A Japanese Corpus of Many Specialized Domains for Word Segmentation and Part-of-Speech Tagging

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Abstract

We present a Japanese morphological corpus of sentences from 27 specialized domains for the two tasks of word segmentation and part-of-speech tagging. Experiments on the corpus demonstrated that recent neural models with domain adaptation techniques and pretrained language models achieved accurate performance for the two tasks for many specialized domains.

1 Introduction

Because the Japanese language has no explicit word delimiters, word segmentation (WS) and part-of-speech (POS) tagging are fundamental and important steps for downstream natural language processing (NLP) tasks, such as linguistic analysis and text mining. In previous studies, researchers devoted much effort to developing WS and POS tagging systems (Kudo et al., 2004; Neubig et al., 2011; Tolmachev et al., 2020), often as Japanese morphological analysis, which simultaneously performs WS, POS tagging, and lemmatization. However, the majority of existing systems were evaluated on general domains, such as news and the web.

Although researchers constructed morphologically annotated corpora of specialized domain text, the domains in publicly available corpora are limited, for example, Mori et al. (2014, 2016); Harashima and Hiramatsu (2020). Moreover, researchers proposed domain-specific or domain-independent adaptation methods (Tsuboi et al., 2008; Fujita et al., 2014; Sudoh et al., 2014; Kameko et al., 2015; Higashiyama et al., 2020); however, they evaluated their systems on one or a few specialized domains. Therefore, a benchmark corpus that includes text for many specialized domains is beneficial for conducting comprehensive system evaluation and developing robust adaptation methods for many domains.

In this paper, we present a Japanese Corpus of Many Specialized Domains (JCMS) for WS and POS tagging. The corpus consists of 32,310 sentences annotated with word boundary and POS tag information for 27 specialized domains. Using our corpus, we evaluated existing morphological analysis and WS systems, including popular non-neural systems and recent neural cross-domain systems. Our experiments demonstrated that (1) most systems trained with general source domain resources resulted in degraded performance for specialized target domains; however, (2) domain adaptation (DA) techniques and pretrained language models (PLMs) contributed to robust performance without annotated text for target domains.¹

2 Construction of the JCMS

2.1 Data Sources and Domains

To construct a multi-domain corpus with public availability and domain diversity, we extracted raw sentences from several publicly available corpora with their sentence segmentation.

To include various science and engineering text (SCI) in our corpus, we used the ASPEC² (Nakazawa et al., 2016), NITCIR-9 PatentMT test collection³ (Fujii et al., 2010), and NTCIR-11 MedNLP-2 test collection⁴ (Aramaki et al., 2014). The ASPEC is a parallel corpus of paper abstracts in various scientific fields; we extracted 24K Japanese sentences for 20 domains (from AGR to TRA, as shown in Table 1). The PatentMT data form a parallel corpus of patent documents (PAT); we extracted 1K sentences. The MedNLP-2 data consist of pseudo electronic medical records (EMR); we used all 1.4K unique sentences.

To include other domain text, we used the BC-
Table 1: Statistics of the JCMS SUW data. Scientific (SCI), government document (GOV), and other (OTH) domains are grouped.

| Group | Domain                  | Sent. | Word |
|-------|-------------------------|-------|------|
| SCI   | agriculture, forestry, fisheries | 900   | 19.3k|
| SCI   | biology                 | 1,000 | 20.2k|
| SCI   | chemical eng.           | 1,700 | 38.3k|
| SCI   | chemical industry       | 750   | 18.2k|
| SCI   | construction eng.       | 950   | 18.7k|
| SCI   | construction eng.       | 1,700 | 39.0k|
| SCI   | electrical eng.         | 2,000 | 39.3k|
| SCI   | energy eng.             | 1,360 | 37.5k|
| SCI   | environmental eng.      | 870   | 19.0k|
| SCI   | earth and space science | 800   | 19.2k|
| SCI   | information eng.        | 900   | 18.9k|
| SCI   | management              | 1,500 | 36.8k|
| SCI   | mechanical eng.         | 1,750 | 38.3k|
| SCI   | medicine                | 1,300 | 20.0k|
| SCI   | mining eng.             | 640   | 19.1k|
| SCI   | nuclear eng             | 800   | 18.6k|
| SCI   | physics                 | 1,000 | 17.8k|
| SCI   | system control eng.     | 1,500 | 36.8k|
| SCI   | thermal eng             | 1,500 | 38.3k|
| SCI   | traffic and transportation eng | 1,430 | 37.7k|
| GOV   | electronic medical record | 1,362 | 28.7k|
| GOV   | law                     | 1,060 | 35.9k|
| GOV   | diet minute             | 650   | 36.3k|
| GOV   | PR magazine             | 1,238 | 19.1k|
| OTH   | textbook                | 1,000 | 15.9k|
| OTH   | verse                   | 1,000 | 15.9k|
| OTH   | Total                   | 32,310| 726k |

2.2 Segmentation Criteria and POS Tag Sets

Regarding the word boundary and POS tag annotation, we adopted two WS criteria (and corresponding POS tag sets). One is the short unit word (SUW). The SUW was designed by the National Institute for Japanese Language and Linguistics (NINJAL) to achieve consistent WS and has been adopted in various NINJAL corpora (Oka et al., 2020). Additionally, we defined a new criterion, SUW-SC, by separating conjugate words (verb, adjective, verbal/adjectival suffix, and auxiliary verb) into stems and conjugation endings, similar to EDR (2001) and Mori et al. (2014). This criterion has the advantage that different conjugation forms of (regular) conjugate words (e.g., 読む yo-mu ‘read’, 読ま yo-ma, and 読み yo-mi) can be treated as the same stem token (e.g., 読み yo) without an additional lemmatization process. The SUW-SC POS tags that differ from the SUW POS tags are shown in Appendix A.

2.3 Annotation and Checking Process

Using auto-analyzed sentences with SUW-SC information, five experienced annotators at an annotation company annotated sentences with word boundaries and POS tags, following the SUW-SC criterion and the BCCWJ annotation guidelines (Ogura et al., 2011a,b). After the annotation, the annotators performed (1) unknown word checks to detect erroneous out-of-dictionary words and (2) full-sentence checks to detect any erroneous words, and then fixed annotation errors. Finally, we automatically converted SUW-SC information to SUW information by merging adjacent conjugate word stems and conjugation endings. As a result, we obtained 32,310 sentences with 726k SUW tokens (771k SUW-SC tokens), as shown in Table 1, of which 10,520 sentences included one or more words modified by the annotators.

Through the annotation process, we also found approximately 350 character errors in the original sentences, which may have been caused by, for example, OCR and typographic errors, and replaced them with the correct strings, while retaining the original strings as meta information.

To assess the quality of SUW-SC annotation, the first author randomly sampled and checked 200 annotated sentences comprising 4,928 words. The author found 15 erroneous (multi-) word spans. The F1 scores of the annotators’ annotation were 99.75 (WS), 99.64 (top-level POS), and 99.56 (full POS) when the annotation refined by the author

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5https://clrd.ninjal.ac.jp/bccwj/en/index.html

6The BCCWJ compiles textbooks on ten subjects for elementary, middle, and high schools. The JCMS used sentences from Japanese textbooks for elementary schools.

7We did not separate words with irregular conjugations, such asする suru ‘do;’ we treated them as single words.

8We ignored word attributes, such as the base forms of conjugate words because of the high annotation cost.

9If conjugation type and form information are available, SUW annotation can also be converted to SUW-SC annotation using several simple rules. We will publish the conversion script together with the JCMS data.

10For example, we foundヌクレチド andプログラム but correct forms were assumed to beヌクレオチド ‘nucleotide’ andプログラム ‘program.’

11This check was done on the manually annotated sentences. This means that the reported F1 scores were not inter-annotator agreement on the auto-analyzed sentences.
was regarded as the gold standard.

3 Experiments

3.1 Systems and Language Resources

In this section, we report the experimental results for the JCMS data with the SUW annotation. See Appendix F for the results for the SUW-SC data.

We evaluated popular morphological analysis systems and recent neural WS models: MeCab version 0.996\(^{12}\) (Kudo et al., 2004), KyTea version 0.4.7\(^{13}\) (Neubig et al., 2011), BiLSTM, BiLSTM with Lexicon Features (LF) (Higashiyama et al., 2020), and BERT (Devlin et al., 2019). Additionally, we evaluated two domain-adaptable neural models proposed for Japanese and Chinese WS: BiLSTM with Lexicon Word Prediction (LWP) (Higashiyama et al., 2020) and BERT (Devlin et al., 2019). We used the off-the-shelf MeCab model based on UniDic,\(^{15}\) “unidic-cwj-3.1.0” (Den, 2009), and trained the other systems on the corpora and lexicons described later. We used a pretrained Japanese BERT model\(^ {16}\) with character-level tokenization for the BERT-based models. The detailed settings are described in Appendix B.

As source domain labeled data, we split the BCCWJ core data into 51K/6K/3K sentences and used them as training, development, and test data, respectively, for the above systems. As target domain test data, we used all the sentences in each JCMS domain.

For lexicon-enhanced models, we used entries in UniDic as the source domain lexicon \(D_s\) and entries in the MeCab-IPADIC user dictionaries for science and technology terms\(^ {17}\) as the target domain lexicon \(D_t\).\(^ {18}\) As target domain unlabeled data for BiLSTM-LWP and BERT-WM, we used 0.98M Japanese sentences in the ASPEC extracted from 20+ domains as single unlabeled data \(U_t\) shared for scientific target domains. Using these resources, we trained single domain-adapted model instances for SCI domains. We used no additional resources for the GOV and OTH domains.

3.2 Overall Results

Table 2 shows the WS and POS tagging (top-level POS) F1 scores for each system on the BCCWJ test data (GEN), and the JCMS SCI and GOV domain data; the scores in the SCI and GOV rows are the macro average F1 scores for 22 SCI domains and three GOV domains, respectively. The neural model scores are the mean F1 scores of three runs with random initialization.

For the GEN domain, MeCab, BiLSTM-LF, and BERT-based models achieved high performance: \(\geq 99.4\%\) and \(\geq 98.8\%\) F1 scores for WS and POS tagging, respectively.\(^ {19}\) For the SCI domains, for the two tasks, the systems with only source domain resources (except BERT) had a 0.6–1.8 F1 point degradation from the scores for the GEN domains. Training with target domain resources contributed to robust performance; for example, BiLSTM-LWP achieved a 0.9 F1 point improvement over BiLSTM for each task. BERT achieved the best performance for the GEN domain, MeCab, BiLSTM-LF, and BERT-based models achieved high performance: \(\geq 99.4\%\) and \(\geq 98.8\%\) F1 scores for WS and POS tagging, respectively.\(^ {19}\) For the SCI domains, for the two tasks, the systems with only source domain resources (except BERT) had a 0.6–1.8 F1 point degradation from the scores for the GEN domains. Training with target domain resources contributed to robust performance; for example, BiLSTM-LWP achieved a 0.9 F1 point improvement over BiLSTM for each task. BERT achieved the best performance

\[\text{https://dbarchive.biosciencebdc.jp/en/mecab/download.html}\]

\[\text{Because the dictionaries included many compound words, we split the original entries into substrings at the positions before and after continuous Japanese characters, continuous Latin characters, continuous Arabic numerals, and each symbol character, as preprocessing.}\]

\[\text{Notably, the MeCab model was trained on the BCCWJ core data and other corpora (Den, 2009; Oka, 2017), which may have included the GEN test sentences.}\]

| System         | GEN Seg | GEN POS | SCI Avg. Seg | SCI Avg. POS | GOV Avg. Seg | GOV Avg. POS |
|----------------|---------|---------|--------------|--------------|--------------|--------------|
| MeCab          | 99.6    | 99.0    | 97.9         | 97.2         | 98.0         | 97.6         |
| KyTea          | 99.1    | 98.4    | 98.5         | 96.8         | 97.5         | 96.6         |
| BiLSTM         | 98.7    | 98.1    | 98.0         | 97.2         | 97.6         | 96.9         |
| BiLSTM-LF      | 99.4    | 98.8    | 98.1         | 97.3         | 97.9         | 97.3         |
| BiLSTM-LWP     | 98.9    | 98.3    | 98.9         | 98.1         | 97.7         | 97.1         |
| BERT           | 99.4    | 99.1    | 99.3         | 98.7         | 98.1         | 97.6         |
| BERT-WM        | 99.4    | 99.3    | –            | –            | 98.0         | –            |

Table 2: System performance on the BCCWJ test (GEN), and the JCMS SCI and GOV domain data.
Table 3: System performance for each domain. BL represents BiLSTM.

| Dom. | Unknown | MeCab | BL-LWP | BERT |
|------|---------|-------|--------|------|
|      | Tok/Type |       |        |      |
|      | Ratio    | Ds    | Ds, Ds | U1   |     |
| GEN  | 2.7 / 20.2 | 99.6 | 99.0 | 98.9 | 99.4 |
| EN  | 2.5 / 15.4 | 99.3 | 98.9 | 99.6 | 99.2 |
| TRA | 3.0 / 18.2 | 98.8 | 98.4 | 99.4 | 98.9 |
| ENS | 3.1 / 19.5 | 98.6 | 98.2 | 99.4 | 99.0 |
| MAN | 3.5 / 19.5 | 98.9 | 98.1 | 99.2 | 98.6 |
| CON | 3.4 / 19.5 | 98.6 | 98.2 | 99.4 | 99.0 |
| AGR | 4.5 / 21.0 | 98.5 | 98.0 | 99.0 | 98.4 |
| TBK | 4.2 / 24.0 | 98.4 | 97.7 | 99.1 | 98.3 |
| INF | 4.7 / 22.6 | 97.9 | 97.5 | 99.1 | 98.3 |
| MEC | 5.0 / 23.3 | 98.4 | 97.8 | 99.3 | 98.7 |
| NUC | 5.0 / 22.3 | 98.1 | 97.3 | 98.9 | 99.0 |
| CHE-I | 5.5 / 23.7 | 97.9 | 97.3 | 99.0 | 98.3 |
| ETH | 5.5 / 24.5 | 98.5 | 97.8 | 99.3 | 98.4 |
| MED | 5.6 / 27.0 | 97.1 | 96.6 | 99.1 | 98.6 |
| SYS | 5.6 / 24.8 | 98.4 | 97.7 | 98.9 | 99.0 |
| ELC | 5.8 / 29.4 | 97.4 | 97.0 | 99.0 | 98.5 |
| PAT | 6.0 / 26.8 | 97.0 | 96.8 | 99.1 | 98.7 |
| CHE-E | 6.1 / 23.7 | 97.9 | 97.0 | 99.0 | 98.3 |
| MIN | 6.6 / 22.6 | 98.0 | 97.4 | 98.8 | 99.1 |
| BIO | 6.7 / 30.2 | 96.7 | 96.0 | 98.8 | 99.3 |
| PHY | 7.5 / 29.6 | 97.1 | 96.4 | 98.5 | 97.7 |
| CHE-B | 8.1 / 35.4 | 97.0 | 96.1 | 98.5 | 97.4 |
| EMR | 11.2 / 30.2 | 95.4 | 91.9 | 95.6 | 92.5 |
| TKB | 0.9 / 1.7 | 98.0 | 97.5 | 97.0 | 97.5 |
| LAW | 2.1 / 11.0 | 97.4 | 97.0 | 97.6 | 97.4 |
| PRM | 2.8 / 11.1 | 98.7 | 98.1 | 97.7 | 96.8 |
| TBR | 4.4 / 19.0 | 99.0 | 97.0 | 97.7 | 95.5 |
| VRS | 19.7 / 54.7 | 87.3 | 82.5 | 81.8 | 75.1 |

Table 3: System performance for each domain. BL represents BiLSTM.

without explicit DA steps and demonstrated the strong effectiveness of PLMs. This may be because the BERT representations were pretrained on Wikipedia text, including articles on scientific topics. BERT-WM did not show salient improvements over BERT, even when we used Ut unlabeled data. For the GOV domains, MeCab and BERT achieved the best WS and POS tagging performance. Most systems achieved lower performance than that for the GEN and SCI domains, which may be because of the high proportions of unknown non-noun tokens, such as verbs, in the GOV domains, as shown in Appendix C.

3.3 Results for Each Domain

Table 3 shows the performance (F1 scores) of the three accurate systems for the GEN and each JCMS domain. For each domain group, the domains are shown in descending order of the unknown token ratio (UTR). The performance of the systems for the two tasks tended to decrease as the UTR increased. However, BiLSTM-LWP and BERT achieved robust performance for SCI domains with higher UTR (scores ≥98% and ≥99% are shown with the light blue and blue background). As indicated by the high UTR and low system perfor-

mance, EMR and VRS were two difficult domains.

In Appendices D, E, and G, we present additional experiments for domain-specific enhanced models for EMR and VRS, the evaluation of the differences between the JCMS annotation and original annotation for GOV and OTH, and segmentation examples output by the systems, respectively.

3.4 Discussion

The JCMS comprises well-formed written text from, for example, scientific papers and government documents. Because of this characteristic, systems trained only on source domain resources achieved reasonable performance (WS and POS tagging F1 scores of 96.6–98.5%, on average), and more sophisticated systems enhanced with DA techniques or PLMs, that is, BiLSTM-LWP and BERT, achieved more accurate performance (F1 scores of 97.1–99.3%), as shown in Table 2. Straightforward extensions include the introduction of POS tagging-oriented DA techniques and the integration of DA techniques into PLM-based models.

Furthermore, possible research directions include WS and POS tagging on more challenging text registers, such as speech and social media text on specialized topics. Another important text analysis task is chunking or recognizing multi-word terms because NLP applications in specialized domains can require term-level processing.

4 Related Work

Japanese Morphology Corpora The representative Japanese morphology corpora used in the 1990s and early 2000s include the EDR Japanese Corpus (Miyoshi et al., 1996) and RWCP Text Database (Toyoura et al., 1998), and those used from the 2000s to the present include the Kyoto University Text Corpus (Kurohashi and Nagao, 2003) and BCCWJ (Maekawa et al., 2014). These corpora mainly comprise newspaper articles and other written language text, such as magazines, books, and dictionary example sentences. These corpora have played a significant role in the development of many Japanese morphological analysis and WS systems (Takeuchi and Matsumoto, 1995; Asahara and Matsumoto, 2000; Kudo et al., 2004; Neubig et al., 2011; Tolmachev et al., 2020). Additionally, web corpora (Hashimoto et al., 2011; Hangyo et al., 2012) and transcribed speech corpora (Maekawa, 2003; Koiso et al., 2022) annotated with morphology information have been con-
structured and released. Efforts have also been made to construct and publish corpora of other specialized domain text: patent (Mori et al., 2014), shogi (Japanese chess) commentary (Mori et al., 2016), and recipes (Harashima and Hiramatsu, 2020).

Domain Adaptation Methods To improve Japanese morphological analysis and WS performance on target domains, domain-specific or domain-independent adaptation methods have been proposed. Fujita et al. (2014) explored data augmentation techniques to improve morphological analysis performance on picture book text. Kameko et al. (2015) enhanced a WS model for shogi commentary text using shogi game state information. Partially labeled data have been used to fine-tune general WS models to target domains; Tsuboi et al. (2008) adapted a CRF model to a medical domain and Neubig et al. (2011) adapted a pointwise prediction model to a web domain. Higashiyama et al. (2020) enhanced a BiLSTM-based WS model by introducing an auxiliary word prediction task and adapted the model to several Japanese and Chinese target domains.

5 Conclusion

We presented the JCMS, which is a Japanese corpus of 27 specialized domains annotated with word boundaries and POS tags. The experiments on the corpus demonstrated the robust WS and POS tagging performance of recent neural models on many out-of-domain datasets. Our corpus could be a useful benchmark for developing and evaluating cross-domain systems for WS and POS tagging.

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Table 4: POS tags and example words of the SUW and SUW-SC criteria

| SUW | POS tag | Example |
|-----|---------|---------|
| V1  | 動詞-一般 | ある |
| V2  | 動詞-非自立可能 | すぎる |
| V3  | 動詞-一般 | 有し |
| V4  | 動詞-非自立可能 | する |
| A1  | 形容詞-一様 | 高い |
| A2  | 形容詞-非自立可能 | 欲しい |
| A3  | 形容詞-非自立可能 | ねえ |
| S1  | 接続辞-動詞的 | (欲)ぶる |
| S2  | 接続辞-形容詞的 | ぱぼい |
| AV1 | 助動詞 | させる |
| AV2 | 助動詞 | (行かない) |
| AV3 | 助動詞 | だろう |

| SUW-SC | POS tag (stem) | POS tag (ending) | Example |
|--------|---------------|-----------------|---------|
| V1     | 動詞-語幹-一般 | 活用語尾-動詞型 | ある |
| V2     | 動詞-語幹-非自立可能 | 活用語尾-動詞型 | すぎる |
| V3     | 動詞-特殊型-一般 | 有し |
| V4     | 動詞-特殊型-非自立可能 | する |
| A1     | 形容詞-語幹-一般 | 活用語尾-形容詞型 | 高い |
| A2     | 形容詞-語幹-非自立可能 | 活用語尾-形容詞型 | 欲しい |
| A3     | 形容詞-語幹-非自立可能 | ねえ |
| S1     | 接続辞-動詞の語幹 | 活用語尾-動詞型 | (欲)ぶる |
| S2     | 接続辞-形容詞の語幹 | 活用語尾-形容詞型 | ぱぼい |
| AV1    | 助動詞 | 活用語尾-動詞型 | させる |
| AV2    | 助動詞 | 活用語尾-形容詞型 | (行かない) |
| AV3    | 助動詞 | だろう |

A SUW-SC POS Tags

Table 4 shows the SUW-SC POS tags that differ from the SUW POS tags. Characters in “|” indicate the preceding context and the symbol “|” presents a word boundary.

B Details for the Evaluated Systems

We used the default hyperparameters of KyTea. We used similar model architectures, hyperparameters, and training settings to Higashiyama et al. (2020) for BiLSTM, BiLSTM-LF, and BiLSTM-LWP, except we introduced an additional multi-layer perceptron with one hidden layer (300 hidden units) for POS tagging for each model. We used Tian et al. (2020)'s code for BERT and BERT-WM models with their hyperparameters and training settings for the MSR data, except we used softmax inference similarly to BiLSTM-based models and decreased the mini-batch size to 4 or 8 because of the memory limitation. The BERT model predicted joint segmentation and POS tags, such as B-名詞 (noun), using a single inference layer.

C POS Proportions of Unknown Tokens

Figure 1 shows the proportions of POS tags of unknown tokens for each domain in the JCMS SUW data. Nouns accounted for 95–99% of all unknown tokens for the SCI (AGR to PAT) domains, whereas non-noun tokens, such as verbs and symbols, accounted for 15–60% for the GOV and OTH domains.

D Performance of domain-specific models

The VRS data consisted of Japanese verse sentences written in historical literary styles. The EMR data consisted of medical history summaries of imaginary patients. We additionally evaluated two domain-specific models for the VRS and EMR domains of the SUW data. One is the off-the-shelf MeCab model with the morphological analysis dictionary for historical literary style text: “UniDic-202203_65_novel” $D_h$ (Ogiso et al., 2013). The other is a BiLSTM-LWP model trained with medical domain-specific lexicon $D_m$ and unlabeled data $U_m$, which we describe later. As shown in Table 5, the improved performance of the MeCab model on the VRS domain indicates the alleviation of domain mismatch. The BiLSTM-LWP model adapted for the EMR domain achieved 1.2–1.3 F1 point improvement for WS and POS tagging over the model adapted for all scientific domains, and achieved competitive scores to BERT.
Table 5: Performance of domain-specific models for the EMR or VRS domain of the SUW data

| Domain | McCab | BiLSTM-LWP |
|--------|-------|------------|
|        | \(D_A\) | \(D_s, D_m, U_m\) | \(D_s, D_m, U_m\) |
| EMR    | 99.1  | 99.1       | 98.9  | 97.7 |
| VRS    | 94.1  | 91.3       | --    | --   |

Table 6: Accuracy of original annotation in the BCCWJ non-core data evaluated on the JCMS SUW data

| Domain | FT | Seg | POS | FPOS | FP |
|--------|----|-----|-----|------|----|
| GOV    | DIE | 98.2 | 98.1 | 97.9 | 544 |
|        | LAW | 98.3 | 98.3 | 98.1 | 501 |
|        | PRM | 98.6 | 98.1 | 96.8 | 637 |
| OTH    | TBK | 99.7 | 99.6 | 99.3 | 100 |
|        | VRS | 95.3 | 92.9 | 91.7 | 1,380 |

Table 7: Performance of the three systems on the JCMS SUW-SC data. BL represents BiLSTM.

| Unknown Dom. Tok/Type Ratio | McCab | BL-LWP | BERT |
|-----------------------------|-------|--------|------|
| Gen                          | Seg    | POS    | FPOS | FP |
| SCI Avg.                     | 98.0   | 97.3   | 98.9 | 98.2 |
| GOV Avg.                     | 98.0   | 97.6   | 97.5 | 97.0 |
| \(D_m\)                      | 99.3   | 99.9   | 95.5 | 99.2 |
| \(D_s\)                      | 99.5   | 99.8   | 99.6 | 99.2 |
| \(D_t\)                      | 98.4   | 98.4   | 99.1 | 98.4 |
| \(D_u\)                      | 99.9   | 98.7   | 99.5 | 99.1 |

Table 8: Accuracy of original annotation in the BCCWJ non-core data evaluated on the JCMS SUW-SC data

The original annotation of the BCCWJ non-core data was performed semi-automatically; hence, the average annotation accuracy was 98%. We re-processed the original annotation of the GOV and OTH domain data as system prediction and evaluated it using the SUW annotated sentences in the JCMS as the gold standard. Table 6 shows the WS and POS tagging (top-level POS as “POS” and full POS as “FPOS”) F1 scores and the numbers of false positives (FP) based on the FPOS errors. All domain data contained annotation errors, which corresponded to 100–1380 FPS; however, the original annotation achieved higher F1 scores than the

Received systems trained and evaluated on the SUW-SC annotation data. For McCab, we applied the conversion rules mentioned in §2.3 to SUW results and obtained SUW-SC results. For BiLSTM-LWP and BERT, we trained new model instances with SUW-SC results. For BiLSTM-LWP and BERT, we trained new model instances with SUW-SC results and obtained SUW-SC results. For BiLSTM-LWP and BERT, we trained new model instances with SUW-SC training data. Similar to the results of the SUW experiments, we observed that system performance tended to decrease as the UTR increased.

E Accuracy of the Original BCCWJ annotation

The original annotation of the BCCWJ non-core data was performed semi-automatically; hence, the average annotation accuracy was 98%. We re-processed the original annotation of the GOV and OTH domain data as system prediction and evaluated it using the SUW annotated sentences in the JCMS as the gold standard. Table 6 shows the WS and POS tagging (top-level POS as “POS” and full POS as “FPOS”) F1 scores and the numbers of false positives (FP) based on the FPOS errors. All domain data contained annotation errors, which corresponded to 100–1380 FPS; however, the original annotation achieved higher F1 scores than the

F Results for the SUW-SC POS Tag Set

Table 7 shows the performance of the three systems trained and evaluated on the SUW-SC annotation data. For McCab, we applied the conversion rules mentioned in §2.3 to SUW results and obtained SUW-SC results. For BiLSTM-LWP and BERT, we trained new model instances with SUW-SC training data. Similar to the results of the SUW experiments, we observed that system performance tended to decrease as the UTR increased.

G Segmentation Examples

Table 8 shows the gold standard annotation and segmentation results of several JCMS sentence fragments output by three systems: McCab, BiLSTM-LWP, and BERT. Incorrect segmentation (including incorrect manual annotation) is highlighted in the gray background. System errors include oversegmentation of Latin characters (a–c), oversegmentation of English loanwords written

21http://www2.medis.or.jp/stdcd/byomei/index.html
22https://dbarchive.biosciencedbc.jp/en/mecab/data-2.html
23https://ja.osdn.net/projects/comedic/
24https://sociocom.naist.jp/manbyou-dic/
25https://sociocom.naist.jp/hyakuyaku-dic/
26https://sociocom.naist.jp/medtxt/
27https://clrd.ninjal.ac.jp/bccwj/doc/manual/BCCWJ_Manual_01.pdf
28The Japanese writing system uses multiple script types, including kanji (e.g., ‘漢字’), hiragana (e.g., ‘ひらがな’), katakana (e.g., ‘カタカナ’), Arabic numerals (e.g., ‘012’ or ‘01 2’), Latin characters (e.g., ‘ABC’ or ‘A B C’), and punctuation and auxiliary symbols.
Table 8: Segmentation results of the JCMS sentence examples using the three systems. Characters in “()” indicate the surrounding context. The meanings of the examples are as follows: (a) ‘NaCl (-type),’ (b) ‘Bluetooth,’ (c) ‘HEV (infection),’ (d) ‘(efficiency of) the subroutine,’ (e) ‘(TCP) throughput,’ (f) ‘chromatography,’ (g) ‘(the relevant) municipal mayors,’ (h) ‘B-meson physics,’ (i) ‘rare earth metal,’ (j) ‘proviso (or),’ (k) ‘stir,’ (l) ‘(duration years of) the disorder,’ (m) ‘(pulse) electrostatic field,’ (n) ‘right lower quadrant pain,’ and (o) ‘both lower extremities.’

| Domain | Gold | McCab | BiLSTM-LWP | BERT |
|--------|------|-------|------------|------|
| (a) PHY | Na Cl (型) | Na | Cl | Na Cl |
| (b) INF | Bluetooth | Blue tooth | Blue tooth | Blue tooth |
| (c) BIO | HEV (の感染) | HE | V | HEV |
| (d) INF | サブルーチン (の効率) | サブルーチン | サブルーチン | サブルーチン |
| (e) INF | (TCP)スループット | スルートプト | スループット | スループット |
| (f) CHE-B | クロマトグラフィー | クロマトグラフィー | クロマトグラフィー | クロマトグラフィー |
| (g) LAW | (関係)市町村長 | 市町村長 | 市町村長 | 市町村長 |
| (h) PHY | (B)中間子 (物理) | 中間子 | 中間子 | 中間子 |
| (i) PHY | 希土類金属 | 希土類金属 | 希土類金属 | 希土類金属 |
| (j) LAW | ただし書 (又は) | ただし書 | ただし書 | ただし書 |
| (k) PHY | 揹はん (する) | 揹はん | 揹はん | 揹はん |
| (l) PHY | り患 (年数) | り患 | り患 | り患 |
| (m) PHY | (パルス)静電場 | 静電場 | 静電場 | 静電場 |
| (n) EMR | 右下腹部痛 | 右下腹部痛 | 右下腹部痛 | 右下腹部痛 |
| (o) EMR | 両下肢 | 両下肢 | 両下肢 | 両下肢 |

with katakana (often into English morphemes) (d–f), incorrect segmentation of kanji sequences (g–i), and incorrect segmentation of hiragana and kanji mixed sequences (j–l). We found words that were correctly segmented by the systems but were evaluated as errors because of the annotation errors (m–o).