Bilingual Terminology Extraction from Non-Parallel E-Commerce Corpora

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Abstract

Bilingual terminologies are important resources for natural language processing (NLP) applications. The acquisition of bilingual terminology pairs is either human translation or automatic extraction from parallel data. We notice that comparable corpora could also be a good resource for extracting bilingual terminology pairs, especially for e-commerce domain. The parallel corpora are particularly scarce in e-commerce settings, but the non-parallel corpora in different languages from the same domain are easily available. In this paper, we propose a novel framework of extracting bilingual terminologies from non-parallel comparable corpus in e-commerce. Benefitting from cross-lingual pre-training in e-commerce, our framework can extract the corresponding target terminology by fully utilizing the deep semantic relationship between source-side terminology and target-side sentence. Experimental results on various language pairs show that our approaches achieve significantly better performance than various strong baselines.\(^1\)

1 Introduction

Terminology is usually a multi-words string, carrying key concepts in a sentence. The machine translation model learns translations of the key concepts via parallel corpora containing bilingual terminologies. However, it is challenging since they sometimes appear less frequently in the bilingual corpora [Song et al., 2019b]. In order to obtain high-quality bilingual terminologies, manual construction is a reliable way, but exclusively time-consuming and expensive. To deal with this problem, some researchers have proposed methods to automatically extract bilingual terminology from parallel corpora [Lefever et al., 2009; Gaussier et al., 2000].

Most of the methods to extract terminologies from parallel corpora are rule-based. The framework consists of performing part-of-speech tagging on the parallel corpus, finding structures that conform to certain rules, and then aligning them at word level to find mutually translated words. Nevertheless, this framework relies on linguistic analysis tools such as POS taggers, which might be unavailable for under-resourced languages or domain, such as e-commerce. In addition, in order to be independent of language pair, some statistical-based approaches [Le An Ha et al., 2008; Haque et al., 2014] have been proposed. These methods acquire parallel term-pairs directly from a sentence-aligned corpus. A significant drawback is that they are not effective in extracting low-frequency pairs, since the statistics based on word frequency.

Another research work similar to bilingual terminology extraction is multi-words alignment, which mainly depends on the vector representation of the phrase. The phrase vector usually is obtained by adding vectors of separate words in the phrase [Hazem and Daille, 2018; Liu et al., 2018]. With this method the information of word order is not kept. For example, “control system” and “system control” will have exactly the same representation, resulting to errors in aligning the phrase to the target languages.

The methods we have explored above are either highly dependent on parallel data, or is lack of semantic relationship between cross-lingual words. We have notice that the comparable data could also be a good resource to learn bilingual terminologies, especially for the domain lack of parallel data, such as e-commerce domain. The e-commerce parallel corpora are very scarce. On the contrary, a larger number of...
comparable data exist on websites.

In this paper, we propose a new extraction framework for bilingual terminology extraction in e-commerce, independent on any bilingual resources. Given a terminology in source language and a sentence in target language, our framework can first distinguish whether the target sentence contains the corresponding target translation of the source terminology. If it contains, the framework predicts the positions of the target terminology in the target sentence. The extraction model is initialized with a e-commerce cross-lingual pre-trained vectorized semantic representation. The cross-lingual pre-trained model is trained on the e-commerce corpus of different languages under the same commodity category, by randomly masking the source or target words.

The main contributions of this paper can be summarized as follows:

• We are the first to propose the task of bilingual terminology extraction in e-commerce, and construct the corresponding comparable data in e-commerce domain.

• We are the first to utilize the cross-lingual pre-training model and extraction framework to formalize the task of bilingual terminology extraction from non-parallel data.

• We conduct experiments mainly on three different e-commerce categories, namely outdoor category, toy category and t-shirt category in Chinese-to-English and English-to-French language pairs. Experimental results demonstrate its effectiveness. We wish that our work would inspire the introduction of new paradigms for bilingual terminology extraction.

2 Related Work

In this section we present three concepts related to our method. First we describe Bilingual Lexicon Induction, which is the task of word-level alignment. Then, several works about bilingual terminology extraction from parallel corpora will be discussed. Finally we describe several cross-lingual language model pre-training methods.

Cross-Lingual Word Embeddings for Bilingual Lexicon Induction Following the success of word embeddings [Mikolov et al., 2013] trained on monolingual data, a large proportion of research aimed at mapping word embeddings into a common space for multiple languages [Zhang et al., 2017; Conneau et al., 2017; Lample et al., 2017; Lazaridou et al., 2015], which were implemented by optimizing a linear transformation matrix. Based on these efforts, [Artetxe et al., 2018] proposed the extension of skip-gram to learn n-gram embeddings and mapped them to a shared space to obtain cross-lingual n-gram embeddings. However, these n-gram embeddings are based on the co-occurrence frequency.

Bilingual Terminology Extraction from Parallel Corpora Several influential approaches [Le An Ha et al., 2008; Küpiec, 1993; Haque et al., 2014; Gaussier et al., 2000] have been proposed to extract bilingual terminology from parallel corpus, which mainly rely on the linguistic feature, statistical feature or the hybrid of them. [Kupiec, 1993] proposed an algorithm, which adopted English and French text taggers to associate noun phrases in the aligned English-to-French parallel corpus. The taggers provided part-of-speech categories which were used by finite-state recognizers to extract simple noun phrases for both languages. [Lefever et al., 2009] proposed a sub-sentential alignment terminology extraction module that links linguistically motivated phrases in parallel texts.

In their work, the statistical filters were applied on the bilingual list of candidate terms that was extracted from the alignment outputs. [Haque et al., 2014] applied a statistical based log-likelihood comparison method to extract monolingual terminology from the source and target sides of a parallel corpus. Then, they utilized a Phrase-Based Statistical Machine Translation model to create a bilingual terminology with the extracted monolingual term lists. However, unlike our methods, these feature-driven (statistics or linguistic) methods are usually not language-independent, and lack semantic information.

Cross-lingual Language Model Pre-training Multilingual BERT (M-BERT) [Devlin et al., 2019], which performs masked language modeling on a multilingual corpus with shared vocabulary and weights, achieves surprising performance on cross-lingual natural language inference (XNLI) [Conneau et al., 2018] task in 15 languages. XLM [Conneau and Lample, 2019] further improve the multilingual BERT by introducing new pre-training objectives based on a bilingual corpus. Inspired by XLM, many pre-training tasks [Song et al., 2019a; Ji et al., 2020; Duan et al., 2020] are proposed to tackle other cross-lingual tasks such as unsupervised and zero-shot machine translation.

3 Our Proposed Task and Solution

To our knowledge, we are the first to propose the task of bilingual terminology extraction based on comparable corpus in e-commerce, independent on any parallel sentences. We present the definition of our task and our proposed solution in the following.

3.1 Task Definition

Our proposed task of bilingual terminology extraction in e-commerce aims to extract the potential bilingual terminologies in e-commercial non-parallel corpus, which can be described as commonly specialized phrases with lengths of 2-5 grams.

In detail, given a terminology in source language and an e-commercial sentence in target language, we aim to distinguish whether the target sentence contains the corresponding target translation of the source terminology. If contains, we expect the system to find the position of the target terminology correctly. For example, as shown in Figure 1, the terminology in source language is “华为P40移动5G手机”, and the sentence in target language is “Global Version Huawei P40 Mobile 5G Phone 6.1 Inch Kirin 990 Android 10”, the task is to predict the span of the potential terminology spans in the target sentence, i.e., “Huawei P40 Mobile 5G Phone”, if not exists, return None.
3.2 Our Solution

In this section, we describe our two-stage bilingual terminology extraction framework. In the first stage, we employ a large number of e-commerce corpus consists of different languages to perform cross-lingual pre-training in e-commerce. In the second stage, we extract the target terminology from the target sentence by utilizing Extractor_Attn or Extractor_Concat initialized by cross-lingual pre-trained language models.

**Cross-lingual Pre-training in E-Commerce:** The cross-lingual language model pre-training (XLM) [Conneau and Lample, 2019] method contains Masked Language Model (MLM) objective and Translation Language Model (TLM) objective, and has demonstrated its effectiveness on tasks such as XNLI cross-lingual classification and unsupervised machine translation. MLM is conducted over large monolingual corpora by randomly masking words, and training to predict them as a Cloze task [Taylor, 1953]. Since MLM is only dependent on monolingual corpora, TLM is designed to utilize parallel data to drive better alignment between source and target language representations, by the means of concatenating parallel sentences into a whole sentence and randomly masking words in both the source and target side.

Inspired by these, we adopt MLM objective to perform cross-lingual pre-training on monolingual e-commerce corpus, which is the mixture of monolingual product titles in e-commerce domain from different languages. Besides, to gain better alignment between source and target language representations, we further propose to conduct TLM over the training sets of bilingual terminology pairs and the pairs of source terminology and target sentence in e-commerce.

**Target Terminology Extraction:** Figure 2 generally illustrates our proposed framework. Given an e-commerce source terminology $S_{term}$ consisting of $m$ tokens $\{s_1, s_2, \ldots, s_m\}$, we need to extract its corresponding translation span $T_{term}$ from the target sentence $T$ containing $n$ tokens $\{t_1, t_2, \ldots, t_n\}$. We use the Transformer [Vaswani et al., 2017] encoder initialized by cross-lingual pre-trained models in e-commerce as the backbone to fully extract the deep semantic relationship between the source-side terminology and target-side sentence, so that our framework could correctly distinguish or even extract the target-side terminology. We propose two methods Extractor_Attn and Extractor_Concat to proceed the extraction of representation.

**Extractor_Attn:** As illustrated in Figure 2(a), $S_{term} = \{[/s], s_1, s_2, \ldots, s_m, [/s]\}$ and $T = \{[/s], t_1, t_2, \ldots, t_n, [/s]\}$, consisting of the adding sum of language embedding, position embedding and token embedding of corresponding tokens, are fed into the Transformer encoder respectively to get the final representation matrix $H_{src,term} \in \mathbb{R}^{(m+2) \times d}$ and $H_{tgt,ste} \in \mathbb{R}^{(n+2) \times d}$. Then we obtain the final representation matrix $H$ by doing representational fusion between source-side terminology and target-side sentence as follows:

$$F(H_{tgt,ste}) = MultiHead(Q = H_{tgt,ste}, K = H_{src,term}, V = H_{src,term})$$

(1)

$$H = FFN(LayerNorm(H_{tgt,ste} + F(H_{tgt,ste})))$$

(2)

where MultiHead, LayerNorm, FFN are basic components of the Transformer model. By the attention-style fusion in this way, the model can utilize the representation of source-side terminology as weight to attend the most related span of target-side sentence. Note that the encoders of source-side terminology and target-side sentence share the same parameters.

**Extractor_Concat:** As illustrated in Figure 2(b), the input sequence consists of $S_{term}$ concatenated with $T$, i.e., $\{[/s], s_1, s_2, \ldots, s_m, /s, t_1, t_2, \ldots, t_n, /s\}$ where $[/s]$ is a special token. Then the Transformer encoder utilizes the embedding representation of input sequence, which is calculated as the adding sum of language embedding, position embedding and token embedding of corresponding tokens, to perform self-attention computation. As a result, the encoder will outputs a cross-lingual context representation matrix $H \in \mathbb{R}^{(m+n+3) \times d}$, where $d$ is the vector dimension of the last layer of the encoder. In this way, the model can attend to both source-side terminology and target-side sentence, encouraging the model to learn and align the source and target representations.

**Span Detector:** Given the representation matrix output $H$ from Extractor_Attn/Extractor_Concat, we then input it to the linear layer, so as to separately predict the start index
and the end index of the target terminology in target sentence. It can be formulated as follows:

\[ p_{\text{start}} = \text{softmax}(W_{\text{start}} \cdot H) \]  
\[ p_{\text{end}} = \text{softmax}(W_{\text{end}} \cdot H) \]

where both of the \( W_{\text{start}} \in \mathbb{R}^{d \times 2} \) and \( W_{\text{end}} \in \mathbb{R}^{d \times 2} \) are linear layers with learnable parameters.

**Loss Function:** During the training, we separately calculate the loss of predicting the start index and end index of the target terminology, which are given as follows:

\[ L_{\text{start}} = \text{CE}(p_{\text{start}}, y_{\text{start}}) \]  
\[ L_{\text{end}} = \text{CE}(p_{\text{end}}, y_{\text{end}}) \]

where \( \text{CE}(\cdot) \) refers to cross-entropy computation. Then, the overall training objective to be minimized is as follows:

\[ L = \frac{1}{2}(L_{\text{start}} + L_{\text{end}}) \]

The two losses are jointly trained, with parameters shared at the linear layer. At the test time, the start and end indexes will be predicted respectively. If both of them equal 0, it means that there are no corresponding target terminology in the current sentence, if not, leading to the final extracted results of target terminology.

4 Experiments

We conduct experiments on Chinese→English and English→French language pairs in e-commerce to demonstrate the performance of our proposed solutions.

4.1 Data Construction

In this section, we describe the process of constructing e-commerce comparable corpus and extracting bilingual terminologies in detail. We first adopt manually labeled bilingual parallel terminology pairs in e-commerce on Chinese→English and English→French, which contain three e-commercial categories, namely toy, outdoor and t-shirt. Monolingual corpora of product titles in e-commerce is also available. Then we use these predefined bilingual terminologies to search the e-commerce title corpus for the e-commercial title sentences containing the source and target terminologies respectively, resulting in comparable corpus in e-commerce.

4.2 Experimental Setup

**Data Sets:** Following the data construction method described in 4.1, we construct data of bilingual terminology pairs and comparable corpora in e-commerce on Chinese→English and English→French language pairs. To evaluate the ability of our model to distinguish whether target-side sentence contains target-side terminology, we also construct negative cases, i.e., target-side sentence does not contain the corresponding target-side terminology. In training/validation/test sets, the ratio of positive and negative cases remains at 1:1. The statistics of data sets are summarized in Table 1.

| Data Sets       | E-commercial Categories       |       |
|-----------------|-------------------------------|-------|
|                 | t-shirts toy outdoor          |       |
| zh→en training  | 0.68M 0.46M 0.60M             |       |
| validation set  | 1000 1000 1000               |       |
| test set        | 2694 2426 2396               |       |
| en→fr training  | 0.61M 0.61M 0.61M             |       |
| validation set  | 1000 1000 1000               |       |
| test set        | 2266 2442 2334               |       |

Table 1: Statistics of the date sets.

For cross-lingual pre-training in e-commerce, we use all the available monolingual title corpus to perform MLM, which contains 5.5M, 7.4M, 4.1M for English, Chinese and French, respectively. Specially, we conduct TLM over the bilingual terminology pairs and the positive portion of the training set. The training sets of bilingual terminology pairs consist of 21,500 for Chinese→English and 19,500 for English→French.

**Training Configuration:** For cross-lingual pre-training stage, we conduct joint byte-pair encoding (BPE) on the monolingual or comparable corpora of both languages with a shared vocabulary. We use the cross-lingual pretrained models released by XLM\(^2\) for the model initialization. During training, following Conneau and Lample\[2019\], 15% of BPE tokens are selected to be masked. Among the selected tokens, 80% of them are replaced with [MASK] token, 10% are replaced with a random BPE token within the vocabulary, and 10% remain unchanged.

For target terminology extraction phase, we adopt the commonly used Transformer encoder with 1024 embedding/hidden units, 4096 feed-forward filter size, 6 layers and 8 heads per layer as the basic. During training, the batch size is set to 128 and the sentence length is limited to 100 BPE tokens. We employ the Adam [Kingma and Ba, 2014] optimizer with \( lr = 0.0001, \) \( t_{\text{warm-up}} = 4000 \) and \( \text{dropout} = 0.1 \).

During evaluating, we calculate the precision whether the model correctly predict both the start and end indexes of the target-side terminology.

**Baselines:** We adopt the following methods as our baselines:

- **NMT/SMT:** We take the task of bilingual terminology extraction as an MT problem, i.e., bilingual terminology generation. Source terminology is fed into the MT model and the output sequence is target terminology. We adopt Transformer\(^3\) and Moses\(^4\) as the NMT model and SMT system respectively.

- **Multiple MT Voting:** We firstly utilize Google\(^5\),

\(^2\)https://github.com/facebookresearch/XLM
\(^3\)https://github.com/pytorch/fairseq. We use Transformer\(_{base}\) as our model.
\(^4\)http://www.statmt.org/moses/. We use the default setting of Moses.
\(^5\)https://translate.google.com/
$$\begin{array}{cccccc}
\text{System} & \text{zh→en} & \text{en→fr} \\
\hline
\text{Baselines} & & \\
\text{NMT} & 51.51 & 44.42 & 43.32 & 46.42 \\
\text{SMT} & 54.31 & 47.13 & 47.63 & 49.69 \\
\text{Multiple MT Voting} & 47.92 & 56.22 & 53.84 & 52.66 \\
\text{Seq2Seq-Term} & 65.26 & 50.78 & 54.01 & 56.68 \\
\hline
\text{Extractor_Attn} & & \\
\text{RAND} & 77.13 & 56.55 & 57.51 & 63.73 \\
\text{MLM}_{\text{eco}} & 84.86 & 70.57 & 73.54 & 76.32 \\
\text{TLM}_{\text{eco}} & 85.67 & 74.11 & 75.38 & 78.39 \\
\hline
\text{Extractor_Concat} & & \\
\text{RAND} & 83.67 & 68.26 & 69.78 & 73.90 \\
\text{MLM}_{\text{eco}} & 92.72 & 86.89 & 85.64 & 88.42 \\
\text{TLM}_{\text{eco}} & 94.21 & 91.18 & 90.23 & 91.87 \\
\hline
\end{array}$$

Table 2: Experimental results(%) of Extractor_Concat.

Table 2 presents the performance of our proposed approach and other baseline models on different categories of different language pairs. It is obvious that our approaches outperform the baselines significantly in all language pairs and categories, which strongly demonstrate the superiority of cross-lingual pre-training and our proposed bilingual terminology extraction models.

The performances of SMT systems are consistently superior to NMT systems, which indicates that directly using SMT trained on bilingual terminology pairs is more suitable for the task of bilingual terminology generation than NMT. In particular, we can find that Multiple MT Voting achieves better performance, mainly because it acquires the final translation results by voting among several top-tier MT engines.

Compared with various baselines, our proposed Extractor_Attn and Extractor_Concat with random initialization both show clear superiority, which demonstrates the effectiveness of our proposed bilingual terminology extraction models. Especially in comparison with the most related Seq2Seq-Term, our models show better performances, indicating that Extractor_Attn and Extractor_Concat are more suitable for the task of bilingual terminology mining than the seq2seq method. When equipped with MLM_{eco} and TLM_{eco}, our models gain great improvements (+8.54%-30.05%), proving the significance of cross-lingual pre-training in e-commerce for the extraction models. Obviously, the models could learn rich cross-lingual alignment information by cross-lingual pre-training in e-commerce, which encourages the extraction models to better distinguish and even extract the target-side terminology.

Particularly, when comparing Extractor_Attn and Extractor_Concat, we note that Extractor_Concat outperforms Extractor_Attn under all model initialization conditions. Moreover, Extractor_Concat initialized with TLM_{eco} obtains the best performances in all languages and all categories. It is because that Extractor_Concat conducts self-attention computation on both source-side terminology and target-side sentence at the same time, while Extractor_Attn calculates self-attention on source-side terminology and target-side sentence separately. We argue that Extractor_Concat learns richer cross-lingual semantic relationship between source terminology and target sentence, and pay more attention to the most related span of target-side sentence.

4.4 Analyses
Effect of Source Terminology: In our proposed Extractor_Concat, source terminology and target sentence are concatenated as an input sequence to the model, forming the final representation after self-attention com-

References:
Baidu⁶, Youdao¹, bing⁸ and sogou⁴ Translate Systems to directly translate the source terminology in our test set and get the corresponding translation candidates. Then we vote according to the results of different MT systems, with the highest number of votes as the final translation.

• Seq2Seq-Term: We regard the task as a sequence-to-sequence (seq2seq) learning problem by encoding the input of source terminology concatenated with target sentence and decoding the output sequence of target terminology. Our Seq2Seq-Term system builds on Transformer, a state-of-the-art seq2seq model, with the shared vocabulary between input and output. This is the most related baseline to our approaches, which utilizes the same data resources.
Figure 3: Visualized attention weights for source-side terminology and target-side sentence by ExtractorConcat. “Positive” and “Negative” in column “Polarity” indicate whether the target sentence contains the corresponding translation of the source terminology or not.

Figure 4: Performances(%) of varying size(M) of training samples for ExtractorConcat initialized by TLMeco.

5 Conclusion

In this paper, we propose a novel task of extracting bilingual terminologies from non-parallel comparable corpus in e-commerce and construct the correspond data sets. We apply a two-stage neural framework to tackle this task. When equipped with cross-lingual pre-training in e-commerce, our proposed ExtractorConcat and ExtractorAttn can extract the corresponding target terminology by fully utilizing the deep semantic relationship between source-side terminology and target-side sentence. Experimental results show that on both Chinese→English and English→French language pairs, our methods outperform all strong baselines in all categories. To our knowledge, we are the first to utilize cross-lingual pre-training and extraction model to solve the problem of bilingual terminology extraction from non-parallel e-commerce corpora. We wish that our work will inspire the introduction of new paradigms for bilingual terminology extraction or other related research.
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