Mining Japanese Compound Words and Their Pronunciations from Web Pages and Tweets

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Abstract

Mining compound words and their pronunciations is essential for Japanese input method editors (IMEs). We propose to use a chunk-based dependency parser to mine new words, collocations and predicate-argument phrases from large-scale Japanese Web pages and tweets. The pronunciations of the compound words are automatically rewritten by a statistical machine translation (SMT) model. Experiments on applying the mined lexicon to a state-of-the-art Japanese IME system show that the precision of Kana-Kanji conversion is significantly improved.

1 Introduction

New compound words are appearing everyday. Person names, technical terms and organization names are newly created and used in Web pages such as news, blogs, question-answering systems. Abbreviations, food names and event names are formed and shared in Twitter and Facebook. Mining of these new compound words, together with their pronunciations, is an important step for numerous natural language processing (NLP) applications. Taking Japanese as an example, the lexicons containing compound words (in a mixture of Kanjis and Kanas) and their pronunciations (in a sequence of Kanas) significantly influence the accuracies of speech generation (Schroeter et al., 2002) and IME systems (Kudo et al., 2011). In addition, monolingual compound words are shown to be helpful for bilingual SMTs (Liu et al., 2010).

In this paper, we mine three types (Figure 1) of new (i.e., not included in given lexicons) Japanese compound words and their pronunciations: (1) words, which are combinations of single characters and/or shorter words; (2) collocations, which are combinations of words; and (3) predicate-argument phrases, which are combinations of chunks constrained by semantic dependency relations. The sentences were parsed by a state-of-the-art chunk-based Japanese dependency parser, Cabocha2 (Kudo and Matsumoto, 2002a) which makes use of Mecab3 with IPA dictionary4 for word segmenting, POS tagging, and pronunciation annotating.

The first sentence in Figure 1 contains two new words which were not correctly recognized by Mecab. We call them “new words”, since new semantic meanings are generated by the combination of single characters. There is one Kana collocation in the second sentence. Different from many former researches (Manning and Schütze, 1999; Liu et al., 2009) which only mine collocations of two words, we do not limit the number of words in our collocation lexicon. The third sentence contains two predicate-argument phrases of noun-noun modifiers and object-verb relations.

The main contribution of this paper is that the

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2http://code.google.com/p/cabocha/
3http://mecab.googlecode.com/svn/trunk/mecab/doc/index.html
4http://code.google.com/p/mecab/downloads/detail?name=mecab-ipadic-2.7.0-20070801.tar.gz
Figure 2: The lexicon mining processes.

The Japanese morphological analyser (e.g., Mecab) tends to split one out-of-vocabulary (OOV) word into a sequence of known Kanji characters. The point is that, most of the known Kanji characters are annotated to be notional words such as nouns. Consequently, Cabocha, which takes words/characters and their POS tags as features for discriminative training using a SVM model (Kudo and Matsumoto, 2002b), can still correctly tend to include these single-Kanji-character words into one chunk. Thus, we can re-combine the wrongly separated pieces into one (compound) word.

2 Compound Word Mining

Figure 2 shows our major lexicon mining process: lexicon mining in a top-down flow and pronunciation rewriting in a bottom-up flow.

2.1 Mining single chunks

**Definition 1 (Japanese chunk)** Suppose w being the Japanese vocabulary set, a Japanese chunk is defined as a sequence of contiguous words, \( C = w_1^+ w_p^* \), where \( w_n^+ \in w \) is a sequence of notional words with no less than one \( w_n \), and \( w_p^* \in w \) contains zero or more particles \( w_p \). New words and collocations come from \( w_n^+ \) without \( w_p^* \).

This mining idea is based on the fact that an Japanese morphological analyser (e.g., Mecab) tends to split one out-of-vocabulary (OOV) word into a sequence of known Kanji characters. The point is that, most of the known Kanji characters are annotated to be notional words such as nouns. Consequently, Cabocha, which takes words/characters and their POS tags as features for discriminative training using a SVM model (Kudo and Matsumoto, 2002b), can still correctly tend to include these single-Kanji-character words into one chunk. Thus, we can re-combine the wrongly separated pieces into one (compound) word.

2.2 Mining predicate-argument phrases

**Definition 2 (Predicate-argument phrase)** A predicate-argument phrase is defined as a labelled graph structure, \( A = (w_h, w_n, \tau, \rho) \), where \( w_h, w_n \in w \) are a predicate and an argument word (or chunk) of the dependency, \( \tau \) is a predicate type (e.g., transitive verb), and \( \rho \) is a label of the dependency of \( w_h \) and \( w_n \). We append one constraint during mining: \( w_h \) and \( w_n \) are adjacent. That is, the phrases mined are all contiguous without gaps. The predicate-argument phrases mined in this way is helpful for context-based Kana-Kanji conversion of Japanese IME.

Japanese is a typical Subject-Object-Verb language. The direct object phrase normally appears before the verb. For example, for two input Kana sequences “やさいをいためる” (野菜/vegetables を/particle 炒める/cooking: stir-fried vegetables) and “こころをいためる” (心/heart を/particle 損める/hurt: hurt ones heart), even “いためる” takes the similar keyboard typing, the first candidate Kanji words are totally different. The users will be angry to see the candidate of “心を炒める” (stir-fried heart) for “こころをいためる”. It is the pre-verb objects that determines the dynamic choosing of the correct Kanji verbs.

2.3 Experiments on compound word mining

We use two data sets for compound word mining. The first set contains 200G Japanese Web pages (1.9 billion sentences) which were downloaded by an in-house Web crawler. The second set contains 44.7 million Japanese tweets (28.8 words/tweet) which were downloaded by using an open source Java library twitter4j\(^5\) which implemented the Twitter Streaming API\(^6\).

![Table 1: The number of compound words mined.](https://example.com/table1.png)

\(^5\)http://twitter4j.org/ja/index.html
\(^6\)https://dev.twitter.com/docs/streaming-apis
Table 2: The number of entries and precisions of the alignment method (Liu et al., 2009) and our approach, using 2M sentences.

| Lexicons             | Frequency ≥ 20 | Precision |
|----------------------|----------------|-----------|
| alignment method     | 2,562          | 76.5%     |
| single chunk         | 16,673         | 93.0%     |
| double chunks        | 9,099          | 91.5%     |

Table 1 shows the statistics of the single/double chunk lexicons (of frequencies ≥ 20 or 500). We compared the novel entries included in the twitter lexicons but not the web. The ratio ranges from 8.0% to 22.0%, reflecting a special bag of compound words used in tweets instead of the traditional web pages.

We compare our lexicons with two baselines, one is the C-value approach (Frantzi and Ananiadou, 1999) with given POS sequences and the other is the monolingual word alignment approach (Liu et al., 2009). We ask Japanese linguists to give a POS sequence set with 128 rules for compound word mining. Applying C-value approach with these rules to the 200G web data yields a lexicon of 884,766 entries (frequency ≥ 500). Our single (double) chunk lexicon shares around 30% (7%) with this lexicon. This lexicon is used in our baseline Japanese IME system (Table 5).

During our re-implementation of the alignment approach, we found that the EM algorithm (Dempster et al., 1977) for word aligning the 1.9 billion sentences is too time-consuming. Instead, we only used the first 2M sentences (28.4 words/sentence) of the web data for intuitive comparison. The statistics are shown in Table 2. The precisions are computed by manually evaluating the top-200 entries (with higher frequencies) in each lexicon. The lexicons mined by our approach outperform the baseline in a big distance, both precision and the number of entries successfully mined.

3 Pronunciation Rewriting Model

Our pronunciation rewriting model mapping from the compound words’ original pronunciations to their correct pronunciations. It is a generative model based on the phrasal SMT framework. We limit the model monotonically rewrite initial Kana sequences to their correct forms without reordering. We use Moses\(^7\) (Koehn et al., 2007) to implement this model by setting the source and target sides to be Kana sequences.

The Kana-Kana rewriting model improves the traditional Kanji-Kana predication models (Hatori and Suzuki, 2011) in the following aspects. First, data sparseness problem of Kanji-Kana approach can be mitigated in a sense, since the number of Kanas in Japanese is no more than 50 yet the number of Kanjis is tens of thousands. Second, Kana-Kana pairs are easier to be aligned with each other, since most Kanjis are pronounced by no less than two Kanas and consequently the number of Kanas almost doubles the number of Kanjis in the experiment sets. Finally, the entries in the final lexicons contain two Kana pronunciations, before and after correcting. We argue this is helpful to improve the user experiences of IME systems where we need to cover the users’ typing mistakes.

3.1 Mining Kanji-Kana entries from Wiki

For training the rewriting model, we mine a Kanji-Kana lexicon from parenthetical expressions in Japanese Wikipedia pages\(^8\), a high quality collection of new words. The only problem is to determine the pre-brackets Kanji sequence that exactly corresponds to the in-bracket Kana sequence.

Our method is inspired by (Okazaki and Ananiadou, 2006; Wu et al., 2009). They used a term recognition approach to build monolingual abbreviation dictionaries from English articles (Okazaki and Ananiadou, 2006) and to build Chinese-English abbreviation dictionaries from Chinese Web pages (Wu et al., 2009). For locating a textual fragment with a Kanji sequence and its Kana pronunciation in a pattern of “Kanji sequence (Kana sequence)”, we use the heuristic formula:

$$LH(c) = \frac{\sum_{t \in T_c} freq(t) \times freq(c)}{\sum_{t \in T_c} freq(t)}.$$  

Here, \(c\) is a Kanji candidate (sub-)sequence; \(freq(c)\) denotes the frequency of co-occurrence of \(c\) with the in-brackets Kana sequence; and \(T_c\) is a set of nested Kanji sequence candidates, each of which consists of a preceding Kanji or Kana character followed by the candidate \(c\).

Table 3 shows the number of entries mined by setting the LH score to be ≥ 3, 4, or 5. From the table, we observe that as LH threshold is added by one, the number of entries is cut nearly a half. For each entry set, we further randomly selected 200 entries and checked their correctnesses by

\(^7\)http://www.statmt.org/moses/

\(^8\)All the Japanese pages until 2012.06.03 were used. Examples can be found in http://ja.wikipedia.org/wiki/三日月
| LH | # of Entries | Precision |
|----|--------------|-----------|
| 3  | 32,223       | 95.0%     |
| 4  | 18,348       | 95.5%     |
| 5  | 10,234       | 96.0%     |

Table 3: Kanji-Kana entries mined from Wiki.

We run Mecab on Hadoop [10] 2.5TB Japanese Web pages as the training data. For training the n-pos model, we used a system that implemented the Map-Reduce framework [11] (Dean and Ghemawat, 2004), for parallel word segmenting and POS tagging the data. For testifying the lexicons mined from the 200G Web data and from the tweets, we respectively use three test sets: (1) “twitter.net” with 149 entries which is a manually collected Twitter new word lexicon [11]; (2) partial “JDMWE” (Shudo et al., 2011) lexicon with 2,169 entries; and (3) “Nagoya” compound word lexicon [12] with 3,628 entries such as idioms.

The top-n (=1, 3, 5, 9) precisions are listed in Table 5. In the baseline system, we used the compound lexicon that was mined by the C-value approach using 128 POS sequences. For direct comparison, we replace this compound lexicon respectively by the web and twitter lexicons (frequency ≥ 500). In the twitter.net test set, the precision of the top-1 candidate significantly (p < 0.01) improves from 38.93% to 48.99% (+10.06%). In the JDMWE and Nagoya test sets, the web lexicon can also significantly improve the top-1 precisions of around 2% (p < 0.05). Through these numbers, we can say that the proposed approach is helpful for improving the accuracies of real-world Japanese IME application.

5 Conclusion

We have proposed an approach for mining new Japanese compound words from single/double chunks generated by a chunk-based dependency parser. Experiments show that the approach works well on mining new words, collocations and predicate-argument phrases from large-scale Web pages and tweets. We achieved significant improvements on top-n precisions when integrating the mined compound words together with their Kana pronunciations into a state-of-the-art Japanese IME system with million level users.

Table 5: The top-n precision improvements of appending the mined twitter/web lexicons to a baseline IME system.
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