An Exploration of Data Augmentation Techniques for Improving English to Tigrinya Translation

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Abstract
It has been shown that the performance of neural machine translation (NMT) drops starkly in low-resource conditions, often requiring large amounts of auxiliary data to achieve competitive results. An effective method of generating auxiliary data is back-translation of target language sentences. In this work, we present a case study of Tigrinya where we investigate several back-translation methods to generate synthetic source sentences. We find that in low-resource conditions, back-translation by pivoting through a higher-resource language related to the target language, proves most effective resulting in substantial improvements over baselines.

1 Introduction

Tigrinya is a Semitic language spoken by around 8 million people in the African countries of Eritrea, accounting for more than half of its population, and Ethiopia where it is used as informal lingua franca. However, over 60% of the internet’s content is in English, while Tigrinya, for example, accounts for less than 0.1% of it (W3Techs, 2020). With 40% of the Tigrinya speakers being monolingual1, this essentially locks away the majority of the internet content for them. Availability of machine translation systems capable for translating English to Tigrinya and vice-versa is an imperative for its speakers to be able to function in an increasingly-global online world.

Despite recent advances in neural machine translation (Bahdanau et al., 2015; Vaswani et al., 2017), such systems are difficult to develop for many African languages including Tigrinya primarily due to the lack of large amounts of high quality parallel data. Phrase-based statistical machine translation (PBSMT) (Koehn et al., 2003; Lample et al., 2018c) has been shown to perform well under low data conditions but is challenging to develop for Tigrinya owing to its complex morphological structure (Keleta et al., 2016). For many low-resource languages, this challenge has led to various proposals for leveraging monolingual data that exist in either or both source and target languages, which are usually more abundant. Prior approaches include self-training (Imamura and Sumita, 2018), transfer learning (Zoph et al., 2016) and data-augmentation techniques like forward translation (Zhang and Zong, 2016) and back-translation (Sennrich et al., 2016a).

Back-translation has been used in current state-of-the-art NMT systems, outperforming other approaches in high resource languages (Ng et al., 2019) and improving performance in low resource conditions (Hoang et al., 2018). The approach involves training a target-to-source (backward) model on the available parallel data and using that model to generate synthetic translations of a large number of monolingual sentences in the target language. The available authentic parallel data is then mixed with the generated synthetic parallel data without differentiating between the two (Sennrich et al., 2016a) to train a final source-to-target (forward) model. However, in low resource scenarios, the authentic parallel data available is not sufficient to train a backward model that will generate quality synthetic data.

In this work, we explore this setting in detail. Combining techniques from transfer learning and back-translation, we propose several data-augmentation strategies to improve English-to-Tigrinya translation. In our experiments, we show that leveraging Amharic—a higher resource language closely related to Tigrinya—for data augmentation, gives improvements of up to +7 BLEU points over baselines.

1https://african-languages.com/tigrinya-language/
2 Background and Methods

We first formalize the task setup. Given a source language (SRC), a target language (TGT) and a typologically related language of TGT, REL, our goal is train a model \( f(\cdot; \theta) \) which takes a SRC sentence \( x \) as input and generates its translation, \( \hat{y}_{TGT} = f(x; \theta) \). Here, \( \theta \) are learnable parameters of \( f \). We are given sentence aligned SRC–TGT, REL–TGT parallel corpora, and monolingual corpora in REL and TGT.

In this work, we use transformer based encoder-decoder models (Vaswani et al., 2017) as \( f \).

We assume that the parallel SRC–TGT corpus is small, which makes training \( f \) challenging (Sennrich and Zhang, 2019). We now describe ways of leveraging the available monolingual data in TGT and resources in REL to generate synthetic SRC–TGT sentences which can be augmented with the authentic SRC–TGT corpus to improve the generation quality of \( f \).

**BT-Direct: TGT→SRC** This is the most common way to create synthetic parallel data by translating TGT monolingual data to SRC (Sennrich et al., 2016a). The backward model TGT→SRC is trained using the available SRC–TGT parallel data. While this provides a natural way to utilize monolingual data, when the parallel data is scarce, the backward model’s quality is as limited as the vanilla forward model. This results in poor quality synthetic data which is detrimental, as we show in our experiments. Hoang et al. (2018) proposed an iterative BT to alleviate this issue, but this technique requires multiple rounds of retraining models in both directions which are slow and expensive.

**BT-Indirect: REL→SRC** We train a REL→SRC model using more abundant REL–SRC parallel data and use this model to translate monolingual data in TGT to SRC. Given that REL and TGT are closely related and written in the same script, this can serve as a proxy back-translation model allowing transfer between the two languages.

**BT-Pivot: TGT→REL→SRC** Despite closeness of REL and TGT, back-translating TGT using a STD→SRC model can result in noisy translations which can hurt the final performance of SRC→TGT. Here, we exploit closeness of REL and TGT using the following method to generate synthetic SRC–TGT data. We train two models, one to translate TGT→REL and another to translate REL→SRC. For the former, depending on available parallel and monolingual resources in TGT and REL, the TGT→REL model can be trained either in (1) a supervised manner (we refer to this setting as BT-Pivot-SUP), or (2) in an unsupervised manner (Lample et al., 2018d) (BT-Pivot-UNSUP). The latter is trained with more easily available SRC–REL parallel data. To backtranslate a given TGT sentence, we first translate it to REL using the TGT→REL model, and then to SRC using the REL→SRC model.

3 Experimental Setup

**Datasets** We evaluate our methods with English (EN), Tigrinya (TI) and Amharic (AN) as SRC, TGT and REL. Both TI and AM are Ge’ez-scripted Semitic languages and have considerable morphological and lexical similarity (Feleke, 2017). The EN–TI data consists of a total of 900K sentence pairs taken from Opus (Tiedemann, 2012) and consist of 300K and 36K sentence pairs respectively containing text from religious domain. The EN–AM data consists of 1M sentence pairs taken from Opus (JW300) and Teferra Abate et al. (2018) (News domain). After deduplication, we created dev/test sets of 2K sentences each for both language pairs (EN-TI and EN-AM) by randomly sampling from the JW300 corpora. We use the remaining sentences as training set. To train unsupervised MT models, we use the REL and TGT size of the parallel corpora as the monolingual corpus. To create synthetic parallel data by back-translation, we create a monolingual Tigrinya corpus by crawling sentences from the official website of Eritrean Ministry of Information\(^2\). After cleaning and deduplication, we get a corpus with 100K sentences.

**Implementation and Evaluation** We use a transformer based encoder-decoder model to conduct all our experiments (Vaswani et al., 2017). We use the BASE architecture which consists of 6 encoder and decoder layers with 8 attention heads. We first tokenize all the sentences using Moses (Koehn et al., 2007). For each language pair considered, we then tokenize the corpora using a BPE (Sennrich et al., 2016b) model trained on the concatenation of the parallel corpora with 32K merge operations. We use OpenNMT-py toolkit (Klein et al., 2017) for all our exper-

\(^2\)https://www.shabait.com/
periments, with the hyperparameters recommended by Vaswani et al. (2017). We train all our supervised models (with or without data-augmentation) for 200K steps with early stopping based on validation loss. Finally, we evaluate the generated translations using the BLEU score (Papineni et al., 2002)\(^3\).

**Baselines** We compare the data-augmentation methods described in §2 with the following baselines

- **UNSUP**(SRC→TGT) To evaluate the impact of available parallel data and feasibility of translating between unrelated languages SRC and TGT, we train an unsupervised NMT model to translate SRC to TGT using the available monolingual corpora only in the two languages.

- **SUP**(SRC→TGT) Here, we train a supervised EN→TI model with available parallel data only.

  **Pivot through REL** Here, we train two translation models, a SRC→REL model and REL→TGT model. Given a SRC test sentence, we first translate it to REL, which we then feed to the second model to generate text in TGT. We experiment with two REL→TGT models leading to two baselines. First, trained with parallel supervision, we call this baseline (Pivot: SUP(SRC→REL)+SUP(REL→TGT)); and second, trained in an unsupervised manner, which we refer to as (Pivot: SUP(SRC→REL)+UNSUP(REL→TGT)).

  For unsupervised TGT↔REL models, we use the same architecture for this baseline and for BT-Pivot as described above (since it can translate in both directions). We train this model based on (Lample et al., 2018a) with their recommended settings\(^4\) with a few changes as follows: (1) For each word in TGT vocabulary, we find its neighbors in the REL vocabulary within the Levenshtein distance of 2 (after removing vowel-marking diacritics). This resulted in a dictionary with 1,200 pairs. (2) We train fasttext (Bojanowski et al., 2016) embeddings for both corpora and then align them with supervision (Lample et al., 2018b) from the created dictionary. (3) We initialize the embedding tables of the encoder and decoder with the aligned embeddings and train the model parameters using autoencoding and iterative back-translation based objectives as described in Lample et al. (2018a).

**4 Results and Analysis**

The results are detailed in table 1. We observe that both unsupervised and supervised EN→TI models perform poorly owing to unrelatedness of English and Tigrinya and scarcity of parallel data, respectively. We get some performance improvement by first translating EN to a related language first (Amharic in our case) and then translating it to TI.

However, the gains diminish if we switch the supervised AM→TI model with an unsupervised one. We hypothesize this is due to small size of the monolingual corpora used to train this unsupervised model.

Next, using a simple TI→EN model directly to augment data to the parallel corpus (BT-DIRECT) also gives some improvement over the best performing baseline (+2.3 BLEU). We conjecture that while additional monolingual data for Tigrinya improves the decoder language model improving the translation fluency, the improvement is hampered due to poor back-translations.

On the other hand, using a AM→EN model for back-translation TI sentences results in a drop in performance likely due to very noisy examples being added to the training corpus.

We get further improvements as we consider more sophisticated methods involving pivoting through Amharic (BT-Pivot-SUP). We identify two potential reasons: a strong AM→EN model on account of being trained with a larger parallel corpus, a strong TI→AM model owing to the similarity between two languages despite the parallel TI→AM model being small.

| Method | BLEU |
|--------|------|
| UNSUP(SRC→TGT) | 2.01 |
| SUP(SRC→TGT) | 7.4 |
| Pivot: SUP(SRC→REL)+SUP(REL→TGT) | 8.4 |
| Pivot: SUP(SRC→REL)+UNSUP(REL→TGT) | 5.6 |
| BT-DIRECT | 10.9 |
| BT-INDIRECT | 6.2 |
| BT-Pivot-SUP | 11.54 |
| BT-Pivot-UNSUP | 15.52 |

Table 1: BLEU scores obtained for EN→TI translation using different baselines and data-augmentation methods described in §2

\(^3\)While we recognize the limitations of BLEU especially for evaluating generations in morphologically rich languages (Mathur et al., 2020), METEOR (Banerjee and Lavie, 2005) or embedding based metrics (Zhang et al., 2020; Sellam et al., 2020) are simply not available for low resource languages like Tigrinya.

\(^4\)We do not experiment with more sophisticated UNMT methods (Lample and Conneau, 2019) due to their high monolingual resource requirements which are not available for either Amharic or Tigrinya.
AM and TI such as named entities or prepositions. The shared vocabulary especially benefits pivoting based back-translation where they are just copied with the TI→AM model resulting in their perfect translations. The AM→EN model then is able to accurately translate it English (since it is trained on a larger parallel corpus). This is in contrast with direct TI→EN back-translation (BT-DIRECT) trained on a smaller parallel corpus, where these tokens often get mis-translated resulting in poorer final performance.

Finally, we present selected examples where BT-PIVOT-UNSUP performs well and compare it with examples where it suffers (compared to the baseline model SUP(EN→TGT) (see figure 2). We again observe in the examples that BT-PIVOT-UNSUP is good at generating named entities as well as tokens shared by Amharic and Tigrinya. We also note that BT-PIVOT-UNSUP fails to perform well when translating numerals (which have to be copied), often hallucinating content. We attribute these errors to noise in the back-translated data and domain mismatch between the authentic parallel corpus (containing religious text) and the synthetic parallel corpus (containing government announcements).

5 Conclusion

We present and compare different methods of generating synthetic parallel data and evaluate their utility for data-augmentation for low-resource machine translation. With extensive experiments on English to Tigrinya translation, we show when parallel corpora are limited, using higher-resource related languages to develop back-translation models can lead to substantial boost in MT performance.

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