Character Feature Engineering for Japanese Word Segmentation

Mike Tian-Jian Jiang
Independent†
tmjiang@gmail.com

Abstract

On word segmentation problem, machine learning architecture engineering often draws attention. The problem representation itself, however, has remained almost static as either word lattice ranking or character sequence tagging, for at least two decades. The latter often shows stronger predictive power than the former for out-of-vocabulary (OOV) issue. When the issue escalating to rapid adaptation, which is a common scenario for industrial applications, active learning of partial annotations or re-training with additional lexical resources is usually applied, however, from a somewhat word-based perspective. Not only it is uneasy for end users to comply linguistically consistent word boundary decisions, but also the risk/cost of forking models permanently with estimated weights is seldom affordable. To overcome the obstacle, this work provides an alternative, which uses linguistic intuition about character compositions, such that a sophisticated feature set and its derived scheme can enable dynamic lexicon expansion with the model remaining intact. Experiment results suggest that the proposed solution, with or without external lexemes, performs competitively in terms of F1 score and OOV recall across various datasets.

1 Introduction

According to ISO/DIS 24614-1, word segmentation is a process to divide a sentence into meaningful tokens called “word” conventionally (Choi et al., 2009). This process is usually considered fundamental and essential for many Asian languages to properly deal with downstream natural language processing applications. Unlike most writing systems in the world, an Asian language like Japanese normally retain no specific symbols such as whitespace for being word boundary delimiter, and word boundaries are often ambiguous if only looking up lexemes without taking context into account. Furthermore, Japanese writing system comprises three types of scripts, namely hiragana, katakana, and Chinese character in Sino-Japanese form (referred as kanji hereafter) (Joyce et al., 2012). For example, considering a phrase in gibberish “Lubbadubdub!” to be segmented as “Lubba dub-dub!” whereas “Lu” can be a word and “bad” can be another under different circumstances, while “L” could be “l” or “ℓ” in other types of scripts. Even when representing the same meaning, with or without a hyphen indicating a compound can formulate alternate standards of word segmentation. On the other hand, once the inevitable out-of-vocabulary (OOV) situation occurs with diverse language varieties, genres, registers, or domains, a robust Asian word segmentation system is expected to induce and adapt unseen usages morphologically (Tseng et al., 2005; Saito et al., 2014; Morita et al., 2015; Xu et al., 2006; Li et al., 2015; Jin and Wong, 2002; Gao and Stephan, 2010; Murawaki and Kurohashi, 2010), say realizing “Wubba” being an unknown word and then correctly segment another sentence in gibberish “Wubba lubba dub dub!”

Japanese word segmentation (JWS) task has been mostly integrated within morphological analysis (MA) task, which not only splits an input sentence into words, but also jointly annotates morphemes with their corresponding part-of-speech (POS) tags. The joint learning task has usually been defined as a word lattice ranking problem and approached differently with handcrafted rules†, hidden Markov models (HMMs) (Nagata, 1994; Asahara and Matsumoto, 2000), maximum entropy Markov models (MEMMs) (Uchimoto et al., 2001; Uchimoto et al., 2002; Uchimoto et al., 2003), support vector machines (SVMs) (Sassano, 2002), linear-chain conditional random fields (linear-chain CRFs) (Kudo et al., 2004), averaged structured perceptron (Kaji and Kitsuregawa, 2013), exact soft confidence-weighted learning with recurrent neural network language model (RNNLM) estimated words (Morita et al., 2015),

† This work was partially done while the author was affiliated with DG Lab, Digital Garage, Inc.
†† http://nlp.ist.i.kyoto-u.ac.jp/EN/index.php?JUMAN
etc. With the intention of exploring a wider range of approaches, Chinese word segmentation (CWS) works may be relevant. Because not only kanji is believed being a core building block for Japanese morphology (Joyce et al., 2014), but also affecting adjacent hiragana/katakana morpho-phonologically (Irwin, 2005; Kurisu, 2000; mis.; Kawahara and Nishimura, 2002; mis, 1998; mis.; mis, 1996). So far the dominant viewpoint for CWS task, however, is character sequence tagging (Huang and Hai, 2007; Hai et al., 2017), and (Ng and Low, 2004) show that POS-joint learning might be optional. Intriguingly, recent developments on JWS emerge to character-based methods with POS (Nakagawa and Uchimoto, 2007) or without it, either performing a two-step MA (Neubig et al., 2013) or just JWS itself (Nakagawa, 2004; Kitagawa and Komachi, 2017), while some of CWS researches begin revisiting word-based (Cai and Zhao, 2016; Cai et al., 2017) ones.

This work then aims to empirically deepen the understanding of character compositionality on JWS. The expected contribution is twofold: first rationalizing a systematic label and feature induction procedure, and secondly utilizing the outcome to demonstrate dynamic lexicon expansion in a pragmatic fashion. Although a previous work have demonstrated that active learning with partially annotated keyword-in-context (KWIC) is more effective than lexicon expansion (Mori and Neubig, 2014), KWIC acquisition can be still costly for rapid adaptation. Despite partial annotations are relatively easier to acquire than thoroughly curated corpora, it is likely that industrial/end-users possess no linguistic expertise but domain knowledge. In this work, the hypothesis is that one can form each user-defined word dynamically, by properly engineering innate variables of character sequence, instead of having the original model forked permanently with an estimated weight for every unknown lexeme.

2 Reproducibility

2.1 Evaluation Metrics, Significant Figure, and Statistical Significance Test

This work follows the convention of JWS, CWS, and many other natural language processing (NLP) tasks, using F1 score in terms of character and word. Some works treat them based on word boundary or longest common subsequence. This work opts out of those treatments since they are virtually correlated to the character/word based ones. As for the F1 scores in percentage, the second decimal place sometimes suffers from randomness according to preliminary tests, especially when experiments are conducted with inconsistent machine/compiler combinations. Despite character-wise scores being reported with two decimal places for the purpose of discussion, the significant figure should be always the first one. The significant figure difference may also be related to the character-word proportions, which can be somewhat deduced from Table 1 in the next subsection of datasets. For the choice of evaluation metrics itself, unfortunately there are several studies reporting incomparability issues, due to the differences ranging from downstream application requirements (Jiang et al., 2011), cognitive costs (Qian et al., 2016), segmentation standard disagreements (Shao et al., 2017), to the inherent Prevalence/Bias inconsistencies among various samples and systems (Powers, 2011), in spite of morphophonemics for Japanese and other languages usually apply unbiased metrics such as Markedness (Irwin, 2005). Ironically, while dataset-oriented bias will be an issue addressed in the next subsection, the point of this work can be seen as fitting it as much as possible with extensive feature engineering. Nevertheless, the biased metrics such as F1 score will likely render its statistical significance tests questionable among non-equivalent works even with the same dataset. Sometimes sequential labeling tasks in general adopt confidence intervals (Sproat and Emerson, 2003; Emerson, 2005; Levow, 2006; Jin and Chen, 2008) and McNemar’s test (Sha and Pereira, 2003; Kudo et al., 2004; Song and Sarkar, 2008; Shen et al., 2014; Matsumoto et al., 2004; Okanohara et al., 2006; Fujinuma and Grissom, 2017), whereas both of them are arguably too conservative (Fagerland et al., 2013; Wolfe and Hanley, 2002; Goldstein and Healy, 1995), and the majority of JWS/CWS works seem happy without them. Proper significance tests may exist, e.g., the mid-p variation of McNemar’s test (Fagerland et al., 2013), yet this work would like to stay ignorant for the time being, unless their accessibilities to JWS has been further established.
2.2 Datasets

This work studies JWS with version 1.1 of the Balanced Corpus of Contemporary Written Japanese (BCCWJ) (Maekawa et al., 2013) that contains modern texts written in multiple domains and registers. For the sake of reproducibility and with respect to strictly closed test criteria of machine learning common practice, sub-subsections below describe dataset specifications that are compatible with previous works.

**Construction:** When both analyzing overall phenomena and investigating adaptation ability, the document file ID list\(^2\) applied for extracting test set here, is identical to what has been assigned by the MA team of Project Next NLP (NextNLPMa)\(^3\). This work arbitrarily picks IDs from the training set to define a reusable development set\(^4\) for hyper-parameter tuning. For adaptation, although it is preferred to have a domain/register-specific separation setup like what a series of JWS works defined (Mori et al., 2011a; Mori et al., 2011b; Neubig et al., 2011; Mori and Neubig, 2014), it is unfortunately uneasy to reproduce. They select “Yahoo! Answers” documents as web texts for adaptation target. For the target’s counterpart, some works see book, news, and whitepaper files as generic texts (Mori et al., 2011a; Mori et al., 2011b; Neubig et al., 2011), while another one additionally include Yahoo! Blog and magazine files (Mori and Neubig, 2014). According to yet another study (Mori et al., 2011b), each remainder of a document ID’s serial number divided by 10 is used to partition training/test sets for both web texts and generic texts, which is the only known description to regenerate the data sets, but this work still fails to replicate them with acceptable margin of word counts.

**Script:** The latest BCCWJ provides two script variations across the whole corpus, namely original texts (OT) and their number-transformed (NT) counterparts, where consecutive digits and separators are translated into corresponding Han-character numbers.

**Granularity:** BCCWJ regulation defines rules to form morphemes into short-unit word (SSUW). (Mori et al., 2014) derive it with inflectional verbs further split into stems and suffixes, hence super-short-unit word (SSUW), which can be prepared by NextNLPMa’s conversion tool\(^5\) with a patch\(^6\) to accommodate the latest BCCWJ.

**Comparison:** Table 1 lists statistics and traits of dataset constructs for this and related works, in order to examine how comparable the results among them would be. For related works that have used BCCWJ, “K. & M. ’17” refers to one of the latest JWS work (Kitagawa and Komachi, 2017), “M. & N. ’14” denotes a study of language resource addition (Mori and Neubig, 2014), while “M. et al. ’11” covers

| Reference       | Doc. Type | #Sentence | Spec. | #Word | #IVs | #Character |
|-----------------|-----------|-----------|-------|-------|------|------------|
|                 |           | Training  | Test  | T     | UW   | Training   | Test  | Training   | Test  |
| This work       | HOM       | 56,760    | 3,010 | O     | S    | 1,203,331  | 67,435| 45,477     | 1,906,452| 105,323 |
|                 |           |           |       |       |      | 1,323,653  | 74,054| 40,995     |       |
|                 |           |           |       |       |      | 1,196,233  | 67,089| 45,477     | 1,908,733| 105,491 |
|                 |           |           |       |       |      | 1,316,555  | 73,708| 40,977     |       |
| K. & M. ’17     | GEN       | 56,448    | 2,984 | N     | SS   | -         | -     | -          | -     |
| NextNLP-MA      | GEN       | 57,281    | 3,024 | N     | SS   | -         | -     | 74,865     | -     |
| This work       | GEN       | 31,064    | 2,091 | N     | SS   | 816,882   | 64,727| 28,733     | 1,180,008| 92,642 |
|                 | HET       | 5,720     | 658   |       |      | 115,070   | 12,091| 31,305     | 159,159| 16,838 |
| M. & N. ’14     | GEN       | -        | -     |       |      | 784k      | -     | 29.7k      | -     |
|                 | HET       | -        | -     |       |      | 114k      | 13.0k | 32.5k      | -     |
| M. et al. ’11   | GEN       | 27,338    | 3,038 |       |      | 782,584   | 87,458| 28,315     | 1,131,317| 126,154 |
|                 | HET       | 5,800     | 645   |       |      | 114,265   | 13,018| 158,000    | 17,980 |
| N. et al. ’11   | GEN       | -        | -     |       |      | 782k      | 87.5k | -          | -     |
|                 | HET       | -        | -     |       |      | 153k      | 17.3k | -          | -     |

Table 1: Comparison of Datasets Arranged from BCCWJ.

Each cell containing only a "-" indicates the number is unreported from the reference.

\(^2\) [http://plata.ar.media.kyoto-u.ac.jp/mori/research/NLR/JDC/ClassA-1.list](http://plata.ar.media.kyoto-u.ac.jp/mori/research/NLR/JDC/ClassA-1.list)

\(^3\) [http://plata.ar.media.kyoto-u.ac.jp/mori/research/topics/PST/NextNLP.html](http://plata.ar.media.kyoto-u.ac.jp/mori/research/topics/PST/NextNLP.html)

\(^4\) Anonymous for the time being

\(^5\) [http://plata.ar.media.kyoto-u.ac.jp/mori/research/NLR/JDC/bccwjconv.tar.gz](http://plata.ar.media.kyoto-u.ac.jp/mori/research/NLR/JDC/bccwjconv.tar.gz)

\(^6\) An anonymous patch file for the time being
Table 2: Label Variations

| Labels | Label Strings by Word Length n |
|--------|-------------------------------|
| T > 1  | B | B \{1, n\} © |   |
| B, I   | B | B \{1, n\} © |   |
| B, I, S| S | B \{1, n\} © |   |
| B, I, E| B | B E; B \{1, n-2\} E |   |
| B, I, E, S| B | B E; B \{1, n-2\} E |   |
| B, 2, I, E, S| B | B E; B2E; B2\{1, n-3\} E |   |
| B, 2, 3, I, E, S| B | B E; B2E; B23E; B23I\{1, n-4\} E |   |
| S      | ... | S ... |   |

Table 3: Sentence-wise Information

| C | O | L | T | R | La | S | Ls |
|---|---|---|---|---|----|---|----|
| L | 0 | 5 | L | Lu | 2 | Lu | 2 |
| u | 1 |   | dub, Lu | 2, 3 | Lu | 2 |
| b | 2 |   | bad, dub | 3 | bad | 3 |
| b | 3 |   |   |   |   |   |   |
| a | 4 |   | a, bad | 2 | a, bad | 1, 3 |
| d | 0 | 3 | bad, dub | 3 | bad, dub | 3 |
| u | 1 |   | dub, Lu | 2, 3 | dub | 3 |
| b | 2 |   | bad, dub | 3 |   |   |   |
| t | 0 | 1 | P |   |   |   |   |

two related works (Mori et al., 2011a; Mori et al., 2011b), and “N. et al. ’11” stands for another (Neubig et al., 2011). The column “Doc. Type” indicates whether the dataset is for adaptation to web texts that are heterogeneous (HET) to the generic ones (GEN), or just for typically homogeneous training/test sets (HOM) designated by NextNLP-MA’s file ID list. Among the datasets of the HOM type, NextNLP-MA’s statistics seems unmatched with published works except the website and its listed slides. Besides, sentence counts of this type all vary a little, possibly due to the version differences of BCCWJ. For script MA’s statistics seems unmatched with published works except the website and its listed slides. Besides, as expected that, word counts between OT and NT groups are slightly different, and character counts remain intact within each group, since the SSUW treatment is fully reversible. A much bigger concern lies in the GEN-HET partitioned sets, where count/ratio gaps exist between this and related works, especially for GEN parts.

3 Character Sequence Tagging

Natural language processing often involves breaking a given string into smaller building blocks. After the inside-outside-beginning (IOB) tagging scheme has been introduced by a pioneer work (Ramshaw and Marcus, 1995), its variations studied for noun phrase (NP) chunking (Sang and Veenstra, 1999), and latter widely adopted by the SIGNLL Conference on Computational Natural Language Learning (CoNLL) for several tasks such as NP bracketing, phrase chunking, clause identification, named entity recognition, etc., therefore empirically proving this boundary-indicator tagging scheme is quite flexible. The resemblance between those tasks and word segmentation has probably inspired some participants of the Special Interest Group on Chinese Language Processing (SIGHAN) word segmentation bakeoffs. CWS-specific versions that classify Chinese characters for their word-belonging positions have gradually evolved ever since. A summary has examined those versions and drawn a conclusion that, while most recent works usually stick to a four-tag—BIET (or BMES) for beginning, inside (or middle), ending, and single character of a word, respectively—format, a six-tag extension with additional labels for the second and the third characters, is the best choice for contemporary Mandarin Chinese (Zhao et al., 2010). JWS-related works to date, however, may have only applied BIES (Kitagawa and Komachi, 2017) or two-tag (Neubig et al., 2011; Sassano, 2002) schemes.

Subsequently, this work intends to explore more complex labeling schemes. Table 2 demonstrates how those positional label variations extend forwardly. By producing combinations of class labels as random variables and feature tags as observed variables, many configurations are experimented with linear-chain CRFs (Lafferty et al., 2001), and their critical outcomes will be reported accordingly. As for hyper-parameter, \( \ell^1 \) and \( \ell^2 \) norms are roughly tuned to 0.000015 and 0.0025, respectively, based on the designated development set, and then applied to every experiment throughout.

3.1 Sentence-wise Information

Table 3 summarizes sentence-wise information about a test case in gibberish “Lubba dub !” and known-segments from an imaginary training set is just \{a, bad, dub, Lu, \}. such that the test sentence suffers from OOV issues. For each character C, O indicates of-word offset and implies word boundaries; L records word length; T stands for character type based on Unicode character categories, e.g., \( L \) for letter and P for punctuation; R collects character appearances of any known segment; S selects R items that match substrings of the sentence; \( L_R \) and \( L_S \) count distinct lengths of R and S items, respectively. Real
cases of course have more concrete pieces of information and their details will be discussed in latter subsections. \(R\) reflects the prior knowledge of lexicon. Besides that, \(T\) is the only external information of character mimicking practical situation. Information acquired by unsupervised methods, such as accessor variety (Feng et al., 2004), branching entropy (Jin and Tanaka-Ishii, 2006), frequent patterns (Jiang et al., 2012), etc., can be quite useful, but it is excluded to keep this work focused on character-word relations.

Word-based methods utilize \(R\) directly as path-finding lattice with count-based weights, where \(L_R\) implies implicitly. Since \(R\) is uneasy for character-based methods to incorporate explicitly, a feature type called “word indicator” (W) often identifies \(S\) with a limitation of maximum \(L_S\), ranging from three to six characters. Some works even extend the word indicator to adjacent substrings, such that it imitates word bigrams (Sun, 2011; Sun, 2010). \(T\) has had been somewhat forbidden from strictly closed test for CWS bakeoffs (Sproat and Emerson, 2003; Emerson, 2005; Levow, 2006; Jin and Chen, 2008) before 2010 (mis.; mis, 2012; Duan et al., 2014), but still widely adopted anyway. In JWS, it is only natural to include \(T\), considering Japanese writing system consists of three scripts, hiragana, katakana, and kanji. Generally \(O\) is used by character-based method to design class labels, yet its traits is embedded in \(W\). What this work intends to explore are:

- Classify characters with not only \(O\) but also \(L\) as long as \(T\);
- Invent a new feature type for \(L_R\);
- Enhance \(W\) with \(C, S\) and a more general \(L_S\).

### 3.2 Class Labels

A series of CWS works have reasoned that \(O/L\) coverage of a labeling scheme is related to its word segmentation performance, and concluded B23IES works best (Zhao et al., 2006; Zhao et al., 2010; Zhao and Kit, 2007; Huang and Zhao, 2006). The same method is hereby applied on BCCWJ and the result is listed in Table 5. The percentages suggest that B23IES can also work well on BCCWJ. To verify it, two vanilla models of linear-chain CRFs models for BIES and B23IES are trained with NT-SSUW dataset, using CRFsuite\(^7\). Features are just an intersection among common choices of previous works, namely character unigrams, bigrams, and (1-character-jumped) skip-grams within a ±1-character window. The result shown in Table 4 confirms that B23IES is slightly better than BIES in terms of word \(F_1\) score and recall of OOV (\(R_{OOV}\)). In terms of label-wise statistics, however, per class performance varies. Specifically, I of BIES classifies better than 2, 3, I of B23IES combined (6,857 > 6,784 = 3,764 + 1,603 + 1,417). Characters labeled with the same class may deserve to be more equal.

**Inspection:** Like the empirical supports for B23IES scheme in CWS, resemble linguistic intuitions may also stand for JWS (Joyce et al., 2014; Joyce et al., 2012; Ando and Lee, 2002; Fujinuma and Grissom, 2017), such as the second character of a three-character word may act differently than the one of a four-or-five-character word, cf. 2 for B23IES and I for BIES. However, judging by the earlier mentioned inferior performance of I for B23IES, the marginal probability \(P_{B23IES}(I|B,2,3)\) could still be less

---

Table 5: Word-Length Coverage (%)

| Length Range | SUW | SSUW |
|--------------|-----|------|
|              | NT  | OT   | NT  | OT   |
| 1            | 56.01 | 57.05 | 66.70 | 67.59 |
| ≤ 2          | 90.86 | 90.91 | 93.50 | 93.53 |
| ≤ 3          | 96.19 | 96.21 | 97.07 | 97.08 |
| ≤ 4          | 98.71 | 98.71 | 98.94 | 98.94 |
| ≤ 5          | 99.45 | 99.45 | 99.52 | 99.52 |
| ≤ 6          | 99.78 | 99.79 | 99.81 | 99.81 |
| ≤ 7          | 99.92 | 99.92 | 99.92 | 99.92 |
| ≤ 8          | 99.96 | 99.96 | 99.96 | 99.96 |
| ≤ 9          | 99.97 | 99.97 | 99.98 | 99.98 |
| ≤ 10         | 99.98 | 99.98 | 99.98 | 99.98 |

Table 4: BIES v. B23IES

| Word | BIES | B23IES |
|------|------|--------|
|      | \(F_1\) | \(F_1\) |
| B    | 24,086 | 98.14 |- 24,146 | 98.34 |
| 2    | - | - | 3,764 | 94.82 |
| 3    | - | - | 1,603 | 93.58 |
| I    | 6,857 | 94.37 | 1,417 | 91.30 |
| E    | 23,777 | 97.70 | 24,048 | 98.15 |
| S    | 48,555 | 98.81 | 48,595 | 98.87 |
| All  | 103,475 | 98.09 | 103,743 | 98.18 |
appropriate than $P_{\text{BIES}}(I|B)$, even though label and length biases are supposedly light in linear-chain CRFs (Kudo et al., 2004). A negative ripple effect can also back-propagate for $P_{\text{B23IES}}(E|I)$ in comparison with $P_{\text{BIES}}(E|I)$. Additionally, perhaps character n-gram features within 3-character window just lack sufficient information. For instance, all of the above speculated issues might inhabit in a frequently used phrase, 好き かける いり かた かた〈ka-ta〉 “a way of doing,” which consists of a noun かた〈ka-ta〉 “method” (a. k. a. 方) and a verb やる〈ya-ru〉 “act” lexicalized with a continuative suffix り〈ri〉. B23IES and BIES models have concatenated it incorrectly as a four-character word and a pair of two-character words, respectively. On one hand, the correct segmentation is unseen in the training set, except for one of its equivalent forms やり 方. On the other hand, 44 cases of four-character words begin with a consecutive やり, such as やり とり 〈ya-ri-to-ri〉 “give-and-take” since it is a compound noun. Those compounds have likely motivated B23IES model in favor of four-character words for やり〈ri〉 being a disyllabic prefix. Meanwhile, 515 two-character words that contain monosyllabic や as a prefix or 里〈ri〉 as a suffix might just cause BIES model biased naively.

**Correlation:** Goodman and Kruskal’s tau (G. & K.’s $\tau$) tests have been applied in the preliminary study. G. & K.’s $\tau$ is convenient yet informative about conditional variable importance of machine learning (Strobl et al., 2008), which could provide some insight before blindly jumping into various models. With an R package¹, associations are measured between the centered character trigram $x_{i}, x_{i-1}, x_{i-2}$ ($x_{0}$ indicates the character in question) and various label schemes. Besides the well-studied BIES and B23IES schemes, combinations of them and L/T information are tested, too. Interestingly, the trade-off between variability and sparseness is probably balanced when expanding BIES/B23IES with bi-class tags of both L and T (marked with a suffix -LT). Instead of multiplying the full populations of L and T (marked with a suffix -LT) and producing more than a hundred classes, bi-class L and T distinguish lengthy words and non-Japanese letters, respectively. Their specifications will be addressed in latter subsections. An important trick here is appending the trigram with the previous label $y_{-1}$ for simulating the edge feature of the first-order linear chain CRFs. The measurements listed in Table 6 may provide information for designing labels and features in addition to the word-length coverage from previous works, and become guidance in the next subsection. Other character n-grams are also tested and collaborated the same trend. Their statistics is skipped here for brevity.

### 3.3 Features

While G. & K.’s $\tau$ from various character n-grams to label schemes remain unlisted, an intriguing asymmetry should be noted here. Character n-grams using left-side characters associate stronger than their

|               | BIES | B23IES | BIES-LT | B23IES-LT | BIES-LT | B23IES-LT |
|---------------|------|--------|---------|-----------|---------|-----------|
| $\tau$ ($y_{-1}$,$x_{i}, x_{i-1}, x_{i-2}$) | 0.99665 | 0.99683 | 0.99677  | 0.99686  | 0.99527  | 0.99533   |
| #Class        | 4    | 6      | 14      | 22        | 102     | 131       |

Table 6: G. & K.’s $\tau$ between Centered Character Trigram and Class Labels

---

¹ https://cran.r-project.org/package=GoodmanKruskal

---

Figure 2. Individual Character n-gram’s $F_{1:IV}$

Figure 1. Individual Character n-gram’s $F_{1:OOV}$
counterparts with right-side ones, which may correlate to the left-to-right fashion of the labeling scheme or of the underlying natural language behavior, perhaps both. Previous works of point-wise models choose feature n-grams in this way, partly due to the their boundary decision point is at the end of each word (Neubig et al., 2011; Sassano, 2002). The asymmetric importance of n-grams shown here could be one of explanations, and the next question would be if it still applies with structured models. A series of simple models for each n-gram variation in a ±2-character window are therefore built with liner-chain CRFs. Their F1 scores for both in-vocabulary (IV) and OOV words are separately illustrated in Figure 2 and Figure 1, with horizontal axis denotes u, b, j, and t for unigram, bigram, skip-gram (jump), and trigram, respectively. They confirm not only the asymmetric tendency and a related work that has performed similar evaluations for feature induction (Ren and Li, 2017). The only notable exception here is for OOV F1 between trigram’s conjunctive forms, namely $x_{3:2}\cdot x_0$ and $x_0x_{1:2}$.

**Scaling:** An heuristic scaling trick has been implicitly applied first in a CWS work (Jiang et al., 2008) and then consciously reproduced (Wang et al., 2010b; Wang et al., 2010a) for its remarkable usefulness. The trick performs weight boosting by 2 for $x_0$ and by 3 for both $x_{1:2}$ and $x_0x_1$ of character n-gram features. The usefulness implies that the centered unigram and bigram characters have more predictive powers than other conjunctive ones. Their influences seem quantifiable if considering F1 scores of IV and OOV at the same time. Incrementally testing feature conjunctions is a well-known technique for CRFs, and subsequently binning feature clusters by frequency scales is also a popular choice (McCallum, 2003; McCallum and Li, 2003; Peng et al., 2004; Peng and McCallum, 2004). On the other hand, studying n-gram behaviors for back-off in language modeling has a long tradition. A caveat is that regularization plays a crucial part for using back-off features, otherwise large weights may polarize the model (Sutton and McCallum, 2012). Besides regularizing and selecting by $\ell^p$ norm (Lavergne et al., 2010), normalizing real valued features to have zero-mean and unit-variance, a. k. a. feature standardization, is also a common technique. This work tries to exploit all the above experience as much as possible without information beyond sentence level, such that lexicon expansion on the fly can execute with a constant model. After evaluating feature conjunctions with certain metrics for IV and OOV words defined by the development set, a linear interpolation is then applied to the paired scores, i.e.: \( (1 - \alpha) \times \text{Score}(\text{IV}) + \alpha \times \text{Score}(\text{OOV}) \) for \( 0 \leq \alpha \leq 1 \).

Finally, performing feature standardization to weigh each feature. In this work, a better choice of $\text{Score}(\cdot)$ is Recall rather than F1, which may be task-oriented (Powers, 2011), and $\alpha$ is empirically set to 0.325 as a newly invented hyper-parameter.

**Length-category code (LC):** Utilizing the referred word length ($L_R$) and Unicode category ($T$) for each character is the next step in the plan. Preliminary test results help realize a new type of compound feature, which concatenate $T$ and $L_R$ together as one. For example, the character 東 ‘tō’ “east” has a “K|1234+” coding “K” for kanji character and “1234+” for that this character has participated in forming all-length words except five-character ones, where “+” represents for words longer than five characters.

![Figure 3: G. & K.’s $r$ Matrix of Sentence-wise Information](image)

|                      | F1-Before | F1-After |
|----------------------|-----------|----------|
| SSUW NT              | 98.7      | 98.9     |
| OT                   | 98.7      | 98.9     |
| SUW NT               | 98.7      | 99.0     |
| OT                   | 98.7      | 99.1     |

Table 8: Final Design’s Performances Before/After Dynamic Lexicon Expansion

| Software   | F1     |
|------------|--------|
| MeCab 0.996 | SSUW-NT | 99.4 |
| KyTea 0.46  | SSUW-NT | 98.5 |
| KyTea 0.47  |        | 99.9  |

Table 7: Industrial-grade Accuracy
The rationale behind this compound feature is again based on G. & K.’s \( \tau \). Figure 3 represents predictive powers between sentence-wise information, and the top two are \( \tau(L_R, T) = 0.59 \) and \( \tau(T, L_R) = 0.38 \). Separated and combined performances of them are evaluated like the character n-grams with the same scaling trick involved, and the outcome concurs.

**Word-character code (WC):** The last type of feature combines the in-place character (C), word-matched substring (S), and substring lengths (L_S). A vector of the latter two is usually called word indicator (W), and often implemented in one-hot encoding. In order to gain a better comprehension about the details, please refer to a previous work for a nicely drawn figure of it (Kitagawa and Komachi, 2017). This work relaxes the length limitation: instead of giving up on matching long words, the new implementation here will try to find all possible words, and encode any one longer than five characters into a preserved bucket as another code point, and then match both the “\( + \)” treatment of length-category code and the coverage of B23IES labeling scheme. For example, when 東京 〈kyō-to〉 “Kyoto” in a test sentence, its W can be decoded as “S|B-2|B-3|…” to represent that it has been a prefix for a bi-character word 東京 〈ō-kyō “Tokyo” and a tri-character one 東京都 〈ō-kyō-to “Tokyo Metropolitan.” If it happens to also match a word longer than five characters, the decoded form may be “S|B-2|B-3|…|B-+|…” with “B-+” denoting the relationship. Based on Figure 3, it is somewhat difficult to decide whether grouping C with W or not. Preliminary experiments realize that, in exchange for a better finalization of fully trained models, a WC concatenated vector like “S|B-2|B-3|…|C” should apply in the example above, while giving up some potential of dynamic lexicon expansion. Please take a sneak peek of Table 7 and a glimpse of Table 8, as they are eventually affected, and kindly note that using standalone W may increase F1-After to 99.6 at most, but decreases F1-Before to 97.5 or even lower.

### 3.4 Final Design

With all the additional features on the above, a 22-class labeling scheme is then designed empirically with combinations of \( \{B, 2, 3, I, E, S\} \times \{+, \varepsilon\} \times \{F, \varepsilon\} \), tag sets for B23IES, word length, and character type, respectively. The word length class set marks a character of a six-or-more-character word as “+,” otherwise blank. The character types are categorized as either Japanese letters or not. “F” covers the latter by including both functional symbols like punctuations and foreign alphanumerical characters. Labels for Japanese letters remain intact.

The templates that diversify species of feature conjunctions within the 3 families C, LC, and WC, are shared generating functions as previous subsection applied:

- 5 unigrams: \( X_i(\cdot) \) for \( -2 \leq i \leq 2 \)
- 4 bigrams: \( XX_{i+1}(\cdot) \) for \( -2 \leq i \leq 1 \)
- 3 skip-grams: \( X_{i-1}X_{i+1}(\cdot) \) for \(-1 \leq i \leq 1 \)
- 3 trigrams: \( XX_{i-1}X_{i+2}(\cdot) \) for \(-2 \leq i \leq 0 \)

Consequently, there are \( 3 \times (5 + 4 + 3 + 3) \) resultant species. Those binary features are then factorized with Recall-biased scales indicating each species’ average adaptive capability. A linear-chain CRFs model thereby estimates individual’s strength to a struggle of 22 classes.

### 4 Adaptation by Dynamic Lexicon Expansion

This section describes a somewhat unrealistic scenario: oracle tests without OOV issues. The purpose is merely to demonstrate the ability of hot-swapping lexicon. For every test sample, acquiring LC/WC related traits to mutate building blocks of binary feature species could slightly alter the behavior the constant model and slightly improve the accuracy. Table 8 presents the experiment results of BCCWJ variations. To get a sense about how good an industrial-grade system can be, while accommodating different word segmentation regulations, the test set of SUW-NT are also used to evaluate MeCab\(^9\) 0.996 with UniDic\(^10\) 2.1.2, since this latest UniDic is highly likely including all the words from BCCWJ and

---

\(^9\) [http://taku910.github.io/mecab/](http://taku910.github.io/mecab/)

\(^10\) [https://osdn.net/projects/unidic/](https://osdn.net/projects/unidic/)
Table 9: Selected Error Cases from Previous Works

| Script Form | Segmentation (* marks wrong predictions) | Alternative Script Form (Transliteration) “Translation” | Reference |
|-------------|------------------------------------------|--------------------------------------------------------|-----------|
| 1           | エルマー | と | りゅう *エルマー | と | 竜 え-ru-mâ to ryû “Elmer and (the) dragon” | (Kitagawa and Komachi, 2017) |
| 1           | キ | ニ | ナリ | マス *キ | ニ | ナリ | マス | 気 | に | なり | ます き ni na-ri ma-su “concerning” | (Kaji and Kitsuregawa, 2014) |
| 1 & 2       | おやつ | たー | いむ | お | や | つ | たー | いむ | お八つ | タイム o-ya-tsu ta-i-mu “(prefix for polite) tea time” | |

Table 9 collects related works’ error cases (Kaji and Kitsuregawa, 2014; Kaji et al., 2015; Kitagawa and Komachi, 2016; Kitagawa and Komachi, 2017) that are also segmented inappropriately by the proposed method. At least 14 previously reported errors are correctly predicted and therefore omitted here. Inconsistent segmentation standards are listed first and then converted to SSUW without loss of generality. False predictions from this work’s system are all related to alternate forms of scripts, e.g., (1) replacing kanji/hiragana with hiragana/katakana and (2) spelling loan words differently. The system makes no mistakes if those cases were in lexically normalized forms. It is probably worth mentioning that りゅう vs. 竜 ryû “dragon” in the first case is commonly interchangeable, and the former one is usually preferred (as it is the officially translated title of a children’s novel), unless it is forming 竜王 ryû ō “dragon king” or any similar multi-kanji word. Sometimes a non-kanji usage also implies western dragons rather than Asian ones. Furthermore, only X persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | persona | person
Reference

Rie Kubota Ando and Lillian Lee. 2002. Mostly-Unsupervised Statistical Segmentation of Japanese Kanji Sequences. May.

Masayuki Asahara and Yuji Matsumoto. 2000. Extended models and tools for high-performance part-of-speech tagger. In volume 1, pages 21–27, Morristown, NJ, USA. Association for Computational Linguistics.

Deng Cai and Hai Zhao. 2016. Neural Word Segmentation Learning for Chinese. In pages 409–420, Berlin, Germany, August. Association for Computational Linguistics.

Deng Cai, Hai Zhao, Zhisong Zhang, Yuan Xin, Yongjian Wu, and Feiyue Huang. 2017. Fast and Accurate Neural Word Segmentation for Chinese. In pages 608–615, Vancouver, Canada, July. Association for Computational Linguistics.

Key-Sun Choi, Hitoshi Isahara, Kyoko Kanzaki, Hansaem Kim, Seok Mun Pak, and Maosong Sun. 2009. Word segmentation standard in Chinese, Japanese and Korean. In pages 179–186, Morristown, NJ, USA. Association for Computational Linguistics.

Huiming Duan, Zhifang Sui, and Tao Ge. 2014. The CIPS-SIGHAN CLP 2014 Chinese Word Segmentation Bake-off. In pages 90–95, Stroudsburg, PA, USA.

Thomas Emerson. 2005. The Second International Chinese Word Segmentation Bakeoff. In

Morten W Fagerland, Stian Lydersen, and Petter Laake. 2013. The McNemar test for binary matched-pairs data: mid-p and asymptotic are better than exact conditional. *BMC medical research methodology*, 13(1):91, July.

Haodi Feng, Kang Chen, Chunyu Kit, and Xiaotie Deng. 2004. Unsupervised Segmentation of Chinese Corpus Using Accessor Variety. In

Yoshinari Fujinuma and Alvin C. Grissom II. 2017. Substring Frequency Features for Segmentation of Japanese Katakana Words with Unlabeled Corpora. In

Q Gao and Vogel Stephan. 2010. A Multi-layer Chinese Word Segmentation System Optimized for Out-of-domain Tasks. In pages 1–6.

Harvey Goldstein and Michael J R Healy. 1995. The Graphical Presentation of a Collection of Means. *Journal of the Royal Statistical Society. Series A (Statistics in Society)*, 158(1):175.

Zhao Hai, Deng Cai, Changning Huang, Chunyu Kit, Kit. 2017. Chinese Word Segmentation: Another Decade Review (2007-2017). *The Frontier of Empirical and Corpus Linguistics*.

C. N. Huang and H Zhao. 2006. Which is essential for Chinese word segmentation: Character versus word. :1–12.

Chang-ning Huang and Zhao Hai. 2007. Chinese word segmentation: A decade review. *Journal of Chinese Information Processing*, 21(3), May.

Mark Irwin. 2005. Rendaku-Based Lexical Hierarchies in Japanese: The Behaviour of Sino-Japanese Mononoms in Hybrid Noun compounds. *Journal of East Asian Linguistics*, 14(2):121–153, April.

Mike Tian-Jian Jiang, Cheng-Wei Shih, Richard Tzong-Han Tsai, and Wen-Lian Hsu. 2011. Evaluation via Negative of Chinese Word Segmentation for Information Retrieval. In

Mike Tian-Jian Jiang, Cheng-Wei Shih, Ting-Hao Yang, Chan-Hung Kuo, Richard Tzong-Han Tsai, and Wen-Lian Hsu. 2012. Enhancement of Feature Engineering for Conditional Random Field Learning in Chinese Word Segmentation Using Unlabeled Data. *IJCLCLP*.

Wenbin Jiang, Liang Huang, Qun Liu, and Yajuan Lü. 2008. A Cascaded Linear Model for Joint Chinese Word Segmentation and Part-of-Speech Tagging. In
Guangjin Jin and Xiao Chen. 2008. The Fourth International Chinese Language Processing Bakeoff - Chinese Word Segmentation, Named Entity Recognition and Chinese POS Tagging. In

Honglan Jin and Kam-Fai Wong. 2002. A Chinese dictionary construction algorithm for information retrieval. *ACM Transactions on Asian Language Information Processing*, 1(4):281–296.

Zhihui Jin and Kumiko Tanaka-Ishii. 2006. Unsupervised Segmentation of Chinese Text by Use of Branching Entropy. In

Terry Joyce, Bor Hodošček, and Kikuko Nishina. 2012. Orthographic representation and variation within the Japanese writing system: Some corpus-based observations. *Written Language & Literacy*, 15(2):254–278, August.

Terry Joyce, Hisashi Masuda, and Taeko Ogawa. 2014. Jōyō kanji as core building blocks of the Japanese writing system: Some observations from database construction. *Written Language & Literacy*, 17(2):173–194, September.

Nobuhiro Kaji and Masaru Kitsuregawa. 2013. Efficient Word Lattice Generation for Joint Word Segmentation and POS Tagging in Japanese. In

Nobuhiro Kaji and Masaru Kitsuregawa. 2014. Accurate Word Segmentation and POS Tagging for Japanese Microblogs: Corpus Annotation and Joint Modeling with Lexical Normalization. In

Nobuhiro Kaji, Shin'ichi Mori, Fumihiko Takahashi, Tetsuro Sasada, Itsumi Saito, Keigo Hattori, Yugo Murakami, and Kei Uchiumi. 2015. Error Analysis of Morphological Analysis. In

S Kawahara and K Nishimura. 2002. Unveiling the unmarkedness of Sino-Japanese. *rci.rutgers.edu*

Yoshiaki Kitagawa and Mamoru Komachi. 2016. Japanese Word Segmentation using Deep Neural Network. In pages 933–936.

Yoshiaki Kitagawa and Mamoru Komachi. 2017. Long Short-Term Memory for Japanese Word Segmentation.

Taku Kudo, Kaoru Yamamoto, and Yuji Matsumoto. 2004. Applying Conditional Random Fields to Japanese Morphological Analysis. In

Kazutaka Kurisu. 2000. Richness of the Base and Root Fusion in Sino-Japanese. *Journal of East Asian Linguistics*, 9(2):147–185.

John D. Lafferty, Andrew McCallum, and Fernando C. N. Pereira. 2001. Conditional random fields: Probabilistic models for segmenting and labeling sequence data. In pages 282–289.

Thomas Lavergne, Olivier Cappé, and François Yvon. 2010. Practical Very Large Scale CRFs. In

Gina-Anne Levow. 2006. The Third International Chinese Language Processing Bakeoff - Word Segmentation and Named Entity Recognition. In

Xiaoqing Li, Chengqing Zong, and Keh-Yih Su. 2015. A Unified Model for Solving the OOV Problem of Chinese Word Segmentation. *ACM Trans. Asian & Low-Resource Lang. Inf. Process.*, 14(3):1–29.

Kikuo Maekawa, Makoto Yamazaki, Toshinobu Ogiso, Takehiko Maruyama, Hideki Ogura, Wakako Kashino, Hanae Koiso, Masaya Yamaguchi, Makiro Tanaka, and Yasuharu Den. 2013. Balanced corpus of contemporary written Japanese. *Language Resources and Evaluation*, 48(2):345–371, December.

Yuji Matsumoto, Aishan Wumaier, Taku Kudo, Kaoru Yamamoto, Tuergen Yibulayin, Zaokere Kadeer, and Shengwei Tian. 2004. Conditional Random Fields combined FSM stemming method for Uyghur. In volume 4, pages 295–299. IEEE.

Andrew McCallum. 2003. Efficiently Inducing Features of Conditional Random Fields. *UAI*. 
Andrew McCallum and Wei Li. 2003. Early results for named entity recognition with conditional random fields, feature induction and web-enhanced lexicons. In volume 4, pages 188–191, Morristown, NJ, USA. Association for Computational Linguistics.

Shinsuke Mori and Graham Neubig. 2014. Language Resource Addition - Dictionary or Corpus? In pages 1631–1636.

Shinsuke Mori, Yosuke Nakata, Graham Neubig, and Tatsuya Kawahara. 2011a. Morphological Analysis with Pointwise Predictors. Journal of Natural Language Processing, 18(4):367–381.

Shinsuke Mori, Graham Neubig, and Yuta Tsuboi. 2011b. A Pointwise Approach to Automatic Word Segmentation. IPSJ Journal, 52(10):2944–2952, October.

Shinsuke Mori, Hideki Ogura, and Tetsuro Sasada. 2014. A Japanese Word Dependency Corpus. In

Hajime Morita, Daisuke Kawahara, and Sadao Kurohashi. 2015. Morphological Analysis for Unsegmented Languages using Recurrent Neural Network Language Model. In pages 2292–2297.

Y. Murawaki and S. Kurohashi. 2010. Online Japanese Unknown Morpheme Detection using Orthographic Variation.

Masaaki Nagata. 1994. A stochastic Japanese morphological analyzer using a forward-DP backward- A*N-best search algorithm. In volume 1, pages 201–207, Morristown, NJ, USA. Association for Computational Linguistics.

T. Nakagawa and K. Uchimoto. 2007. A hybrid approach to word segmentation and POS tagging. :217–220.

Tetsuji Nakagawa. 2004. Chinese and Japanese Word Segmentation Using Word-Level and Character-Level Information. In

Graham Neubig, Yosuke Nakata, and Shinsuke Mori. 2011. Pointwise Prediction for Robust, Adaptable Japanese Morphological Analysis. In

H.T. Ng and J.K. Low. 2004. Chinese part-of-speech tagging: One-at-a-time or all-at-once? word-based or character-based. In volume 2004, page 277.

Daisuke Okanohara, Yusuke Miyao, Yoshimasa Tsuruoka, and Jun’ichi Tsujii. 2006. Improving the Scalability of Semi-Markov Conditional Random Fields for Named Entity Recognition. In

Fuchun Peng and Andrew McCallum. 2004. Accurate Information Extraction from Research Papers using Conditional Random Fields. In

Fuchun Peng, Fangfang Feng, and Andrew McCallum. 2004. Chinese segmentation and new word detection using conditional random fields. In pages 562–es, Morristown, NJ, USA. Association for Computational Linguistics.

David Martin Powers. 2011. Evaluation: from Precision, Recall and F-measure to ROC, Informedness, Markedness and Correlation. Journal of Machine Learning Technologies, 2(1):37–63, December.

Peng Qian, Xipeng Qiu, and Xuanjing Huang. 2016. A New Psychometric-inspired Evaluation Metric for Chinese Word Segmentation. In

LA Ramashaw and MP Marcus. 1995. Text chunking using transformation-based learning. In volume 176, pages 82–94.

Yulin Ren and Dehua Li. 2017. Fast and Robust Wrapper Method for N-gram Feature Template Induction in Structured Prediction. IEEE Access, 5:19897–19908.

Itsumi Saito, Kugatsu Sadamitsu, Hisako Asano, and Yoshihiro Matsuo. 2014. Morphological Analysis for Japanese Noisy Text based on Character-level and Word-level Normalization. In
Erik F Tjong Kim Sang and Jorn Veenstra. 1999. Representing Text Chunks. In

Manabu Sassano. 2002. An Empirical Study of Active Learning with Support Vector Machines for Japanese Word Segmentation. In

Fei Sha and Fernando Pereira. 2003. Shallow parsing with conditional random fields. In volume 1, pages 134–141, Morristown, NJ, USA. Association for Computational Linguistics.

Yan Shao, Christian Hardmeier, and Joakim Nivre. 2017. Recall is the Proper Evaluation Metric for Word Segmentation. In

Mo Shen, Hongxiao Liu, Daisuke Kawahara, and Sadao Kurohashi. 2014. Chinese Morphological Analysis with Character-level POS Tagging. In

D. Song and A. Sarkar. 2008. Training a perceptron with global and local features for chinese word segmentation.

Richard Sproat and Thomas Emerson. 2003. The First International Chinese Word Segmentation Bakeoff. In

Carolin Strobl, Anne-Laure Boulesteix, Thomas Kneib, Thomas Augustin, and Achim Zeileis. 2008. Conditional variable importance for random forests. *BMC Bioinformatics*, 9(1):307.

Weiwei Sun. 2010. Word-based and Character-based Word Segmentation Models - Comparison and Combination. In

Weiwei Sun. 2011. A Stacked Sub-Word Model for Joint Chinese Word Segmentation and Part-of-Speech Tagging. In

Charles Sutton and Andrew McCallum. 2012. An Introduction to Conditional Random Fields. *Foundations and Trends® in Machine Learning*, 4(4):267–373.

Huihsin Tseng, Daniel Jurafsky, and Christopher D Manning. 2005. Morphological features help POS tagging of unknown words across language varieties. In

Kiyotaka Uchimoto, Chikashi Nobata, Atsushi Yamada, Satoshi Sekine, and Hitoshi Isahara. 2002. Morphological Analysis of the Spontaneous Speech Corpus. In

Kiyotaka Uchimoto, Chikashi Nobata, Atsushi Yamada, Satoshi Sekine, and Hitoshi Isahara. 2003. Morphological analysis of a large spontaneous speech corpus in Japanese. In volume 1, pages 479–488, Morristown, NJ, USA. Association for Computational Linguistics.

Kiyotaka Uchimoto, Satoshi Sekine, and Hitoshi Isahara. 2001. The Unknown Word Problem - a Morphological Analysis of Japanese Using Maximum Entropy Aided by a Dictionary. In

Kun Wang, Chengqing Zong, and Keh-Yih Su. 2010a. A Character-Based Joint Model for Chinese Word Segmentation. In

Kun Wang, Chengqing Zong, and Keh-Yih Su. 2010b. A Character-Based Joint Model for CIPS-SIGHAN Word Segmentation Bakeoff 2010. In

Rory Wolfe and James Hanley. 2002. If we’re so different, why do we keep overlapping? When 1 plus 1 doesn’t make 2. *CMAJ : Canadian Medical Association journal = journal de l’Association medicale canadienne*, 166(1):65–66, January.

Xiaoming Xu, Muhua Zhu, Xiaoxu Fei, and Jingbo Zhu. 2006. High OOV-Recall Chinese Word Segmenter. *Engineering*:252–255.

Hai Zhao and Chunyu Kit. 2007. Effective Subsequence-based Tagging for Chinese Word Segmentation.
Hai Zhao, Chang-Ning Huang, Mu Li, and Bao-Liang Lu. 2010. A Unified Character-Based Tagging Framework for Chinese Word Segmentation. *ACM Transactions on Asian Language Information Processing*, 9(2):1–32, June.

Hai Zhao, Changning Huang, Mu Li, and Bao-Liang Lu. 2006. Effective Tag Set Selection in Chinese Word Segmentation via Conditional Random Field Modeling.