Building a Bilingual Lexicon Using Phrase-based Statistical Machine Translation via a Pivot Language

Takashi Tsunakawa† Naoaki Okazaki† Jun’ichi Tsujii‡

†Department of Computer Science, Graduate School of Information Science and Technology, University of Tokyo 7-3-1, Hongo, Bunkyo-ku, Tokyo, 113-0033 Japan
‡School of Computer Science, University of Manchester / National Centre for Text Mining 131 Princess Street, Manchester, M1 7DN, UK {tuna, okazaki, tsujii}@is.s.u-tokyo.ac.jp

Abstract

This paper proposes a novel method for building a bilingual lexicon through a pivot language by using phrase-based statistical machine translation (SMT). Given two bilingual lexicons between language pairs \( L_f-L_p \) and \( L_p-L_e \), we assume these lexicons as parallel corpora. Then, we merge the extracted two phrase tables into one phrase table between \( L_f \) and \( L_e \). Finally, we construct a phrase-based SMT system for translating the terms in the lexicon \( L_f-L_p \) into terms of \( L_e \) and obtain a new lexicon \( L_f-L_e \). In our experiments with Chinese-English and Japanese-English lexicons, our system could cover 72.8% of Chinese terms and drastically improve the utilization ratio.

1 Introduction

The bilingual lexicon is a crucial resource for multilingual applications in natural language processing including machine translation (Brown et al., 1990) and cross-lingual information retrieval (Nie et al., 1999). A number of bilingual lexicons have been constructed manually, despite their expensive compilation costs. However, it is unrealistic to build a bilingual lexicon for every language pair; thus, comprehensible bilingual lexicons are available only for a limited number of language pairs.

One of the solutions is to build a bilingual lexicon of the source language \( L_f \) and the target language \( L_e \) through a pivot language \( L_p \), when large bilingual lexicons \( L_f-L_p \) and \( L_p-L_e \) are available. Numerous researchers have explored the use of pivot languages (Tanaka and Umemura, 1994; Schafer and Yarowsky, 2002; Zhang et al., 2005). This approach is advantageous because we can obtain a bilingual lexicon between \( L_e \) and \( L_f \), even if no bilingual lexicon exists between these languages.

Pivot-based methods for dictionary construction may produce incorrect translations when the word \( w_e \) is translated from a word \( w_f \) by a polysemous pivot word \( w_p \).1 Previous work addressed the polysemous problem in pivot-based methods (Tanaka and Umemura, 1994; Schafer and Yarowsky, 2002). Pivot-based methods also suffer from a mismatch problem, in which a pivot word \( w_p \) from a source word \( w_f \) does not exist in the bilingual lexicon \( L_p-L_e \). Moreover, a bilingual lexicon for technical terms is prone to include a number of pivot terms that are not included in another lexicon.

This paper proposes a method for building a bilingual lexicon through a pivot language by using phrase-based statistical machine translation (SMT) (Koehn et al., 2003). We build a translation model between \( L_f \) and \( L_e \) by assuming two lexicons \( L_f-L_p \) and \( L_p-L_e \) as parallel corpora, in order to increase the obtained lexicon size by handling multi-word expressions appropriately. The main advantage of this method is its ability to incorporate various translation models that associate languages \( L_f-L_e \); for example, we can further improve the translation model by integrating a small bilingual lexicon \( L_f-L_e \).

1A Japanese term “士手”: dote, embankment, may be associated with a Chinese term “银行”, yíngháng: banking institution, using the pivot word bank in English.

2It is impossible to associate two translation pairs (“地球 溫暖化” (chìqìwēnnuàihà): global warming), and “全球 变暖” (quánqiúbiànhuà): because of the difference in English (pivot) terms.
2 Merging two bilingual lexicons

We introduce phrase-based SMT for merging the lexicons, in order to improve both the merged lexicon size and its accuracy. Recently, several researchers proposed the use of the pivot language for phrase-based SMT (Utiyama and Isahara, 2007; Wu and Wang, 2007). We employ a similar approach for obtaining phrase translations with the translation probabilities by assuming the bilingual lexicons as parallel corpora. Figure 1 illustrates the framework of our approach.

Let us suppose that we have two bilingual lexicons \( L_f \) and \( L_p \). We obtain word alignments of these lexicons by applying GIZA++ (Och and Ney, 2003), and \textit{grow-diag-final} heuristics (Koehn et al., 2007). Let \( \hat{w}_x \) be a phrase that represents a sequence of words in the language \( L_x \). For phrase pairs \((\hat{w}_p, \hat{w}_f)\) and \((\hat{w}_e, \hat{w}_p)\), the translation probabilities \( p(\hat{w}_p | \hat{w}_f) \) and \( p(\hat{w}_e | \hat{w}_p) \) are computed using the maximum likelihood estimation from the co-occurrence frequencies, consistent with the word alignment in the bilingual lexicons. We calculate the direct translation probabilities between source and target phrases,

\[
p(\hat{w}_e | \hat{w}_f) = \frac{\sum_{\hat{w}_p} p(\hat{w}_e | \hat{w}_p)p(\hat{w}_p | \hat{w}_f)}{\sum_{\hat{w}_p} \sum_{\hat{w}_p'} p(\hat{w}_e | \hat{w}_p)p(\hat{w}_p' | \hat{w}_f)}.
\]

We employ the log-linear model of phrase-based SMT (Och and Ney, 2002) for translating the source term \( \hat{w}_f \) in the lexicon \( L_f \) into the target language by finding a term \( \hat{w}_e \) that maximizes the translation probability,

\[
\hat{w}_e = \arg \max_{w_e} \Pr(\hat{w}_e | \hat{w}_f)
= \arg \max_{w_e} \sum_{m=1}^{M} \lambda_m h_m(\hat{w}_e, \hat{w}_f),
\]

where we have \( M \) feature functions \( h_m(\hat{w}_e, \hat{w}_f) \) and model parameters \( \lambda_m \).

In addition to the typical features for the SMT framework, we introduce two features: character-based similarity, and additional bilingual lexicon. We define a character-based similarity feature,

\[
h_{\text{char.sim}}(\hat{w}_e, \hat{w}_f) = 1 - \frac{\text{ED}(\hat{w}_e, \hat{w}_f)}{\max(\hat{w}_e, \hat{w}_f)},
\]

where \( \text{ED}(x, y) \) represents a Levenshtein distance of characters between the two terms \( x \) and \( y \). We also define an additional bilingual lexicon feature,

\[
h_{\text{add-lex}}(\hat{w}_e, \hat{w}_f) = \sum_i \log p'(\hat{w}_e(i) | \hat{w}_f(i)),
\]

where \( \hat{w}_e(i) \) and \( \hat{w}_f(i) \) represent an \( i \)-th translated phrase pair on the term pair \((\hat{w}_e, \hat{w}_f)\) during the decoding, and \( p'(\hat{w}_e(i) | \hat{w}_f(i)) \) represents the phrase translation probabilities derived from the additional lexicon. The probability \( p'(\hat{w}_e(i) | \hat{w}_f(i)) \) is calculated using the maximum likelihood estimation.

3 Experiment

3.1 Data

For building a Chinese-to-Japanese lexicon, we used the Japanese-English lexicon released by JST\(^4\) (527,206 term pairs), and the Chinese-English lexicon compiled by Wanfang Data\(^5\) (552,259 term pairs). Both cover a wide range of named entities and technical terms that may not be included in an ordinary dictionary. As an additional lexicon, we used the Japanese-English-Chinese trilingual lexicon\(^6\) (596,967 term pairs) generated from EDR\(^7\) Japanese-English lexicon.

We lower-cased and tokenized all terms by the following analyzers: JUMAN\(^8\) for Japanese, the MEMM-based POS tagger\(^9\) for English, and \textit{cjma} (Nakagawa and Uchimoto, 2007) for Chinese.

3.2 The sizes and coverage of merged lexicons

Table 1 shows the distinct numbers of terms in the original and merged lexicons, and the uti-
We also conducted another experiment to generate Japanese translations for Chinese terms included in an external resource. We randomly extracted 500 Chinese-English term pairs from the Wanfang Data lexicon, for which the English term cannot be mapped by the JST lexicon, but can be mapped by another lexicon Eijiro.11 Table 3 shows the results for these 500 terms. Prec1 or Prec10 are the precisions that the 1- or 10-best translations include the correct one, respectively. MRR (mean reciprocal rank) is \(\left(\frac{1}{500}\right)\sum_{i=1}^{500}\frac{1}{r_i}\), where \(r_i\) is the highest rank of the correct translations for the \(i\)-th term.

Since the input lexicons are Chinese-English term pairs, their Japanese translations can be generated directly from the English terms by applying an English-Chinese translation system. We compared our system to an English-Japanese phrase-based SMT system (E-to-J translation), constructed from the JST Japanese-English lexicon. Table 3 shows that our system outperformed the English-to-Japanese direct translation system.

Table 4 displays translation examples. The first example shows that our system could output a correct translation (denoted by [T]); and the E-to-J system failed to translate the source term ([F]), because it could not reorder the source English words and translate the word pubis correctly. In the second example, our system could reproduce Chinese characters “流体 (fluid)”, but the E-to-J system output a semantically acceptable but awkward Japanese term. In the last example, the word segmentation of the source Chinese term was incorrect (“中间 腰 (lumber) 淋巴 (lymph) 结” is correct). Thus, our system received an invalid word “腰淋” and could not find a translation for the word.

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**Table 1**: The statistics of lexicons

<table>
<thead>
<tr>
<th>Lexicon</th>
<th>(L_C) size</th>
<th>(L_E) size</th>
<th>(L_J) size</th>
</tr>
</thead>
<tbody>
<tr>
<td>(L_C-L_E)</td>
<td>375,990</td>
<td>429,807</td>
<td>-</td>
</tr>
<tr>
<td>(L_E-L_J)</td>
<td>-</td>
<td>418,044</td>
<td>465,563</td>
</tr>
<tr>
<td>(L_E) (distinct)</td>
<td>-</td>
<td>783,414</td>
<td>-</td>
</tr>
<tr>
<td>Additional lex.</td>
<td>94,928</td>
<td>-</td>
<td>90,605</td>
</tr>
<tr>
<td><strong>Exact matching</strong></td>
<td>98,537</td>
<td>68,996</td>
<td>103,437</td>
</tr>
<tr>
<td>(26.2%)</td>
<td>(22.2%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Unique matching</strong></td>
<td>4,875</td>
<td>4,875</td>
<td>4,875</td>
</tr>
<tr>
<td>(1.3%)</td>
<td>(1.0%)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Table 2**: Translation performance on the test set

<table>
<thead>
<tr>
<th>Features</th>
<th>BLEU</th>
<th>NIST</th>
<th>Acc.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Typical features</td>
<td>0.4519</td>
<td>7.4060</td>
<td>0.676</td>
</tr>
<tr>
<td>(wl\ character similarity)</td>
<td>0.4670</td>
<td>7.4963</td>
<td>0.682</td>
</tr>
<tr>
<td>(wl\ additional lexicon)</td>
<td>0.4800</td>
<td>7.5907</td>
<td>0.674</td>
</tr>
<tr>
<td>All</td>
<td>0.4952</td>
<td>7.7046</td>
<td>0.685</td>
</tr>
</tbody>
</table>

**Table 3**: Evaluation results for the Eijiro dictionary

<table>
<thead>
<tr>
<th>Features/Models</th>
<th>Prec1</th>
<th>Prec10</th>
<th>MRR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Typical features</td>
<td>0.142</td>
<td>0.232</td>
<td>0.1719</td>
</tr>
<tr>
<td>(wl\ character similarity)</td>
<td>0.136</td>
<td>0.224</td>
<td>0.1654</td>
</tr>
<tr>
<td>(wl\ additional lexicon)</td>
<td>0.140</td>
<td>0.230</td>
<td>0.1704</td>
</tr>
<tr>
<td>All</td>
<td>0.140</td>
<td>0.230</td>
<td>0.1714</td>
</tr>
<tr>
<td>E-to-J translation</td>
<td>0.090</td>
<td>0.206</td>
<td>0.1256</td>
</tr>
</tbody>
</table>

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10 The number of terms in the original lexicon used for building the merged lexicon.

11 http://www.eijiro.jp/
4 Conclusion

This paper proposed a novel method for building a bilingual lexicon by using a pivot language. Given two bilingual lexicons $L_f$–$L_p$ and $L_p$–$L_e$, we constructed a phrase-based SMT system from $L_f$–$L_e$ by merging the lexicons into a phrase translation table $L_f$–$L_e$. The experimental results demonstrated that our method improves the utilization ratio of given lexicons drastically. We also showed that the pivot approach was more effective than the SMT system that translates from $L_p$ to $L_e$ directly.

The future direction would be to introduce other resources such as the parallel corpora and other pivot languages into the SMT system for improving the precision and the coverage of the obtained lexicon. We are also planning on evaluating a machine translation system that integrates our model.

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References


