Supervised Syntax-based Alignment between English Sentences and Abstract Meaning Representation Graphs

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Abstract

As alignment links are not given between English sentences and Abstract Meaning Representation (AMR) graphs in the AMR annotation, automatic alignment becomes indispensable for training an AMR parser. Previous studies formalize it as a string-to-string problem, and solve it in an unsupervised way. In this paper, we formalize it as a syntax-based alignment problem, and solve it in a supervised manner based on the syntax trees. Experiments verify the effectiveness of the proposed method.

1 Introduction

Abstract Meaning Representation (AMR) is a sentence level semantic annotation, which is represented in a rooted, directed, and edge-labeled graph (Banarescu et al., 2013). Nodes of a graph are concepts (e.g., “possible” in Figure 1), while edges are labeled with semantic roles (e.g., “:ARG4” in Figure 1). As AMR annotation has no explicit alignment with the words in the English sentence, automatic alignment becomes a requirement for training AMR parsers (Flanigan et al., 2014, Werling et al., 2015, Pust et al., 2015).

The alignment problem between English sentences and AMR graphs is not trivial. There are two reasons. Firstly, the problem itself is complicated. Concepts do not always have a direct matching among the English words in a given sentence. For example, in Figure 1 the English word “could” is represented as the concept “possible”, and aligning them is not easy. It becomes more difficult in the English word-to-role alignment case. For example, in Figure 1 we should align the English word “to” to the role “:ARG4”. Secondly, the training data for English/AMR alignment is very small. The biggest publicly available data set only contains 13,050 English/AMR pairs, which is significantly smaller than conventional alignment settings in machine translation (MT).

(Flanigan et al., 2014) is the first study of English/AMR alignment, which proposes a rule-based method. The limitation of the rule-based method is that it cannot benefit from more annotation of English/AMR pairs. A data driven alignment method also has been proposed (Pourdamghani et al., 2014). They formalize the string-to-graph alignment problem as a string-to-string problem by linearizing the AMR graph. Then they apply the conventional unsupervised string-to-string alignment models (i.e. IBM models (Brown et al., 1993)) for this problem.

Using syntax trees in a supervised manner has shown its effectiveness in the alignment problem in MT (Riesa et al., 2011). Motivated by this, in this...

Figure 1: An example of English/AMR alignment.
paper, we formalize the English/AMR graph alignment problem as a syntax-based alignment problem. We then apply the supervised syntax-based alignment model \cite{riesa2011} for this. Our proposed method outperforms the unsupervised alignment model of \cite{pourdamghani2014} by 1.7$\%$ F-score on alignment accuracy, although it is trained on only 100 English/AMR pairs that are annotated with gold alignments.

2 Baseline Method

The baseline method that we compare to is the ISI alignment \cite{pourdamghani2014}. The ISI alignment method formalizes the English/AMR graph alignment problem as a string-to-string alignment problem, by linearizing an AMR graph to a string. It includes three steps: preprocessing, string-to-string alignment, and postprocessing.

2.1 Preprocessing

- Linearize the AMR using a depth-first traversal. For example, the AMR graph in Figure 1 will be linearized to “possible :domain go-01 :ARG1 thing :ARG2-of price-01 :ARG1 gas :quant volume-quantity :quant 1 :unit gallon :ARG4 monetary-quantity :quant 10 :unit dollar”.
- Remove the tokens that are rarely aligned, to improve the precision with a small sacrifice of recall. On the English side, this removes stop words, such as articles “a”, “an”, “the”; On the AMR side, this removes special concepts, and roles, such as “:arg0”, “:quant”, “:opt1” etc. that do not usually align, quotes, and sense tags. After this step, the English sentence in Figure 1 becomes “Gas could go to $10 gallon”; the AMR is transferred to “possible :domain go thing :arg2-of price gas 1 gallon :arg4 10 dollar”.
- Lowercase and stem both sides to the first four letters. This is necessary to address the sparseness of the training data, which is very small compared to the size of the training data for conventional word alignments of MT. This converts English to “gas coul go to $10 gall”, and AMR to “poss :domain go thin :arg2-of pric gas 1 gall :arg4 10 doll” in Figure 1.

2.2 String-to-String Alignment

As the preprocessing step has converted it to a string-to-string alignment problem, the widely used IBM alignment models \cite{brown1993} that are based on word sequences can be applied. To further improve the alignment accuracy, \cite{pourdamghani2014} also proposed a symmetrization constraint that encourages agreement of the parameter learning in two directions for the IBM models.

2.3 Postprocessing

The string-to-string alignments are finally projected back to the original English sentence and the AMR graph to obtain English/AMR graph alignments. This can be done easily by memorizing the corresponding token positions before and after the pre-processing.

3 Proposed Method

We use the same pipeline as \cite{pourdamghani2014}, however, we formalize it as a constituency tree based alignment problem, and apply the hierarchical alignment model of \cite{riesa2011}. This method has been proposed for conventional word alignments of MT, however, it has not been used for English/AMR graph alignments.

3.1 Constituency Trees for English and AMR

Constituency trees for English can be obtained via a conventional syntactic parser. In this study, we parse original English sentences with the Berkeley parser\footnote{https://github.com/slavpetrov/berkeleyparser}. We process obtained constituency trees by discarding the stop words, and replacing the leaf words with their stems. An example of the final tree is shown in Figure 2.

For AMR, we convert AMRs to constituency trees using the method proposed in \cite{pust2015} with the following steps:

- Arbitrarily disconnect multiple parents from each node.
- Propagate the edge labels (roles) to leaves, and add pre-terminals X.
- Restructure the tree with role labels as intermediates.
Figure 2: Proposed method.

We do not apply the reordering steps, because it requires alignments. For more details of these steps, please refer to (Pust et al., 2015).

We then process converted AMR trees by discarding special concepts and roles that are rarely aligned, and replacing leaf words with their stems. Note that converted AMR trees usually are not isomorphic to the English trees. For example, “could” is the grand-child of the root in the English tree, while in the converted AMR tree “possible” is the direct child of the root.

3.2 Hierarchical Alignment on Constituency Trees

Figure 2 shows an overview of our proposed method. Our model hierarchically searches for the k-best alignment by constructing partial alignments over a target constituency tree in a bottom-up manner (from leaf nodes to the root). Each node in the tree has partial alignments, which are sorted by alignment scores. A partial alignment for a node is an alignment matrix of AMR tokens or null, covered by the node, and it is represented as a black square. We only keep a beam size of \( k \) for partial alignments for each node, to reduce the computational cost. For example, in Figure 2 the beam size \( k = 5 \). Firstly, 5-best partial alignments are generated for all the leaf nodes. These partial alignments are then linearly combined to generate partial alignments for the non-terminals in the constituency tree.

For example, the partial alignments of the leaf node “$” and “10” are combined to generate 5-best partial alignments for the node “NP”. We hierarchically perform this process until we reach the root node.

One important merit of this model is that it is a discriminative model that can incorporate various features, including syntactic information, lexical translation probabilities, same word, third party alignment features, etc. The score of a partial alignment is a linear combination of these features by their weights. The weights of the features are learnt against a set of pairs with gold alignments, using the online averaged perceptron algorithm (Collins, 2002). For more details of the features and the learning algorithm, please refer to (Riesa et al., 2011).

4 Experiments

4.1 Settings

The data used in our experiments was the Linguistic Data Consortium AMR release 1.0 (LDC2014T12), consisting of 13,050 AMR/English sentence pairs. 200 of them were manually annotated with gold alignments (Pourdamghani et al., 2014). These 200 pairs were originally split into the dev and test sets in LDC2014T12 for AMR parsing, respectively. As reported in (Pourdamghani et al., 2014), the test 100 sentences were intrinsically harder than the development 100 sentences. Therefore, we mixed these two sets sentence by sentence, and split it into 100, 50, 50 for train, dev, test, respectively in our alignment experiments. Table 1 shows the statistics of the data.

|          | T12 | train | dev | test |
|----------|-----|-------|-----|------|
| # pairs  | 13,050 | 100 | 50 | 50 |
| # AMR tokens | 465k | 3.0k | 1.5k | 1.6k | (54.7%) | (51.6%) | (52.2%) |
| # AMR roles | 226k | 1.5k | 0.7k | 0.8k | (23.5%) | (21.0%) | (21.6%) |
| # English tokens | 248k | 2.0k | 0.9k | 1.1k | (74.9%) | (75.8%) | (75.4%) |

Table 1: Statistics of the alignment data (The numbers in parentheses are the percentages of the tokens aligned in the gold alignment data).

3 https://catalog.ldc.upenn.edu/LDC2014T12
4 http://www.isi.edu/natural-language/mt/dev-gold.txt
5 http://www.isi.edu/natural-language/mt/test-gold.txt

The source side could be either a constituency tree or a word sequence.
| Type    | Method       | Precision | Recall | F-score |
|---------|--------------|-----------|--------|---------|
| Concept | ISI          | 95.4%     | 84.9%  | 89.9%   |
|         | Proposed     | **95.8%** | **87.6%** | **91.5%** |
|         | Upper bound  | 99.7%     | 94.4%  | 97.0%   |
| Role    | ISI          | 70.5%     | 44.4%  | 54.5%   |
|         | Proposed     | **77.6%** | **42.3%** | **54.7%** |
|         | Upper bound  | 95.4%     | 66.1%  | 78.1%   |
| Concept | ISI          | 91.6%     | 76.7%  | 83.5%   |
| +Role   | Proposed     | **93.4%** | **78.4%** | **85.2%** |
|         | Upper bound  | 99.0%     | 88.6%  | 93.5%   |

Table 2: Alignment results ("Proposed" shows the best results among the different syntax usages, "Upper bound is" the upper bound after removing stop words in English and rarely aligned concepts, roles in AMR).

For the baseline method, we run the publicly available toolkit ISI aligner on the entire LDC2014T12 data, which is an implementation of the method described in (Pourdamghani et al., 2014). For our proposed method, we trained and tuned the alignment model on the 100 train and 50 dev pairs, respectively, with the open source supervised alignment toolkit Nile (Riesa et al., 2011). As the third party alignment feature for Nile, we used ISI alignments. Lexical translation probabilities were generated from the ISI alignments on the entire LDC2014T12 data. The alignment results were reported on the 50 test pairs. In addition, we compared different ways of using syntax trees:

- **AMR(string)-En(tree)**: Use AMR strings as the source side, and English trees as the target side.
- **AMR(tree)-En(tree)**: Use converted AMR trees as the source side, and English trees as the target side.
- **En(tree)-AMR(tree)**: Use English trees as the source side, and converted AMR trees as the target side.
- **Grow-diag-final-and**: A symmetrization of the alignment results of AMR(tree)-En(tree) and En(tree)-AMR(tree) with the grow-diag-final-and heuristic (Och and Ney, 2003), which is commonly used in MT.

Table 3: Syntax usage comparison results.

### 4.2 Results

Table 2 shows the alignment results. We report the alignment accuracies for the concept, role and both types of tokens, respectively. We can see that our proposed method outperforms the ISI alignment for all the alignment types. However, there is still a gap between it and the upper bound.

Table 5 shows the results of using syntax trees in different ways for the proposed method. AMR(tree)-English(tree) only slightly outperforms AMR(string)-English(tree), due to the bad isomorphism between converted AMR trees and English trees. Using converted AMR trees as the target side seems to be a bad idea. The reason for this is that English-to-AMR is a one-to-many alignment problem, while En(tree)-AMR(tree) could produce many-to-one alignments for English-to-AMR due to the peculiarities of Nile, which decreases the precision. The grow-diag-final-and heuristic seems to be not helpful either.

Figure 3 shows an alignment example, comparing the ISI alignment and our proposed method. We can see that our proposed method has a better role precision, which correctly aligns the AMR role token “thing” to the English token “How” while the ISI alignment fails. However, the proposed method has a worse concept precision, which aligns the two “i” tokens in AMR and English. This happens because of two reasons. Firstly, the correct alignment “:ARG1 i” has been removed in the preprocessing; Secondly, Nile has a feature that tends to align same words.
The alignment between English sentences and AMR graphs is necessary for AMR parsing. We improved the alignment accuracy with a supervised alignment method based on constituency trees. We showed the effectiveness of the supervised method, even when only a very small training data set is available (i.e., 100 pairs).

As future work, firstly, we plan to improve the alignment accuracy for roles. Semantic role labeling (Gildea and Jurafsky, 2000) for the English sentences and use the obtained roles for alignment maybe a solution for this. Secondly, we plan to apply the improved alignment method for AMR parsing. The system of (Pust et al., 2015) can be one good candidate for applying the improved alignment, which originally used the ISI alignment. Finally, we plan to increase the number of AMR/English sentence pairs with gold alignments for training a more accurate alignment model. One possible way is to exploit the other golden data annotated with different annotation criteria. For example, (Flanigan et al., 2014) annotated 200 pairs that aligns graph fragment to span of words, (Werling et al., 2015) annotated 100 pairs that aligns each AMR concept to some token in the English sentence even when unsure. In addition, we strongly call for the annotation of more AMR/English gold alignment data.

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