Online Japanese Unknown Morpheme Detection using Orthographic Variation

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Abstract
To solve the unknown morpheme problem in Japanese morphological analysis, we previously proposed a novel framework of online unknown morpheme acquisition and its implementation. This framework poses a previously unexplored problem, online unknown morpheme detection. Online unknown morpheme detection is a task of finding morphemes in each sentence that are not listed in a given lexicon. Unlike in English, it is a non-trivial task because Japanese does not delimit words by white space. We first present a baseline method that simply uses the output of the morphological analyzer. We then show that it fails to detect some unknown morphemes because they are over-segmented into shorter registered morphemes. To cope with this problem, we present a simple solution, the use of orthographic variation of Japanese. Under the assumption that orthographic variants behave similarly, each over-segmentation candidate is checked against its counterparts. Experiments show that the proposed method improves the recall of detection and contributes to improving unknown morpheme acquisition.

1. Introduction
Dictionaries are indispensable resources in natural language processing. This is especially true for Japanese morphological analysis because it is not just part-of-speech (POS) tagging but segmentation is also required. Japanese, like Chinese and Thai, does not delimit words by white space, and due to boundary ambiguities, the joint task of segmentation and POS tagging has a much larger search space than simple POS tagging. In order to limit the search space, the enumeration of morpheme candidates is done by looking up a pre-defined dictionary. Historically, extensive human resources were used to build high-coverage dictionaries (Yokoi, 1995). They now cover almost all but rare proper nouns in newspaper articles. Thus research concentrated on finding an optimal path when a high-coverage dictionary is available, and the F-score of nearly 99% was achieved (Kurohashi et al., 1994; Asahara and Matsumoto, 2000; Kudo et al., 2004). Manually-constructed dictionaries do not, however, suffice for texts other than newspaper articles, web pages in particular, where morphological analysis is prone to more errors owing to unknown morphemes, or morphemes not in a dictionary. For example, the unknown verb “ググる” (gugu-ru, to google) is erroneously segmented into “ググ”(gugu) and “る”(ru).

One solution to the problem is to automatically augment the dictionary by acquiring unknown morphemes from text (Mori and Nagao, 1996). We previously proposed the novel framework of online acquisition of unknown morphemes (Murawaki and Kurohashi, 2008). Unlike traditional batch extraction (Mori and Nagao, 1996), the proposed method has the ability to acquire unknown morphemes in an online mode. The lexicon acquirer processes text on a sentence by sentence basis. It directly updates the dictionary of the analyzer when it successfully disambiguates an unknown morpheme.

The framework of online acquisition poses a previously un-explored problem, online unknown morpheme detection. It is a task of finding morphemes in each sentence that are not listed in a given lexicon. Unlike in English, it is a non-trivial task because, again, Japanese does not delimit words by white space. We have to compare the whole sentence, not words, with the morphemes registered in the dictionary.

In this paper, we first present a baseline method of detection that simply uses the output of the morphological analyzer. The baseline method can easily detect most unknown morphemes because they cannot be interpreted as registered morphemes. We then show that it fails to detect some unknown morphemes because they are over-segmented into shorter registered morphemes. To cope with this problem, we propose the use of orthographic variation of Japanese. Under the assumption that orthographic variants behave similarly, each over-segmentation candidate is checked against its counterparts. Experiments show that the proposed method improves the recall of detection and contributes to improving unknown morpheme acquisition.

2. Related Work

2.1. Morpheme Extraction from Text
Various methods are proposed to extract morphemes from text. For languages delimited by white space, they can be extracted from a word list (Kurimo et al., 2006; Poon et al., 2009).

For languages where even word boundaries are unmarked, two major approaches are used. One is to segment the whole corpus and to build the dictionary, or the list of morphemes, from the segmented corpus. Segmentation models can be learnt from a manually-segmented training cor-

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1Throughout this paper, we distinguish words from morphemes. Each word consists of one or more morphemes.
pus (Asahara and Matsumoto, 2000; Kudo et al., 2004) and from raw text by unsupervised methods (Goldwater et al., 2009; Zhao and Kit, 2008; Mochihashi et al., 2009). Unsupervised segmentation can incorporate supervised segmentation using it as the initial model (Xu et al., 2008). Unsupervised segmentation are usually evaluated in terms of token (corpus segmentation) and type (the list of unique morphemes). It is reported that type accuracy is considerably lower than token accuracy, suggesting that low frequency morphemes tend to be wrongly segmented.

Another approach is to directly extract morphemes from a raw corpus that satisfy certain criteria. Mori and Nagao (1996) and Feng et al. (2004) examine the surrounding context of each morpheme candidate to evaluate how likely it is a true morpheme. To improve precision, candidates with low frequencies are usually discarded.

In both approaches, a morpheme list is extracted from a corpus in a batch mode. If we have a manually constructed dictionary, those not in the dictionary are considered unknown morphemes. Here we face a dilemma. Since the manually constructed lexicon covers basic morphemes, unknown morphemes to be extracted generally occur infrequently, but they are often misidentified or ignored in these approaches.

Practical applications of these approaches are automatic speech recognition (ASR) and kana-kanji (phoneme-to-text) conversion, where the nosiness of the extracted data is not critical (Kurata et al., 2006; Kurata et al., 2007; Sasada et al., 2008). In fact, Kurata et al. (2007) point out that most of the morpheme candidates are just useless and meaningless character strings. In these tasks, segmented text is just an intermediate representation between the input (speech/phoneme) and the output (unsegmented text). Incorrectly segmented morphemes in the language models can produce correct unsegmented text. For example, even if the language model is build from a corpus where "うざい" (uza-i, "annoying") is always segmented into "う" (u) and "ざい" (zai), the system would wrongly recognize the input u, za, i as "う" (u) and "ざい" (zai) with high probability. However, this is transformed into a correct unsegmented output "うざい" (uzai) and it is indeed judged correct in the standard Character Error Rate (CER) evaluation. By contrast, Japanese morphological analysis requires a clean dictionary, and segmentation errors in morphological analysis have a serious negative effect on its applications such as dependency parsing and named entity recognition. Thus this approach cannot directly be applied to morphological analysis.

### 2.2. Unknown Morpheme Processing

Another line of research focuses on identifying unknown morphemes on demand. In Japanese morphological analysis, the analyzer enumerates morpheme candidates with unknown morpheme processing in addition to dictionary look-up, as illustrated in Figure 1. Unknown morpheme candidates generated by unknown morpheme processing are given the special POS tag UNK. When the analyzer selects an optional path, registered morphemes are generally preferred. However, if they do not explain the input well, UNK morphemes are selected.

The widely adopted heuristics in unknown morpheme processing are based on character types because Japanese is written with several different scripts, or character types, such as hiragana and katakana (syllabaries), and kanji (logographs). Hiragana is used for functional elements while content words are usually written in kanji with some supplementary hiragana. Loan words are written in katakana. The choice of these scripts gives some clues on morpheme boundaries.

In the case of the morphological analyzer JUMAN, a sequence of katakana characters becomes one UNK morpheme, while hiragana and kanji are segmented per character. For example, the katakana loan word "グーグル" (guguru, "Google") out of "グーグルが" (guguru ga, plus NOM) is listed as an UNK morpheme.

These heuristics are simple and effective, but far from perfect. The hiragana noun "ようつべ" (youtsube, "YouTube") in an unconventional spelling is wrongly divided into "よ" (yo), "つ" (u-tsu) and "べ" (be), where the last element is UNK. In addition, they can never identify mixed-script morphemes, verbs and adjectives correctly. For example, the verb "ググる" (gugu-ru) is wrongly divided into the katakana UNK "ググ" (gugu) and the hiragana suffix "る" (ru).

More sophisticated unknown morpheme models can be introduced to morphological analysis (Nagata, 1999; Uchimoto et al., 2001; Asahara and Matsumoto, 2004; Nakagawa, 2004). However, it is difficult and computationally expensive to identify both the boundaries and POS of each unknown morpheme. In fact, Asahara and Matsumoto (2004) and Nakagawa (2004) only identify the boundaries. Even so, the accuracy of unknown morpheme identification is not high.

### 3. Online Unknown Morpheme Acquisition

We previously proposed the novel framework of online acquisition of unknown morphemes (Murawaki and Kurohashi, 2008). This framework is in line of on-demand identification of unknown morphemes, but further relaxes the requirement of identification; the detection of unknown morphemes does not require correct boundary identification. Instead of trying to identify the boundaries and POS of a single unknown morpheme, detected unknown morphemes are accumulated and compared with each other to solve the ambiguity.

The key idea behind this framework is that although each instance of an unknown morpheme is ambiguous in terms of both boundaries and POS, we can solve the ambiguity by accumulating its multiple instances and comparing them. Take the verb "ググる" (gugu-ru) for example. The goal is to identify its stem and POS tag: <gugu, consonant-verb>. When the lexicon acquirer receives its instance in text “グッってみた。“ (gugu-te mi-ta, "to have tried to google"), it enumerates its morphologically acceptable interpretations including <gugu, consonant-verb>, <gugu, consonant-w-verb>, and <gugu-te, consonant-m-verb> (note the different stem candidates). The acquirer then receives other instances such as “ググるのは”

[2]http://nlp.kuee.kyoto-u.ac.jp/nl-resource/juman-e.html
UNKs are often incorrect in terms of segmentation. They usually meet the criterion of unknown morpheme detection.

4.3. Over-segmentation Problem

The baseline method cannot detect some unknown morphemes because they are over-segmented into shorter registered morphemes. Some of them are loan words written in katakana:

- カースト (kâsuto, “caste”)
- カー (kâ, “car”)
- スト (suto, abbr. of “strike”)
- モニタリング (monitariNgu, “monitoring”)
- モニタ (monita, “monitor”)
- リング (ringu, “ring”)

In these examples, single loan words are divided into multiple loan words. The knowledge on the source languages (e.g. original spellings) would be useful for detecting them, but we do not discuss it in this paper.

Another type of over-segmentation typically involves hiragana characters:

- うざい (uzai, “annoying” in plain form of conjugation)
  ⇒ う (u, “hare,” “rain” or “cormorant”)
  + ざい (zai, “medicinal preparation,” “residing,” “material,” “guilt” or “wealth”)
- うざくて (uzakute, “annoying” in type-ta continuous -form)
  ⇒ う (u, “hare,” “rain” or “cormorant”)
  + ざ (za, “seat”)
  + く (ku, “ward” or “pain”)
  + て (te, “hand”)
- めんどうかった (menDo-kaqta, “tiresome” in ta-form)
  ⇒ めん (men, “evasion,” “cotton,” “plane” or “noodle”)
  + ど (do, “degree”)
  + かった (kaqta, “buy,” “raise animals,” “win,” “reap,” “hunt” or “drive” in ta-form)
guity among registered morphemes, it is difficult to dis-
tional morphemes but only uses POS bigrams (Kudo et
does not employ lexicalized bigrams except for some func-
be useful to investigate the reason why the analyzer does
In order to tackle the over-segmentation problem, it would
5.1. Orthographic Variation
Among the above four examples, “furniture and princess”
In order to detect over-segmented unknown morphemes, we
5.2. Training the Model
Given the mappings of orthographic variation, we prepare
5.3. Detection
In online detection, every sequence of morphemes output
We assume that orthographic variants behave similarly. For
each over-segmentation candidate, we check the occur-
cences of its orthographic counterparts in a corpus, and
determine if it is a correct segmentation. For example, if
“うざい” (uzai-i) actually consists of “う” (u) and “ざい”
(za-i), it is expected that its variants such as “卯ざい,” “卯
処,” and “雨ざい” also appear in a corpus. This is indeed
not the case and we can detect the unknown morpheme.
We formalize the idea as follows. Suppose that we have a
mapping from morpheme \( m_i \) to the set of its orthographic
variants \( V_{m_i} \) (e.g. \( \{ \text{卯, 雨, 鳥} \} \)). When we find
\( m_i \) in morpheme sequence \( \ldots m_{i-1}, m_i, m_{i+1}, \ldots \)
given by the analyzer, it is considered as an over-segmenta-
candidate. We first examine the forward bigram \( m_i, m_{i+1} \), cal-
culating the log likelihood ratio,
\[
L_f(m_i, r_{i+1}) = \log \frac{P(r_{i+1}|m_i)}{P(r_{i+1}|V_{m_i})},
\]
where \( r_{i+1} \) is the repname of \( m_{i+1} \). We detect \( m_i \) if
the ratio is greater than a threshold. Due to polysemy,
\( m_{i+1} \) can also have more than one repname (“ざい” is con-
tained by repnames “助,” “在,” and three oth-
ers.). In such a case, we check the possible combinations of
\( L_f(m_i, r_{i+1}) \), and detect \( m_i \) if all of them satisfy the
above condition.
The bigram probabilities can be estimated using the maxi-
mum likelihood method,
\[
P(r_{i+1}|m_i) = \frac{f(m_i, r_{i+1})}{f(m_i)},
\]
and
\[
P(r_{i+1}|V_{m_i}) = \frac{\sum_{m_i \in V_{m_i}} f(m_i, r_{i+1})}{\sum_{m_i \in V_{m_i}} f(m_i)}.
\]
Similarly, we check the backward bigram \( m_{i-1}, m_i \),
\[
L_b(r_{i-1}, m_i) = \log \frac{P(r_{i-1}|m_i)}{P(r_{i-1}|V_{m_i})}.
\]
5.2. Training the Model
Given the mappings of orthographic variation, we prepare
the initial N-grams. Note that we can also update the fre-
cQUENCY counts of the N-gram model during detection.
We use texts segmented and tagged by the morphological
analyzer. For the over-segmentation candidate \( m_i \) and its
variant \( m_i' \in V_{m_i} \), we need the frequency counts \( f(m_i), f(m_i, r_{i+1}) \) and \( f(r_{i-1}, m_i) \). We scan the morpheme se-
quence and increment the corresponding counts.
5.3. Detection
In online detection, every sequence of morphemes output
by the analyzer is given as an input. The sequence is
scanned from beginning to end to detect unknown mor-
phemes. At each position \( i \), the baseline method based
on unknown morpheme processing is first applied. If they
do not match \( m_i \) and it has orthographic variants, then
orthographic variation is examined. The forward bigram
\( m_i, m_{i+1} \) is checked, and if it satisfies the condition, \( m_i \)
In training, we count and the backward bigram are smoothed in similar ways. Sand basic morphemes. If spelling variants were expanded, we used the default dictionary of the morphological analyzer JUMAN and its dictionary have been developed using it as the benchmark corpus (Kurohashi and Nagao, 1998).

6. Experiments

We evaluate the proposed method in terms of (1) the performance of unknown morpheme detection and (2) its contribution to unknown morpheme acquisition.

6.1. Data

We used the default dictionary of the morphological analyzer JUMAN as the initial lexicon. It contained 30 thousand basic morphemes. If spelling variants were expanded and proper nouns were counted, the total number of morphemes was 120 thousands.

For repnames or groups of orthographic variants, we used those listed in the dictionary of JUMAN version 5.0 or later. We semi-automatically constructed the mappings of orthographic variation as follows. First morphemes extracted from the dictionary were grouped by repname. Next, over-segmentation candidates were selected from each repname with some hand-written rules. Finally the mappings were manually corrected. We selected short hiragana, mixed-script spellings and some katakana morphemes as over-segmentation candidates. We obtained 12,082 over-segmentation candidates (conjugation variation of verbs and adjectives are not distinguished). We trained the N-gram model on the web corpus that consists of 100 million pages. To keep the data size manageable, all bigram counts below the threshold 10 were ignored. We updated the counts during online acquisition.

We used the dependency parser KNP to obtain bunsetsu boundaries. KNP chunked morphemes into bunsetsu in preprocessing.

6.2. Detection

6.2.1. Settings

We evaluate unknown morpheme detection with precision and recall. For the evaluation of Japanese morphological analysis, Kyoto Text Corpus is widely used. This is the very reason that it is not applicable to the evaluation of unknown morpheme detection. It contains a unnaturally small number of unknown morphemes since the morphological analyzer JUMAN and its dictionary have been developed using it as the benchmark corpus (Kurohashi and Nagao, 1998).

In order to evaluate performance concerning unknown morphemes, we need a large annotated corpus because unknown morphemes occur infrequently in general. However, fully annotating a large amount of text is too time-consuming and costly. We adopt an approximate but more efficient approach instead.

Precision is measured by manually judging the system output. We omit from judgment detected morphemes that consist solely of katakana characters because they are overwhelming in number, generally correct and easily detected with the baseline method. We randomly select 500 detected morphemes for evaluation.

As for recall, we only focus on over-segmentation. We create a gold standard by manually correcting automatically extracted over-segmentation candidates. First, over-segmentation candidates are automatically extracted from text in the following steps.

1. Segment and tag each sentence with the morphological analyzer JUMAN.
2. Scan each morpheme sequence and extract as candidates the pairs of morphemes which any of the following rules matches:

   1. Segment and tag each sentence with the morphological analyzer JUMAN.
   2. Scan each morpheme sequence and extract as candidates the pairs of morphemes which any of the following rules matches:

   3. http://nip.kuee.kyoto-u.ac.jp/nl-resource/knp-e.html
   4. http://nip.kuee.kyoto-u.ac.jp/nl-resource/corpus-e.html
Table 1: Result of unknown morpheme detection.

|                | baseline | proposed |
|----------------|----------|----------|
| recall         | 346 / 1,004 (34.5%) | 723 / 1,004 (72.0%) |
| precision      | 452 / 500 (90.4%)  | 412 / 500 (82.4%)  |
| total          | 13,952    | 15,612    |
| excl. katakana | 3,206     | 4,727     |

(a) One-character hiragana + one-character hiragana,
(b) Two-character hiragana + one-character hiragana, and
(c) One-character hiragana + two-character hiragana.

3. Filter out candidates that are unlikely to be unknown morphemes. We use as “stop words” the pairs of morphemes that are extracted from Kyoto Text Corpus using the same rules.

We manually check every over-segmentation candidate. 2,870 over-segmentation candidates were extracted, and 1,004 unknown morphemes were manually tagged. The system output is judged correct if it satisfies the condition described in Section 4.1. For the evaluation of recall, we do not skip detection after one morpheme is detected. Note that the F-score cannot be calculated due to the above approximations.

6.2.2. Results

Table 1 shows the recall and precision of detection. The proposed method significantly improved recall over the baseline while the number of detected morphemes increased only moderately (by 11.9%). This is because an overwhelming number of unknown morphemes were written in katakana. If katakana ones were excluded, the proposed method considerably increased the number of detected morphemes.

Newly detected true positives include (detected morphemes are marked by underscores):

- かもめ (kamome, “gull”) ⇒ かも (kamo, “duck”) + め (me, “eye”)
- ちゃがい (chachi-i, “cheap”; colloquial) ⇒ ちゃ (cha, “tea”) + がい (chii, “status” or “search shock”)
- よさこい (yosakoi, a folk song) ⇒ よ (yo, “good” in bare stem form) + さ (sa, nominal predicative suffix) + こい (koi, “love,” “intent” or “curp”)

Most false negatives can be classified into two types. The first is the lack of orthographic variation. For example, “あすみ” (azumi, a given name) is segmented into “あ” (a, interjection) and “すみ” (zumi, nominal suffix), and neither has orthographic variants. The second one is that the local scope of bigram does not suffice for detection. Unknown morphemes that fall into this type often contain particles in decomposed forms:

- めも (memo, “memo”) ⇒ め (me, “eye”) + も (mo, “too”)
- でかい (deka-i, “jumbo”) ⇒ で (de, “go out” in plain continuative form) + かい (kai, final particle)

These segmentations alone are completely natural. Since in most cases they are inconsistent with the whole sentences, wider consistency should be considered in future work. The detection of some unknown morphemes depends on their surrounding context. For example, “ててな” (hatena, “question mark”) alone is not detected because “な” (na) is interpreted as a particle. On the other hand, it is detected from “はてなが” (plus NOM) and “はてなを” (plus ACC), where “な” is interpreted as a noun by the analyzer because the particle cannot be followed by a case marker.

Errors of the baseline method in precision evaluation included 16 informal spelling alternates, 4 sentence extraction errors and one typo. One example of informal spellings was “なんでね” (nante ne, “just kidding”), an emphasized form of conventional “なんでね” (nande ne). Some of these spellings can probably be filtered out with heuristic rules, but this problem should ultimately be solved with more robust morphological analysis.

6.3. Acquisition

6.3.1. Settings

Next, we evaluate the detection method by incorporating it into online unknown morpheme acquisition (Murawaki and Kurohashi, 2008). We examine the accuracy of acquired morphemes and their contribution to the improvement of morphological analysis.

We use domain-specific corpora as target texts because efficient acquisition is expected. If target texts share a topic, relevant unknown morphemes are frequently used. We use search engine TSUBAKI (Shinzato et al., 2008) and cast the search results as domain-specific corpora. For each query, our system sequentially reads pages from the top of the result and acquires morphemes. We terminate the acquisition at the 1,000th page and analyze the same 1,000 pages with the augmented lexicon. The queries used are “捕鯨問題” (whaling issue), “赤ちゃんポスト” (baby hatch) and “ジャスラック” (JASRAC, a copyright collective).

A morpheme is judged correct if both segmentation and POS are correct. Since segmentation criteria are a nontrivial problem for evaluation and not necessarily important in practice (Murawaki and Kurohashi, 2008), the segmentation is judged correct unless morpheme boundaries are clearly wrong.
To examine the effect of acquisition, we analyze the target texts with both the initial lexicon and the augmented lexicon. Then we check differences between the two analyses and extract sentences that were affected by the augmentation. For each query, we use for evaluation 200 sentences randomly selected from them. We check the accuracy of each “diff” block, which is illustrated in Figure 3. Katakana blocks are, again, omitted from judgment. A “diff” is judged correct if for all morphemes in the block, both segmentation and POS are correct. We compare the baseline method and the proposed method with smoothing.

6.3.2. Results

Table 2 shows the results of acquisition. Compared with the baseline method, the proposed method slightly increased the number of acquired morphemes without seriously hurting accuracy. This improvement may look small, but it is because the overwhelming majority were katakana morphemes (75.6–79.7% of in the baseline method).

Table 3 shows the evaluation of “diff” blocks. The randomly selected data show almost no difference, but the numbers of sentences which contain “diff” blocks were increased by 7–38%.

Few false positives in detection led to wrong acquisition. Actually some erroneously detected registered morphemes accumulated enough examples for acquisition, but they were dropped at the time of acquisition simply because they conflicted with the registered morphemes.

Unknown morphemes newly acquired in the proposed method include "めんどうくさい" (meNDokusai-i, "tiresome"), "わんこ" (wanko, "doggy"), "ねとら" (netoraji, abbr. of "internet radio"), "かがみ" (kagamin, a person name) and "ドラえもん" (doraemon, a robot cat; note the mixed-script spelling). These morphemes are much smaller in number than katakana morphemes like "Google". However, they play more important role in NLP applications since the misidentification of these morphemes causes a serious negative effect on dependency parsing and other applications. For example, if "かがみ" (kagamin) is not registered in the dictionary, it is transformed into a nonsensical parse tree that can be interpreted as "Summer did not see."

| query        | baseline E→C | baseline C→E | baseline E→E | baseline C→E | baseline total | proposed E→C | proposed C→E | proposed E→E | proposed C→E | proposed total |
|--------------|--------------|--------------|--------------|--------------|---------------|--------------|--------------|--------------|--------------|---------------|
| whaling issue     | 111          | 121          | 0            | 11           | 243           | 137          | 79           | 1            | 15           | 232           |
| baby hatch     | 158          | 38           | 11           | 5            | 212           | 149          | 39           | 10           | 7            | 205           |
| JASRAC         | 100          | 81           | 21           | 9            | 211           | 124          | 67           | 13           | 6            | 210           |

(Legend – C: correct; E: erroneous)

7. Conclusion

In this paper, we examine the previously unexplored problem of unknown morpheme detection. In order to detect unknown morphemes that are over-segmented into shorter registered morphemes, we present a simple solution, the use of orthographic variation of Japanese. Complete detection remains unresolved because we know of no grammar or form of linguistic knowledge that exactly recognizes the set of acceptable languages. Yet we demonstrate that simple bigrams can detect a significant portion of over-segmentation.

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