A Supervised Word Alignment Method based on Cross-Language Span Prediction using Multilingual BERT

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Abstract
We present a novel supervised word alignment method based on cross-language span prediction. We first formalize a word alignment problem as a collection of independent predictions from a token in the source sentence to a span in the target sentence. As this is equivalent to a SQuAD v2.0 style question answering task, we then solve this problem by using multilingual BERT, which is fine-tuned on a manually created gold word alignment data. We greatly improved the word alignment accuracy by adding the context of the token to the question. In the experiments using five word alignment datasets among Chinese, Japanese, German, Romanian, French, and English, we show that the proposed method significantly outperforms previous supervised and unsupervised word alignment methods without using any bitexts for pretraining. For example, we achieved an F1 score of 86.7 for the Chinese-English data, which is 13.3 points higher than the previous state-of-the-art supervised methods.

1 Introduction
Over the past six years, machine translation accuracy has greatly improved by using neural networks (Cho et al., 2014; Sutskever et al., 2014; Bahdanau et al., 2015; Luong et al., 2015; Vaswani et al., 2017). Unfortunately, word alignment accuracy has not greatly improved nearly 20 years. Word alignment tools, which were developed during the age of statistical machine translation (Brown et al., 1993; Koehn et al., 2007) such as GIZA++ (Och and Ney, 2003), MGIZA (Gao and Vogel, 2008) and FastAlign (Dyer et al., 2013), remain widely used.

This situation is unfortunate because word alignment could be used for many downstream tasks include projecting linguistic annotation (Yarowsky et al., 2001), projecting XML markups (Hashimoto et al., 2019), and enforcing terminology constraints (pre-specified translation) (Song et al., 2019). We could also use it for user interfaces of post-editing to detect problems such as under-translation (Tu et al., 2016).

Previous works used neural networks for word alignment (Yang et al., 2013; Tamura et al., 2014; Legrand et al., 2016), but their accuracies were at most comparable to that of GIZA++. Recent works (Zenkel et al., 2019; Garg et al., 2019) try to make the attention of the Transformer to be close to word alignment, and Garg et al. (2019) achieved slightly better word alignment accuracy than that of GIZA++ when alignments obtained from GIZA++ is used for supervision.

In contrast to these unsupervised approaches, Stengel-Eskin et al. (2019) proposed a supervised word alignment method that significantly outperforms FastAlign (11-27 F1 points) using a small number of gold word alignments (1.7K-5K sentences). However, both (Garg et al., 2019) and (Stengel-Eskin et al., 2019) require more than a million parallel sentences to pretrain their transformer-based model.

In this paper, we present a novel supervised word alignment method that does not require parallel sentences for pretraining and can be trained an even smaller number of gold word alignments (150-300 sentences). It formalizes word alignment as a collection of SQuAD-style span prediction problems (Rajpurkar et al., 2016) and uses multilingual BERT (Devlin et al., 2019) to solve them. We show that, by experiment, the proposed model significantly outperforms both (Garg et al., 2019) and (Stengel-Eskin et al., 2019) in word alignment accuracy.

McCann et al. (2018) formalizes a variety of natural language tasks as a question answering problem. Multilingual BERT can be used for a variety of (zero-shot) cross-language applica-
2 Proposed Method

2.1 Word Alignment as Question Answering

Fig. 1 shows an example of word alignment data. It consists of a token sequence of the L1 language (Japanese), a token sequence of the L2 language (English), a sequence of aligned token pairs, the original L1 sentence, and the original L2 sentence. For example, the first item of the third line, “0-1,” represents the first token, “足利,” of the L1 sentence is aligned to the second token “ashikaga” of the L2 sentence. The index of the tokens starts from zero.

Fig. 2 shows an example in which the aligned tokens are converted to the SQuAD-style span prediction. Here the L1 (Japanese) sentence is given as the context. A token in the L2 (English) sentence “was” is given as the question whose answer is span “である” in the L1 sentence. It corresponds to the three aligned token pairs “24-2 25-2 26-2” in the third line of Fig. 1.

As shown in the above examples, we can convert word alignments for a sentence to a set of queries from a token in the L1 sentence to a span in the L2 sentence, and a set of queries from a token in the L2 sentence to a span in the L1 sentence. If a token is aligned to multiple spans, we treat the question has multiple answers. If a token has no alignment, we treat there are no answers to the question.

In this paper, we call the language of the question the source language and the language of the context (and the answer) the target language. In Fig. 2, the source language is English and the target language is Japanese. We call the query English-to-Japanese query.

Suppose the question is such a high-frequency word as “of”, which might be found many times in the source sentence, we could easily have difficulty in finding the corresponding span in the target sentence without the source token’s context.

Fig. 3 shows an example of a question with a short context of the source token. The two preceding words “Yoshimitsu ASHIKAGA” and two following words “the 3rd” in the source sentence are attached to the source token “was” with ‘¶’ (pilcrow: paragraph mark) as a boundary marker.

As we show in the experiment, the longer the context is, the better. We decided to use the whole source sentence as a context. Since there are many null alignments in word alignment, we adopted SQuAD v2.0 format (Rajpurkar et al., 2018), which supports cases when there are no answer spans to the question in the given context.

2.2 Cross-Language Span Prediction using Multilingual BERT

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

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

We used the model for SQuAD v2.0 described in Devlin et al. (2019). It adds two independent output layers to pretrained (multilingual) BERT to predict the start and end positions in the context. Suppose $p_{start}$ and $p_{end}$ are the probabilities that each position in the target sentence is the start and end positions of the answer span to the source to-
Yoshimitsu ASHIKAGA was the 3rd Seii Taishogun of the Muromachi Shogunate and reigned from 1368 to 1394.

In the SQuAD model of BERT, first, the question and the context is 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.

Unfortunately, since the original implementation of the BERT SQuAD model only outputs an answer string, we extended it to output the answer’s start and end positions. Inside BERT, the input sequence is first tokenized by WordPiece. It then splits the CJK characters into a sequence of a single character. As the start and end positions are indexes to the BERT subtokens, we converted them to the character indexes to the context, considering that the offset for the context tokens is the length of question tokens plus two ([CLS] and [SEP]).

### 2.3 Symmetrization of Word Alignments

Since the proposed span prediction model predicts a target span for a source token, it is asymmetric as the IBM model Brown et al. (1993). To support a one-to-many-span alignment, and to make the prediction of spans more reliable, we designed a simple heuristics to symmetrize the span predictions of different directions.

Symmetrizing IBM model alignments was first proposed by (Och and Ney, 2003). One of the most popular Statistical Machine Translation Toolkit, Moses (Koehn et al., 2007), supports a variety of symmetrization heuristics, such as intersection and union, in which grow-diag-final-and is the default. The intersection of the two alignments yields an alignment that consists of only one-to-one alignments with higher precision and lower recall than either one separately. The union of the two alignments yields higher recall and lower precision.

As a symmetrization method, for an alignment that consists of a pair of a L1 token and a L2 token, we average the probabilities of the best spans for each token for each direction. We treat a token as aligned if it is completely included in the predicted span. We then extract the alignments with the average probabilities that exceed a threshold \( \theta \).

Let \( p \) and \( q \) be start and end character indexes to sentence \( F \), and let \( r \) and \( s \) be the start and end character indexes to sentence \( E \). Let \( \omega^F_{ijkl} \) be the probability that a token that starts \( p \) and ends \( q \) in \( F \), predicts a span that starts \( r \) and ends \( s \) in \( E \). Let \( \omega^E_{pqrs} \) be the probability that a token that starts \( r \) and ends \( s \) in \( E \), predicts a span that starts \( p \) and end \( q \) in \( F \). We define the probability of alignment \( a_{ijkl} \), which represents that a token stats \( i \) and ends \( j \) in \( E \):

\[
P(a_{ijkl}) = \frac{1}{2}( \sum_{r \leq k \leq s} \omega^F_{ijrs} + \sum_{p \leq l \leq q} \omega^E_{pqkl} )
\]

Here, we set the threshold to 0.4, which means that, if the sum of the probabilities of both direc-
context: "足利義満（あしかがよしみつ）は室町幕府の第3代征夷大将軍（在位1368年-1394年）である。"
question: "Yoshimitsu ASHIKAGA was the 3rd"
answer: "である。"

Figure 3: Example of an English-to-Japanese query with a short source context

Figure 4: SQuAD v2.0 json format of a Japanese-to-English query with full source context.

We determined a threshold of 0.4 in a preliminary experiment in which we divided the Japanese-English training data into two halves for training and test sets. We used this threshold for all the experiments reported in this paper. Although the span prediction of each direction is made independently, we did not normalize the scores before averaging because both directions are trained in one model.

Zenkel et al. (2019) subtokenized words by Byte Pair Encoding (Sennrich et al., 2016) and applied GIZA++ over the subtokens. They then considered two words to be aligned if any subtokens are aligned. In Eq. 3, we could treat two tokens as aligned if a token and the predicted span overlap. We could use not only the best span but also the nbest spans for the summation in Eq. 3. These are our future works.

| Language | Train | Test | Reserve |
|----------|-------|------|---------|
| Zh-En    | 4,879 | 610  | 610     |
| Ja-En    | 653   | 357  | 225     |
| De-En    | 300   | 208  | 0       |
| Ro-En    | 150   | 98   | 0       |
| En-Fr    | 300   | 147  | 0       |

Table 1: Number of gold alignment sentences and their train/test splits.

3 Experiments

3.1 Data

Table 1 shows the number of training and test sentences of the five gold word alignment datasets used in our experiments: Chinese-English (Zh-En), Japanese-English (Ja-En), German-English (De-En), Romanian-English (Ro-En), and English-French (En-Fr).

Stengel-Eskin et al. (2019) used the Zh-En dataset and Garg et al. (2019) used the De-En, Ro-En, and En-Fr datasets. We added a Ja-En dataset because Japanese is one of the most distant languages from English.

The Zh-En data were obtained from GALE.

Stengel-Eskin et al. (2019) also used an Arabic-English (Ar-En) dataset. We did not use it here due to time constraints.
Chinese-English Parallel Aligned Treebank (Li et al., 2015), which consists of broadcasting news, news wire, and web data. To make the experiment’s condition as close as possible to (Stengel-Eskin et al., 2019), we used Chinese character-tokenized bitexts, cleaned them (by removing mismatched bitexts, time stamps, etc.), and randomly split them as follows: 80% for training, 10% for testing, and 10% for future reserves.

The Japanese-English data were obtained from the KFTT word alignment data (Neubig, 2011). KFTT (Kyoto Free Translation Task)\(^3\) was made by manually translating Japanese Wikipedia pages about Kyoto into English. It is one of the most popular Japanese-English translation benchmarks. It consists of 440k training sentences, 1166 development sentences, and 1160 test sentences. The KFTT word alignment data were made by manually word aligning a part of the dev and the test sets. The aligned dev set has eight files and the aligned test set has seven files. We used all eight dev set files for training, and four test set files for testing, and three other files for future reserves.

De-En, Ro-En, and En-Fr data are the same ones described in (Zenkel et al., 2019). They provide pre-processing and scoring scripts\(^4\). Garg et al. (2019) also used these three datasets for their experiments. The De-En data were originally provided by (Vilar et al., 2006)\(^5\). Ro-En and En-Fr data were used in the shared task of the HLT-NAACL-2003 workshop on Building and Using Parallel Texts (Mihalcea and Pedersen, 2003)\(^6\). The En-Fr data were originally provided by (Och and Ney, 2000). The numbers of test sentences in the De-En, Ro-En, and En-Fr datasets are 508, 248, and 447, respectively. In De-En and En-Fr, we used 300 sentences for training. In Ro-En, we used 150 sentences for training. The other sentences were used for testing.

### 3.2 Implementation Details

We used BERT-Base, Multilingual Cased (104 languages, 12-layer, 768-hidden, 12-heads, 110M parameters, November 23rd, 2018) in our experiments\(^7\). We basically used the script for SQuAD as it is. The following are the parameters: \(\text{train\_batch\_size} = 12\), \(\text{learning\_rate} = 3\times10^{-5}\), num\_train\_epochs = 2, max\_seq\_length = 384, max\_query\_length = 160, and max\_answer\_length = 15.

In Devlin et al. (2019), they used the following threshold for the squad-2.0 model,

\[
s_{ij} > s_{null} + \tau
\]

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

We used two NVIDIA TESLA V100 (16GB) for our experiments. Most of them were performed in one GPU, but we sometimes faced out of memory errors with just one GPU. If we set the training batch size to 6, the experiments could be performed in NVIDIA GEFORCE RTX 2080 Ti (1GB) with no significant differences in accuracy. It takes about 30 minutes for an epoch for Ja-En data (653 sentences) to fine-tune.

### 3.3 Measures for Word Alignment Quality

We evaluated the quality of word alignment using F1 score that assigns equal weights to precision (P) and recall (R):

\[
F_1 = 2 \times \frac{P \times R}{(P + R)}
\]

We also used alignment error rate (AER) (Och and Ney, 2003) if necessary because some previous works only reported it. Let the quality of alignment \(A\) be measured against a gold word alignment that contains sure \((S)\) and possible \((P)\) alignments. Precision, recall, and AER are defined as follows:

\[
\text{Precision}(A, P) = \frac{|P \cap A|}{|A|}
\]

\[
\text{Recall}(A, S) = \frac{|S \cap A|}{|S|}
\]

\[
AER(S, P, A) = 1 - \frac{|S \cap A| + |P \cap A|}{|S| + |A|}
\]
As Fraser and Marcu (2007) pointed out, “AER is broken in a way that favors precision”. It should be used sparingly. In previous works, Stengel-Eskin et al. (2019) uses precision, recall, and F1, while Garg et al. (2019) and Zenkel et al. (2019) used the precision, recall, and AER based on (Och and Ney, 2003). If no distinction exists between sure and possible alignments, the two definitions of precision and recall agree. Among the five datasets we used, De-En and En-Fr makes a distinction between sure and possible alignments.

3.4 Results

Table 2 compares the proposed method with previous works. In all five datasets, our method outperformed the previous methods. In Zh-En data, our method achieved an F1 score of 86.7, which is 13.3 points higher than that of DiscAlign 73.4 reported in (Stengel-Eskin et al., 2019), which is the state-of-the-art supervised word alignment method. Stengel-Eskin et al. (2019) used 4M bitexts for pretraining, while our method needs no bitexts for pretraining. In Ja-En data, our method achieved an F1 score of 77.7, which is 20 points higher than that of GIZA++ 57.8 reported in the document attached to KFTT word alignment (Neubig, 2011).

For the De-EN, Ro-EN, and En-Fr datasets, Garg et al. (2019), which is the state-of-the-art unsupervised method, only reported AER in their paper. For reference, we show the precision, recall, and AER (based on (Och and Ney, 2003)) of MGIZA to the same datasets, as reported in (Zenkel et al., 2019).8

For the three datasets, we trained our model without distinguishing between sure and possible and predicted spans without the distinction. We report both the ordinary measures of precision, recall, and F1, as well as Och and Ney (2003)’s definition of precision, recall. We used the scoring script provided by Zenkel et al. (2019) for the latter.

For the De-En and Ro-En datasets, the AERs of the proposed method were 11.4 and 12.2, which are significantly smaller than those of (Garg et al., 2019): 16.0 and 23.1. For En-Fr, our method’s AER is 9.4, which is significantly larger than the 4.6, of (Garg et al., 2019). However, if we train our model using sure alignments and predicts only sure alignments, the AER of our method becomes 4.0, which is 0.6 smaller than that of (Garg et al., 2019).

4 Analysis

4.1 Symmetrization Heuristics

To show the effectiveness of our proposed symmetrization heuristics, Table 3 shows the word alignment accuracies of two directions, intersection, unison, and the symmetrization method of Eq. 3 , which averages the probabilities of the two directional predictions and applies thresholding9.

For languages whose words are not delimited by white spaces, such as Chinese and Japanese, the span prediction accuracy “to English” is significantly higher than that of “from English”. German has the same tendency because compound words don’t have spaces between their elemental words. By contract, for languages with spaces between words, such as Romanian and French, no significant differences exist between the “to English” and “from English” accuracies. Since the proposed symmetrization method of Eq. 3 works relatively well for both cases, we used the heuristics as a default method for combining the predictions of both directions.

4.2 Importance of Source Context

Table 4 shows the word alignment accuracies for questions of different source contexts. Here we used Ja-En data and found that the source context information is critical for predicting the target span. Without it, the F1 score of the proposed method is 59.3, which is slightly higher than that of GIZA++, 57.6. If we add the short context, namely, the two preceding words and the two following words, the F1 score is improved more than 10 points to 72.0. If we use the whole source sentence as the context, the F1 score is improved by 5.6 points to 77.6.

4.3 Learning Curve

Table 5 shows the learning curve of the proposed method using the Zh-En data. Compared to previous methods, our method achieves higher accuracy using less training data. Even for 300 sentences, the F1 score of our method was 79.6, which is 6.2 points higher than that of (Stengel-Eskin et al., 2019) (73.4), which used more than 4800 sentences for training.

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8 We took these numbers from their GitHub.

9 We use “bidi sum th” for the shorthand for this method.
It is relatively easy to make gold word alignment of 300 sentences, once the guideline of the word alignment is established. Since the proposed method does not require bitexts for pretraining, we assume that we can achieve a higher word alignment accuracy for low-resource language pairs than that is currently achieved for high-resource language pairs using the GIZA++.

### 4.4 Zero-shot Word Alignment

Since we achieved a higher word alignment accuracy than GIZA++ with as few as 300 sentences, we tested whether we can perform word alignment without using the gold alignment of specific language pairs. Here we define “zero-shot word alignment” as testing the word alignment for a language pair that is different from the language pair used for training the model.

Table 6 shows the zero-shot word alignment accuracies. Compared with Table 2, if we train the model using Zh-En data, and test it using the Ja-En data, it achieves an F1 score of 58.8, which is slightly higher than that of GIZA++ (57.6) trained using the Ja-EN data. If we train the model using De-En data and test it using Ro-En data, it achieves a 77.8 F1, which is 4.2 points higher than that of MGIZA (73.6).

We suspect the reason for the lower zero-shot accuracy between Zh-En and Ja-En is the difference of tokenization. Although Chinese and Japanese do share some Chinese characters, Chinese data are character tokenized, but Japanese data are word tokenized. Future work will seek a method to utilize word alignment data with different tokenizations.

### 5 Related Works

Although the accuracy of machine translation was improved greatly by neural networks, the accuracy of word alignment using them cannot outperform using statistical methods, such as the IBM model (Brown et al., 1993) and the HMM alignment model (Vogel et al., 1996).

Recently, Stengel-Eskin et al. (2019) proposed a supervised method using a small number of annotated data (1.7K-5K sentences) and significantly outperformed the accuracy of GIZA++. In this method, they first mapped the source and target word representations obtained from the encoder and decoder of the Transformer to a shared space by using a three-layer feed-forward neural network. They then applied 3 × 3 convolution and softmax to obtain the alignment score of the source word and target words. They used 4M parallel sentences to pretrain the Transformer. We achieved significantly better word alignment accuracy than (Stengel-Eskin et al., 2019) with less annotated training data without using parallel sen-

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**Table 2: Best-effort comparison of proposed method with previous works**

| Test set | Method | P   | R   | F1  | AER |
|----------|--------|-----|-----|-----|-----|
| Zh-En    | FastAlign (Stengel-Eskin et al., 2019) | 80.5 | 50.5 | 62.0 | -   |
|          | DiscAlign (Stengel-Eskin et al., 2019) | 72.9 | 74.0 | 73.4 | -   |
|          | Our method | 84.4 | 89.2 | 86.7 | 13.3|
| Ja-En    | Giza++ (Neubig, 2011) | 59.5 | 55.6 | 57.6 | 42.4|
|          | Our method | 77.3 | 78.0 | 77.6 | 22.4|
| De-En    | MGIZA (BPE, Grow-Diag-Final) (Zenkel et al., 2019) | 91.3 | 70.2 | - | 20.6|
|          | Multi-task + GIZA++ supervised (Garg et al., 2019) | - | - | - | 16.0|
|          | Our method (sure + possible) | 89.9 | 81.7 | 85.6 | 14.4|
|          | (based on (Och and Ney, 2003)) | 89.9 | 87.3 | - | 11.4|
| Ro-En    | MGIZA (BPE, Grow-Diag-Final) (Zenkel et al., 2019) | 90.9 | 61.8 | - | 26.4|
|          | Multi-task + GIZA++ supervised (Garg et al., 2019) | - | - | - | 23.1|
|          | Our method | 90.4 | 85.3 | 86.7 | 12.2|
| En-Fr    | MGIZA (BPE, Grow-Diag) (Zenkel et al., 2019) | 97.5 | 89.7 | - | 5.9 |
|          | Multi-task + GIZA++ supervised (Garg et al., 2019) | - | - | - | 4.6 |
|          | Our method (sure + possible) | 88.6 | 53.4 | 66.6 | 33.3|
|          | (based on (Och and Ney, 2003)) | 88.6 | 96.7 | - | 9.4 |
|          | Our method (sure only) | 86.2 | 70.8 | 77.8 | 22.2|
|          | (based on (Och and Ney, 2003)) | 97.7 | 93.9 | - | 4.0 |


### Table 3: Effects of symmetrization for various language pairs

| Test set | Method         | P   | R   | F1  |
|-----------|----------------|-----|-----|-----|
| Zh-En     | Zh to En       | 89.9| 85.8| **87.8** |
|           | En to Zh       | 82.0| 81.8| 81.9 |
|           | intersection   | 95.5| 74.9| 83.9 |
|           | union          | 79.4| 92.7| 85.5 |
|           | bidi sum th    | 84.4| 89.2| 86.7 |
| Ja-En     | Ja to En       | 80.6| 79.7| **80.2** |
|           | En to Ja       | 61.9| 69.0| 65.2 |
|           | intersection   | 90.8| 63.1| 74.5 |
|           | union          | 60.8| 85.6| 71.1 |
|           | bidi sum th    | 77.3| 78.0| 77.6 |
| De-En     | De to En       | 89.9| 85.8| **87.8** |
|           | En to De       | 82.0| 81.8| 81.9 |
|           | intersection   | 95.5| 74.9| 83.9 |
|           | union          | 79.4| 92.7| 85.5 |
|           | bidi sum th    | 84.4| 89.2| 86.7 |
| Ro-En     | Ro to En       | 84.6| 86.5| 85.5 |
|           | En to Ro       | 87.2| 86.3| 86.7 |
|           | intersection   | 93.1| 82.2| 87.3 |
|           | union          | 80.2| 90.6| 85.0 |
|           | bidi sum th    | 90.4| 85.3| **87.8** |
| En-Fr     | En to Fr       | 79.9| 91.7| 85.4 |
|           | Fr to En       | 79.5| 91.3| 85.0 |
|           | intersection   | 85.3| 88.1| 86.7 |
|           | union          | 75.2| 94.9| 83.9 |
|           | bidi sum th    | 79.6| 93.9| **86.2** |

### Table 4: Importance of source context

| Test set | Context       | P   | R   | F1  |
|-----------|---------------|-----|-----|-----|
| Ja-En     | no context    | 67.3| 53.0| 59.3 |
|           | ±2 words      | 73.9| 70.2| 72.0 |
|           | whole sentence| 77.3| 78.0| 77.6 |

Table 5: Test set performance when trained on subsamples of the Chinese gold word alignment data

| Training | Model  | Test   | P   | R   | F1  |
|----------|--------|--------|-----|-----|-----|
| Ja-En    | GIZA++ | Ja-En  | 59.5| 55.9| 57.6|
| Zh-En    | Ours   | Ja-En  | 55.6| 62.4| **58.8** |
| Ro-En    | MGIZA  | Ro-En  | 90.9| 61.8| 73.6|
| De-En    | Ours   | Ro-En  | 86.2| 70.8| **77.8** |

Table 6: Zero-shot word alignment

6 Conclusion

We presented a novel supervised word alignment method using multilingual BERT, which requires as few as 300 training sentences to outperform previous supervised and unsupervised methods. We also show that the zero-shot word alignment accuracy of our method is comparable to or better than that of statistical methods such as GIZA++.

The future works include utilizing parallel texts in our model. One of the obvious options is to use XLM (Lample and Conneau, 2019), which is pretrained on parallel texts, as a drop-in replacement for multilingual BERT. It is also important to utilize word alignment data with different tokenizations for languages whose words are not delimited by spaces.

Ouyang and McKeown (2019) proposed a monolingual phrase alignment method using pointer network (Vinyals et al., 2015) that can align phrases of arbitrary length. They first segment the source and target sentences into chunks and compute an embedding for each chunk. They then use a pointer-network to calculate alignment scores for each pair of source and target chunks. Compared to our span prediction method, their method is not flexible because they operate on fixed target chunks for all fixed source chunks, while our method can change the target span for each source token.

Garg et al. (2019) proposed an unsupervised method that jointly optimizes translation and alignment objectives. They achieved a significantly better alignment error rate (AER) than GIZA++ when they supervised their model using the alignments obtained from GIZA++. Their model requires about a million parallel sentences for training the underlying Transformer. We experimentally showed that we can outperform their results with just 150 to 300 annotated sentences for training. We also showed that we can achieve word alignment accuracy comparable to or slightly better than GIZA++ without using gold alignments for specific language pairs (zero-shot word alignment).
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