Neural machine translation for low-resource languages

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Abstract

Neural machine translation (NMT) approaches have improved the state of the art in many machine translation settings over the last couple of years, but they require large amounts of training data to produce sensible output. We demonstrate that NMT can be used for low-resource languages as well, by introducing more local dependencies and using word alignments to learn sentence reordering during translation. In addition to our novel model, we also present an empirical evaluation of low-resource phrase-based statistical machine translation (SMT) and NMT to investigate the lower limits of the respective technologies. We find that while SMT remains the best option for low-resource settings, our method can produce acceptable translations with only 70,000 tokens of training data, a level where the baseline NMT system fails completely.

1 Introduction

Neural machine translation (NMT) has made rapid progress over the last few years (Sutskever et al., 2014; Bahdanau et al., 2014; Wu et al., 2016), emerging as a serious alternative to phrase-based statistical machine translation (Koehn et al., 2003). Most of the previous literature perform empirical evaluations using training data in the order of millions to tens of millions of parallel sentence pairs. In contrast, we want to see how low you can push the training data requirement for neural machine translation. To the best of our knowledge, there is no previous systematic treatment of this question. Zoph et al. (2016) did explore low-resource NMT, but by assuming the existence of large amounts of data from related languages.

2 Low-resource model

The current de-facto standard approach to NMT (Bahdanau et al., 2014) has two components: a target-side RNN language model (Mikolov et al., 2010; Sundermeyer et al., 2012), and an encoder plus attention mechanism that is used to condition on the source sentence. While an acceptable language model can be trained using relatively small amounts of data, more data is required to train the attention mechanism and encoder. This has the effect that a standard NMT system trained on too little data essentially becomes an elaborate language model, capable of generating sentences in the target language that have little to do with the source sentences.

We approach this problem by reversing the mode of operation of the translation model. Instead of setting loose a target-side language model with a weak coupling to the source sentence, our model steps through the source sentence token by token, generating one (possibly empty) chunk of the target sentence at a time. The generated chunk is then inserted into the partial target sentence into a position predicted by a reordering mechanism. Table 1 demonstrates this procedure. While reordering is a difficult problem, word order errors are preferable to a nonsensical output. We translate each token using a character-to-character model conditioned on the local source context, which is a relatively simple problem since data is not so sparse at the token level. This also results in open vocabularies for the source and target languages.

Our model consists of the following components, whose relation are also summarized in Al-
We use the term empty string as well as multi-word expressions with spaces.

Table 1: Generation of a German translation of “I can not do that” in our model.

| Source | Target | Pos. | Partial hypothesis |
|--------|--------|------|--------------------|
| ich    | ich    | 1    | ich                |
| kann   | ich    | 2    | kann               |
| nicht  | ich    | 3    | nicht              |
| tun    | ich    | 4    | nicht tun          |
| das    | ich    | 3    | kann das nicht tun |

Algorithm 1: Our proposed translation model.

```
function TRANSLATE(w_i^...,N)
    ▷ Encode each source token
    for all i ∈ 1...N do
        e_i ∈ SRC-TOK-ENC(w_i^)
    end for
    ▷ Encode source token sequence
    s_1...N ← SRC-ENC(e_1^...N)
    ▷ Translate one source token at a time
    for all i ∈ 1...N do
        ▷ Encode previous target token
        e_i ← TRG-TOK-ENC(w_i^−1)
        ▷ Generate target state vector
        h_i ← TRG-ENC(e_i||s_i)
        ▷ Generate target token
        p(w_i) ∼ TRG-TOK-DEC(h_i)
        ▷ Predict insertion position
        p(k_i) ∼ POSITION(h_1...i, k_1...i−1)
    end for
    ▷ Search for a high-probability target
    ▷ sequence and ordering, and return it
end function
```

Note that on the target side, a token may contain the empty string as well as multi-word expressions with spaces. We use the term token to reflect that we seek to approximate a 1-to-1 correspondence between source and target tokens.

3 Training

Since our intended application is translation of low-resource languages, we rely on word alignments to provide supervision for the reordering model. We use the EFMARAL aligner (Östling and Tiedemann, 2016), which uses a Bayesian model with priors that generate good results even for rather small corpora. From this, we get estimates of the alignment probabilities P_f(a_i = j) and P_b(a_j = i) in the forward and backward directions, respectively.

Our model requires a sequence of source tokens and a sequence of target tokens of the same length. We extract this by first finding the most confident 1-to-1 word alignments, that is, the set of consistent pairs (i, j) with maximum \( \prod_{(i,j)} P_f(a_i = j) \).
Then we use the source sentence as a fixed point, so that the final training sequence is the same length of the source sentence. Unaligned source tokens are assumed to generate the empty string, and source tokens aligned to a target token followed by unaligned target tokens are assumed to generate the whole sequence (with spaces between tokens). While this prohibits a single source token to generate multiple dislocated target words (e.g., standard negation in French), our intention is that this constraint will result in overall better translations when data is sparse.

Once the aligned token sequences have been extracted, we train our model using backpropagation with stochastic gradient descent. For this we use the Chainer library (Tokui et al., 2015), with Adam (Kingma and Ba, 2015) for optimization. We use early stopping based on cross-entropy from held-out sentences in the training data. For the smaller Watchtower data, we stopped after about 10 epochs, while about 25–40 were required for the 20% Bible data. We use a dimensionality of 256 for all layers except the character embeddings (which are of size 64).

4 Baseline systems

In addition to our proposed model, we two public translation systems: Moses (Koehn et al., 2007) for phrase-based statistical machine translation (SMT), and HNMT3 for neural machine translation (NMT). For comparability, we use the same word alignment method (Östling and Tiedemann, 2016) with Moses as with our proposed model (see Section 3).

For the SMT system, we use 5-gram modified Kneser-Ney language models estimated with KenLM (Heafield et al., 2013). We symmetrize the word alignments using the GROW-DIAG-FINAL heuristic. Otherwise, standard settings are used for phrase extraction and estimation of translation probabilities and lexical weights. Parameters are tuned using MERT (Och, 2003) with 200-best lists.

The baseline NMT system, HNMT, uses standard attention-based translation with the hybrid source encoder architecture of Luong and Manning (2016) and a character-based decoder. We run it with parameters comparable to those of our proposed model: 256-dimensional word embeddings and encoder LSTM, 64-dimensional character embeddings, and an attention hidden layer size of 256. We used a decoder LSTM size of 512 to account for the fact that this model generates whole sentences, as opposed to our model which generates only small chunks.

5 Data

The most widely translated publicly available parallel text is the Bible, which has been used previously for multilingual NLP (e.g. Yarowsky et al., 2001; Agić et al., 2015). In addition to this, the Watchtower magazine is also publicly available and translated into a large number of languages. Although generally containing less text than the Bible, Agić et al. (2016) showed that its more modern style and consistent translations can outweigh this disadvantage for out-of-domain tasks. The Bible and Watchtower texts are quite similar, so we also evaluate on data from the WMT shared tasks from the news domain (newstest2016 for Czech and German, newstest2008 for French and Spanish). These are four languages that occur in all three data sets, and we use them with English as the target language in all experiments.

The Watchtower texts are the shortest, after removing 1000 random sentences each for development and test, we have 62–71 thousand tokens in each language for training. For the Bible, we used every 5th sentence in order to get a subset similar in size to the New Testament.4 After removing 1000 sentences for development and test, this yielded 130–175 thousand tokens per language for training.

6 Results

Table 3 summarizes the results of our evaluation, and Table 2 shows some example translations. For evaluation we use the BLEU metric (Papineni et al., 2002). To summarize, it is clear that SMT remains the best method for low-resource machine translation, but that current methods are not able to produce acceptable general machine translation systems given the parallel data available for low-resource languages.

Our model manages to reduce the gap between phrase-based and neural machine translation, with

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3https://github.com/robertostling/hnmt

4The reason we did not simply use the New Testament is because it consists largely of four redundant gospels, which makes it difficult to use for machine translation evaluation.
Source: pues bien, la biblia da respuestas satisfactorias.
Reference: the bible provides satisfying answers to these questions.
SMT: well, the bible gives satisfactorias answers.
HNMT: jehovah’s witness.
Our: the bible to answers satisf.

Source: 4, 5. cules son algunas de las preguntas ms importantes que podemos hacernos, y por qu debemos buscar las respuestas?
Reference: 4, 5. what are some of the most important questions we can ask in life, and why should we seek the answers?
SMT: 4, 5. what are some of the questions that matter most that we can make, and why should we find answers?
HNMT: 4, 5. what are some of the bible, and why?
Our: 4, 5. what are some of the special more important that can, and we why should feel the answers

Table 2: Example translations from the different systems (Spanish-English; Watchtower test set, trained on Watchtower data).

|                | BIBLE | Trained on 20% of Bible | Trained on Watchtower |
|----------------|-------|-------------------------|------------------------|
| Source         | BLEU (%) | SMT | HNMT | Our |
| Test           |        |     |     |
| Bible German   | 25.7   | 7.9 | 10.2 |
| Bible Czech    | 24.2   | 5.5 | 9.3  |
| Bible French   | 39.7   | 19.8| 25.7 |
| Bible Spanish  | 22.5   | 3.9 | 9.3  |
| Watchtower German | 9.2    | 1.3 | 4.7  |
| Watchtower Czech | 7.5   | 0.7 | 3.5  |
| Watchtower French | 12.3  | 3.1 | 6.6  |
| Watchtower Spanish | 12.5 | 0.5 | 5.9  |
| News German    | 4.1    | 0.1 | 1.7  |
| News Czech     | 7.1    | 0.0 | 1.0  |
| News French    | 9.0    | 0.0 | 2.4  |
| News Spanish   | 6.5    | 0.0 | 1.7  |

7 Discussion

We have demonstrated a possible road towards better neural machine translation for low-resource languages, where we can assume no data beyond a small parallel text. In our evaluation, we see that it outperforms a standard NMT baseline, but is not currently better than the SMT system. In the future, we hope to use the insights gained from this work to further explore the possibility of constraining NMT models to perform better under severe data sparsity. In particular, we would like to explore models that preserve more of the fluency characteristic of NMT, while ensuring that adequacy does not suffer too much when data is sparse.

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