languages are morphologically rich, complex, isolated and opaque (Aissen et al., 2017; Clemens et al., 2015; England, 2011). English is closely related to many languages due to colonization and globalization even though it is artificially constrained in size (Bird, 2020). This may explain why Eastern Pokomchi benefits less.

To simulate human translation efforts in Step 7 and 8 in Algorithm, we rank 66 books of the Bible by BLEU scores on English’s FAMD and Eastern Pokomchi’s FAMO⁺. We assume that BLEU ranking is available to us to simulate human judgment. In reality, this step is realized by human translators skimming through the translation draft and comparing performances of different books by intuition and experience. In Section 6, we will discuss the limitation of this assumption. Performance ranking of the simulated low resource language may differ from that of the actual low resource language. But the top few may coincide because of the nature of the text, independent of the language. In our results, we observe that narrative books performs better than philosophical or poetic books. The book of 1 Chronicles performs best for both English and Eastern Pokomchi with random sampling. A possible explanation is that the book of 1 Chronicles is mainly narrative, and contains many named entities that are translated well by the order-preserving lexiconized model. We included the BLEU scores of the best-performing book in Table 2 and 3. Note that only scores of “All” are comparable across experiments trained on the book of Luke with those trained by random sampling as they evaluate on the same set.

For the best-performing book, it is the book of 1 Chronicles for random sampling, and the
Table 4: Comparing three ways of adding the newly post-edited book of 1 Chronicles. Seed is the baseline of training on the seed corpus alone, Old-Vocab skips the vocabulary update while Updated-Vocab has vocabulary update. Self-Supervised adds the complete translation draft in addition to the new book.

| Source      | Seed | Self-Supervised | Old-Vocab | Updated-Vocab |
|-------------|------|-----------------|-----------|---------------|
| Combined    | 30.8 | 24.4 (-6.4)     | 32.1 (+1.3) | 32.4 (+1.6)   |
| Danish      | 27.7 | 21.6 (-6.1)     | 28.8 (+1.1) | 29.2 (+1.5)   |
| Norwegian   | 28.6 | 22.5 (-6.1)     | 29.8 (+1.2) | 30.2 (+1.6)   |
| Italian     | 28.7 | 22.3 (-6.4)     | 29.8 (+1.1) | 30.2 (+1.5)   |
| Afrikaans   | 30.1 | 23.8 (-6.3)     | 31.4 (+1.3) | 31.6 (+1.5)   |
| Dutch       | 29.2 | 22.9 (-6.3)     | 30.3 (+1.1) | 30.6 (+1.4)   |
| Portuguese  | 23.8 | 18.3 (-5.5)     | 24.6 (+0.8) | 25.0 (+1.2)   |
| French      | 27.8 | 21.7 (-6.1)     | 28.9 (+1.1) | 29.4 (+1.6)   |
| German      | 28.4 | 22.4 (-6.0)     | 29.5 (+1.1) | 29.9 (+1.5)   |
| Marshallese | 28.4 | 22.4 (-6.0)     | 29.5 (+1.1) | 29.9 (+1.5)   |
| Frisian     | 29.3 | 23.2 (-6.1)     | 30.4 (+1.1) | 30.8 (+1.5)   |

In Table 4, we compare three different ways of updating the machine translation models by adding a newly post-edited book that human translators produced. We call the baseline without addition of the new book Seed. Updated-Vocab adds the new book to training with updated vocabulary while Old-Vocab skips the vocabulary update. Self-Supervised adds the whole translation draft of ~30,000 lines to pretraining in addition to the new book. Self-supervision refers to using the small seed corpus to translate the rest of the text which is subsequently used to train the model. We observe that the Self-Supervised performs the worst among the three. Indeed, Self-Supervised performs even worse than the baseline Seed. This shows that quality is much more important than quantity in severely low resource translation. It is better for us not to add the whole translation draft to the pretraining as it affects performance adversely.

On the other hand, we see that both Updated-Vocab and Old-Vocab performs better than Seed and Self-Supervised. Updated-Vocab’s performance is better than Old-Vocab. An explanation could be that Updated-Vocab has more expressive power with updated vocabulary. Therefore, in our proposed algorithm, we prefer vocabulary update in each iteration. If the vocabulary has not increased, we may skip pretraining to expedite the process.

We show how the algorithm is put into practice for English and Eastern Pokomchi in Figure 2a and 2b. We take the worst-performing 11 books as the held-out test set, and divide the other 55 books of the Bible into 5 portions. Each portion contains 11 books. We translate the text by using the randomly sampled ~1,000 lines of seed corpus first, and then proceed with human-machine translation in Algorithm in 5 iterations with increasing number of post-edited portions.

For English, we observe that philosophical books like “Proverbs” and poetry books like “Song of Solomon” perform very badly in the beginning, but begin to achieve above 20 BLEU scores after adding 11 books of training data. This reinforces our earlier result that ~20% of the text is sufficient for achieving high-quality translation [Zhou et al., 2018a]. However, some books like “Titus” remains difficult to translate even after adding 33 books of training data. This shows that adding data may benefit some books more than the others. A possible explanation is
that there are multiple authors of the Bible, and books differ from each other in style and content. Some books are closely related to each other, and may benefit from translations of other books. But some may be very different and benefit much less.

For Eastern Pokomchi, though the performance of the most difficult 11 books never reach BLEU score of 20s like that of English experiments, all books have BLEU scores that are steadily increasing. Challenges remain for Eastern Pokomchi, a Resource 0 language (Joshi et al., 2020). We hope to work with native Mayan speakers to see ways we may improve the results.

6 Conclusion

We propose to use random sampling to build seed parallel corpora instead of using the portion-based approach in severely low resource settings. Training on $\sim$1,000 lines, the random sampling approach outperforms the portion-based approach by +8.5 for English’s FAMD, and by +1.9 for Eastern Pokomchi’s FAMO$^+$. We also compare three different ways of updating the machine translation models by adding newly post-edited data iteratively. We find that vocabulary update is necessary, but self-supervision by pretraining with whole translation draft is best to be avoided.

One limitation of our work is that in real life scenarios, we do not have the reference text in low resource languages to produce the BLEU scores to decide the post-editing order. Consequently, field linguists need to skim through and decide the post-editing order based on intuition. However, computational models can still help. One potential way to tackle it is that we can train on $\sim$1,000 lines from another language with available text and test on the 66 books. Since our results show that the literary genre plays important role in the performance ranking, it would be reasonable to determine the order using a “held-out language” and then using that to determine order in the target low resource language. In the future, we would like to work with human translators who understand and speak low resource languages.

Another concern human translators may have is the creation of randomly sampled seed corpora. To gauge the amount of interest or inertia, we have interviewed some human translators and many are interested. However, it is unclear whether human translation quality of randomly sampled data differs from that of the traditional portion-based approach. We hope to work with human translators closely to determine whether the translation quality difference is manageable.

We are also curious how our model will perform with large literary works like “Lord of the Rings” and "Les Misérables". We would like to see whether it will translate well with philosophical depth and literary complexity. However, these books often have copyright issues and are not as easily available as the Bible data. We are interested in collaboration with teams who have multilingual data for large texts, especially multilingual COVID-19 data.
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