Leveraging Rule-Based Machine Translation Knowledge for Under-Resourced Neural Machine Translation Models

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Abstract

Rule-based machine translation is a machine translation paradigm where linguistic knowledge is encoded by an expert in the form of rules that translate from source to target language. While this approach grants total control over the output of the system, the cost of formalising the needed linguistic knowledge is much higher than training a corpus-based system, where a machine learning approach is used to automatically learn to translate from examples. In this paper, we describe different approaches to leverage the information contained in rule-based machine translation systems to improve a corpus-based one, namely, a neural machine translation model, with a focus on a low-resource scenario. Our results suggest that adding morphological information to the source language is as effective as using subword units in this particular setting.

1 Introduction

In rule-based machine translation (RBMT), a linguist formalises linguistic knowledge into lexicons and grammar rules. This knowledge is used by the system to analyse sentences in the source language and translate them. While this approach does not require any training corpora and grants control over the translations created by the system, the process of encoding linguistic knowledge requires great amounts of expert time. Notable examples of RBMT systems are the original, rule-based Systran (Toma, 1977), Lucy LT (Alonso and Thurmair, 2003) and Apertium (Forcada et al., 2011).

Instead, corpus-based machine translation systems learn to translate from examples, usually in

the form of sentence-level aligned corpora. On the one hand, this approach is generally more computationally expensive and offers limited control over the generated translations. Furthermore, it is not feasible for language pairs that have little to no available parallel resources. On the other hand, it boasts a much higher coverage of the targeted language pair, depending on the availability of parallel corpora. Examples of corpus-based machine translation paradigms are statistical phrase-based translation (Koehn et al., 2003) and neural machine translation (NMT) models (Bahdanau et al., 2015).

In this work, we focused on leveraging RBMT knowledge for improving the performance of NMT systems in an under-resourced scenario. Namely, we used information contained in Lucy LT, an RBMT system where the linguistic knowledge is formalised by human linguists as computational grammars, monolingual and bilingual lexicons. Monolingual lexicons are collections of lexical entries; each lexical entry is a set of feature-value pairs containing morphological, syntactic and semantic information. Bilingual lexicon entries include source-target lexical correspondences and, optionally, contextual conditions and actions. Grammars are collections of transformations to annotated trees. The Lucy LT system divides the translation process into three sequential phases: analysis, transfer, and generation. During the analysis phase, the source sentence is tokenised and morphologically analysed by means of a lexicon that identifies each surface form and all its plausible morphological readings. Next, the Lucy LT chart parser together with a analysis grammar consisting of augmented syntactic rules extracts the underlying syntax tree structure and annotates it. The transfer and generation grammars are then applied in succession on that tree, which undergoes multiple annotations and transformations that add information about the equivalences in the target language and adapt the

original source language structures to the appropriate ones in the target language. Finally, the terminal nodes of the generation tree are assembled into the translated sentence. We focused on the analysis phase, with special interest for two of the features used: the morphological category (`CAT`) and the inflection class (`CL`) or classes of the lexical entries.

In order to test this approach, we focused on English-Spanish (both generic and medical domain), English-Basque, English-Irish and English-Simplified Chinese in an under-resourced scenario, using corpora with around one million parallel entries. Results suggested that adding morphological information to the source language is as effective as using subword units in this particular setting.

2 Related work

Sennrich and Haddow (2016) demonstrated the inclusion of various linguistic knowledge, such as morphological features, part of speech (POS) tags and syntactic dependency labels, as input features for the English-German and English-Romanian NMT systems. Baniata et al. (2018) proposed a multitask-based NMT system with POS information for translation between English, modern standard Arabic and Arabic dialects, i.e. Levantine Arabic and Maghrebi Arabic. The work demonstrated that the POS information for the low resourced Arabic dialects was beneficial for the translation quality, specifically if pre-trained FastText models were injected during the NMT training step. Niehues and Cho (2017) jointly trained several English-German natural language processing tasks in one system with shared encoder and one attention model and decoder per task. By integrating additional linguistic resources via multitask learning, the performance of each individual task was improved. Bastings et al. (2017) showed that incorporating syntactic structure such as dependency tree using graph convolutional encoders was beneficial for neural machine translation. Their work focused on exploiting structural information on the source side by adding a second encoder. The goal of their work was to provide the encoder with access to rich syntactic information without placing rigid constraints on the interaction between syntax and the translation task

Etchegoyhen et al. (2018) studied NMT, RBMT, and phrase-based statistical machine translation approaches for Basque-Spanish. The authors focus on different subword unit representations, i.e. linguistically-motivated or frequency-based word segmentation method. Shi et al. (2016) investigated whether an encoder-decoder translation system learns syntactic information on the source side as a side affect of training the neural models. Several syntactic labels of the source sentence were created and logistic regression models using the learned sentence encoding vectors or learned word by word hidden vectors were used to predict these syntactic labels. Aharoni and Goldberg (2017) presented a method to incorporate syntactic information of the target language in an NMT system, showing improved word reordering compared to their baseline system. Eriguchi et al. (2016) proposed an NMT model leveraging syntactic information to improve the accuracy for English→Japanese translation. The phrase structure of the source sentence was recursively encoded in a bottom-up fashion to first produce a vector representation of the sentence, then decode it while aligning the input phrases and words with the output. Bastings et al. (2017) relied on graph-convolutional networks primarily developed for modelling graph-structured data. These networks used predicted syntactic dependency trees of source sentences to produce representations of words that are sensitive to their syntactic neighbourhoods. Nadejde et al. (2017) introduced CCG supertags within the target word sequence as syntactic information, processed by the decoder of their NMT system. Their evaluation showed translation quality improvements for the German→English and Romanian→English translation directions. Similarly, their approach outperformed multi-tasking approach for the same language pairs. García-Martínez et al. (2016) trained their NMT model to simultaneously generate the lemma and its corresponding factors, i.e. POS, gender, and number, demonstrating that factored architecture increases the vocabulary coverage while decreasing the number of unknown words. Ataman and Federico (2018) described the addition of a recurrent neural network to generate compositional representations of the input words, obtaining better results than systems using byte-pair encoding when translating from morphologically rich languages to English. Banerjee and Bhattacharyya (2018) compared two different approaches for subword units when translating from English to Hindi and Bengali, byte pair encoding and morpheme-based segmentation, showing that the latter approach improves the translations, and further improvements can be achieved by combining both.

```
("snake" NST ALO "snake" CL (P-S S-01) KN CNT ON CO SX (N) TYN (ANI))
("snake" VST ALO "snak" ARGS ((($SUBJ N1 (TYN CNC LOC C-POT)) ($ADV DIR)))
     CL (G-ING I-E P-ED PA-ED PR-ES1) ON CO PLC (NF))
```

Figure 1: The word *snake* as a noun (NST) and a verb (VST) in Lucy LT dictionaries. Each entry is composed of a canonical form, the category (POS), and a list of key-value features, such as the inflection class (CL), the vocalic onset (ON), etc.
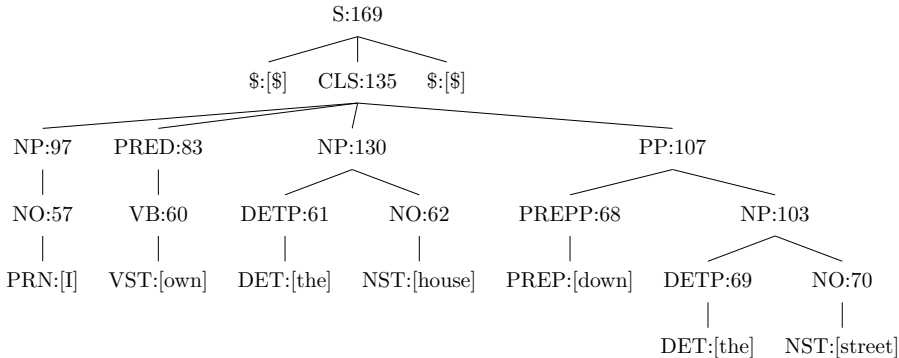
Figure 2: Example of the parse tree for the English sentence *I own the house down the street*.

3 Methodology

In this section, we describe the methodology to leverage rule-based machine translation (RBMT) information in neural machine translation (NMT).

3.1 Information acquisition from RBMT

Lucy LT monolingual lexicons are language-pair independent (i.e. the same English knowledge is used for all translation pairs including English as a source or target language) and mainly encode morphological and contextual information. Each entry has a word or multi-word expression (MWE) along with several features, such as the part of speech (POS) and morphological features. The bilingual lexicons mainly encode word-to-word or MWE-to-MWE translations and describe which target language word should replace each source language word. Still, the direct usage of the lexicon entries as a source of information presented a challenge, as there is no means to determine ambiguous surface words. For example, in English, most nouns will also be classified as verbs, as they share the same surface form; e.g. the word *snake* can be both a noun and a verb (Figure 1). For addressing this problem, we took two different approaches: using **ambiguity classes** that describe all the possible analysis for a given surface word; and using **external information** (in the form of a monolingual POS tagger) to disambiguate. For the former approach, we used a unique tag for each possible CAT and CL values concatenation; e.g. the categories NST and VST and all the inflection classes (CL) for *snake* (Figure 1). For the latter, we used the Stanford POS tagger (Toutanova et al., 2003), that uses the Penn Treebank (Marcus et al., 1994) tag set for English, and the AnCora (Civit and Martí, 2004) tag set for Spanish, and the IXA pipeline POS tagger (Agerri et al., 2014) with the Universal Dependencies POS tag set (Nivre et al., 2018) for Basque. All POS tag sets were mapped to the tag set used by Lucy LT. If the tagger provided POS tag was equivalent to one or more Lucy LT tags, then the non matching Lucy LT tags were removed. Otherwise, we kept the set of tags; e.g. if the POS tag emits noun as the most likely tag, then only NST and the concatenation of all the inflection classes for the corresponding entry would be used as additional information. As a comparison, we also evaluated NMT models trained with Stanford or IXA POS tags as additional information.

3.2 Leveraging Syntactic Tree Information

In addition to the direct use of the linguistic knowledge in lexicon entries, the grammars (monolingual and bilingual lexicons) were indirectly used by exploring the results of each internal intermediate stage of the translation process, which Lucy LT expresses as annotated trees. For example, the sentence parsed in Figure 2,

I own the house down the street

is encoded as

⟪*I own* ⟪*the house*⟫ ⟪*down* ⟪*the street*⟫⟫⟫.[1]

We use this representation as source text when training the NMT models, as sequence-to-sequence deep neural network models do not generally accept hierarchical information. We also used an additional feature: the linguistic phrase the word belongs to. This information is present in the grandparent of

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[1]To avoid collisions with parenthesis in the text, we used the left (⟪, U+2985) and right (⟫, U+2986) white parenthesis.

		Source (English)		Target		
		# of Subwords	# of Uniq. Subwords	# of Subwords	# of Uniq. Subwords	# of Lines
English– –Spanish (generic)	train validation evaluation	17,919,926 180,290 178,841	33,212 15,714 15,031	18,408,749 185,662 181,188	33,076 18,804 18,810	1,000,000 10,000 10,000
English– –Spanish (EMEA)	train validation evaluation	14,440,740 186,685 219,752	27,112 11,599 9,412	15,872,405 204,174 242,137	29,290 14,306 10,979	1,036,058 10,000 10,000
English– –Basque	train validation evaluation	11,760,808 85,919 85,163	30,946 9,150 9,283	10,309,229 76,532 75,309	32,369 13,593 13,546	1,357,475 10,000 10,000
English– –Irish	train validation evaluation	15,234,432 135,986 140,696	31,834 12,648 11,613	16,983,046 152,224 152,064	32,183 16,113 16,174	1,090,418 10,000 10,000
English– –Simplified Chinese	train validation evaluation	27,878,268 138,640 129,440	31,471 12,451 12,175	25,199,106 126,191 119,577	41,458 14,490 14,431	995,000 5,000 4,500

Table 1: Statistics on the used training, validation and evaluation datasets.

each node; e.g. in Figure 2 the noun *house* appears in a noun phrase (NP).

4 Experimental Setting

In this section, we describe the resources we used to train and evaluate the systems, along with the neural machine translation framework used.

4.1 Training and Evaluation Datasets

In this work, we focused on NMT for under-resourced scenarios. On the one hand, we consider languages, such as Basque or Irish, which do not have a significant amount of parallel data necessary to train a neural model. On the other hand, an under-resourced scenario can be a specific domain, e.g. medical, where a significant amount of data exists, but does not cover the targeted domain. The Table 1 shows the statistics on the used datasets.

For Basque and Irish, we used the available corpora stored on the OPUS webpage.[2] We used OpenSubtitles2018 (Lison and Tiedemann, 2016),[3] Gnome and KDE4 datasets (Tiedemann, 2012). Additionally, the English-Irish parallel corpus is augmented with second level education textbooks (*Cuimhne na dTéacsleabhar*) in the domain of economics and geography (Arcan et al., 2016).

In addition to that, we also focused on well resourced languages (Spanish and Simplified Chinese), but limited the training datasets to around one million aligned sentences. To ensure a broad lexical and domain coverage of our NMT system, we merged the existing English-Spanish parallel corpora from the OPUS web page into one parallel data set and randomly extracted the sentences. In addition to the previous corpora, we added Europarl (Koehn, 2005), DGT (Steinberger et al., 2014), MultiUN corpus (Eisele and Chen, 2010), EMEA and OpenOffice (Tiedemann, 2009). To evaluate the targeted under-resourced scenario within medical domain, we exclusively used the EMEA corpus. For Simplified Chinese, we used a parallel corpus provided by the industry partner, which was collected from bilingual English-Simplified Chinese news portals.

The corpora were tokenised using the OpenNMT toolkit, with the exception of Simplified Chinese, that was tokenized using Jieba,[4] and lowercased.

4.2 NMT framework

We used OpenNMT (Klein et al., 2017), a generic deep learning framework mainly specialised in sequence-to-sequence models covering a variety of tasks such as machine translation, summarisation, speech processing and question answering as NMT framework. Due to computational complexity, the vocabulary in NMT models had to be limited. In order to overcome this limitation, we used byte pair encoding (BPE) to generate subword units (Sennrich et al., 2016). BPE is a form of data compression that iteratively replaces the most frequent pair of bytes in a sequence with a single, unused byte. We also added the different morphological and syntactic information as word features.

We used the following default neural network training parameters: two hidden layers, 500 hidden

LSTM (long short term memory) units per layer, input feeding enabled, 13 epochs, batch size of 64, 0.3 dropout probability, dynamic learning rate decay, 500 dimension embeddings, maximum vocabulary size of 50,000 subwords, maximum of 32,000 unique BPE merge operations, unlimited different values for the word features and between 11 and 23 dimension embeddings for word features.[5]

4.3 Evaluation

In order to evaluate the performance of the different systems, we used BLEU (Papineni et al., 2002), an automatic evaluation that boasts high correlation with human judgements, and translation error rate (TER) (Snover et al., 2006), a metric that represents the cost of editing the output of the MT systems to match the reference. Additionally, we used bootstrap resampling (Koehn, 2004) with a sample size of 1,000 and 1,000 iterations, and reported statistical significance with $p < 0.05$. We also presented a box-and-whisker plot with the first, second and third quartiles as a box, and the first (<0.025) and last (≥ 0.975) 40-quantiles as whiskers, corresponding to $p < 0.05$. In addition, we compared the performance of our NMT systems with the NMT-based Google Translate,[6] and the translations performed using Lucy LT RBMT; for the latter, only English-Spanish and English-Basque models are available.

5 Results

In this section we describe the quantitative and qualitative evaluation of the different models: the NMT baseline (Baseline), baseline enhanced with ambiguous `CAT` and `CL` (CAT-CL), baseline with disambiguated `CAT` and `CL` (CAT-CL D), baseline with external POS tags (POS), baseline with indirect `CAT`, `CL` and syntactic information (CAT-CL L), the hierarchical model (Tree), Lucy LT (RBMT) and Google Translate (Google).

5.1 Quantitative results

The quantitative results of the evaluation are presented in Figure 3. All the models tested significantly outperformed the RBMT system Lucy LT both when using BLEU and TER as evaluation metrics. Even when trained with only around a million sentences, the NMT baseline model for English-Basque and English-Irish performed better

than Google Translate with generic domain corpora, and were not statistically significantly different for English→Simplified Chinese. Unsurprisingly, the in-domain medical domain English-Spanish models outperformed Google Translate. Conversely, Google Translate was significantly better than the NMT baselines only for the English-Spanish generic domain, excluding English→Spanish TER. While some of the feature-enriched models obtained slightly better results in terms of BLEU and TER compared to the baseline, no model obtains scores that are statistically significantly different than the baseline subword model. We also observed that the kind of information we added to the system in the form of `CAT` and `CL` features can also be learned by NMT models based on subword units, that may split the root from the rest of the word. In case of the tree model, the results were consistently lower than the rest. Finally, we learned that the system could not cope with this complex representation with the amount of data available.
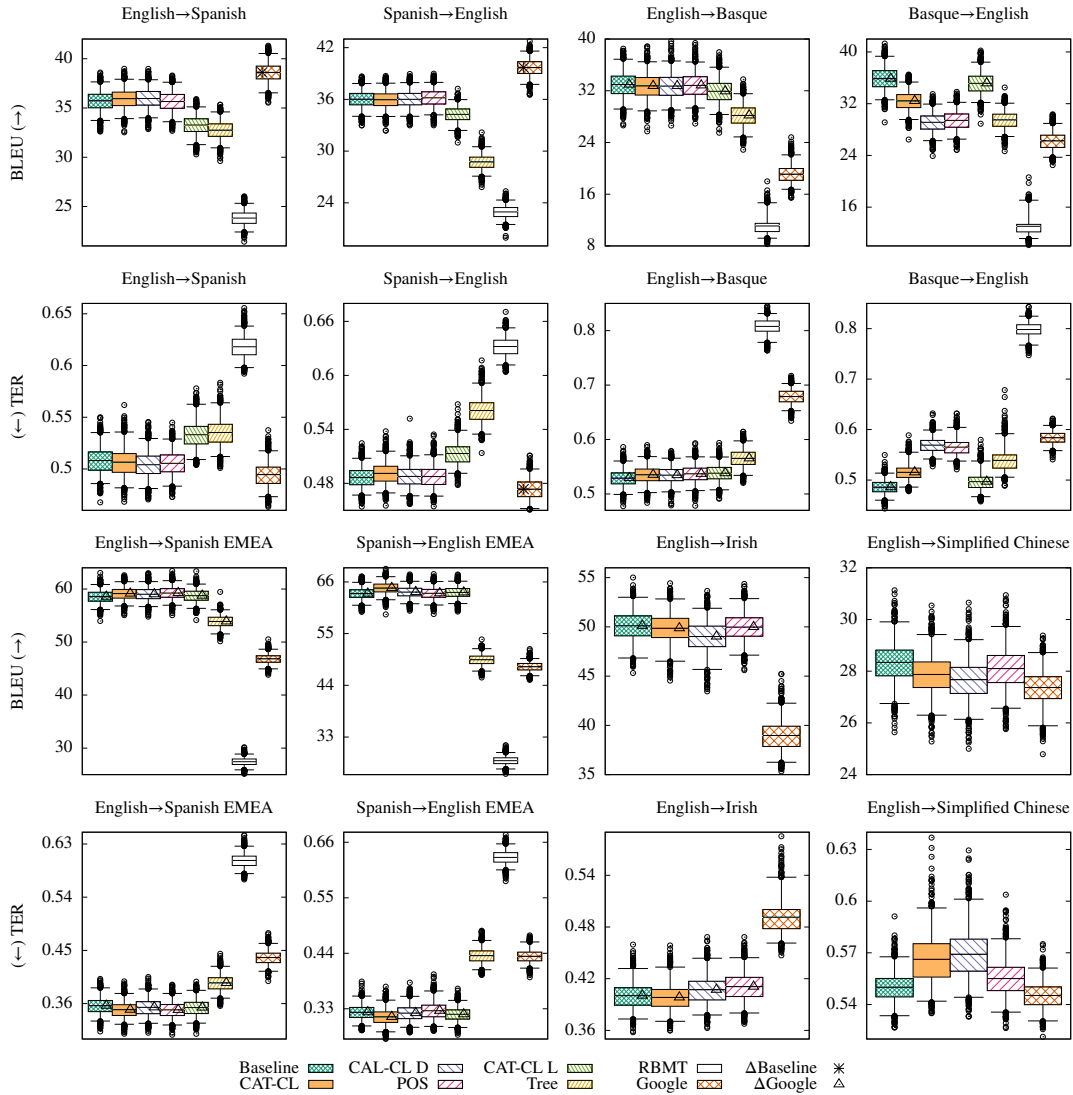
5.2 Qualitative results

Table 2 analyses a sentence translated using all different models from Spanish to English. The analysis showed that, even when RBMT makes some grammatical mistakes, the sentence still conveyed the correct message. Nevertheless, it was the only hypothesis with a BLEU of 0, as it shared no four-gram with the reference, and was the hypothesis with the highest TER. The baseline model hypothesis was tied for the best TER score and the second best BLEU score, but it failed to convey the proper message, as it lacked translation for *easing of price increases*.

6 Conclusions and future work

In this work we explored the use of rule-based machine translation (RBMT) knowledge to improve the performance of neural machine translation (NMT) models in an under-resourced scenario, showing that adding morphological information to the source language is as effective as using subword units in this particular setting. We also found that RBMT translations were often adequate but both BLEU and TER poorly reflected this, often scoring worse than incorrect NMT-generated translations.

One of the paths of our future work will further focus on the extraction of RBMT knowledge and the inclusion of transfer rules to improve the performance of the NMT model. A second improvement

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[5]The size of the embedding for word features depend on the number of unique values for the feature.
[6]`translate.google.com` retrieved March 2019.

Figure 3: Results for the evaluation for English-Spanish, both for generic and medical (EMEA) domains, English-Basque, English→Irish and English→Simplified Chinese. No RMBT models are available for Irish and Simplified Chinese in Lucy LT. Models marked with ∗ are significantly better than the NMT baseline, and models marked with △ are significantly better than Google Translate. All models are statistically significantly better than RBMT.

		BLEU	TER
Source	Pese a que los incrementos de los precios fueron menores en el segundo semestre de 2008 , los precios siguen siendo muy elevados .		
Reference	Despite an easing of price increases in the second half of 2008, prices remain at very high levels.		
Baseline	Despite the increases in prices in the second half of 2008, prices remain very high.	47.48	0.35
CAT-CL	*Although* price increases were **minor** in the second half of 2008, prices remain very high.	47.48	0.35
CAT-CL D	*Although* increases in prices were lower in the second half of 2008, prices remain high.	44.50	0.45
POS	*Despite the fact that* price increases were lower in the second half of 2008, prices remain very high.	48.25	0.35
CAT-CL L	*Although* price increases were lower in the second half of 2008, prices remain very high.	47.48	0.35
Tree	*Although* **prices of** prices were lower in the second half of 2008 prices remain very high.	45.51	0.40
RBMT	*Even though* the increases of the prices **were smaller** in the second *semester* of 2008, the prices **keep being** *sky-high*.	0.00	0.70
Google	*Although* the price increases *were lower* in the second half of 2008, prices *are still* very high.	41.81	0.40

Table 2: Qualitative analysis of a sentence translated by all models for Spanish to English translation. Fragments in bold face are translation mistakes, and fragments in italics are translation alternatives that, while being penalised by TER and BLEU, can be considered correct.

path would be using multiple encoders. This approach has been used to improve the performance NMT (Zoph and Knight, 2016), but, in our scenario, one of the inputs would be the output of the RBMT system. As previously mentioned, corpus-based machine translation gives limited control over the output to the user, specially when dealing with homographs and terminology; instead, RBMT gives total control. Combining the source sentence with the RBMT output that contains the user-selected translations might lead to improvements in domain-specific or low resource scenarios.

Finally, we also plan to leverage information contained in other freely available RBMT systems, such as Apertium. While Apertium is a shallow-transfer system, meaning that there is less syntactic information, features similar to the ones used in this work are available in Apertium.

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