JParaCrawl v3.0: A Large-scale English-Japanese Parallel Corpus

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Abstract
Most current machine translation models are mainly trained with parallel corpora, and their translation accuracy largely depends on the quality and quantity of the corpora. Although there are billions of parallel sentences for a few language pairs, effectively dealing with most language pairs is difficult due to a lack of publicly available parallel corpora. This paper creates a large parallel corpus for English-Japanese, a language pair for which only limited resources are available, compared to such resource-rich languages as English-German. It introduces a new web-based English-Japanese parallel corpus named JParaCrawl v3.0. Our new corpus contains more than 21 million unique parallel sentence pairs, which is more than twice as many as the previous JParaCrawl v2.0 corpus. Through experiments, we empirically show how our new corpus boosts the accuracy of machine translation models on various domains. The JParaCrawl v3.0 corpus will eventually be publicly available online for research purposes.

Keywords: parallel corpus, machine translation, English, Japanese

1. Introduction
The current neural machine translation models are generally trained by supervised approaches (Sutskever et al., 2014; Bahdanau et al., 2015; Luong et al., 2015; Vaswani et al., 2017), denoting reliance on parallel corpora. However, since publicly available parallel corpora remain limited, training a model for many language pairs is difficult. Thus, constructing a parallel corpus is crucial for expanding the applicability of machine translation.

This paper introduces a new large-scale web-based parallel corpus for English-Japanese for which only limited parallel corpora are available. One of the current largest parallel corpora for this language pair is JParaCrawl (Morishita et al., 2020), which is constructed by crawling the web and automatically aligning parallel sentences. However, this corpus contains around 10 million sentence pairs, which is still limited compared to the other resource-rich language pairs, and it is somewhat outdated because it was created two years ago. We entirely re-crawled the web to update the corpus and applied a different approach to extract parallel sentences. We collected more than 21 million unique sentence pairs, which is more than twice as many as the previous JParaCrawl corpus. We experimentally show how the new crawled corpus increases the accuracy of machine translation for English-Japanese and Japanese-English. Our new corpus, named JParaCrawl v3.0, will be publicly available through our website for further researches.

Our contributions can be summarized:
• We constructed a large-scale English-Japanese parallel corpus, which contains more than 21 million sentence pairs, on top of the previous JParaCrawl corpus.
• We empirically confirmed that our corpus boosted the accuracy of English-Japanese and Japanese-English machine translation in broad domains.
• We plan to release our new parallel corpus for further researches.

2. Related Work
There are several sources for creating parallel corpora. One typical source is the parallel documents written by international organizations. An example is Europarl (Koehn, 2005), which was created from the proceedings of the European Parliament. Ziemski et al. (2016) compiled the United Nations parallel corpus from the translated documents of the UN. Professional translators usually translate these texts, which sometimes contain such meta-data as document IDs that allow easy alignment of them. Unfortunately, since these parallel documents are not commonly available, these corpora are limited to a few language pairs and narrow domains.

Another critical source is the web. Many websites are written in several languages, and parallel sentences can be extracted from them. Thus the web is a fruitful source for creating a large parallel corpus in many languages and broader domains. In an earlier work, Uszkoreit et al. (2010) created a large-scale distributed system to mine parallel sentences from the web and books. Smith et al. (2013) proposed a method to mine parallel sentences from Common Crawl, a free web crawl archive. Recently, some works created large parallel corpora from Wikipedia or Common

http://www.kecl.ntt.co.jp/icl/lirg/jparacrawl/
Table 1: Number of unique sentence pairs and words on English side in JParaCrawl corpus. In this work, we created version 3.0.

| Version | # sentences | # words |
|---------|-------------|---------|
| v1.0    | 4,817,172   | 125,216,523 |
| v2.0    | 8,809,771   | 234,393,978 |
| v3.0    | 21,481,513  | 502,445,763 |

We ignored the data released before March 2019 because they were already analyzed by the previous JParaCrawl project and focused more on the latest Common Crawl archive. We checked the website lists generated by this procedure and found that 70% were not listed in the previous JParaCrawl (Morishita et al., 2020).

3.2. Crawl the Found Websites

Next we crawled the websites listed in the previous step with Heritrix at most 48 hours for each one. Although the previous JParaCrawl only focused on plain texts, in this work, we also crawled PDF and Microsoft Word documents in addition to plain text to extract more parallel sentences because the Japanese government and companies sometimes release their news on PDFs.

3.3. Extract Parallel Sentences

Next we extracted parallel sentences from the crawled archives with Bitextor provided by the ParaCrawl project. We added Japanese support on Bitextor 8 and used it for this work. For parallel document and sentence alignment, we used a machine translation-based alignment toolkit bleualign. It first translates the Japanese sentences into English with a machine translation system and finds an English-Japanese sentence pair that maximizes the BLEU scores. For the Japanese-English translations, we used a Transformer-based neural machine translation (NMT) model trained with JParaCrawl v2.0. Preliminary experiments found that bleualign outperformed a bilingual lexicon-based method.

3.4. Filter Out Noisy Sentences

As the last step, we filtered out the incorrectly aligned or poorly translated noisy sentence pairs with the Bicleaner toolkit. Then we concatenated the clean parallel sentences and JParaCrawl v2.0 and deduplicated them. From these steps, we created a new large JParaCrawl v3.0 that contains more than 21 million sentences, which is more than twice as many as the previous JParaCrawl v2.0.

Table I shows the number of unique sentence pairs in the previous and the new JParaCrawl v3.0 corpus. Note that this number is different from our previous paper (Morishita et al., 2020), because here we are reporting the number of unique sentence pairs.
4. Experiments

4.1. Experimental Settings

As an experiment, we trained an NMT model with JParaCrawl v3.0 and evaluated its accuracy on various test sets to confirm the effect of our new collected corpus.

4.1.1. Test Sets

To evaluate the NMT models on various domains, we tested our models on the 15 test sets listed in Table 3. We used all the test sets in our previous work (Morishita et al., 2020), which included the Asian Scientific Paper Excerpt Corpus (ASPEC) (Nakazawa et al., 2016), the Japanese-English Subtitle Corpus (JESC) (Pryzant et al., 2017), the Kyoto Free Translation Task (KFTT) (Neubig, 2011), and TED talks (tst2015) (Cettolo et al., 2012). We also evaluated our models on the Business Scene Dialogue Corpus (Rikters et al., 2019) to check whether they worked on conversations. We also added test sets from shared tasks: WMT 2020, 2021 news translation shared tasks (Barrault et al., 2020; Akhtar et al., 2021), WMT 2019, 2020 robustness shared tasks (Li et al., 2019; Specia et al., 2020), and the IWSLT 2021 simultaneous translation task (Anastasopoulos et al., 2021). Although some of the test sets are intended for specific translation directions (e.g., En→Ja), we used them for both En→Ja and Ja→En directions for reference. Some corpora have an in-domain training set, as shown in Table 3. For comparison, we trained our model with these training sets and reported the BLEU scores.

4.1.2. Training Settings

First, we tokenized the corpus into sub-words with the sentencepiece toolkit with a vocabulary size of 32,000 (Kudo and Richardson, 2018). Then...
Common Settings

| Setting                  | Value |
|-------------------------|-------|
| Architecture            | Transformer (Vaswani et al., 2017) |
| Enc-Dec layers          | 6     |
| Optimizer               | Adam ($\beta_1 = 0.9, \beta_2 = 0.98, \epsilon = 1 \times 10^{-8}$) (Kingma and Ba, 2015) |
| Learning rate schedule  | Inverse square root decay |
| Warmup steps            | 4,000 |
| Max learning rate       | 0.001 |
| Dropout                 | 0.3 (Srivastava et al., 2014) |
| Gradient clipping       | 1.0 (Pascanu et al., 2013) |
| Label smoothing $\epsilon_{ls}$ | 0.1 (Szegedy et al., 2016) |
| Mini-batch size         | 512,000 tokens (Ott et al., 2018) |
| Number of updates       | 36,000 steps (v3.0), 24,000 steps (v1.0, v2.0) |
| Averaging               | Save checkpoint for every 100 steps and take an average of last 8 checkpoints |
| Beam size               | 6 with length normalization (Wu et al., 2016) |

Small Settings

| Setting | Value |
|---------|-------|
| Attention heads | 4 |
| Word-embedding dimension | 512 |
| Feed-forward dimension | 1,024 |

Base Settings

| Setting | Value |
|---------|-------|
| Attention heads | 8 |
| Word-embedding dimension | 512 |
| Feed-forward dimension | 2,048 |

Big Settings

| Setting | Value |
|---------|-------|
| Attention heads | 16 |
| Word-embedding dimension | 1,024 |
| Feed-forward dimension | 4,096 |

Table 4: List of hyperparameters

we trained the NMT models with the fairseq toolkit (Ott et al., 2019). Our models are based on Transformer (Vaswani et al., 2017) and trained with three settings: small, base, and large. Table 4 shows the detailed training settings. We used the small model for TED (tst2015), the base model for KFTT, and the big model for the others. Note that these settings are almost the same as our previous work (Morishita et al., 2020) for a fair comparison, except we changed the number of updates for the v3.0 models because the new corpus is too large to converge in 24,000 steps. We evaluated the model with the sacreBLEU toolkit (Post, 2018) and reported the BLEU scores (Papineni et al., 2002). For the evaluations, we NFKC-normalized all the test sets for consistency with our previous experiments (Morishita et al., 2020).

4.2. Experimental Result

Table 5 shows the BLEU scores on various test sets. Our corpus is not designed as a specific domain but as a general one. Thus, unsurprisingly, the JParaCrawl model did not reach the model’s score trained with in-domain data. The model trained with JParaCrawl v3.0 achieved the best score on all the test sets on Japanese-English and 13 of 15 test sets on English-Japanese. These results clearly show that our new parallel corpus increased the accuracy of the NMT models on various domains, including scientific papers, news, and dialogues.

Our v3.0 model worked especially well on the WMT21 news translation tasks. We believe that this is because the previous JParaCrawl v2.0 was based on the web in 2019, and so it might not have included terms frequently used in 2021. For example, news articles in 2021 cited words related to COVID-19, a term that was not obviously less frequently used in 2019. Perhaps we need to continue to update the parallel corpus to reflect the latest terms.

4.3. Translation Example

Figure 1 shows an example translation of JParaCrawl v1.0, v2.0, and v3.0. We chose this example from the WMT21 news translation test set because it is related to COVID-19. This input includes the Japanese phrase “濃厚接触者”, which should have been translated to “close contacts.” But the v1.0 and v2.0 models incorrectly translated the language to “strong contact person.” In contrast, the model trained with v3.0 correctly translated the phrase to “close contacts.” Similar to this example, we identified many improvements in the articles related to COVID-19. These results support our hypothesis that our model trained with the v3.0 corpus correctly translated the terms and language frequently used in recent years.

5. Conclusion

This paper introduced an updated version of the large English-Japanese parallel corpus called JParaCrawl. We re-crawled parallel websites by analyzing the latest CommonCrawl archive and extended the crawl target to PDF and Word documents. After filtering out noisy sentences, the new JParaCrawl v3.0 included more than 21 million unique sentence pairs. We empirically confirmed that the new corpus boosts the translation accuracy on various domains, especially on the trendiest news articles. Our future work will update the JParaCrawl corpus and propose better alignment/filtering techniques. The new JParaCrawl v3.0 will be available on our website for further research. We expect that JParaCrawl v3.0 will support future research and products.

6. Acknowledgements

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| Test set                      | English-to-Japanese | Japanese-to-English |
|------------------------------|---------------------|---------------------|
|                              | In-domain v1.0 v2.0 v3.0 | In-domain v1.0 v2.0 v3.0 |
| ASPEC                        | 44.3 24.7 26.5 26.8 | 28.7 18.3 19.7 20.8 |
| JESC                         | 14.5 6.6 6.5 6.5   | 17.8 7.0 7.5 8.4   |
| KFTT                         | 31.8 17.1 18.9 18.1 | 23.4 13.7 16.2 17.0 |
| TED (tst2015)                | 11.1 11.5 12.6 13.1 | 13.7 11.0 11.9 12.0 |
| Business Scene Dialogue Corpus | — 12.4 13.5 13.9 | — 17.4 19.6 19.9   |
| WMT20 News En-Ja             | — 20.7 21.9 23.5 | — 21.3 23.3 23.9   |
| WMT20 News Ja-En             | — 20.1 22.8 23.5 | — 19.2 21.0 21.9   |
| WMT21 News En-Ja             | — 21.1 21.8 25.0 | — 21.9 23.1 24.3   |
| WMT21 News Ja-En             | — 19.6 21.5 22.4 | — 18.1 20.7 21.3   |
| WMT19 Robustness En-Ja (MTNT2019) | — 12.4 12.5 14.4 | — 15.6 16.8 17.3   |
| WMT19 Robustness Ja-En (MTNT2019) | — 11.5 12.3 12.8 | — 16.0 17.2 17.7   |
| WMT20 Robustness Set1 En-Ja  | — 15.2 15.8 18.7 | — 20.0 20.6 21.6   |
| WMT20 Robustness Set2 En-Ja  | — 12.7 13.0 14.8 | — 16.4 17.4 17.9   |
| WMT20 Robustness Set2 Ja-En  | — 7.9 8.2 8.6   | — 12.0 12.6 14.0   |
| IWSLT21 Simultaneous Translation En-Ja Dev | — 12.5 13.3 14.5 | — 12.9 14.3 14.5   |

Table 5: BLEU scores of models trained with in-domain training set, JParaCrawl v1.0, v2.0, and v3.0. Best scores among JParaCrawl models are highlighted in bold.

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