Paraphrasing Out-of-Vocabulary Words with Word Embeddings and Semantic Lexicons for Low Resource Statistical Machine Translation

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Abstract
Out-of-vocabulary (OOV) word is a crucial problem in statistical machine translation (SMT) with low resources. OOV paraphrasing that augments the translation model for the OOV words by using the translation knowledge of their paraphrases has been proposed to address the OOV problem. In this paper, we propose using word embeddings and semantic lexicons for OOV paraphrasing. Experiments conducted on a low resource setting of the OLYMPICS task of IWSLT 2012 verify the effectiveness of our proposed method.

Keywords: Paraphrasing, Out-of-Vocabulary Word, Word Embedding, Semantic Lexicon

1. Introduction
In statistical machine translation (SMT) (Koehn et al., 2003), because translation knowledge is acquired from parallel data, the quality and quantity of parallel data are crucial. However, except for a few language pairs, such as English-French, English-Arabic, English-Chinese and several European language pairs, parallel data remains a scarce resource. Moreover, even for these language pairs, the available domains are limited. The scarceness of parallel corpora makes the coverage of the translation model low, which leads to high out-of-vocabulary (OOV) word rates when conducting translation (Callison-Burch et al., 2006). Even we have parallel corpora in sufficient size in one domain, this OOV problem occurs when the domain shifts. Irvine et al. (2013a) showed that SMT performance decreases significantly when using a system trained on one domain to translate texts in different domains mainly because of OOVs.

As one of the ways to address the OOV problem, paraphrasing has been proposed (Callison-Burch et al., 2006; Marton et al., 2009; Razmara et al., 2013). That is augmenting the translation model for the OOV words by using the translation knowledge of their paraphrases in the translation model. Previous studies use paraphrases generated by bilingual pivoting (Callison-Burch et al., 2006), distributional similarity (Marton et al., 2009), and graph propagation (Razmara et al., 2013), which suffer from high computational complexity. In this study, we propose using word embeddings (Mikolov et al., 2013) to address this problem. We also propose using semantic lexicons including WordNet (Miller, 1995), FrameNet (Baker et al., 1998), and the Paraphrase Database (PPDB) (Ganitkevitch et al., 2013) for paraphrasing. In addition, we apply a method to combine these two types of paraphrases (Faruqui et al., 2015), which achieves further improvements in SMT.

2. Paraphrasing Out-of-Vocabulary Words
In this paper, we study on phrase based SMT (Koehn et al., 2003). Figure 1 shows an overview of our proposed method. We first construct a phrase table based on unsupervised word alignments, containing phrase pairs together with their feature scores. From the development and test sets, we extract OOV words that do not exist in the phrase table.

Using the word embeddings trained on monolingual data and semantic lexicons, we obtain a list of paraphrases for each OOV word. For each paraphrase existing in the phrase table, we append a new entry for the OOV word to the phrase table, with the corresponding target translation. The similarity between the OOV word and the paraphrase is added as a new feature in the phrase table.\footnote{This similarity will be tuned along with the other features in a log-linear framework. Following (Razmara et al., 2013), we set the value of this newly introduced feature for original entries in the phrase table to 1. Similarly, the values of original feature scores in the phrase table are set to 1 for the new entries. This newly produced phrase table is then used for tuning and decoding the test sentences.}

2.1. Word Embeddings
There are many publicly available word embedding toolkits. Among which we chose the word2vec tool (Mikolov et al., 2013),\footnote{Note that when we use semantic lexicons for paraphrasing, this similarity is set to 1 consistently.} because of its efficiency and wide uses in nat-
ural language processing. In particular, we used the skip-gram, which inputs each current word to a log-linear classifier with a continuous projection layer, and predicts its context words within a certain window.

Once the word embeddings were trained, we calculate the cosine similarity between the vector of an OOV word and the vectors of the other words in the vocabulary, and obtain a ranked list of paraphrases for the OOV word. From the list, we kept the top 40 paraphrases for the OOV word.

2.2. Semantic Lexicons

In our study, we use three types of semantic lexicons:

- **WordNet** (Miller, 1995): WordNet is a structured semantic lexical database of English. In WordNet, the main relation among words is synonym (word level paraphrase). Words with super/subordinate relations are also linked with hyponym/hypernym labels. In our experiments, we compared two settings
  - WordNet synonyms: only using the words in the synonym relation
  - WordNet all: using the words in all relations

- **FrameNet** (Baker et al., 1998): FrameNet is a large semantic lexical database of English, constructed based on semantic frames. Frame is a description of a type of event, relation, or entity and the participants in it, and thus two words evoking the same frame are semantically related. In our experiments, we collected the words grouped in same frames and used them for paraphrasing.

- **PPDB** (Ganitkevitch et al., 2013): PPDB is a large paraphrase database of English, created from parallel corpora through bilingual pivoting (Callison-Burch et al., 2006). The idea of this method is that if two source phrases $f_1$ and $f_2$ are translated to the same target phrase $e$, we can assume that $f_1$ and $f_2$ are a paraphrase pair. PPDB is packaged in 6 sizes from S to XXXL to leverage precision and coverage, and it is also divided into to lexical and phrasal paraphrases. In our experiments, we used the lexical paraphrases in the XL size.

2.3. Combination

One problem of word embeddings is that they are learnt without supervision, which limits the quality. To achieve better quality embeddings, applying the existing semantic lexicons to change the objective of embedding training (Yu and Dredze, 2014), and relation-specific augmentation (Chang et al., 2013) have been studied.

Here, we apply the word embedding retrofitting method (Faruqui et al., 2015), because of its independence from the embedding learning method and efficiency. This method minimizes the following objective so that the retrofitted word embedding $\hat{q}_i$ will be close to both the original embedding $q_i$ and its neighbor $q_j$ in the semantic lexicons:

$$\Psi(Q) = \sum_{i=1}^{n} \{ \alpha_i \|q_i - \hat{q}_i\|^2 + \sum_{(i,j) \in E} \beta_{ij} \|q_i - q_j\|^2 \}$$ (1)

where $n$ is the vocabulary size; $E$ denotes a relation in the semantic lexicons; $\alpha_i$ and $\beta_{ij}$ control the relative strengths of associations, which we set to both 1 in our experiments. Taking the first derivative of $\Psi$ with respect to one $q_i$ vector, we arrive at the following online update by equating it to zero:

$$q_i = \frac{\sum_{(i,j) \in E} \beta_{ij} q_j + \alpha_i q_i}{\sum_{(i,j) \in E} \beta_{ij} + \alpha_i}$$ (2)

Following (Faruqui et al., 2015), we run 10 iterations for this update. After retrofitting, we use the new embeddings for paraphrasing in the same manner as before.

3. Experiments

We conducted English-to-Chinese translation experiments in a low resource setting. In all our experiments, we pre-processed the data by segmenting Chinese sentences using a segmenter proposed by Chu et al. (2012a), and tokenizing English sentences.

3.1. Task

We conducted our experiments on the OLYMPICS task of IWSLT 2012 (Federico et al., 2012). The OLYMPICS task is carried out using parts of the HIT Olympic Trilingual Corpus (HIT) (Yang et al., 2006) and the Basic Travel Expression Corpus (BTEC) as an additional training corpus. The HIT corpus is a multilingual corpus that covers 5 domains (traveling, dining, sports, traffic and business) that are closely related to the Beijing 2008 Olympic Games. The HIT corpus contains around 52k sentences 2.8 million words in total. The BTEC corpus is a multilingual speech corpus containing tourism-related sentences. The BTEC corpus consists of 20k sentences including the evaluation data sets of previous IWSLT evaluation campaigns. As SMT systems nowadays are trained on millions of sentences, we consider the OLYMPICS task as a low resource setting. We processed the training corpus using sub-sentence splitting following (Chu et al., 2012b). The development and test sets have only one reference, which contain 1,050 and 988 sentences respectively. For more details of this task, please refer to (Federico et al., 2012).

3.2. Settings

For decoding, we used the state-of-the-art phrase based SMT toolkit Moses (Koehn et al., 2007) with default options. We trained a 5-gram language model on the Chinese parallel side of the parallel corpus using the SRILM toolkit with interpolated Kneser-Ney discounting, and used it for all the experiments. Tuning was performed by minimum error rate training (MERT) (Och, 2003), and it was re-run for every experiment.

The skip-gram model (Mikolov et al., 2013) was trained on the English Gigaword version 5.0 with the word2vec tool. We removed the punctuations in the corpus, obtaining about 3.95B tokens with a vocabulary size of 854k. The context window size was set to 5, and the vector size was set to 200.

4http://www.speech.sri.com/projects/srilm
5LDC2011T07
3.3. Results
Translation results using different methods are shown in Table 1. “Baseline” denotes the system without OOV paraphrasing; “Word2vec” denotes the system paraphrased with the word embeddings obtained by word2vec; “WordNet synonyms”, “WordNet all”, “FrameNet” and “PPDB” denote the systems paraphrased with different semantic lexicons. “Word2vec retrofitted” denote the systems paraphrased with the word2vec word embeddings retrofitted by different semantic lexicons. They were evaluated on BLEU-4 scores and OOV rates. The OOV rate was the percentage of the OOV words out of the total number of source words in the development/test sets. The significance test was performed using the bootstrap resampling method proposed by Koehn (2004).

We can see that the OOV rate of the Baseline system is high, because of the small size of the parallel corpus for training. Both Word2vec and semantic lexicons decrease the OOV rate, and thus improve the MT performance. Although Word2vec is unsupervised learnt, it shows better results than the semantic lexicons that are either manual created or collected with supervised data. The reason for this is the lower coverage of the semantic lexicons compared to Word2vec, leading to lower OOV decreases. The combination of Word2vec and the semantic lexicons by retrofitting outperforms either method, because of the quality improvement of the word embeddings. Word2vec retrofitted by PPDB achieved the best performance. We believe the reason for this is the higher coverage of PPDB compared to the other semantic lexicons, leading to more improvement of the word embeddings.

To further understand the reason of the improvement, we analyzed the translation difference between Baseline and Word2vec retrofitted by PPDB. Figure 2 shows two translation examples. In example 1, the Baseline system failed to translate the word “booked”. Although “booked” does not exist in the training corpus, the word “booking” appears several times. By paraphrasing “booked” to “booking”, Word2vec retrofitted by PPDB successfully translated it. The “Briggs” does not exist in the corpus either. However, Word2vec retrofitted by PPDB incorrectly paraphrased it to “Smith”, leading to this incorrect translation. In example 2, the word “noon-time” is paraphrased to “lunch-time” and translated as it is. Although, the meaning of “noon-time” and “lunch-time” are slightly different, it still helps understanding. Based on our analysis, most improvements belong to the “booked” case, while a few improvements belong to the “noon-time” case. There are also many “Briggs” cases that the paraphrases are incorrect, but basically they would not hurt the qualities of the translations as they were OOVs in the Baseline system.

Table 1: Translation results evaluated on BLEU-4 scores and OOV rates (“*” and “†” denote that the result is significantly better than “Baseline” at $p < 0.05$ and $p < 0.01$ respectively).

| Method                                      | Dev (OOV%)    | Test (OOV%)   |
|---------------------------------------------|---------------|---------------|
| Baseline                                    | 12.96 (10.47%)| 10.38 (13.47%)|
| Word2vec                                    | 14.02 (2.00%) | 10.87† (4.49%)|
| WordNet synonyms                            | 13.20 (9.10%) | 10.64 (12.03%)|
| Word2vec retrofitted by WordNet synonyms    | 13.94 (1.97%) | 10.90† (4.40%)|
| WordNet all                                 | 13.04 (8.26%) | 10.28 (11.25%)|
| Word2vec retrofitted by WordNet all         | 14.00 (1.96%) | 10.94† (4.40%)|
| FrameNet                                    | 13.01 (9.84%) | 10.45 (12.58%)|
| Word2vec retrofitted by FrameNet            | 14.07 (2.00%) | 11.09† (4.39%)|
| PPDB                                        | 13.72 (3.26%) | 10.50 (3.40%) |
| Word2vec retrofitted by PPDB                | 14.36 (1.36%) | 11.18† (4.43%)|

Example 1
En: Good evening. I booked a table for two. My name is Briggs.
Baseline: 晚上好。我booked一张两人用餐的饭桌。我的名字是Briggs。
Word2vec retrofitted by PPDB: 晚上好。我预订了一张两人用餐的饭桌。我的名字是史密斯先生。
Reference: 你好，我订两个人的桌位，我姓布里格斯。

Example 2
En: I'll try. you can call us tomorrow at noontime and see if they’re ready.
Baseline: 你能给我打电话，我们明天noontime看看他们准备好。
Word2vec retrofitted by PPDB: 我可以试一下吧。明天打电给我们看看他们准备好。
Reference: 他们会尽快。你可以明天中午来电话看看他们准备好没有。

Figure 2: Translation examples of Baseline and Word2vec retrofitted by PPDB.

4. Related Work
Previous studies have proposed different paraphrase generation methods for OOV paraphrasing. Callison-Burch et al. (2006) use paraphrases generated by bilingual pivoting. In our experiments, we compared the extension of their method, which is the PPDB setting in Section 3. Marton et al. (2009) firstly used distributional similarity to generated paraphrases for OOVs. Razmara et al. (2013) extended the method of (Marton et al., 2009) via graph propagation.
drawback of both (Marton et al., 2009) and (Razmara et al., 2013) is that they suffer from high computational complexity. The monolingual data used in their experiments were only tens of millions of tokens. We address this drawback with word embeddings (Mikolov et al., 2013), making the paraphrase generation scalable to monolingual data with billions of tokens. Moreover, we propose using semantic lexicons together with word embeddings for OOV paraphrasing.

Bilingual lexicon extraction (BLE) (Chu et al., 2014) is another common method to address the OOV problem. BLE extracts the translations for the OOVs from comparable corpora, which are a set of monolingual corpora that describe roughly the same topic in different languages. Daume III et al. (2011) firstly proposed BLE with canonical correlation analysis for the OOV problem. Irvine et al. (2013b) proposed a monolingual marginal matching BLE method for this. Irvine et al. (2013) extracted the translations for the OOV words using a supervised method. All these studies could be complemented with our study.

5. Conclusion

In this paper, we addressed the OOV problem for low-resource SMT by paraphrasing with word embeddings and semantic lexicons. Experimental results verify the effectiveness of our proposed method. As future work, we plan to try other word embeddings methods, and develop more advanced methods for combining with the semantic lexicons. Moreover, we plan to conduct experiments on language pairs that have scarce parallel corpora, to complement the experiments in this paper that were conducted on a language pair that lacks of parallel corpora in a particular domain.

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