Attentive Semantic Role Labeling with Boundary Indicator

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Abstract

The goal of semantic role labeling (SRL) is to discover the predicate-argument structure of a sentence, which plays a critical role in deep processing of natural language. This paper introduces simple yet effective auxiliary tags for dependency-based SRL to enhance a syntax-agnostic model with multi-hop self-attention. Our syntax-agnostic model achieves competitive performance with state-of-the-art models on the CoNLL-2009 benchmarks both for English and Chinese.

1 Introduction

Semantic role labeling (SRL) aims to derive the meaning representation for a sentence, i.e., predicate-argument structure, which plays a critical role in a wide range of natural language processing tasks (Daniel et al., 2018; Huang et al., 2018; Zhu et al., 2018; Zhang and Zhao, 2018; Zhang et al., 2018b). There are two formulizations for semantic predicate-argument structure, one is based on constituents (i.e., phrase or span), the other is based on dependencies. The latter is also called semantic dependency parsing, which annotates the heads of arguments rather than phrasal arguments. SRL can be formed as four subtasks, including predicate detection, predicate disambiguation, argument identification and argument classification.

Recent methods (Zhou and Xu, 2015; Marcheggiani et al., 2017; Marcheggiani and Titov, 2017; He et al., 2017; Tan et al., 2018; He et al., 2018; Li et al., 2018a,b) deal with all words in entire sentence instead of distinguishing arguments and non-arguments which actually differ in quantity.

The indiscriminate treatment would result in a serious unbalanced issue for argument labeling.

We observe that arguments trend to surround their predicates. Capturing the boundary of the semantic relationship beforehand and taking it as an inference constraint is thus particularly significant for argument labeling, which is potential to improve the performance of the labeler. In this work, we propose to introduce two types of auxiliary argument tags as the argument boundary indicators. If an argument candidate is assigned to such either of the tags, the labeling or traversal algorithm will end immediately. In training, this auxiliary tags mean no more samples will be searched for the current predicate, while in inference, the labeler will not search arguments any more. The auxiliary tags could guide the labeler to focus on the potential true candidates.

Besides, most of state-of-the-art models rely heavily on syntactic features (Roth and Lapata, 2016; Marcheggiani and Titov, 2017) which suffer the risk of erroneous syntactic input, leading to undesired error propagation. In fact, there comes a latest advance that shows neural SRL able to effectively capture the discriminative information automatically without syntactic assistance (Marcheggiani et al., 2017). Furthermore, for long and complex sentences with various aspects of semantics, effectively modeling the overall sentence would be quite challenging. To this end, we introduce a multi-hop self-attention mechanism to distill various important parts of the input sentence and model long range dependencies.

This paper focuses on argument identification and classification, which is jointly formulated as a sequence labeling task. For the predicate disambiguation, we follow the previous works (Roth and Lapata, 2016; Marcheggiani et al., 2017). Our model contains two major features: (1) auxiliary tags to indicate the argument boundary. (2) a
| Without AT (%) | With AT (%) |
|---------------|-------------|
| Args | NonArgs | Ratio | Args | NonArgs | Ratio |
| Train | 7.65 | 92.35 | 1:13 | 43.81 | 56.19 | 1:1.3 |
| Dev | 7.35 | 92.65 | 1:13 | 41.22 | 58.78 | 1:1.4 |

Table 1: Label distribution of training and dev set. Arg is short for argument. AT denotes our introduced auxiliary tags.

BiLSTM encoder with multi-hop self-attention to model the sentence representations. Our evaluation is on CoNLL-2009 (Hajič et al., 2009) benchmark for both English and Chinese. We show that with the help of auxiliary tags and self-attention, the syntax-agnostic model could even achieve a competitive performance with syntax-aware ones.

2 Argument Boundary Indicator

Following the observation that arguments usually tend to surround their predicate closely, we introduce two auxiliary tags inspired by (Zhao et al., 2009), namely, beginning of the argument, <BOA> and end of the argument, <EOA> to signify where the labeler should start or stop collecting argument candidates. For training, both tags are correspondingly assigned to the previous or next word as soon as the arguments of the current predicate have been saturated with previously collected words, in light of the original training data. For inference, it informs the labeler to start argument searching when it comes to the <BOA> while <EOA> means to stop. These tags would help the labeler ignore those words too far away from the predicates which are hardly supposed to be ground-truth arguments.

Empirically, the distributions of arguments (Args) and non-arguments (NonArgs) vary largely in quantity. Table 1 shows the data statistics of CoNLL 2009 dataset for English and we find the proportion of Args and NonArgs is 1:13 in the original dataset. After replacing the semantic relationship boundary (both left and right) with our new tags and removing all other NonArg labels, the proportion reaches nearly 1:1. Note that the above operation is only conducted to intuitively show the difference by imitating the enhanced searching guidance with new tags. Actually we only modify the boundary labels of semantic relationships and use them to signal the model where to restrict a search. Without this inference restraint, most argument candidates are irrelevant and far away from the current predicate, inevitably interfering with the informative features from the truly relevant ones in the very small minority and, hence, leading to an unsatisfactory performance.

We give an example below to show how these two tags are used. Suppose a sequence with sense-disambiguated predicate and labeled arguments is

```
a big apple drops from the tree
```

where drops in the input sequence is a predicate with two arguments, labeled with A0 and A1, respectively.

The two tags are assigned to the next two words apple and from, respectively, indicating no more arguments farther than them from the predicate.

```
a big apple drops from the tree
```

The auxiliary tags can be regarded as a reference constraint which indicates the maximum boundary of the argument set for each predicate. They are treated in exactly the same way as all other labels during training and inference, except the extra utility to signal where to stop a search during decoding inference.

3 Bidirectional LSTM Labeler

Figure 1 overviews our model architecture. Given a known predicate, our model reads each word of an input sentence and maps it into latent space to form a word-level representation. Concretely, each word embedding is defined by

$$e_i = [e_{ir}^i, e_{ip}^i, e_{il}^i, e_{ipos}^i, e_{if}^i, e_{im}^i]$$

where $e_{ir}^i$ is randomly initialized word embedding, $e_{ip}^i$ denotes pre-trained word embedding, $e_{il}^i$ represents randomly initialized lemma embedding, $e_{ipos}^i$
is the randomly initialized POS tag embedding and \( e_i \) denotes predicate-specific indicator embedding to indicate whether the current word is the given predicate, which is slightly different from previous work (Marcheggiani et al., 2017) directly using a binary flag either 0 or 1 and \( e_i \) is an external embedding, ELMo (Embeddings from Language Models) (Peters et al., 2018), which is obtained by deep bidirectional language model that takes characters as input.

The concatenated word embeddings \( e_i \) are then fed to a sentence-level module to propagate information along the input sequence. We use a bidirectional LSTM (BiLSTM) (Hochreiter and Schmidhuber, 1997) to process the sequence \( e = (e_1, \ldots, e_n) \) in forward and backward directions to access both past and future contextual information. Finally, we get a contextual representation \( h_i = [\bar{h}_i, \bar{h}_i] \in R^{d \times 2d} \) where \( d \) denotes the number of LSTM hidden units. \( \bar{h}_i \) denotes the hidden states of the sequence from \( e_1 \) to \( e_i \) and \( \bar{h}_i \) represent that from \( e_n \) to \( e_i \).

Attention mechanism has been applied to a wide range of tasks due to its effectiveness of key information extraction (Lin et al., 2017; Zhang et al., 2018a,c). To pinpoint important components of the sentence, such as critical words or phrases, we employ a self-attention mechanism following (Lin et al., 2017) to obtain a vector of weights \( m \).

\[
m = \text{softmax}(W_2 \tan(W_1 H^T))
\]

where \( W_1 \in R^{k \times 2d} \) and \( W_2 \in R^k \) are model parameters where \( k \) is an arbitrary hyper-parameter. In this work, we empirically set \( k = d \). Then we sum up the BiLSTM hidden states \( H = (h_1, \ldots, h_n) \) weighted by \( m \) to obtain an attentive representation \( s \) of the whole input sentence.

In fact, there might be multiple aspects or semantic components of a sentence, especially for a long sentence. Thus, we need multiple \( m \) to focus on different parts of the sentence, which lets us adopt multi-hop attention. Let \( r \) denote the number of different parts to be extracted from the sentence, we expand \( W_2 \) into \( r \) dimension, thus we have \( W_2 \in R^{r \times 2d} \) and the resulting weight vector \( m \) becomes a matrix \( M \). Then, we compute the weighted sums by multiplying \( M \) and BiLSTM hidden states \( H \) to obtain the multi-hop attentive sentence representation \( S = MH \). Intuitively, multi-hop self-attention provides a flexible way to represent, extract and synthesize diverse information of input sentence which would produce a more fine-grained global sentence information.

Then we concatenate each hidden state \( h_i \) with \( S \) to endow each word representation with contextual sentence information. Here, we have the refined output \( \hat{H} = [h_1 \circ S; h_2 \circ S; \cdots; h_n \circ S] \) where \( \circ \) denotes concatenation operation.

Finally, we use a softmax layer over \( \hat{H} \). The training objective is to maximize the logarithm of the likelihood of the labels.

\[
\ell = - \sum_{i=1}^{n} y_i \log \hat{y}_i
\]

where \( y_i \) denotes the prediction, \( \hat{y}_i \) is the target. During inference, we use greedy search to obtain the prediction. Note the search start from the predicate with two directions, forward and backward, until the argument boundary tag is predicted.

| System (syntax-aware) | P   | R   | F₁  |
|-----------------------|-----|-----|-----|
| Single model          |     |     |     |
| Björkelund et al. (2010) | 87.1 | 84.5 | 85.8 |
| Lei et al. (2015)     | --  | --  | 86.6 |
| FitzGerald et al. (2015) | --  | --  | 86.7 |
| Roth and Lapata (2016) | 88.1 | 85.3 | 86.7 |
| Marcheggiani and Titov (2017) | 89.1 | 86.8 | 88.0 |
| Ensemble model        |     |     |     |
| FitzGerald et al. (2015) | --  | --  | 87.7 |
| Roth and Lapata (2016) | 90.3 | 85.7 | 87.9 |
| Marcheggiani and Titov (2017) | 90.5 | 87.7 | 89.1 |
| System (syntax-agnostic) | P   | R   | F₁  |
|Marcheggiani et al. (2017) | 88.7 | 86.8 | 87.7 |
|Ours                   | 89.7 | 88.3 | 89.0 |

Table 2: Results on the English in-domain test set.

4 Experiment

Our model is evaluated on the CoNLL-2009 shared task both for English and Chinese datasets, following the standard training, development and test splits. In our experiments, the pre-trained word embeddings for English are 100-dimensional GloVe vectors (Pennington et al., 2014). For Chinese, we exploit Wikipedia documents to train the same dimensional Word2Vec embeddings (Mikolov et al., 2013). All other vectors are randomly initialized, the dimensions of word and lemma embeddings are 100, while the dimensions of POS tag and predicate indicator embedding are 32 and 16 respectively. In addition, we use 300-dimensional ELMo embedding for English. For
Table 3: Results on the Chinese test set.

| System (syntax-aware) | P  | R  | F₁ |
|-----------------------|----|----|----|
| Björkelund et al. (2009) | 82.4 | 75.1 | 78.6 |
| Roth and Lapata (2016) | 83.2 | 75.9 | 79.4 |
| Marcheggiani and Titov (2017) | 84.6 | 80.4 | 82.5 |
| System (syntax-agnostic) | P  | R  | F₁ |
| Marcheggiani et al. (2017) | 83.4 | 79.1 | 81.2 |
| Ours                  | 84.3 | 79.6 | 81.9 |

Table 4: Results on the English out-of-domain test set.

| System (syntax-aware) | P  | R  | F₁ |
|-----------------------|----|----|----|
| Single model          |    |    |    |
| Björkelund et al. (2010) | 75.7 | 72.2 | 73.9 |
| Lei et al. (2015)     | -- | -- | 75.6 |
| FitzGerald et al. (2015) | -- | -- | 75.2 |
| Roth and Lapata (2016) | 76.9 | 73.8 | 75.3 |
| Marcheggiani and Titov (2017) | 78.5 | 75.9 | 77.2 |
| Ensemble model        |    |    |    |
| FitzGerald et al. (2015) | -- | -- | 75.5 |
| Roth and Lapata (2016) | 79.7 | 73.6 | 76.5 |
| Marcheggiani and Titov (2017) | 80.8 | 77.1 | 78.9 |
| System (syntax-agnostic) | P  | R  | F₁ |
| Marcheggiani et al. (2017) | 79.4 | 76.2 | 77.7 |
| Ours                  | 81.5 | 76.1 | 78.7 |

Table 5: Results on the English in-domain test set.

| System                  | P  | R  | F₁ |
|-------------------------|----|----|----|
| Ours                    | 89.7 | 88.3 | 89.0 |
| -Auxiliary tags         | 89.5 | 88.1 | 88.8 |
| -Self-attention         | 89.7 | 87.9 | 88.7 |
| -Auxiliary tags -self-attention | 88.9 | 88.1 | 88.5 |
| +Adaptive argument pruning | 88.6 | 85.5 | 87.0 |

The experimental results on the in-domain English data and Chinese test set are in Tables 2 and 3, respectively. Notably, our syntax-agnostic model is local (argument identification and classification decisions are conditionally independent) and single without reranking, which neither includes global inference nor combines multiple models.

For English, as shown in Table 2, our model outperforms previously published single models including syntax-aware models, scoring 89.0% F₁ with 1.3% absolute improvement over the syntax-agnostic baseline in the in-domain test set.

For Chinese (Table 3), even though we use the same hyper-parameters as for English, our model also shows competitive performance with state-of-the-art results. Table 4 demonstrates the results on out-of-domain data, where the performance of our model still remains strong.

5 Analysis

Result 5 shows the ablation study of our model which indicates all our proposed strategies contribute to the overall performance. Without auxiliary tags, the performance drops dramatically, which confirms the soundness of the motivation for argument boundary indicators from empirical perspective. The reason might be that our proposed argument boundary indicators could help the labeler focus on the potential true candidates and ignore those words too far away from the predicates which are hardly supposed to be ground-truth arguments. Removing the self-attention module also results in performance decline, the advance might be because the self-attention mechanism could help the model to distill vital information and alleviate the error propagation.

Noting that the work (Zhao et al., 2013) successfully incorporated the syntactic information by applying an adaptive argument pruning, we further perform an experiment to explore whether employing such pruning method enhance or hinder our model. However, as shown in Table 5, the result is far from satisfying.

6 Conclusion

This paper introduced auxiliary tags to indicate the boundary of predicate-argument relationships and employ multi-hop self-attention for further improvement of SRL performance. With the auxiliary tags and the attention mechanism, our simple
yet effective model achieves competitive results on the CoNLL-2009 benchmarks for both English and Chinese, though without any kind of syntactic information.

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