Sparsely Factored Neural Machine Translation

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Abstract

The standard approach to incorporate linguistic information to neural machine translation systems consists in maintaining separate vocabularies for each of the annotated features to be incorporated (e.g. POS tags, dependency relation label), embed them, and then aggregate them with each subword in the word they belong to. This approach, however, cannot easily accommodate annotation schemes that are not dense for every word.

We propose a method suited for such a case, showing large improvements in out-of-domain data, and comparable quality for the in-domain data. Experiments are performed in morphologically-rich languages like Basque and German, for the case of low-resource scenarios.

1 Introduction

Domain shift is one of the main challenges yet to overcome by neural machine translation (NMT) systems (Koehn and Knowles, 2017). This problem happens when using an MT system to translate data that is different from the data used to train it, mainly regarding its domain (e.g. the MT system was trained on news data but is then used to translate biomedical data). The problem consists in a drop in the translation quality with respect to translations of in-domain text.

Injecting linguistic information has been used in the past to improve the translation quality of NMT systems. The improvements obtained for in-domain data are normally small, while those obtained for out-of-domain text are usually larger. The most frequent and straightforward approach to inject linguistic information into NMT systems is to use annotation systems to obtain word lemmas and part-of-speech (POS) tags. These pieces of information are then attached as “factors” to each subword in the original word (Sennrich and Haddow, 2016). In this scheme, however, it is assumed that each word has a value for each of the possible factors. We refer to these as “dense” linguistic annotation schemes.

Nevertheless, not all linguistic annotations are dense. Some examples of morphologically-rich language features that are not dense include noun cases and verb conjugations, where only some type of words can be tagged with such kind of information. These “sparse” linguistic annotation schemes cannot be easily accommodated in factored NMT architectures.

In this work, we propose an approach to inject sparse linguistic annotations into NMT systems. We refer to it as sparsely factored NMT.

2 Related Work

Factored MT was first proposed by Koehn and Hoang (2007) for phrase-based statistical machine translation systems (SMT) (Koehn et al., 2003). They propose to break down the translation process into three stages: first translating input lemmas into output lemmas, then mapping the source factors to target factors, and then generating surface from the outcomes of the two previous stages, using phrase-based SMT framework for each of the three stages.

The factored approach was first introduced in NMT by Sennrich and Haddow (2016). In their approach, lemmas, morphological features (case, number and gender for nouns, person, number, tense and aspect for verbs), POS tags and dependency labels are used as linguistic information to enrich the source-side of an NMT system. These pieces of word-level information were attached to each of the subwords belonging to the associated word, for the source-side sentences. Apart from the linguistic information, subwords were tagged with information about whether they are at the be-
ginning, at the middle or at the tail of the word. Hoang et al. (2016) also proposed the factored NMT approach, and studied the effect of different attention variants on it. While the factored NMT approach was tested on the sequence-to-sequence with attention architecture (Bahdanau et al., 2015), Armengol-Estapé et al. (2020) studied its applicability to the Transformer model (Vaswani et al., 2017).

An analogous approach was used for the target side by García-Martínez et al. (2016) and Burlot et al. (2017) to reduce the size of the word-level output vocabulary, generating both the lemma and the morphological features that, combined by means of an external morphological tool, rendered the specific surface form. A larger study over different translation directions with morphologically-rich languages was performed by (García-Martínez et al., 2020).

3 Sparsely Factored NMT

In our proposed approach, instead of taking raw text as input to translate, like normal NMT systems do, we receive the text annotated by a linguistic annotation system for the source-side. For training, in the target side we take raw text. This aspect is the same as in the work by Sennrich and Haddow (2016). However, in their work, for sparse linguistic annotation schemes, like the morphological features they use, each annotation is a collection of attributes that may or may not be present for each word type. The space of possible values of the morphological features factor is large, as each word can have a combination of such feature values, and a specific combination may seldom appear in the training data, despite the fact that each of its individual feature values may appear frequently. This leads to a situation where many of the embedded vectors of the morphological features factor are updated infrequently during training. This fact is illustrated in Figure 1, where we show the frequency count of the morphological feature combinations versus the frequency count of each individual morphological feature, for the training split of one datasets used in our experiments. In that figure, we can appreciate that the number of different combinations is an order of magnitude larger than the individual features (580 combinations vs. 24 individual feature values), and that the frequency count is also multiple times lower.

Instead of taking each combination as a different factor value, we propose to label each word based on the morphological feature space instead of the morphological feature combination space. For this, we keep an embedding table where each entry is a value of a morphological feature. For instance, in the German sentence “Wir brauchen Daten, keine Hilfe”, taken from the IWSLT14 validation data, in factored NMT pronoun “Wir” would be labeled with the morphological feature combination 1|Pl|_|Nom (first person, plural, nominative case), while in sparsely factored NMT the same word would be labeled with three tags: 1, Pl and Nom.

Also, regarding the use of word tokenization or subword tokenization (e.g. Byte-Pair Encoding (BPE; Sennrich et al., 2016)), we propose the following. Apart from the morphological feature vocabulary described before, we also maintain a lemma-vocabulary; when encoding text for sparsely factored NMT, for each word we check if it is a lemmatizable word (i.e. not a number, punctuation, etc) and if its lemma is present in the lemma vocabulary. If it is, we encode the word as the addition of the embedded vector of the lemma plus the embedded vectors of every morphological feature the word had. If the word could not be lemmatized or if the lemma is not present in the lemma vocabulary, we tokenize the word using BPE, for which we keep also an embedding table. Therefore, our tokens can be either (lemma + morphological features) or subwords. Once the text is encoded as a sequence of embedded vectors, it is passed as input to a standard Transformer model (Vaswani et al., 2017).
Note that our proposal only affects the embedding layer of the encoder of an NMT architecture. Therefore, it can be applied to both sequence-to-sequence with attention or the Transformer.

We propose a further extension on top of the base variant described before: we take a new hyperparameter, the “linguistic dropout” (LD), which represents the probability of using a subword tokenization for a word instead of the (lemma + morphological features) representation. During data preparation, both the subword representation and the lemmatized representation (if available) are prepared and, during training, a sample of the Bernoulli distribution with the LD probability determines which representation is used for each word at batch creation time. The purpose of LD is to make the model learn to handle the situation where there is no linguistic information available (e.g. for out-of-vocabulary words). Using LD, the subword token embeddings are more frequently updated during training, leading to more robust systems, especially on out-of-domain data. This description is further enhanced with an algorithmic presentation in Appendix B.

4 Experimental Setup

In our experiments, we make use of morphologically-rich languages, namely German and Basque, with low-resource scenarios, testing with both in-domain and out-of-domain data.

German is a West Germanic Language with fusional morphology. Its nouns are inflected in terms of number (singular and plural), gender (masculine, feminine and neuter) and case (nominative, accusative, genitive and dative). Verbs inflect for person (1st, 2nd and 3rd), number, mood (indicative, imperative, subjunctive, infinitive), voice, tense (present, preterite, perfect, pluperfect, future, future perfect), grammatical aspect, and completion status. For the German experiments, we use the IWSLT14 German→English dataset (Cettolo et al., 2014) as training data. Its statistics are shown in Table 1. For the in-domain translation quality evaluation, we used the mentioned dataset test split, while for out-of-domain translation evaluation we used the WMT17 biomedical test sets, namely the English-German HimL test set.

Basque is a language isolate (not related to other languages), with agglutinative morphology. Its nouns take suffixes to express number (singular, plural, “mugagabe”) and case (nominative, ergative, genitive, local genitive, dative, allative, inessive, partitive, etc). Verbs’ surface forms differ based on the person of the subject, direct object and indirect object (1st, 2nd, and 3rd), number (singular and plural), tense (present, past, future), aspect (progressive and perfect) and mood (indicative, subjunctive, conditional, potential and imperative). For the Basque experiments, we use the EiTB news corpus (Etchegoyhen et al., 2016). Its statistics are shown in Table 2. We split the original data into training, validation and test subsets. The test split was used for in-domain translation quality evaluation, while a sample of 1000 sentences of the Open Data Euskadi IWSLT18 corpus (Jan et al., 2018) containing documents from the Public Administration, was used for the out-of-domain translation evaluation. The preprocessing for the data consisted in truecasing and tokenization (this preprocessing was already applied in the original data), and the BPE subword vocabulary had 15k merge operations.

The linguistic information used for the experiments was obtained with Lucy LT (Alonso and Thurmair, 2003), a rule-based machine translation (RBMT) system of transfer type. We took the analysis of the source sentences generated in the intermediate stages of the translation, which annotates each word with a bag of linguistic language-

| Corpus | Sents. | Words | Vocab | Max.len. | Avg.len. |
|--------|--------|-------|-------|----------|---------|
| German | 160k   | 3.1M  | 113k  | 172      | 19.4    |
| English| 3.3M   | 53k   | 175   | 20.4     |

Table 1: IWSLT14 German-English training data stats.

| Corpus | Sents. | Words | Vocab | Max.len. | Avg.len. |
|--------|--------|-------|-------|----------|---------|
| Basque | 550k   | 10.1M | 345k  | 318      | 18.3    |
| Spanish| 15.6M  | 225k  | 317   | 28.3     |

Table 2: EiTB Basque-Spanish training data statistics.

1http://www.himl.eu/test-sets
2https://github.com/pytorch/fairseq/master/examples/translation
3https://aholab.ehu.eus/metashare/repository/browse/basque-spanish-eitb-corpus-of-aligned-comparable-sentences/5f5bd86b6f11e6b004f01fae4f1fa8b95c93ec1214a338167e5074ee90d09/
specific features, covering all the morphological and grammatical traits of the word.

We train sparsely factored NMT systems with and without linguistic dropout. For LD, we used $p = 0.25$, that is, there is a 75% probability of using the (lemma + morphological features) representation, if available, and 25% probability of using the word’s subword tokens instead. The neural architecture used for out experiments was the Transformer model.

We included two baseline systems as reference. First, a vanilla Transformer model with BPE vocabulary without any linguistic information. Second, a factored NMT system (Sennrich and Haddow, 2016). The hyperparameter configurations used for the baselines and the evaluated models can be found in Appendix A.

For the German linguistic information we used the ParZu annotation tool (Sennrich et al., 2009, 2013) (which was the tool used by Sennrich and Haddow (2016)), while for Basque we use the analysis by Lucy LT.

In our experiments, we studied the translation quality in terms of BLEU scores (Papineni et al., 2002), obtained with Moses’ multi-bleu.perl script after tokenizing with the Moses tokenizer. Given that our datasets had been truecased/lowercased, we compute the lowercase variant of the BLEU score.

5 Results

Table 3 shows the BLEU scores obtained by our sparsely factored NMT, with and without linguistic dropout, as well as the baseline systems, for the German (DE) → English (EN) and Basque (EU) → Spanish (ES) translation directions, both with in-domain and out-of-domain tests.

We can see that the factored NMT system in general performs worse than the Transformer baseline without linguistic information. This can be associated with the sparsity problem described in Section 3 and illustrated in Figure 1, which is especially relevant for an agglutinative language like Basque, where the difference for in-domain data is 5.6 BLEU points.

We can also appreciate that with sparsely factored NMT without LD, we also suffer a loss in translation quality with respect to the vanilla Transformer. However, using sparsely factored NMT, we have comparable translation quality with respect to the vanilla Transformer for in-domain data, but for out-of-domain data we improve 0.8 BLEU points for Basque and 6 BLEU points for German.

From these results, we understand that, without LD, the subword token embeddings are under-trained. This problem is mitigated by the introduction of LD. The results also suggest that the improvements can be larger in very low resource scenarios, like the German experiments, with 160k sentences in the training data, a much smaller size than Basque, with 550k. For in-domain data, our approach suffers a small loss, 0.4-0.5 BLEU points, which is normally considered comparable.

6 Conclusion

We proposed sparsely factored NMT, which is an approach to inject linguistic information in the source-side of NMT architectures, especially appropriate for annotation schemes where the morphological tags are not applicable to all word types, leading to sparseness of the training signal in classical approaches like factored NMT. We also proposed linguistic dropout, a complement to sparsely factored NMT that improves the training signal for the subword embeddings.

Our results showed that this approach maintains the baseline translation quality, only with a minor loss, and improves drastically the translation quality of out-of-domain text when the system has been trained in a low-resource setting.

Our code is available as open source at https://github.com/noe/sparsely_factored_nmt.
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Supplementary Material: Appendix

A Hyperparameters

All the models presented in Table 3 use the Transformer architecture. For the German→English models (trained on the IWSLT14 de-en dataset), we used the hyperparameter configuration recommended by fairseq for that dataset\(^4\), which is presented in Table 4.

| num. layers | 6          |
|-------------|------------|
| num. heads  | 4          |
| embed. size | 512        |
| feedforward | 1024       |
| total batch | 4096       |

Table 4: Hyperparameters German→English.

For the Basque→Spanish models (trained on the EiTB eu-es dataset), we use the base Transformer configuration, which is presented in Table 5, but with a smaller total batch size of 4096 to avoid overfitting.

| num. layers | 6          |
|-------------|------------|
| num. heads  | 8          |
| embed. size | 512        |
| feedforward | 2048       |
| total batch | 4096       |

Table 5: Hyperparameters for Basque→Spanish.

The value used for LD used for our sparsely factored NMT models was $p = 0.25$ (i.e. 75% probability of using the lemma + morphological features representation, if available, and 25% probability of using the word’s subword tokens instead).

The hyperparameter tuning was done manually, trying less than 8 configurations, focusing on linguistic dropout and number of attention heads. All experiments were performed on a server with 4 nvidia 1080Ti GPUs.

All models were trained once, with no retraining.

B Implementation Details

For the vanilla Transformer we used fairseq (Ott et al., 2019). For the factored NMT, we used OpenNMT (Klein et al., 2017) (which supports token features) with its implementation of the Transformer.

For the sparsely factored NMT system, we used a modified version of fairseq’s Transformer.

C Detailed Encoding Approach

In Section 3 we presented the description of the approach used to encode the sparsely factored annotation schemes. The same information is presented in a more specific way as Algorithm 1, where we can see that, for each word in a sentence, if the word is lemmatizable and the linguistic dropout mechanism (LD) (i.e. avoiding encoding the linguistic information with probability $p$) allows, the word is encoded as a vector obtained by adding the embedded vector of the word’s lemma together with the embedded vector of each of its factors, or otherwise the word is decomposed into subwords with BPE and each subword is embedded and concatenated with the rest of the sentence token vectors.

Algorithm 1: Sparsely factored encoding

Result: token_vectors

```python
token_vectors = [];

foreach word in sentence do
    if is lemmatizable(word) & not LD then
        word_vector = [0, 0, ..., 0];
        lemma = get_lemma(word);
        lemma_vector = embedding[lemma];
        word_vector += lemma_vector;
        factors = get_factors(word);
        foreach factor in factors do
            factor_vector = embedding[factor];
            word_vector += factor_vector;
        end
        token_vectors.append(word_vector);
    else
        foreach subword in BPE(word) do
            subword_vector = embedding[subword];
            token_vectors.append(subword_vector);
        end
    end
end
```

Note that the presented conceptual algorithmic approach is adapted at the implementation level with appropriate parallelization and adapted to work in the automatic differentiation framework offered by fairseq.