A Parallel Corpus of Arabic–Japanese News Articles

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Abstract

Much work has been done on machine translation between major language pairs including Arabic–English and English–Japanese thanks to the availability of large-scale parallel corpora with manually verified subsets of parallel sentences. However, there has been little research conducted on the Arabic–Japanese language pair due to its parallel-data scarcity, despite being a good example of interestingly contrasting differences in typology. In this paper, we describe the creation process and statistics of the Arabic–Japanese portion of the TUF Media Corpus, a parallel corpus of translated news articles collected at Tokyo University of Foreign Studies (TUFs). Part of the corpus is manually aligned at the sentence level for development and testing. The corpus is provided in two formats: A document-level parallel corpus in XML format, and a sentence-level parallel corpus in plain text format. We also report the first results of Arabic–Japanese phrase-based machine translation trained on our corpus.

Keywords: Arabic, Japanese, Parallel Corpus, Sentence Alignment, Machine Translation

1. Introduction

Machine translation (MT) has been a very active research area in natural language processing. Whether its paradigm is statistical or neural, the availability of parallel data is essential for building high-quality systems. In particular, manually verified data sets for development and testing are of great importance for improving and evaluating MT systems. Much work has been done on MT between major language pairs including Arabic–English and Japanese–English, thanks to the availability of large-scale parallel corpora across various domains with manually aligned subsets. However, there has been little research conducted on the Arabic–Japanese language pair due to its parallel-data scarcity, despite being a good example of interestingly contrasting differences in typology. For instance, Arabic is a verb-initial language, while Japanese is a verb-final language, where the position of the verb is completely opposite as shown in Figure 1. An Arabic token can be highly ambiguous in morphological, syntactical, and lexical levels due to the absence of optional diacritics for short vowels and consonant doubling. In addition, Arabic has a complex system of derivation, inflection, and cliticization. In contrast, a Japanese token can be highly ambiguous due to the absence of spaces between tokens. For more details in linguistic issues, see Habash (2010) for Arabic and Bond and Baldwin (2016) for Japanese.

In this paper, we present a parallel corpus of Arabic–Japanese news articles, part of which is manually aligned at the sentence level for tuning and evaluation. We also provide the first results of Arabic–Japanese phrase-based MT trained on our corpus.

The corpus represents an ongoing project carried out at Tokyo University of Foreign Studies (TUFs) entitled TUF Media Project, which produces translated news articles in eight languages (Arabic, Bengali, Burmese, Indonesian, Persian, Turkish, Urdu, and Vietnamese). Our corpus serves as a pilot corpus for building parallel corpora of under-resourced language pairs under this project, as well as a basis for investigating various MT techniques for under-resourced language pairs such as pivoting and domain adaptation in future work.

The corpus is provided in two formats: (a) A document-level parallel corpus of 8,652 document pairs with genre annotation in XML, and (b) a sentence-level parallel corpus in plain text format. The sentence-level parallel corpus consists of 64,488 sentence pairs, with approximately 2.4 million Arabic tokens, and 3.7 million Japanese tokens in total. Our corpus is publicly available for research purposes.

Example of Arabic (a) and Japanese (b) text in Figure 1: Example of Arabic (a) and Japanese (b) text in parallel. Note that Arabic is written from right to left, and Japanese is written from left to right. “Women in Gulf countries have shown a strong presence in the recent labour market.”

Throughout this paper, an Arabic token is defined as a simple tokenization unit (DO) (Habash, 2010) as shown in Table 1.

A Japanese token is defined as a unit used in IPAdic (2.7.0) (Asahara and Matsumoto, 2003).

http://www.el.tufs.ac.jp/tufsmedia/
Table 1: Examples of the various tokenization schemes for the raw input. Arabic characters are transliterated in the Habash-Soudi-Buckwalter transliteration scheme ([Habash et al., 2007]). The symbol " + " denotes a space added after tokenization. CONJ and PART refer to conjunctions and particles, respectively.

| Tokenization | Operation                  | Example                        |
|--------------|----------------------------|--------------------------------|
| raw          | no tokenization            | wokykhbA llTAlb.               |
| D0           | split punctuations and numbers | wokykhbA llTAlb.               |
| D1           | split CONJ                 | w+yokykhbA llTAlb.             |
| D2           | split CONJ and PART        | w+s+yokykhbA l+llTAlb.         |
| ATB          | split all clitics except the definite article | w+s+yokykhb+ha l+lTAlb.       |
| D3           | split all clitics          | w+s+yokykhb+ha l+l+AlTAlb.     |
| D3*          | remove the definite article from D3 | w+s+yokykhb+ha l+Al+TAlb.     |

2. TUFS Media Corpus

In this section, we describe the source of our corpus, details of the corpus construction process, and statistics of our corpus.

2.1. Source of the Corpus

TUFS Media Project is an ongoing project carried out at Tokyo University of Foreign Studies to offer translated news from various countries and regions around the world in order to familiarize the Japanese society with the current world events. The initial version of the project was launched in 2005, offering translated articles from three languages: Arabic, Turkish, and Persian. Currently, the project provides translated articles into Japanese from eight languages, Arabic, Bengali, Burmese, Indonesian, Persian, Turkish, Urdu, and Vietnamese.

Translation of an article is done in two steps, initial translation and proofreading. In the initial translation step, a translator, typically an undergraduate student who majors in Arabic, chooses an appropriate article from one of the news agencies in accordance with the person’s interest following the translation guideline. The guideline describes rules regarding the choice of an article to be translated, formatting, and transcription. The translator then translates title, dateline, and paragraphs in the article. The paragraphs can be omitted as long as the text to be translated contains over 200 words in Arabic. In that case, the translator inserts a phrase that denotes omission in the translated article. The translator also assigns a concise title and classifies the article into 12 categories based on the content. In the proofreading step, a proofreader, who is an expert in Arabic or a graduate student with experience studying in the region, proofreads the translated article and publishes it on the project website.

2.2. Corpus Construction

We describe next the process of corpus construction, from data collection to sentence alignment.

2.2.1. Crawling Documents from Project Website

We crawled the project website, which provides a searchable interface for translated articles, specifying the six news agencies and the issue date that ranges from 2005 to 2016. The crawling yielded 9,915 translated articles in HTML format. For Arabic, we collected original articles by crawling the provided links to the original urls and the archived versions in MHTML format. MHTML files were converted to HTML files in order to simplify the succeeding scraping process. The crawling of original articles yielded 9,056 documents in total.

2.2.2. Scraping Crawled Documents

For Japanese, we extracted translated text, category, issue date, and links to the original articles from the documents using HTML tags as clues. The Japanese data are more structured than the Arabic data thanks to the unified HTML architecture and the translation guidelines, however, there are some cases where we could not find corresponding translations for the original title and/or dateline.

The Arabic data are more difficult to process due to their format variations across six different agencies with periodically different templates within agencies. In some cases, we could not extract main texts from the documents due to their structural issues in HTML. In such cases, we simply discarded these documents from our corpus. Paragraph boundaries are kept in both languages.

2.2.3. Text Cleaning and Formatting

We identified and removed any notes translators may have made, in order to keep the parallel texts as comparable as possible. We also deleted documents that are not detected as Arabic contents by a python library langdetect (1.0.7). Finally, we took the intersection of the parallel documents in both languages, yielding 8,652 document pairs. All documents are segmented into sentences by Pragmatic Segmenter (0.3.16), a rule-based sentence splitter. For Arabic, we used full stop, exclamation mark, and question mark for the set of delimiters. For Japanese, we used the default set of delimiters defined in the segmenter. The document-level aligned corpus is available in XML with UTF-8 encodings as shown in Figure 2.

5The decrease in the number of Arabic documents is due to the absence of valid links to the original ones or conversion error from MHTML to HTML.

6https://pypi.python.org/pypi/langdetect/

7https://github.com/diaksz/pragmatic_segmenter/
2.2.4. Manual Sentence Alignment for Evaluation

We manually aligned the latest 900 documents in publication date for evaluation purposes. We divided 900 documents into three divisions for blind-test, dev-test, and dev-tune sets. The divisions are as follows: The latest 400 documents for the blind-test set, the second latest 400 documents for the dev-test set, and the third latest 100 documents for the dev-tune set. We used the InterText tool (Vondrůvčíka, 2014) to create alignment files.

| Arabic-to-Japanese | Sentence Pairs | Percentage |
|--------------------|----------------|------------|
| 1-to-0             | 7,624          | 58.75      |
| 1-to-1             | 2,758          | 21.25      |
| 1-to-many          | 2,328          | 17.94      |
| 0-to-1             | 102            | 0.79       |
| many-to-1          | 83             | 0.64       |
| many-to-many       | 81             | 0.62       |

Table 2: Types of sentence alignment pairs in manually aligned data set of 900 documents.

Table 2 shows the distribution of types of sentence alignment pairs in our manually aligned data set. The possible combinations of sentence alignment pairs are as follows: One sentence in one language corresponds to one sentence in another (1-to-1), one sentence does not have corresponding sentence (1-to-0, 0-to-1), one sentence corresponds to multiple sentences (1-to-many, many-to-1), and multiple sentences correspond to multiple sentences (many-to-many). Three documents were not aligned in the document level due to the modification in the original article after translation.

The large number of 1-to-0 alignments is due to the extra paragraphs in the Arabic side that are not translated into Japanese. Apart from the null alignments (1-to-0, 0-to-1), 1-to-1 alignments account for 52.53%, whereas 1-to-many ones account for 44.34%. This can be attributed to the difference between Arabic and Japanese in punctuation usage and stylistic preference in the translation process.

2.2.5. Automatic Sentence Alignment

We compare three different alignment tools, a python implementation (Jan and Bond, 2014) of the algorithm of Gale and Church (1993), HunAlign (Nagata et al., 2005), and Gargantua (Braume and Fraser, 2010).

Preprocessing We lemmatized both Arabic and Japanese texts before running a sentence aligner. We used the MADAMIRA toolkit (Pasha et al., 2014) for Arabic and McCab (0.996) (Kudo, 2005) with IPAdic for Japanese. We performed NFKC normalization before lemmatizing Japanese tokens.

We deleted untranslated paragraphs in the Arabic side so that the number of paragraphs should be the same in both documents. This process is done only for the documents with an explicit markup that denotes omission in the latter part of a Japanese document. We used paragraph boundaries as a hard delimiter.
HunAlign To employ HunAlign, we use an approach similar to the three-step workflow used in the JRC-Arquis corpus (Steinberger et al., 2016) and DCEP corpus (Haj jaou et al., 2014), which consists of an initial alignment using length similarity, automatic dictionary construction from the initial alignments, and a second alignment using lexical similarity calculated with the constructed dictionary in the second step. Specifically, we first run HunAlign to obtain the initial alignment without dictionary, randomly sample 10,000 sentence pairs from the 1-to-1 segments in the initial alignment, build a dictionary with minimum occurrence score of 2 and minimum association score of 0.2, and finally, re-align all sentences with the constructed dictionary.

Evaluation We evaluate the quality of sentence alignment using the dev-tune set. We measure precision, recall, and $F_1$ scores in the sentence level. Precision is defined as the ratio of the number of correctly aligned pairs divided by the number of predicted pairs. Recall is defined as the ratio of the number of correctly aligned pairs divided by the number of reference pairs. $F_1$ is defined as the harmonic mean of precision and recall.

Results Table 3 shows the performance of the three alignment algorithms. The low $F_1$ score of the Gale and Church (1993) algorithm can be attributed to the distribution of alignment types and the imperfect alignment in the paragraph level. HunAlign and Gargantua outperformed the Gale and Church (1993) algorithm by large and yielded comparable results.

| Alignment Algorithm       | $P$ | $R$ | $F_1$ |
|---------------------------|-----|-----|-------|
| Gale and Church (1993)    | 0.49| 0.45| 0.47  |
| HunAlign                  | 0.74| 0.77| 0.76  |
| Gargantua                 | 0.76| 0.80| 0.78  |

Table 3: Sentence alignment precision ($P$), recall ($R$), and $F_1$ scores on dev-tune set.

2.3. Corpus Statistics

In Table 4, we provide the distribution of the categories in our corpus as determined by translators. Table 4 shows the basic statistics of sentence-level parallel corpus, including manually aligned sentences and automatically aligned sentences using Gargantua. A large difference in the number of tokens can be attributed to the difference in their tokenization schemes. We segment Japanese tokens in a more fine-grained manner than we segment Arabic tokens. In Modern Standard Arabic, an orthographically single token can have up to four syntactically independent clitics around the stem. If we were to impose D3 tokenization on the Arabic, a scheme which separates all clitics, then we would have a unit much more comparable to Japanese tokens. We ran MADAMIRA on our corpus to obtain the number of D3-tokenized tokens, which was approximately 3.4 million. This is much closer to the number of Japanese tokens, 3.7 million.

3. Machine Translation Baselines

In this section, we present the baseline results of phrase-based MT from Arabic to Japanese.

3.1. Experimental Settings

Phrase-based MT Settings We use the Moses toolkit (Koehn et al., 2007) to build a standard phrase-based MT system. Word alignment was extracted by MGIZA++ (Gao and Vogel, 2008) with a maximum phrase size of 8. We use the grow-diag-final-and and msd-bidirectional-fe options for symmetrization and reordering. We train a 5-gram language model on the target side using KenLM (Heafield, 2011). We use MERT (Och, 2003) for decoding weight optimization.

Data and Preprocessing We use the manually aligned data described in Section 2.1 for tuning and testing, and the automatically aligned data using Gargantua described in Section 2.3 for training.

We tokenize Arabic data using the MADAMIRA toolkit (Pasha et al., 2014) with six tokenization schemes (D0, D1, D2, D3, D3*, and ATB) following Zalimov and Habash (2017). Examples of the six tokenization schemes are shown in Table 1.

We normalize Japanese texts using the NFKC normalization and tokenize them using the MeCab morphological analyzer (0.996) (Kudo, 2003) with IPAdic.

We eliminate long sentences with more than 100 words using the script clean-corpus-n.perl before training translation models. Table 2 shows statistics of training data after cleaning.

Evaluation Before evaluating, we de-tokenize the predicted output by deleting spaces between Japanese characters, and then re-tokenize them using MeCab with IPAdic. We calculate automatic evaluation scores for two metrics: BLEU (Papineni et al., 2002) and RIBES (Isozaki et al., 2010). We use the multi-bleu.perl script in the Moses toolkit to compute BLEU scores. We calculate RIBES scores using the RIBES.py (1.03.1).

Table 4: Category distribution of our entire corpus.

| Category         | Documents | Percentage |
|------------------|-----------|------------|
| Politics         | 4,253     | 49.16      |
| International    | 1,854     | 21.43      |
| Society          | 811       | 9.37       |
| Economy          | 608       | 7.03       |
| Column           | 330       | 3.81       |
| Lebanon Issue    | 280       | 3.24       |
| Culture          | 244       | 2.82       |
| Accident         | 194       | 2.24       |
| Sports           | 48        | 0.55       |
| Others           | 15        | 0.17       |
| Nuclear Issue    | 10        | 0.12       |
| Book Introduction| 5         | 0.06       |
| Total            | 8,652     | 100.00     |
Table 5: The basic statistics of our parallel corpus. Sentences in the training set are aligned using Gargantua.

| Documents | Sentences | Tokens (ar) | Tokens (ja) |
|-----------|-----------|-------------|-------------|
| dev-tune  | 100       | 621         | 23,312      | 36,595      |
| dev-test  | 400       | 2,393       | 92,760      | 147,536     |
| blind-test| 400       | 2,236       | 85,940      | 144,358     |
| train     | 7,752     | 59,238      | 2,175,438   | 3,403,244   |
| Total     | 8,652     | 64,488      | 2,377,460   | 3,731,733   |

Table 6: The statistics of cleaned corpus for training translation models.

| Tokenization | Sentences | Tokens (ar) | Tokens (ja) |
|--------------|-----------|-------------|-------------|
| D0           | 54,223    | 1,811,540   | 2,792,333   |
| D1           | 54,123    | 1,939,953   | 2,785,051   |
| D2           | 54,029    | 2,027,916   | 2,778,315   |
| ATB          | 53,933    | 2,107,024   | 2,771,255   |
| D3           | 53,164    | 2,467,747   | 2,715,485   |
| D3*          | 53,933    | 2,107,024   | 2,771,255   |

Table 7: BLEU and RIBES scores of Arabic–Japanese PBMT systems with different tokenization schemes in the source side.

| Tokenization | dev-test | blind-test |
|--------------|----------|------------|
| D0           | 10.78    | 56.61      | 8.76       | 55.71 |
| D1           | 10.70    | 56.90      | 8.83       | 55.63 |
| D2           | 11.13    | 56.94      | 9.34       | 56.08 |
| ATB          | 11.29    | 57.54      | 9.24       | 56.41 |
| D3           | 10.53    | 56.80      | 8.56       | 55.77 |
| D3*          | 11.48    | 57.86      | 9.38       | 56.63 |

4. Related Work

Much work has been done on building multilingual parallel corpora which include the language pair of Arabic and Japanese. Table 8 summarizes the statistics of publicly available parallel corpora of this language pair. Lienson and Tiedemann (2016) presents the largest corpus, in which they collected movie and TV subtitles from OpenSubtitles. Cettolo and Girardi (2012) constructed a parallel corpus that consists of transcribed and translated TED talks. Abdelali et al. (2014) developed the AMARA corpus that includes subtitles of educational video lectures on Massive Online Open Courses (MOOCs). Christodouloupolous and Steedman (2013) presents a collection of Bible translations across 100 languages. Tiedemann (2012) provides a collection of Quran translations (Tanzil), localization files of technical manuals (GNOME, Ubuntu, and KDE4), as well as the collections of translations in the news domain (Global Voices, Tatoeba, News-Commentary 11). Prokopidis et al. (2016) constructed parallel corpora from Global Voices similar to Tiedemann (2012).

Compared to the domains such as subtitles, religious texts, and technical manuals, the amount of data in the news domain is very limited. Our corpus aims to supplement the lack of parallel data in this domain by constructing a parallel corpus with over 64,000 sentences (2.4 million Arabic tokens and 3.7 million Japanese tokens), including manually aligned sentence pairs for development and evaluation.

5. Conclusion and Future Work

We presented a parallel corpus of Arabic–Japanese news articles comprising 8,652 document pairs. Part of the corpus is manually aligned at the sentence level for development and testing. The corpus is provided in two formats: (a) A document-level parallel corpus with genre annotation in XML, and (b) a sentence-level parallel corpus in plain text format. The sentence-level parallel corpus comprises 64,488 sentence pairs with approximately 2.4 million Arabic tokens and 3.7 million Japanese tokens. We also reported the first results of Arabic–Japanese phrase-based MT trained on our corpus.

As future work, we will explore sentence alignment methods to improve the quality of our corpus. We also plan to explore MT techniques for under-resourced language pairs such as pivoting, and domain adaptation from better resourced domains.

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Table 8: Statistics of publicly available parallel corpora of Arabic and Japanese.

| Corpus                              | Sentences | Tokens (ar) | Tokens (ja) | Domain       |
|-------------------------------------|-----------|-------------|-------------|--------------|
| OpenSubtitles2018 (Lison and Tiedemann, 2016) | 1,834,940 | 11,615,534  | 13,319,298  | Subtitle     |
| TED (Cettolo and Girardi, 2012)      | 205,734   | 1,426,132   | 1,857,188   | Subtitle     |
| AMARA (Abdelali et al., 2014)        | 46,457    | 334,890     | 486,229     | Subtitle     |
| Bible (Christodouloupoulos and Steedman, 2015) | 31,067    | 473,002     | 1,107,641   | Religious    |
| Tanzil (Tiedemann, 2012)             | 12,471    | 526,469     | 526,913     | Religious    |
| KDE4 (Tiedemann, 2012)               | 100,967   | 552,178     | 931,438     | Technical Manual |
| Ubuntu (Tiedemann, 2012)             | 740       | 4,152       | 6,272       | Technical Manual |
| GNOME (Tiedemann, 2012)              | 450       | 1,247       | 1,381       | Technical Manual |
| Global Voices (Tiedemann, 2012)      | 4,929     | 85,961      | 121,234     | News         |
| Global Voices (Prokopidis et al., 2013) | 7,211     | 127,737     | 200,215     | News         |
| Tatoeba (Tiedemann, 2012)            | 1,134     | 6,039       | 10,947      | News         |
| News-Commentary11 (Tiedemann, 2012)  | 569       | 39,937      | 52,085      | News         |
| Our Corpus                          | 64,488    | 2,377,460   | 3,731,733   | News         |

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