Bilingual Text Extraction as Reading Comprehension

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Abstract
In this paper, we propose a method to extract bilingual texts automatically from noisy parallel corpora by framing the problem as a token-level span prediction, such as SQuAD-style Reading Comprehension. To extract a span of the target document that is a translation of a given source sentence (span), we use either QANet or multilingual BERT. QANet can be trained for a specific parallel corpus from scratch, while multilingual BERT can utilize pre-trained multilingual representations. For the span prediction method using QANet, we introduce a total optimization method using integer linear programming to achieve consistency in the predicted parallel spans. We conduct a parallel sentence extraction experiment using simulated noisy parallel corpora with two language pairs (En-Fr and En-Ja) and find that the proposed method using QANet achieves significantly better accuracy than a baseline method using two bi-directional RNN encoders, particularly for distant language pairs (En-Ja). We also conduct a sentence alignment experiment using En-Ja newspaper articles and find that the proposed method using multilingual BERT achieves significantly better accuracy than a baseline method using a bilingual dictionary and dynamic programming.

1 Introduction
Bilingual text extraction is the task of automatically extracting parallel sentences of two languages from noisy parallel corpora. Both the quantity and the quality of the bilingual texts used for training are crucial for developing an accurate machine translation system.

In this paper, we frame bilingual text extraction as a cross-language span prediction problem similar to the SQuAD-style reading comprehension task [Rajpurkar et al., 2016]. Figure 1 shows an example. In SQuAD, given context C (a paragraph from Wikipedia) and a question Q, the reading comprehension system predicts an answer A as a span in the context. Similarly, in bilingual text extraction, given a target text as the context and a source span as a question, the bilingual text extraction system predicts a translation of the source text as the answer, which is a span in the target text.

Recently, bilingual text extraction methods using neural networks have gained popularity [Grêgoire and Langlais, 2018; Artetxe and Schwenk, 2019; Yang et al., 2019; Thompson and Koehn, 2019]. These systems have two sentence encoders to obtain source and target sentence embeddings and a scoring function to predict whether the two sentences are parallel. Such approaches can be classified into two categories: whether the two sentence embeddings are mapped into a shared vector space [Artetxe and Schwenk, 2019; Yang et al., 2019] or they are not [Grêgoire and Langlais, 2018]. The former type uses cosine similarity with margin-based extensions for the scoring function to solve the global inconsistency problem, while the latter uses a feed-forward neural network for binary decisions (parallel or not). These approaches can also be classified by the type of encoder used, such as a bi-directional Recurrent Neural Network [Grêgoire and Langlais, 2018], a Long-Short Term Memory network [Artetxe and Schwenk, 2019], a Deep Averaging Network [Yang et al., 2019], or multilingual BERT [Yang et al., 2019].

Dual encoder approaches have also been used for reading comprehension (question answering) [Seo et al., 2017; Yu et al., 2018; Devlin et al., 2019]. As for the encoder, BiDAF [Seo et al., 2017] uses LSTM, while QANet [Yu et al., 2018] uses a combination of CNN and self-attention.

In meteorology, precipitation is any product of the condensation of atmospheric water vapour that falls under gravity. The main forms of precipitation include drizzle, rain, sleet, snow, graupel and hail...

Q. What causes precipitation to fall?
A. gravity

I said, “Would you go to governments and lobby and use the system?” He said, “No, I’d take to the individuals.” It’s all about the individuals. It’s all about you and me. It’s all about partnerships...

Q. 全ては個人についてのことであり
A. It’s all about the individuals.

Figure 1: Sample data of SQuAD dataset (upper) and the task of extraction from parallel corpora (lower).
attention, which is virtually equivalent to the Transformer [Vaswani et al., 2017]. One of the architectural differences between previous bilingual text extraction and reading comprehension is that the latter adopts bidirectional cross attention (context-to-query attention and query-to-context attention), which is effective for capturing monolingual word-to-word interaction between context and query.

We propose a novel bilingual sentence alignment method based on the cross-language span prediction using reading comprehension techniques. It essentially means that we use bidirectional cross attention between context (target document) and query (source sentence). We first used QANet [Yu et al., 2018] because it is a Transformer-based dual encoder with cross attention, which is more powerful than a bidirectional RNN-based dual encoder [Grégoire and Langlais, 2018]. We then used multilingual BERT [Devlin et al., 2019] because it is also a Transformer-based encoder and its self-attention effectively includes cross attention between source and target sentences when they are concatenated as its input. Moreover, it can take full advantage of its powerful pre-trained multilingual representations.

Since this span prediction method independently predicts target spans for each source span, the target spans could have overlaps. Moreover, because this method is asymmetric, the source-to-target predictions could differ from the target-to-source predictions. For the method using QANet, we used an optimization method based on Integer Linear Programming, which is a simplified version of a previous work [Nishino et al., 2016]. For the method using multilingual BERT, we simply averaged prediction probabilities from both directions.

We conducted two experiments to evaluate the proposed methods: parallel sentence extraction from simulated noisy parallel corpora (En-Fr and En-Ja) and sentence alignment for real newspaper articles (En-Ja). We used a method using bi-directional RNN encoder [Grégoire and Langlais, 2018] as a baseline for parallel sentence extraction because it can be trained for a specific parallel corpus from scratch. We found that the proposed method using QANet achieves significantly better accuracy than the baseline, particularly for distant language pairs (En-Ja). We used a method using a bilingual dictionary and dynamic programming [Utiyama and Isahara, 2003] as a baseline for sentence alignment because it is commonly used for building publicly available English-Japanese parallel corpora, including the shared task data for NTCIR Patent Translation1 and WAT (Workshop on Asian Translation)2. We found that the proposed method using multilingual BERT achieves significantly better accuracy than the baseline and the method using QANet.

2 Proposed Method

2.1 Cross-Language Span Prediction by QANet

The cross-language span prediction task is defined as follows: Suppose we have a source document with N tokens \( F = \{f_1, f_2, \ldots, f_N\} \), and a target document with M tokens \( E = \{e_1, e_2, \ldots, e_M\} \). Given a source text \( Q = \{f_i, f_{i+1}, \ldots, f_j\} \) that spans \((i, j)\) in the source document \( F \), the task is to extract target text \( R = \{e_k, e_{k+1}, \ldots, e_l\} \) that spans \((k, l)\) in the target document \( E \).

We first applied QANet [Yu et al., 2018] to this task although it is designed for reading comprehension, which is a monolingual span prediction task. To solve the span prediction task, QANet chooses a span \((k, l)\) of target text \( R \) corresponding to the source text \( Q \) in the target document \( E \) through the following five layers: Input Embedding, Embedding Encoder, Context-Query Attention, Model Encoder and Output Layers.

The embedding encoder layer is a stack of the block composed of depthwise separable convolutions [Kaiser et al., 2017], self-attention with a multi-head attention mechanism [Vaswani et al., 2017], and a feed-forward layer. The context-query attention layer calculates context-to-query and query-to-context attentions from \( Q \) and \( E \) to obtain weighted token vectors of \( Q \) and \( E \) by considering each other’s information. The output layer predicts the probability of each position \( p_1 \) and \( p_2 \) in the target document becoming the start or end of an output span. The score of a span \( \omega \) is defined as the product of its start and end position probabilities.

The best span \((k, l)\) is chosen by maximizing the conditional probability, as follows:

\[
\omega_{ijkl} = p_1(k|E, Q) \cdot p_2(l|E, Q),
\]

\[
(k, l) = \arg \max_{(k,l):1 \leq k \leq l \leq M} \omega_{ijkl}.
\]

Furthermore, we need to determine whether the target text corresponding to the source text exists since actual noisy parallel corpora contain non-parallel sentences as noise. For such a case, we add an artificial token \(<NA>\) at the beginning of the target document, and if the model extracts only this token, we assume that the corresponding target text does not exist.

We used a publicly available implementation of QANet [Yu et al., 2018] but made two important changes: First, we applied Byte Pair Encoding [Sennrich et al., 2016; Kudo and Richardson, 2018] after tokenization to decrease out-of-vocabulary words. Source and target vocabulary are shared, and the size of the shared vocabulary is set to 36,000. Secondly, we initialize the word (sub-word) embeddings with uniform random values, while the original QANet used pre-trained Glove word embeddings [Pennington et al., 2014] and converted all unknown words into \(<UNK>\) tokens. In our preliminary experiment, we found that the accuracy of the proposed model could be improved by about 10% using subword tokenization.

2.2 Optimization of Predicted Spans by ILP

We define a score \( \omega_{ijkl} \) for the target span \((k, l)\) given source span \((i, j)\), which is obtained from the proposed model. By exchanging the source text and the target text in the model, we also define a score \( \omega_{ijkl} \) for the same span pairs. Since the proposed model predicts a target span independently for the given source span, there might be some overlap between predicted target spans, even if the given source spans do not have
overlap. Moreover, because the proposed model is asymmetric, the predictions from the source text are very likely to be different from those from the target text. We need a total optimization method that can prevent spans from overlapping and maximize the sum of predicted scores in both unidirectional and bidirectional cases.

For total optimization of sentence alignment, dynamic programming [Gale and Church, 1993] is commonly used although it assumes monotonic alignment between the source and target sentences. We use a simplified version of a previous method [Nishino et al., 2016] because it can handle non-monotonic alignment and null alignment of continuous segments using integer linear programming (ILP). We formalize this problem as predicting a corresponding target span for a given source span using a neural network and finding a maximally non-overlapping pair of spans using ILP.

Let $d_{ijkl}$ be a pair of span $(i, j)$ in source text $F$ and span $(k, l)$ in target text $E$, and let $P$ be the set of all possible pairs $d_{ijkl}$. We can define a bilingual alignment $D$ for a document pair as a subset of span pairs $P$ ($D \subseteq P$), where there is no overlap for any two span pairs in $D$. The ILP formalization is as follows:

$$\text{Maximum } \sum_{ijkl} \Omega_{ijkl} y_{ijkl}$$

Subject to

$$y_{ijkl} \in \{0, 1\}$$

$$\sum_{i\leq x \leq j} y_{ijkl} \leq 1 \quad \forall x \colon 1 \leq x \leq N$$

$$\sum_{i, j} \sum_{k \leq x \leq l} y_{ijkl} \leq 1 \quad \forall x \colon 1 \leq x \leq M$$

where $\Omega_{ijkl}$ is a score obtained from $\omega_{ijkl}$ and $\omega'_{ijkl}$. $y_{ijkl}$ is a variable used to indicate whether the span pair $d_{ijkl}$ is included in the alignment with $y_{ijkl} = 1$ showing that it is included. Equation (5) guarantees that for each token in source text $F$, there is at most one span pair $d_{ijkl}$ in the alignment that includes the source token. Equation (6) guarantees the same constraints for the target text $E$. By combining the above two constraints, each token in $E$ and $F$ is guaranteed to be included at most once in the alignment. We defined $\Omega_{ijkl}$ as follows:

$$\Omega_{ijkl} = c\omega_{ijkl} + c'\omega'_{ijkl}.$$  

where $c$ and $c'$ are hyperparameters used to define the relative importance of the source-to-target and target-to-source scores. By setting $c = 1$, $c' = 0$ or $c = 0$, $c' = 1$, the optimization becomes unidirectional; by setting them to a positive value other than 0, it becomes bidirectional. In the experiment, we set $c$ to 1 and $c'$ to the quotient of $\max(\omega_{ijkl})$ divided by $\max(\omega'_{ijkl})$.

Since the references manually created for sentence alignment are based on sentence boundaries, we searched for the nearest sentence boundaries from the predicted span and regarded them as sentence-level prediction. Furthermore, because the sentence-level units obtained in this way may have more than one score, we filtered out the spans whose score was less than $10^{-6}$ and took the average score of the remaining spans for optimization. We used ILOG CPLEX as a solver for ILP.

### 2.3 Cross-Language Span Prediction by BERT

We then applied multilingual BERT [Devlin et al., 2019] for the cross-language span prediction. Although it is designed for such monolingual language understanding tasks as question answering and natural language inference, it works surprisingly well for the cross-language span prediction task.

Since there are many null alignments in the sentence alignment of comparable corpora, we adopted the SQuAD v2.0 format [Rajpurkar et al., 2018], which supports cases where there are no answer spans to the question in the given context. We used the SQuAD v2.0 model [Devlin et al., 2019], which adds two independent output layers to pre-trained (multilingual) BERT to predict the start and end positions in the context. In the SQuAD model of BERT, first, the question and the context are concatenated to generate a sequence “[CLS] question [SEP] context [SEP]” as input, where ‘[CLS]’ and ‘[SEP]’ are classification token and separator token, respectively. Then, the start and end positions are predicted as indexes to the sequence. In the SQuAD v2.0 model, the start and end positions are the indexes to the [CLS] token if there are no answers. Since the original implementation of the BERT SQuAD model only outputs an answer string, we modified it to output the answer’s start and end positions.

As for symmetrization (and optimization), we average the probabilities of the best spans for each sentence in each direction. We treat a sentence as aligned if it is completely included in the predicted span. We then extract the alignments with the average probabilities that exceed a threshold $\theta$. We set the threshold to 0.4 from the results of preliminary experiments. Although the span prediction of each direction is made independently, we did not normalize the scores before averaging because both directions are trained in a single model.

As for null alignments, Devlin et al. [2019] used the following threshold for the squad-2.0 model,

$$s_{ij} > s_{null} + \tau$$

Here, if the difference between the score of the best non-null span $s_{ij}$ and that of a null (no-answer) span $s_{null}$ exceeds threshold $\tau$, a non-null span is predicted. The default value of $\tau = 0.0$, and its optimal threshold is decided using the development set. We used the default value because we assumed the score of a null alignment is appropriately estimated since there are many null alignments in the training data.

### 3 Experiments on Noisy Parallel Corpora

#### 3.1 Baseline method

To show the effectiveness of the proposed approach, we first conducted experiments on parallel sentence extraction. To evaluate the performance of cross-language span projection using QANet without total optimization, We extracted 1-to-1 bilingual texts from simulated noisy parallel corpora and compared the results with those of an earlier work [Grégoire and Langlais, 2018] for a similar language pair (En–Fr) and a distant language pair (En–Ja).

Grégoire and Langlais [2018] first encode both source and target sentences into two fixed-size continuous vectors using two bidirectional RNNs (BiRNN). From these sentence
representations in a shared vector space, they then estimated the conditional probability that these sentences are parallel by applying a feed-forward neural network. For the training dataset, they used parallel sentence pairs in parallel corpora as positive examples. For negative examples, they used negative sampling through sampling \( m \) non-parallel sentences for every positive sentence.

### 3.2 Dataset

We used three parallel corpora composed of different language pairs: Europarl En-Fr\(^3\), KFTT\(^4\), and IWSLT17 En-Ja dataset\(^5\). For the Europarl dataset, we randomly chose 500,000 sentences for the training set. Table 1 shows their detailed statistics.

We created a dataset that has the same format as SQuAD v1.1 with parallel corpus \( P = \{(p^X_k, p^Y_k)\}_{k=1}^K \), where \( X \) and \( Y \) are arbitrary languages. To create the \( k \)-th data, we used a source sentence \( p^X_k \) as a query and a target sentence \( p^Y_k \) as an answer. To generate context, we used negative sampling to insert \( u \) negative sentences in front of and \( (U - u) \) negative sentences behind the output, where \( U \) is the number of negative examples, and \( u \) is a random number from 0 to \( U \). On Europarl and KFTT, the negative examples were sampled randomly. On IWSLT17, we used sentences in front of and behind the answer in the original document to keep the context information. By keeping this information, sentences that are not parallel but similar to the query tend to appear in documents. As a result, the problem with context is more difficult than that without context.

### 3.3 Implementation Details

We used a QANet model for SQuAD v1.1, which is implemented by PyTorch\(^6\). All datasets were tokenized with SentencePiece\(^7\). We inserted nine negative sentences and filtered out from the training set the queries and answers whose number of tokens was more than 100 tokens and the context was more than 1,000 tokens. The vocabularies are shared between language pairs, and their total size is set to 36,000.

Adam [Kingma and Ba, 2015] was used for optimization, where the minibatch size is 12. We used a learning rate warm-up plan with the inverse exponential increasing to 0.001 during the first 1,000 steps. The dropout probability was set to 0.1, the gradient clipping was set to 5.0, and the coefficient value of weight decay was set to \( 5 \times 10^{-8} \). Then, we chose the best parameter with the smallest validation loss during 20 epochs.

As the baseline model, we used an implementation provided by its authors\(^8\). To generate negative examples, English and French sentences were tokenized by the Moses tokenizer\(^9\) and the Japanese sentences were tokenized by KyTea\(^10\). Based on the original paper, the number of negative examples was set to six, the noise ratio was set to 0%, and the threshold \( \rho \) was set to 0.99. In the test set, the model first calculated the similarity between the sentences of each document and the input sentence, and then extracted sentences whose similarity was greater than or equal to a decision threshold \( \rho \).

For evaluation metrics, we used the token-level \( F_1 \) score and Exact Match (EM) on the test sets. The \( F_1 \) score was calculated against the tokens of correct parallel sentence (span) pairs and predicted parallel sentence (span) pairs. EM is defined as the accuracy of how many predicted parallel sentences are exactly the same as the correct parallel sentences.

### 3.4 Results

The experimental results in Table 2 shows that our method using QANet is substantially better than the baseline for all settings. It resulted in a higher \( F_1 \) score and EM than did the baseline for both a similar language pair (En-Fr) with Europarl and a distant language pair (En-Ja) with KFTT, even though it predicts a span (sentence boundaries) by itself while the baseline uses given sentence boundaries. In a more difficult setting with IWSLT17, whose documents contain contextual information, our method achieved remarkable improvements of +34.64 points in \( F_1 \) score and +31.13 points in EM, compared with the baseline.

### 4 Experiments on Comparable News Articles

#### 4.1 Baseline method

In the second experiment, we conducted a sentence alignment on actual En-Ja newspaper articles. Since newspaper articles contain many-to-many alignments and null alignments (sentences with no translations), the problem is substantially more complicated than the one described in the previous subsection.

We used the method of a previous work [Utiyama and Isahara, 2003] as a baseline. To obtain article alignment, they first translated each Japanese article into a set of English words using a bilingual dictionary. Then they used each English article as query and searched for the most similar Japanese article in terms of BM25 [Robertson and Walker, 1994]. They then aligned sentences in the aligned articles using DP matching [Gale and Church, 1993; Utsuro et al., 1994] based on the similarity measure SIM, which is defined as the relative frequency of one-to-one correspondence between Japanese and English words obtained from a bilingual dictionary. As a reliable measure for article

| Corpus   | Lang. | Number of Sentences | Train  | Valid. | Test  |
|----------|-------|----------------------|--------|--------|-------|
| Europarl | En-Fr | 500,000              | 1,000  | 1,000  |
| KFTT     | En-Ja | 440,288              | 1,166  | 1,160  |
| IWSLT17  | En-Ja | 218,174              | 2,577  | 2,357  |

Table 1: Number of sentences for each corpus used in experiments.
alignment, they used AVSIM, the average of SIMs obtained from the sentence pairs in the article pair. As a reliable measure for sentence alignment, they used the product of article similarity AVSIM and the sentence similarity SIM.

### 4.2 Dataset

We used a collection of newspaper articles and editorials from the Yomiuri Shimbun and their translations published in The Japan News (formerly the Daily Yomiuri), which is the newspaper’s English edition. We purchased the newspaper’s CD-ROMS for research purpose\(^\text{11}\), and created the manually and automatically aligned dataset as follows.

The manually aligned dataset consists of 157 bilingual document pairs obtained by manually searching through 182 English documents for the corresponding Japanese documents during two one-week periods (2013/02/01-2013/02/07 and 2013/08/01-2013/08/07). It consists of 131 articles and 26 editorials. We manually aligned sentences for the 157 document-pairs and obtained 2243 many-to-many alignments\(^\text{12}\).

Among the manually aligned data, we used the first 100 articles for the training set, the next 15 articles for the test set, and the remaining 16 articles as a future reserve. We also used the automatically aligned data obtained using our implementation of the previous method [Utiiyama and Isahara, 2003] as training data, because the number of manually aligned documents and sentences is too small.

For QANet, we used automatically aligned editorials as training data because we found that the editorial pairs were highly accurate sentence-by-sentence translations of each other. It is probably because they represented the official opinions of the newspaper company. From 19,113 Japanese editorials and 11,434 English editorials from 1989 to 2016, we automatically extracted 11,414 bilingual documents and obtained 299,178 many-to-many alignments. We used all automatically aligned editorials (except those used for the development set) and the first 100 articles and all 26 editorials in the manually aligned dataset for the training set, and we used the final 50 editorials in the automatically aligned data for the development set.

For multilingual BERT, we used all articles and editorials in 2012. It consists of 24,293 Japanese documents and 4,878 English documents. We automatically obtained 663 editorial pairs and 2,989 article pairs, and then extracted 16,409 and 40,373 many-to-many alignments, respectively. Articles contain a fair amount of non-parallel sentences because some English articles are abstracts of Japanese articles and sometimes additional explanations are added to the English articles for readers who are not familiar with Japan and Japanese culture. Since the SQuAD v2.0 model of multilingual BERT explicitly models null alignments, we assumed it is better to use articles for training the model.

For the QANet model, we treat the manually aligned data and automatically aligned data equally. We used an entire document as context and removed alignments in the context having non-continuous spans. We made negative examples to learn null alignments as follows: For editorials, we sampled random sentences that are not included in the context as negative examples. For articles, we sampled sentences with no alignment relations as negative examples. Negative examples selected for editorials amounted to as much as 10% of the total sentences.

For the SQuAD v2.0 model of multilingual BERT, we first used the automatically aligned data for fine-tuning of 5 epochs. We then used the manually aligned data for fine-tuning of another 5 epochs. We also removed alignments with non-continuous spans from the training data.

### 4.3 Implementation Details

We used BERT-Base, Multilingual Cased (104 languages, 12-layer, 768-hidden, 12-heads, 110M parameters, November 23, 2018) in our experiments\(^\text{13}\). We used the script for SQuAD v2.0 as is. The parameters are as follows: train batch size is 6, learning rate is 3e-5, number of training epochs is 5, maximum sequence length is 384, maximum query length

### Table 2: Experimental results with noisy parallel corpora. Direction indicates which language is a query and which is the answer.

| Corpus   | Model       | Direction | \(F_1\) score | Exact Match |
|----------|-------------|-----------|---------------|-------------|
| Europarl | [Grégoire and Langlais, 2018] | En-Fr     | 94.56         | 94.50       |
|          |             | Fr-En     | 94.60         | 94.60       |
|          | QANet       | En-Fr     | 98.57 (+4.01) | 97.67 (+3.17) |
|          |             | Fr-En     | 98.35 (+3.75) | 98.17 (+3.57) |
| KFTT     | [Grégoire and Langlais, 2018] | En-Ja     | 81.84         | 81.38       |
|          |             | Ja-En     | 81.52         | 80.78       |
|          | QANet       | En-Ja     | 98.06 (+16.22) | 96.25 (+14.87) |
|          |             | Ja-En     | 97.43 (+15.91) | 92.23 (+11.45) |
| IWSLT17  | [Grégoire and Langlais, 2018] | En-Ja     | 62.73         | 62.70       |
|          |             | Ja-En     | 62.35         | 62.31       |
|          | QANet       | En-Ja     | 95.58 (+32.85) | 86.50 (+23.80) |
|          |             | Ja-En     | 96.99 (+34.64) | 93.44 (+31.13) |

\(^{11}\)https://database.yomiuri.co.jp/about/glossary

\(^{12}\)We will make these annotations (both document alignment and sentence alignment) publicly available after our paper is published

\(^{13}\)https://github.com/google-research/bert
Table 3: Experimental results using actual newspaper articles. Bold indicates the highest value for QANet and BERT.

| Model                               | Precision | Recall | $F_1$ |
|-------------------------------------|-----------|--------|-------|
| [Utiyama and Isahara, 2003]         | 54.1      | 50.0   | 51.9  |
| QANet (Ja-En)                       | 56.3      | 67.3   | 61.3  |
| QANet (En-Ja)                       | 57.2      | 67.3   | 61.8  |
| QANet (Ja-En) + ILP                 | 72.5      | 65.8   | 69.0  |
| QANet (En-Ja) + ILP                 | 64.8      | 59.6   | 62.1  |
| QANet (Bidi) + ILP                  | 67.3      | 67.3   | 67.3  |
| BERT (Ja-En)                        | 83.5      | 70.6   | 76.5  |
| BERT (En-Ja)                        | 86.0      | 69.9   | 77.1  |
| BERT (Bidi)                         | 86.4      | 74.6   | 80.1  |

The evaluation was done based on the number of sentences extracted by the alignment methods. We used Precision/Recall/$F_1$ score as the evaluation measure for sentence alignment.

### 4.4 Results

Table 3 shows the results. Our method using QANet and bidirectional ILP optimization is significantly better (15.4 $F_1$ points) than the baseline. Our method using multilingual BERT and symmetrization is significantly better (12.8 $F_1$ points) than that using QANet.

Japanese-to-English and English-to-Japanese predictions have about the same accuracies for both QANet and multilingual BERT. ILP optimization improves precision at the cost of recall. For QANet, we think bidirectional ILP optimization is better in terms of the balance between precision and recall although the $F_1$ of Ja-En uni-directional ILP optimization is higher. In multilingual BERT, a simple combination (symmetrization) of two directional predictions improves both precision and recall, which results in 3 $F_1$ points improvement.

### 5 Related Works

Previous methods for sentence alignment are based on context-independent similarity of source and target sentences such as sentence length [Gale and Church, 1993], bilingual dictionaries [Utsuro et al., 1994; Utiyama and Isahara, 2003; Varga et al., 2005], and sentence embeddings [Grégoire and Langlais, 2018; Artetxe and Schwenk, 2019; Yang et al., 2019; Thompson and Koehn, 2019]. They usually use dynamic programming, which assumes that the alignments are monotonic. On the contrary, the proposed method considers the context of a target sentence and can handle non-monotonic alignments.

Grégoire and Langlais [2018] proposed a method to extract parallel sentences by using a dual encoder based on bi-directional RNN, and they achieved high accuracy in sentence alignment between English and French, but their experiment was done only on synthesized data. Artetxe and Schwenk [2019] and Yang et al. [2019] proposed parallel corpus mining methods based on multilingual sentence embedding in a shared vector space. Both works used pre-trained encoders and a scoring function using cosine distance with some margin-based extension. Moreover, both works reported state-of-the-art results in the BUCC shared task on parallel corpus mining [Zweigenbaum et al., 2018].

Since the targets of previous works on parallel corpus mining using neural networks were mainly among European languages, it is not clear whether these methods work effectively on distant language pairs such as English and Japanese. Furthermore, these methods were tested in an easier setting than that of the real problem. For example, the BUCC shared task [Zweigenbaum et al., 2018] assumes sparse 1-to-1 sentence alignment in synthesized bilingual documents and the WMT corpus filtering task [Koehn et al., 2018] assumes that the sentences are already aligned. We applied our method to sentence alignment of real newspaper articles in a distant language pair and showed its effectiveness.

Recently, Thompson and Koehn [2019] proposed a sentence alignment method, called Vecalign, which uses bilingual sentence embeddings [Artetxe and Schwenk, 2019] and recursive DP approximation. They used a German-French test set and achieved state-of-the-art results. Comparing our method with theirs remains future work. It should be noted that we can use their outputs for fine-tuning our model before using the manually created data to fine-tune it further.

### 6 Conclusion

In this paper, we proposed a novel sentence alignment method based on cross-language span prediction, which can be implemented either by QANet or multilingual BERT. Future works include investigating the best practice for combining manually and automatically aligned data because the amount of manually aligned data for training is usually limited.
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