Combining (Second-Order) Graph-Based and Headed-Span-Based Projective Dependency Parsing

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Abstract

Graph-based methods are popular in dependency parsing for decades, which decompose the score of a dependency tree into scores of dependency arcs. Recently, Yang and Tu (2021) propose a headed-span-based method that decomposes the score of a dependency tree into scores of headed spans. In this paper, we combine the two types of methods by considering both arc scores and headed-span scores, designing three scoring methods and the corresponding dynamic programming algorithms for joint inference. Experiments show the effectiveness of our proposed methods.

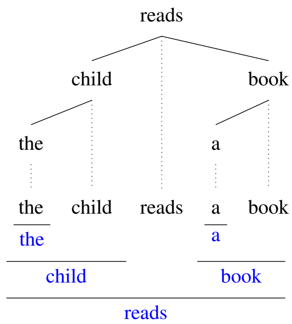


Figure 1: An example projective dependency parse tree with all its headed-spans.

1 Introduction

Dependency parsing is an important task in natural language processing. There are many methods to tackle projective dependency parsing. In this paper, we focus on two kinds of *global methods*: graph-based methods and headed-span-based methods. They both score all parse trees and globally find the highest scoring tree. The difference between the two is how they score dependency trees. The simplest first-order graph-based methods (McDonald et al., 2005) decompose the score of a dependency tree into the scores of dependency arcs. Second-order graph-based methods (McDonald and Pereira, 2006) additionally score adjacent siblings, i.e., pairs of adjacent arcs with a shared head. There are many other higher-order graph-based methods (Carreras, 2007; Koo and Collins, 2010; Ma and Zhao, 2012). In contrast, headed-span-based method (Yang and Tu, 2021) decomposes the score of a dependency tree into the scores of *headed-spans*: in a projective tree, a headed-span is a word-span pair such that the subtree rooted at the word covers the span in the surface order. Figure 1 shows an example projective parse tree and all its headed-spans. Because graph-based methods and the headed-span-based method take very different perspectives (i.e., composition of arcs vs. headed-spans) towards projective dependency parsing, it is theoretically interesting and intuitively beneficial to combine them.

We design three different ways to score a dependency tree with both arc and headed-span decomposition and propose the following dynamic programming algorithms for joint inference. We first design an $O(n^4)$ algorithm adapted from the Eisner-Satta algorithm (Eisner and Satta, 1999) to combine first-order graph-based and headed-span-based methods using the *hook trick*. Then we design two $O(n^3)$ algorithms adapted from the Eisner algorithm (Eisner, 1997) and its second-order extension (McDonald and Pereira, 2006) to combine first/second-order graph-based methods and the headed-span-based method using the *head-splitting trick*: we decompose the score of a headed-span into two terms assuming that the score of the left span boundary is independent to that of the right span boundary for each headword. We conduct extensive experiments on PTB, CTB, and UD, showing the effectiveness of our proposed methods.

2 Model

2.1 Scoring

Given an input sentences $x_1, ..., x_n$, we add <bos> (beginning of sentence) and <eos> (end of sentence) as x_0 and x_{n+1}. We apply mean-pooling at the last layer of BERT (Devlin et al., 2019) (i.e., averaging all subwords embeddings) to obtain the word-level embeddings e_i[1]. Then we feed $e_0, ..., e_{n+1}$ into a three-layer BiLSTM (Hochreiter and Schmidhuber, 1997) network to get $c_0, ..., c_{n+1}$, where $c_i = [f_i; b_i]$, f_i and b_i are the forward and backward hidden states of the last BiLSTM layer at position i respectively. We use $h_k = [f_k, b_{k+1}]$ to represent the kth boundary lying between x_k and x_{k+1}, and use $e_{i,j} = h_j - h_{i-1}$ to represent span (i, j) from position i to j inclusive where $1 \le i \le j \le n$. Then we compute:

- $s^{\text{arc}}_{i,j}$ (for arc $x_i \to x_j$, used in all three models) by feeding c_i, c_j into a deep biaffine function (Dozat and Manning, 2017).
- $s^{\text{span}}_{i,j,k}$ (for headed-span (i, j, k) where x_k is the headword of span (i, j), used in §3.1) by feeding $e_{i,j}, c_k$ to a deep biaffine function.
- $s^{\text{left}}_{k,i}$ and $s^{\text{right}}_{k,j}$ (for headed-span (i, j, k), used in §3.2 and §3.3) by feeding c_k, h_{i-1} and c_k, h_j into two different deep biaffine functions.
- $s^{\text{sib}}_{i,j,k}$ (for adjacent siblings $x_i \to \{x_j, x_k\}$ with $k < j < i$ or $i < j < k$, used in §3.3) by feeding c_i, c_k, c_j into a deep triaffine function (Zhang et al., 2020).

2.2 Learning

We decompose the training loss L into $L_{\text{parse}} + L_{\text{label}}$. For L_{parse}, we use the max-margin loss (Taskar et al., 2004):

$$L_{\text{parse}} = \max(0, \max_{y' \neq y}(s(y') + \Delta(y', y) - s(y))$$

where Δ measures the difference between the incorrect tree and gold tree y. Here we let Δ to be the Hamming distance (i.e., the total number of mismatches of arcs, sibling pairs, and (split) headed-spans depending on the setting). We use the same label loss L_{label} in Dozat and Manning (2017).

3 Parsing

We use the parsing-as-deduction framework (Pereira and Warren, 1983) to describe the parsing algorithms of our proposed models.

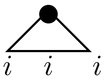
[1]For some datasets requiring the use of gold POS tags, we additionally concatenate the POS tag embedding to obtain e_i

3.1 $O(n^4)$ modified Eisner-Satta algorithm

In this case, we combine first-order graph-based parsing and headed-span-based parsing. The score of a dependency tree y is defined as:

$$s(y) = \sum_{(x_i \to x_j) \in y} s^{\text{arc}}_{i,j} + \sum_{(l_i, r_i, x_i) \in y} s^{\text{span}}_{l_i, r_i, i}$$

We design a dynamic programming algorithm adapted from the Eisner-Satta algorithm, which uses the hook trick to accelerate bilexicalized context-free parsing. The axiom items are



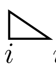
with initial score 0 and the deduction rules are listed in Figure 2. Unlike the original Eisner-Satta algorithm, we distinguish between "finished" spans and "unfinished" spans. An "unfinished" span can absorb a child span to form a larger span, while in a "finished" span, the headword has already generated all its children, so it cannot expand anymore and corresponds to a headed-span for the given headword. By explicitly distinguishing between "unfinished" spans and "finished" spans, we can incorporate headed-span scores s^{span} into parsing via the newly introduced rule `FINISH`. We then modify the rule `L-LINK` and `R-LINK` accordingly as only a "finished" span can be attached.

3.2 $O(n^3)$ modifed Eisner algorithm

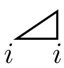
In order to decrease the inference time complexity from $O(n^4)$ to $O(n^3)$, we decompose $s^{\text{span}}_{l,r,i}$ into two terms:

$$s(y) = \sum_{(x_i \to x_j) \in y} s^{\text{arc}}_{i,j} + \sum_{(l_i, r_i, x_i) \in y} (s^{\text{left}}_{i,l_i} + s^{\text{right}}_{i,r_i})$$

and modify the Eisner algorithm accordingly. The axiom items are



and



with initial score 0 and the deduction rules are shown in the first two rows of Figure 3. Similar to the case in the previous subsection, the original Eisner algorithm does not distinguish between "finished" complete spans and "unfinished" complete spans. An "unfinished" complete span can absorb another complete span to form a larger incomplete span, while a "finished" complete span has no more child in the given direction and thus cannot expand anymore. We introduce new rules `L-FINISH` and `R-FINISH` to incorporate the left or right span boundary scores respectively, and adjust other rules accordingly.

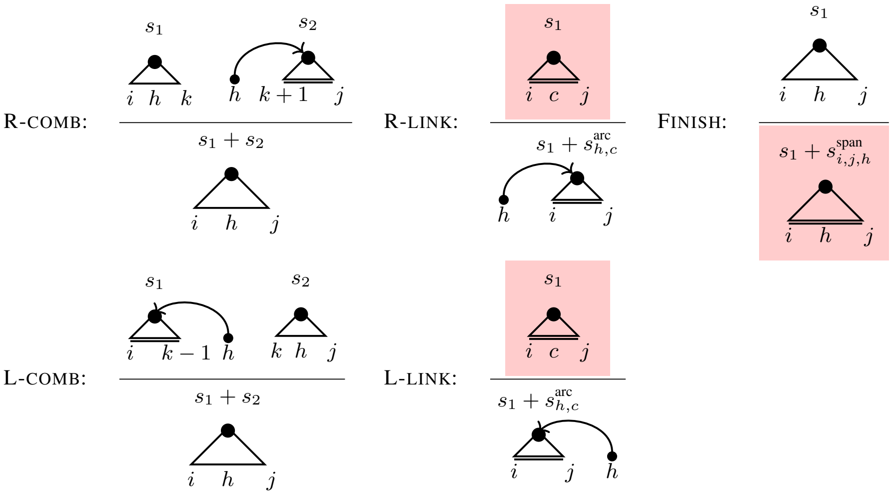


Figure 2: Deduction rules for our modified Eisner-Satta algorithm (Eisner and Satta, 1999). Our modifications are highlighted in red. All deduction items are annotated with their scores.

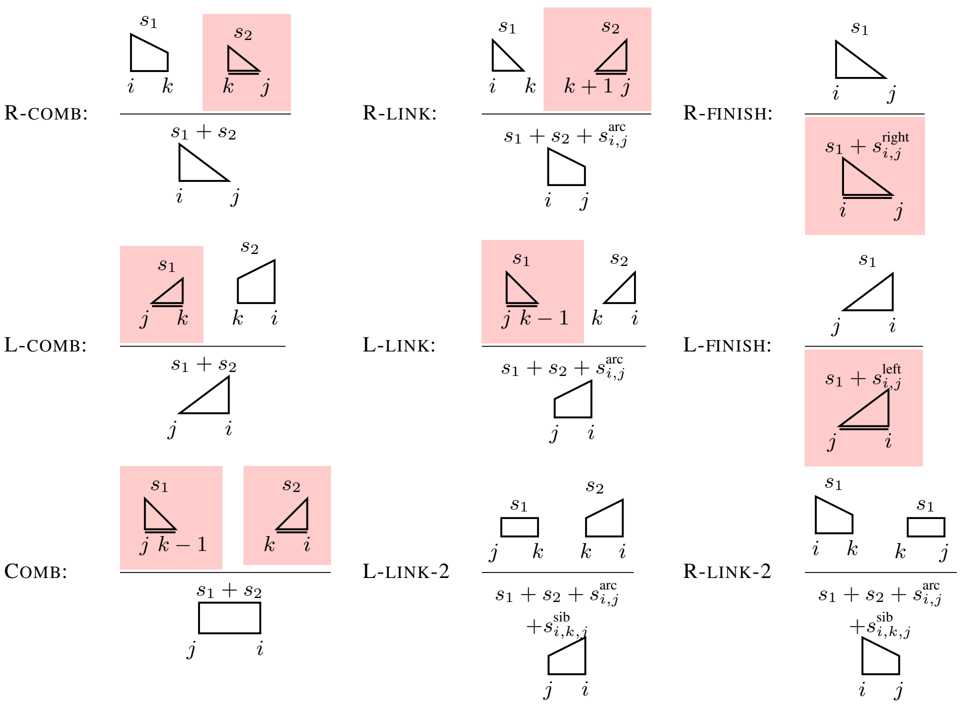


Figure 3: Deduction rules for our modified Eisner algorithm (Eisner, 1997) (first two rows) and its second-order extension (McDonald and Pereira, 2006) (all rows). Our modifications are highlighted in red. All deduction items are annotated with their scores.

3.3 $O(n^3)$ modified second-order Eisner algorithm

We further enhance the model with adjacent sibling information:

$$s(y) = \sum_{(x_i \to x_j) \in y} s^{\text{arc}}_{i,j} + \sum_{(x_i \to \{x_j, x_k\}) \in y} s^{\text{sib}}_{i,j,k} + \sum_{(l_i, r_i, x_i) \in y} (s^{\text{left}}_{i,l_i} + s^{\text{right}}_{i,r_i})$$

where for each adjacent sibling part $x_i \to \{x_j, x_k\}$, x_j and x_k are two adjacent dependents of x_i.

Similarly, we modify the second-order extension of the Eisner algorithm (McDonald and Pereira, 2006) by distinguishing between "unfinished" and "finished" complete spans. The additional deductive rules for second-order parsing are shown in the last row of Figure 3 and the length of the "unfinished" complete span is forced to be 1 in the rule `L-LINK` and `R-LINK`.

	bg	ca	cs	de	en	es	fr	it	nl	no	ro	ru	Avg
						+BERT$_{\text{multilingual}}$							
Biaffine+MM†	90.30	94.49	92.65	**85.98**	91.13	93.78	91.77	94.72	91.04	94.21	87.24	94.53	91.82
Span	91.10	94.46	92.57	85.87	**91.32**	93.84	91.69	94.78	91.65	94.28	87.48	94.45	91.96
1O+Span	91.44	94.54	92.68	85.75	91.23	93.84	91.67	**94.97**	**91.81**	94.35	87.17	94.49	91.99
1O+Span+Headsplit	91.46	94.53	92.63	85.78	91.25	93.77	**91.91**	94.88	91.59	94.18	87.45	94.47	91.99
Biaffine+2O+MM	91.58	94.48	**92.69**	85.72	91.28	93.80	91.89	94.88	91.30	94.23	87.55	**94.55**	92.00
2O+Span+Headsplit	**91.82**	**94.58**	92.59	85.65	91.28	**93.86**	91.80	94.75	91.50	**94.40**	**87.71**	94.51	**92.04**
						For reference							
MFVI2O	91.30	93.60	92.09	82.00	90.75	92.62	89.32	93.66	91.21	91.74	86.40	92.61	90.61

Table 1: Labeled Attachment Score (LAS) on twelves languages in UD 2.2. We use ISO 639-1 codes to represent languages. † means reported by Yang and Tu (2021). MFVI2O: Wang and Tu (2020). Span: Yang and Tu (2021).

	PTB		**CTB**	
	UAS	LAS	UAS	LAS
	+BERT$_{\text{large}}$		+BERT$_{\text{base}}$	
Biaffine+MM†	97.22	95.71	93.18	92.10
Span	97.24	95.73	93.33	92.30
1O+Span	97.26	95.68	93.56	**92.49**
1O+Span+HeadSplit	**97.30**	**95.77**	93.46	92.42
Biaffine+2O+MM	97.28	95.73	93.42	92.34
2O+Span+HeadSplit	97.23	95.69	**93.57**	92.47
	For reference			
MFVI2O	96.91	95.34	92.55	91.69
HierPtr	97.01	95.48	92.65	91.47
	+XLNet$_{\text{large}}$		+BERT$_{\text{base}}$	
HPSG♭	97.20	95.72	-	-
HPSG+LAL♭	97.42	96.26	94.56	89.28

Table 2: Results on PTB and CTB. ♭ denotes use of additional constituency tree data and thus not comparable to our work. † denotes results reported by Yang and Tu (2021). HPSG: Zhou and Zhao (2019); HPSG+LAL: Mrini et al. (2020); HierPtr: Fernández-González and Gómez-Rodríguez (2021).

4 Experiments

4.1 Setup

We conduct experiments on in Penn Treebank (PTB) 3.0 (Marcus et al., 1993), Chinese Treebank (CTB) 5.1 (Xue et al., 2005) and 12 languages on Universal Dependencies (UD) 2.2. We use the same data processing, evaluation methods, and hyperparameters as Yang and Tu (2021) for fair comparison and we refer readers to their paper for details due to the limit of space. We set the hidden size of the Triaffine function to 300 additionally. The reported results are averaged over three runs with different random seeds.

4.2 Main result

Table 1 and 2 show the results on UD, PTB and CTB respectively. We additionally reimplement `Biaffine+2O+MM` by replacing the TreeCRF loss of Zhang et al. (2020) with the max-margin loss for fair comparison. We refer to our proposed models as `1O+Span` (§3.1), `1O+Span+Headsplit` (§3.2), and `2O+Span+Headsplit` (§3.3) respectively.

We draw the following observations:

- Second-order information is still helpful even with powerful encoders (i.e., BERT). `Biaffine+2O+MM` outperforms `Biaffine+MM` in almost all cases.
- Combining first-order graph-based and headed-span-based methods is effective. Both `1O+Span` and `1O+Span+Headsplit` beat `Biaffine+MM` and `Span` in almost all cases. However, when incorporating span information into the second-order model, the improvement is slight: only +0.04 average LAS on UD, +0.13 LAS on CTB, and worse performance (-0.04 LAS) on PTB. We speculate that the utility of adjacent sibling information and span information is overlapping.
- Decomposing the headed-span scores is effective. `1O+Span+Headsplit` has a comparable performance to `1O+Span` while manages to decrease the time complexity from $O(n^4)$ to $O(n^3)$. We speculate that powerful encoders mitigate the issue of independent scoring.

5 Conclusion

In this paper we have presented three scoring and decoding methods to combine graph-based and headed-span-based methods for projective dependency parsing. Experiments show the effectiveness of our proposed methods.

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