Language Resource Addition: Dictionary or Corpus?

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Abstract

In this paper, we investigate the relative effect of two strategies of language resource additions to the word segmentation problem and part-of-speech tagging problem in Japanese. The first strategy is adding entries to the dictionary and the second is adding annotated sentences to the training corpus. The experimental results showed that the annotated sentence addition to the training corpus is better than the entries addition to the dictionary. And the annotated sentence addition is efficient especially when we add new words with contexts of three real occurrences as partially annotated sentences. According to this knowledge, we executed annotation on the invention disclosure texts and observed word segmentation accuracy.

Keywords: Partial annotation, Dictionary, Word segmentation, POS tagging

1. Introduction

The importance of language resources continues to increase in the era of natural language processing (NLP) based on machine learning techniques. For mature NLP applied to real problems, such as word segmentation, part-of-speech (POS) tagging, etc., relatively high accuracies are achieved on general-domain data, and much of the problem lies in adaptation to new domains. To cope with this problem, there are many attempts at semi-supervised training and active learning (Tomanek and Hahn, 2009; Settles et al., 2008; Sassano, 2002). However, the simple strategies of corpus annotation or dictionary expansion are highly effective and not so costly. In fact, according to authors’ experiences it only took 7 hours × 10 days to annotate 5,000 sentences precisely with word boundary information, enough to achieve large gains in a domain adaptation setting.

Within the context of sequence labeling, a variety of resources can be used, including annotated training data, which gives us information about word use in context, and dictionaries, which lack context information but are often available at large scale. In this paper, we investigate the relative effect of dictionary expansion and annotated corpus addition (full annotation and partial annotation) to the Japanese morphological analysis problem (MA; a joint task of word segmentation and POS tagging) and word segmentation problem.

2. Morphological Analysis

Japanese MA takes an unsegmented string of characters $x^I$ as input, segments it into morphemes $w^I$, and annotates each morpheme with a part of speech $t^I$. This can be formulated as a two-step process of first segmenting words, then estimating POSs (Ng and Low, 2004; Neubig et al., 2011), or as a single joint process of finding a morpheme/POS string from unsegmented text (Nagata, 1994; Mori and Kurata, 2005; Kudo et al., 2004; Nakagawa, 2004; Kruengkrai et al., 2009).

![Figure 1: Joint MA (a) performs maximization over the entire sequence, while two-step MA (b) maximizes the 4 boundary and 4 POS tags independently.](image)

2.1. Joint Sequence-Based MA

Japanese MA has traditionally used sequence based models, finding a maximal POS sequence for entire sentences as in Figure 1 (a). The CRF-based method presented by Kudo et al. (2004) is generally accepted as the state-of-the-art in this paradigm. CRFs are trained over segmentation lattices, which allows for the handling of variable length sequences that occur due to multiple segmentations. The model is able to take into account arbitrary features, as well as the context between neighboring tags.

The main feature of this approach in the context of the current paper is that it relies heavily on a complete and accurate dictionary. In general when building the lattice of candidates from which to choose, it is common to consider only candidates that are in a pre-defined dictionary, only adding character sequences that are not in the dictionary.
when there are no in-vocabulary candidates.\footnote{1} Thus, if the
dictionary contains all of the words present in the sentences
we want to analyze, these methods will obtain relatively
high accuracy, but any words not included in the dictionary
will almost certainly be given a mistaken analysis.

2.2. 2-Step Pointwise MA

In the two-step approach (Neubig et al., 2011), on the other
hand, we first segment character sequence $x_1^n$ into the word
sequence $w_1^n$ with the highest probability, then tag each
word with parts of speech $t_1^n$. This approach is shown in
Figure 1 (b).

Word segmentation is formulated as a binary classification
problem, estimating boundary tags $b_1^{n-1}$. Tag $b_i = 1$
indicates that a word boundary exists between characters $x_i$ and
$x_{i+1}$, while $b_i = 0$ indicates that a word boundary does not
exist. POS estimation can also be formulated as a multi-
classification problem, where we choose one tag $t_j$ for each word $w_j$. These two classification problems can
be solved by tools in the standard machine learning toolbox
such as logistic regression (LR), support vector machines
(SVMs), or conditional random fields (CRFs).

As features for these classification problems, it is common
to use information about the surrounding characters (char-
acter and character-type $n$-grams), as well as the presence
or absence of words in the dictionary. The details of the
features can be found in Neubig et al. (2011), but as dic-
tionary features are particularly important in the context of
this paper we explain them shortly here. Dictionary fea-
tures for word segmentation can include, for example, $l_s$ and
$r_s$ which are active if a string of length $s$ included in
the dictionary is present directly to the left or right of the
present word boundary, and $i_s$ which is active if the present
word boundary is included in a dictionary word of length
$s$. Dictionary feature $d_{j,k}$ for POS estimation can indicate
whether the current word $w_j$ occurs as a dictionary entry
with tag $t_k$.

Compared to the joint sequence-based method described in
the previous section, the two-step approach is a dictionary-
light method. In fact, given a corpus of segmented and
POS-tagged sentences, it is possible to perform analysis
without the dictionary features, relying entirely on the in-
formation about the surrounding $n$-grams learned from the
corpus. However, as large-coverage dictionaries often ex-
inist in many domains for consumption by either computer
or human, having the possibility to use these as additional
features is expected to give a gain in accuracy, which we
verify experimentally in the following section.

3. Experimental Evaluation

To observe the difference between the addition of annotated
sentences to the training corpus, and addition of entries to
the dictionary, we conducted the experiments described be-
low.

\begin{table}
\centering
\begin{tabular}{|l|c|c|}
\hline
Adaptation strategy & MeCab & KyTea \\
\hline
No adaptation & 95.20\% & 95.54\% \\
Dict. addition (no re-training) & 96.59\% & - \\
Dict. addition (re-training) & 96.55\% & 96.75\% \\
Corpus addition & 96.85\% & 97.15\% \\
\hline
\end{tabular}
\caption{Word Segmentation Accuracy (F-measure).}
\end{table}

3.1. Experimental Setting

The task we use as our test bed is the domain adaptation
of Japanese morphological analysis. We use the Balanced
Corpus of Contemporary Written Japanese (BCCWJ) as the
testbed for our experiments (Maekawa, 2008). BCCWJ is
divided into several sections, each from a different source,
so this is ideal for domain adaptation experiments.

As our target domain, we use data from the Web (Yahoo!
Chiebukuro in BCCWJ) and as the source domain we use
the other five domains of BCCWJ Core data. Table 1 shows
the specification of the corpus and dictionary. As morphological analyzers, we use the following two pub-
licly available tools:\footnote{2}

1. MeCab: CRF-based joint method (Kudo et al., 2004)
2. KyTea: 2-step pointwise method (Neubig et al., 2011)

We compare the following adaptation strategies for the two
morphological analyzers.

- No adaptation: Use the corpus and the dictionary in
  the general domain.
- Dictionary addition (no re-training): Add words appear-
ing in the Web training corpus to the dictionary. As the
dictionary includes costs, we set the cost of all
new words to the same value as infrequent words of
the same POS tag, following the instructions on the
MeCab Web page\footnote{3} (MeCab only).
- Dictionary addition (re-training): Add words appear-
ing in the Web corpus to the dictionary and estimate
the weights of the model on the general domain train-
ing data again.
- Corpus addition: Create a dictionary from both the
general and Web domains, and train the parameters on
the same corpus from both domains.

\begin{table}
\centering
\begin{tabular}{|l|c|}
\hline
Corpus & \#words \\
\hline
General & 784k \\
General + Web & 898k \\
Web for test & 13.0k \\
\hline
\end{tabular}
\caption{Language Resource Specification.}
\end{table}

\begin{table}
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\end{table}

\footnote{1}It should be noted that there has been a recently proposed
method to loosen this restriction, although this adds some com-
plexity to the decoding process and reduces speed somewhat (Kaji
and Kitsuregawa, 2013).

\footnote{2}We did not precisely tune the parameters, so there still may
be room for further improvement.

\footnote{3}http://mecab.sourceforge.net/dic.html
3.2. Evaluation Criterion

As an evaluation criterion we follow (Nagata, 1994) and use precision and recall based on word-POS pairs. First the longest common subsequence (LCS) is found between the correct answer and system output. Then let $N_{REF}$ be the number of word-POS pairs in the correct sentence, $N_{SYS}$ be that in the output in a system, and $N_{LCS}$ be that in the LCS of the correct sentence and the output of the system, so the recall $R$ and precision $P$ are defined as follows:

$$ R = \frac{N_{LCS}}{N_{REF}}, \quad P = \frac{N_{LCS}}{N_{SYS}} $$

Finally we calculate F-measure defined as the harmonic mean of the recall and the precision:

$$ F = \left\{ \frac{1}{2}(R^{-1} + P^{-1}) \right\}^{-1} = \frac{2N_{LCS}}{N_{REF} + N_{SYS}}. $$

3.3. Result and Discussion

Table 2 shows the experimental result. From this table, we can see that just adding entries to the dictionary has a large positive effect on the accuracy. By adding entries to the dictionary (no re-training in MeCab case\(^4\)) the accuracies of MeCab and KyTea increase by 1.35% and 1.21% respectively. However, by actually adding annotated sentences to the training corpus we can further increase by 0.30% and 0.40% respectively. That is to say, 75~80% of accuracy increase can be achieved through dictionary expansion and the remaining 20~25% can realized only by adding the context information included in the corpus.

The followings are the examples of increases realized only by the corpus addition for MeCab.

- *な / ん ⇒ な (freq.=4)*
  In books and newspaper articles “ななる”(what) is written in the Chinese character “個” instead of the hiragana “ななる.” Thus the morphological analyzer divides the string into the auxiliary verb “な” and its inflectional ending “なる” which appear many times in these domains.

- *^ / ~ ⇒ ^ (freq.=3)*
  Smiley faces are rare in the general domain but often used in Web domain. And characters including “^_” make a word in many cases. Thus we need to add a Web domain training corpus to estimate that the smiley face is sufficiently common as a single word and should not be divided.

- *感 / じ ⇒ 感 (freq.=2)*
  “感じ”(feeling) as a noun does not appear in the general domain corpus and is segmented into a verb “感” and inflectional endings “じ”，but using this word as a noun is common in the Web domain.

Another remark is that the accuracy gain is almost the same in CRF-based joint method (MeCab) and 2-step pointwise method (KyTea) contrary to our expectation that MeCab depends more on the dictionary than KyTea. Thus both morphological analyzers are making good use of dictionary information, but also can be improved with the context provided by the corpus.

4. Realistic Cases

The experimental results that we described in the previous section are somewhat artificial or in-vitro. In the corpus adaptation case, it is assumed that the sentences are entirely annotated with word boundary information and all the words are annotated with their POSs. In this section, we report results under two other adaptation methods used in real or in-vivo adaptation scenarios. In both cases, the language resources to be added are partially annotated corpora (Neubig and Mori, 2010). Because MeCab is not capable of training a model from such corpora, we only report the result of KyTea.

As the problem, we focus on word segmentation, because in Japanese most ambiguity in MA lies in word segmentation, especially in the domain adaptation situation where most of unknown words are nouns and the rest fall into other content word categories such as verbs, adjectives, etc.

Figure 2

4.1. Recipe Domain

The first case is the adaptation to cooking recipe texts. We used recipe flow graph corpus (r-FG corpus) (Mori et al., 2014) in which word sequences important for cooking are annotated with types (recipe named entities; recipe NEs). They are also correctly segmented into words (see Figure 2).

4.1.1. Experimental Setting

Table 3 shows the specifications of the r-FG corpus relating to the word segmentation experiment. As the adaptation strategies, we used the following two methods in addition to “No adaptation.” The examples are taken from Figure 2.

|            | #Sent. | #NEs  | #Words | #Char. |
|------------|--------|-------|--------|--------|
| Training   | 1,760  | 13,197| 33,088 | 50,002 |
| Test       | 724    | –     | 13,147 | 19,975 |

Table 3: Specifications of the recipe corpus.
1. Extract $n$ occurrences at maximum of the NEs from the training data (see Figure 2, where the NE in focus is ホットドッグ and $n = 2$).

2. Convert them into partially segmented sentences in which only both edges of the NEs and the inside of the NEs are annotated with word boundary information.

Ex.) If the NE in focus is ホットドッグ, then

各ホットドッグにチリフライ→チリフライ→チリフライ→チリフライ

where the symbols “|”, “~” and “” mean word boundary, not a word boundary, and no information, respectively.

3. Use the partially annotated data as the additional language resource to train the model.

### 4.1.2. Result and Discussion

Table 4 shows the word segmentation accuracies (WS F-measure) of “No adaptation” and the strategies that we explained above. The results of the partial annotation strategy varies depending on the parameter $n$ (the maximum occurrences). The table shows these results with the real average occurrences in the partially segmented sentences.

From the result we can note the following. First, the addition of new words as the dictionary to the training data improves the word segmenter. This is consistent with the results shown in Table 2. Second, the partial annotation strategy with one occurrence ($n = 1$) is as good as the dictionary addition strategy. And as we increase the number of occurrences ($n$), the segmenter improves. The degree of improvement, however, shrinks as $n$ increases. In a real situation, we have to prepare such partially annotated data and the annotation cost is proportional to the number of occurrences to be annotated. Therefore it is good to start annotating new words in descending order of frequency, selecting a threshold based on the number of occurrences.

#### 4.2. Invention Disclosure Domain

Finally we report the result of a real adaptation that performed. The target domain is the invention disclosure texts, which are one of the important domains for NLP, especially information extraction and machine translation.

### 4.2.1. Setting

Based on the knowledge we described above, we adopted the partial annotation strategy. Concretely, we performed the following procedures.

1. Extract unknown word candidates based on the distributional similarity from a large raw corpus in the target domain (Mori and Nagao, 1996).

2. Annotate three occurrences with word boundary information to make partially segmented sentences for each unknown word candidate in the descending order of the expected frequencies.

For frequent word candidates, i.e. in the beginning of the annotation work, the three-occurrence annotation corresponds to the case of those with the maximum occurrence count of 4 and 8 in Table 4, because the average number of the occurrences is expected to be three.

In the practice, we asked an annotator to check unknown word candidates with three different contexts in the raw sentences.

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The expected frequency of a word candidate is the frequency as a string in the raw corpus multiplied by the word likelihood estimated by the comparison between its distribution and that of the words. See (Mori and Nagao, 1996) for more detail.
In the experimental evaluations, we first showed that the corpus addition strategy is better than the dictionary addition strategy in the Japanese morphological task. Then we introduced the partial annotation strategy, in which only important points are annotated with word boundary information, and reported the real cases focusing on the word segmentation in Japanese. The experiment showed that adding word candidates to the training data as partially annotated data with about three different contexts is efficient to improve the word segmenter.

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| #Sent. | #Words | #Char. |
|--------|--------|--------|
| Test   | 500    | 20,658 | 32,139 |

Table 5: Specifications of the invention disclosure corpus.

Figure 3: Accuracy increase.

corpus and correct the word boundary information if the default\(^6\) is incorrect.

Every time the annotator finished one hour work, we built a word segmenter by adding the partially annotated sentences and measured the accuracy (WS F-measure) on the test set shown in Table 5.

4.2.2. Result and Discussion

The learning curve shown in Figure 3. The left most point corresponds to the “No adaptation” case. The accuracy in this case is high compared with the recipe domain (Table 4). The reason is that the invention disclosure domain is not much different from the general domain containing newspaper articles etc. The most important remark is that the accuracy gets higher as we add more unknown word candidates to the training data as partially annotated sentences. After 12 hours of annotation work, we succeeded to eliminate 20% of the errors. The absolute F-measure is almost the same as that of the state-of-the-art word segmenter on the test set in the same domain as the training data (Neubig et al., 2011). Thus the word segmenter model itself is capable of contributing to various NLP applications in the invention disclosure domain in Japanese. In addition the accuracy does not seem to be saturating, thus we can improve more by only more annotator’s work based on the partial annotation strategy.

5. Conclusion

In this paper, we reported to what extent two strategies of language resource additions contribute to improvement in the word segmentation problem and POS tagging problem in Japanese. The first strategy is adding entries to the dictionary and the second is adding annotated sentences to the training corpus.

\(^6\)The default segmentation assumes that the candidate word is a word. That is to say, there are word boundaries on the both edges and no word boundary inside the string.
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