Abstract

Existing work shows that lexical dependencies are helpful for constituent tree parsing. However, only first-order lexical dependencies have been employed and investigated in previous work. In this paper, we propose a method to employing higher-order lexical dependencies for constituent tree evaluation. Our method is based on a parse reranking framework, which provides a constrained search space (via N-best lists or parse forests) and enables our parser to employ relatively complicated dependency features. We evaluate our models on the Penn Chinese Treebank. The highest F1 score reaches 85.74%, thus outperforming all previously reported state-of-the-art systems. The dependency accuracy of constituent trees generated by our parser has been significantly improved as well.

1 Introduction

The most commonly used grammar for constituent structure parsing is probabilistic context-free grammar (PCFG). However, as demonstrated in Klein and Manning (2003a), PCFG estimated straightforwardly from Treebank does not perform well. The reason is that the basic PCFG has certain recognized drawbacks: its independence assumption is too strong, and it lacks of lexical conditioning (Jurafsky and Martin, 2008). To address these drawbacks, several variants of PCFG-based models have been proposed (Klein and Manning, 2003a; Matsuzaki et al., 2005; Petrov et al., 2006; Petrov and Klein, 2007). Lexicalized PCFG (LPCFG) (Collins, 1999; Charniak, 2000; Bikel, 2004) is a representative work that tries to ameliorate the deficiency of lexical conditioning. In LPCFG, non-terminals are annotated with lexical heads and the probabilities of CFG rules are estimated conditioned upon these lexical heads. Thus LPCFG becomes sensitive to lexical heads, and its performance is improved. However, the information provided by lexical heads is limited. To obtain higher parsing performance, we must seek additional information. We believe that dependency trees are good candidates because they encode grammatical relations between words and provide much more lexical conditioning than lexical heads for PCFG.

Dependency trees are usually factored into sets of lexical dependency parts for evaluation. The order of a lexical dependency part can be defined according to the number of dependency arcs it contains. For example, in Figure 1, dependency is first-order, sibling and grandchild are second-order and grand-sibling and tri-sibling are third-order. During the past few years, higher-order lexical dependencies have been successfully used for dependency parsing (McDonald et al., 2005; McDonald and Pereira, 2006; Koo and Collins, 2010). But for constituent tree evaluation, only first-order (bigram) lexical dependencies have been used (Collins, 1996; Klein and Manning, 2003a; Collins and Koo, 2005). However, first-order lexical dependency parts are quite limited and thus lose much of the contextual information within the dependency tree. To improve parsing performance, we propose to evaluate constituent trees with higher-order lexical dependencies.

In this paper, we propose a method for evaluating constituent trees using higher-order lexical dependencies within a parse reranking framework. We evaluate our method on the Penn Chinese Treebank (CTB). The F1 score reaches 85.74%, thus outperforming the best previously reported systems. Thanks to the lexical dependencies, the dependency accuracy of the generated constituent trees is improved as well. These experimental results show that higher-order lexical...
cal dependencies are highly beneficial for constituent tree evaluation.

The remainder of this paper is organized as follows: Section 2 briefly reviews related work and proposes our ideas. Section 3 describes our parsing approach. Section 4 describes our parse reranking algorithms based on higher-order lexical dependencies. In Section 5, we describe our training algorithms. We discuss and analyze our experiments in Section 6. Finally, we conclude and mention future work in Section 7.

2 Related Work and Our Ideas

Over the past few years, two kinds of parse reranking methods have been proposed. The first is \( N \)-best reranking (Charniak and Johnson, 2005; Collins and Koo, 2005). In this method, an existing generative parser is used to enumerate \( N \)-best parse trees for an input sentence, and then a reranking model is used to rescore the \( N \)-best lists with the help of various sorts of features. However, the \( N \)-best reranking method suffers from the limited scope of the \( N \)-best list in that potentially good alternatives may have been ruled out. The second method, called the forest reranking model, was proposed by Huang (2008). In Huang’s method, a forest, instead of an \( N \)-best list, is generated first. Then a beam search algorithm is used to generate \( N \)-best sub-trees for each node in bottom-up order and the best-first sub-tree of the root node is chosen as the final parse tree.

In recent years, there have been many attempts to use dependency trees for constituent parsing. All these approaches can be classified into three types. The first type is dependency-driven constituent parsing (Hall et al., 2007; Hall and Nivre, 2008). Given an input sentence, this approach first parses it into a labeled dependency tree (with complex arc labels, which makes it possible to recover the constituent tree) and then transforms the dependency tree into a constituent tree. The second approach is dependency-constrained constituent parsing (Xia and Palmer, 2001; Xia et al., 2008; Wang and Zhang, 2010; Wang and Zong, 2010). In this approach, dependency trees, once generated, are used to constrain the search space of a constituent parser. The third approach is dependency-based constituent parsing (Collins, 1996; Klein and Manning, 2003b). In this approach, the constituent tree is evaluated with the help of its corresponding lexical dependencies.

All three existing approaches have certain limitations. In the first approach, the dependency-driven constituent parser is not constrained by the Treebank grammar, so a constituent tree transformed from its corresponding dependency tree may contain context-free productions not seen in the Treebank grammar. Although this limitation may not affect the parsing \( F_1 \) score, it often has undesirable effects on applications. For the second approach, if the generated dependency tree includes some erroneous parts, the correct constituent tree may be pruned out directly, leaving no way to recover the correct tree again. The third approach parses sentences making use of first-order lexical dependencies only. As mentioned, first-order lexical dependencies are quite limited, and thus may lose much information about the grammatical relations between words. Consequently, the performance improvement of this approach is limited as well.

To overcome the drawbacks of the existing approaches, we propose to evaluate constituent trees using higher-order lexical dependencies within a parse reranking framework. Our approach has the following advantages: 1) It utilizes the higher-order lexical dependencies, which provide more contextual information within the dependency tree for constituent tree evaluation; 2) the parse reranking method provides high-quality candidates (\( N \)-best list or parse forest) which yields a small search space, enabling the use of relatively complicated features.

3 Our Approach

For a sentence \( x \), we define constituent parsing as a search for the highest-scoring parse \( c^* \) of \( x \):

\[
c^* = \arg \max_{c \in \text{GEN}(x)} \text{Score}(x,c)
\]  

(1)

Where, \( \text{GEN}(x) \) is a set of candidate parsers for \( x \), and \( \text{Score}(x,c) \) evaluates the event that tree \( c \) is the parse of sentence \( x \).

In order to evaluate \( c \) with higher-order lexical dependencies, we define:

\[
\text{Score}(x,c) = \Phi(x,c) \cdot \alpha = \sum_i \alpha_i \Phi_i(x,c)
\]

(2)

Where, \( \Phi \) maps each \( (x,c) \in X \times C \) to lexical dependency feature vector \( \Phi(x,y) \in \mathbb{R}^d \), and \( \alpha \in \mathbb{R}^d \) is the corresponding weight vector.

3.1 Representation of Constituent Tree with Labeled Dependency Tree

The discriminative parsing model in Eq. (1) takes lexical dependencies as features, so we must design a method of representing constituent trees
with associated dependency trees. Our method includes the following two steps:

**Step 1: Lexicalize the constituent tree**, i.e. annotate each node in the constituent tree with its head-word. First, find the head-child of each non-terminal node using a head percolation table (Yamada and Matsumoto, 2003). For example, in Figure 2(a), node B is identified as the head-child of rule A → B C D E. Then the head-words propagate up through the leaf nodes and each parent receives its head-word from its head-child. For example, in Figure 2(b), w₀ is propagated up from node B to A. According to this procedure, we can get the lexicalized constituent tree shown in Figure 2(b)) for the constituent fragment shown in Figure 2(a).

**Step 2: Transform the lexicalized tree into a labeled dependency tree.** First, let the head-word of each non-head-child depend on the head-word of the head-child for each rule. For example, in Figure 2(b) for rule A → B C D E, the head words of non-head-child (node C, D and E) which are w₁, w₂ and w₃ should depend on w₀ which is the head word of head-child (node B). In order to encode the syntactic symbols in the constituent tree into dependency tree, we annotate each dependency arc with a label \( N_h : P : N_m \), where \( N_h \) is the head-child’s syntactic category, \( P \) is the parent’s syntactic category and \( N_m \) is the non-head-child’s syntactic category. For example, in Figure 2(c), the dependency arc between w₁ and w₀ is built through rule A → B C D E, where w₀ associates with B, w₁ associates with C and the parent node is A, so we can annotate the dependency arc with B:A:C. According to the procedure, the lexicalized tree in Figure 2(b) can be transformed into the labeled dependency tree shown in Figure 2(c).

### 3.2 Mapping Higher-Order Lexical Dependencies into Feature Vectors

To map lexical dependencies into feature vectors, we define certain feature templates, as shown in Table 1. We work with binary indicator features² for each lexical dependency. The feature vector \( \Phi(x, C) \) of constituent tree \( C \) can be calculated through the dependency tree \( D \) transformed from \( C \) using the follow formula:

\[
\Phi(x, C) = \sum_{d \in S(D)} \phi(d)
\]

In this formula \( S(D) \) is a set of all the lexical dependencies extracted from \( D \), and \( d \) is a lexical dependency in \( S(D) \). The function \( \phi \) is used to map each lexical dependency \( d \) into feature vector according to the templates in Table 1.

### 4 Parse Reranking Algorithms

A critical problem when training the discriminative model in Eq. (1) is the extensive training time required, in which we must parse all the sentences in the training set repeatedly. In this paper, we adopt an approximate method: parse reranking. In parse reranking, \( GEN(S) \) in Eq. (1) is an \( N \)-best list or a parse forest which provides a small and well-formed search space for constituent parsing. Given this small space, we can exploit higher-order lexical dependencies efficiently.

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² Binary indicator features are defined as follows: if a certain feature is observed in an instance, the value of that feature is 1; otherwise, the value is 0.
4.1 N-best Reranking Based on Higher-Order Lexical Dependencies

The method of sub-section 3.1 determines that each constituent sub-tree must have a corresponding dependency sub-tree. Accordingly, we now describe an efficient algorithm for evaluating constituent trees with higher-order lexical dependencies. We define a quadruple \(<C_N,D_N,\text{score}(C_N),W_N>\) for each non-terminal node \(N\), in which \(C_N\) is the constituent sub-tree rooted at \(N\); \(D_N\) is the dependency sub-tree transformed from \(C_N\); \text{score}(C_N) is the score of \(C_N\) evaluated using Eq. (2); and \(W_N\) is the head-word of \(N\) in the tree.

Our algorithm (Algorithm 1) works bottom-up to fill \(<C_N,D_N,\text{score}(C_N),W_N>\) for each node \(N\). For a constituent \(P\) in the parse tree, we first find the head-child \(N_h\) for \(P\) (line 8), then propagate the head-word of \(N_h\) to \(P\) (line 9). To build \(D_P\), we simply build dependency arcs for current constituent \(P\); then link \(D_N\) with these dependency arcs; and then let the root of \(D_N\) be \(D_P\)’s root (line 11 to line 14). We extract all the lexical dependencies rooted at \(P\)’s head-word \(W_P\) through \(D_P\). For example, in Figure 2(b), all the lexical dependencies rooted at node A’s head-word \(w_0\) can be extracted from the dependency tree in Figure 2(c); and all the lexical dependencies have been shown in

| Basic Uni-gram Features | Basic Bi-gram Features | Surrounding Word POS Features |
|-------------------------|------------------------|-------------------------------|
| h, POS(h), N(h)        | h, POS(h), N(h), N(m)   | N(h), POS(h), N(h), N(m)     |
| m, POS(m), N(m)        | m, POS(m), N(m), N(m)   | N(m), POS(m), N(m), N(m)     |
|                          | N(m), POS(m), N(m), N(m)|                               |

| Basic Bi-gram Features | Surrounding Word POS Features |
|------------------------|-------------------------------|
| h, POS(h), N(h), N(m)   | N(h), POS(h), N(h), N(m)     |
| m, POS(m), N(m)        | N(m), POS(m), N(m), N(m)     |
|                          | N(m), POS(m), N(m), N(m)     |

| Table 1. Feature templates of various lexical dependency types. The lowercase letters h, m, s, g are words in a sentence. POS(x) is x’s POS tag. POS(x)+1 is the POS tag of the word to the right of x. POS(x)-1 is the POS tag of the word to the left of x. P(x), N(x) are syntactic categories of \(P\) and \(N\), which are annotated on dependency arcs. (We ignore dependency arc labels in the table for simplicity. More details can be found in section 3.2). |

4.2 Forest Reranking Based on Higher-Order Lexical Dependencies

As mentioned, N-best reranking suffers from the limited scope of N-best list. Forest reranking, by contrast, can rerank a packed forest of exponentially many parses, and thus provides a good way to overcome these limitations. Thus we also use the forest reranking method, based on higher-order lexical dependencies.

Figure 3. Then we map the lexical dependencies into feature vectors and sum over them as the feature vector \(\Phi(P)\) for \(P\). Finally, we evaluate the score of \(C_p\) using formula (4) below:

\[ \text{Score}(C_p) = \Phi(P) \cdot \alpha + \sum_{i=1}^{n} \text{Score}(C_{N_i}) \]
A forest is a compact representation of many parse trees. Figure 4(c) is a sample forest which is the compact representation of the constituent trees shown in Figures 4(a) and 4(b). To obtain forests, Huang (2008) tried to modify the Charniak parser to output forest directly. Inspired by parser combination methods (Sagae and Lavie, 2006; Fossum and Knight, 2009), we have designed a simple method of building forests starting from N-best lists. First, we convert each parse tree in an N-best list into context-free productions and label each constituent in each production with its span and syntactic category. Then these converted context-free productions are used to build the forest. For example, in Figure 4, given two candidates (Figure 4(a) and Figure 4(b)), we first convert them into context-free productions, e.g. NP0,3 → ADJP0,1 NP1,3, NP0,3 → NP0,2 NP2,3 and so on. Then we combine these productions into the forest shown in Figure 4(c). The recombined forest probably contains some parse trees that are not included in the N-best list, as will be shown in sub-section 6.1.

Our algorithm for forest reranking is similar to Algorithm 1. The only difference is that there may be more than one hyperedge for each node in a forest. So we make use of a beam search algorithm (Huang and Chiang, 2005) and store N-best sub-trees for each internal node. Finally, we choose the best-first sub-tree of the root node as the result.

5 Training Algorithm

The training task is to tune the parameter weights in Eq. (1) using the training examples as evidence. We employ the online-learning algorithm shown in Algorithm 2 because it has been proven to be effective and efficient in many studies (Collins, 2002; Collins and Roark, 2004; McDonald et al., 2005). For Algorithm 2, we define two parameter update strategies (line 5 in Algorithm 2) as follows.

The first strategy is perceptron updating. We first obtain the oracle tree \( c^*_i \) that has the highest \( F_1 \) score according to the gold-standard tree \( c_i \),

\[
c^*_i = \arg \max_{c \in \text{GEN}(x)} F_i(c, c_i)
\]

(5)

Then we get the highest scoring tree \( \hat{c}_i \) with current weights \( \vec{\alpha}^{(i)} \),

\[
\hat{c}_i = \arg \max_{c \in \text{GEN}(x)} \Phi(x, c) \cdot \vec{\alpha}^{(i)}
\]

(6)

If \( \hat{c}_i \) is not equal to \( c^*_i \), the weights will be updated through

\[
\vec{\alpha}^{(i+1)} \leftarrow \vec{\alpha}^{(i)} + \Phi(c^*_i) - \Phi(\hat{c}_i)
\]

(7)

Otherwise, the current weights are kept.

Although the perceptron updating strategy works well, parameter updating must wait until the entire tree has been built. We believe that this strategy probably misses the best opportunity for parameter updating and introduces some noise into the updating procedure. So, inspired by Collins and Roark (2004), we propose an early updating strategy for forest reranking. The key idea is to insert the parameter updating procedure into the forest reranking procedure. We parse a forest bottom up with the current parameter \( \vec{\alpha}^{(i)} \). When the best-first sub-tree \( \mathcal{s}_n \) for internal node \( N \) is different from oracle sub-tree \( s^*_n \), we stop the parsing procedure and update the parameters immediately using the following formula:

\[
\vec{\alpha}^{(i+1)} \leftarrow \vec{\alpha}^{(i)} + \Phi(s^*_n) - \Phi(\mathcal{s}_n)
\]

Then we continue to parse the current forest with the newer parameters \( \vec{\alpha}^{(i+1)} \). Unlike the perceptron updating strategy, this strategy updates parameters at the moment that an error sub-tree is built, and this is why we call it the early updating strategy.
6 Experiments and Analysis

We evaluate our method on the Penn Chinese Treebank Version 5.0 with the standard division: Art.301-325 as the development set, Art. 271-300 as the test set and others as the training set. All the F1 scores are evaluated with EVALB3.

6.1 To Obtain N-best Lists and Forests

We first employ existing parsers to generate N-best lists and then recombine the N-best lists into forests according to the method described in subsection 4.2. We split the training set into 20 folds averagely and generate 50-best lists for one fold with both the Berkeley parser4 and the Charniak parser5 (trained on the remaining 19 folds) individually. The development set and the test set are parsed with models trained on the entire training set.

|              | Berkeley(50) | Charniak(50) | Comb(100) |
|--------------|--------------|--------------|-----------|
| Nbest        | 89.13        | 89.20        | 91.61     |
| Forest       | 90.22        | 90.38        | 94.05     |

Table 2. Oracle F1 (%) of N-best lists and forests

The oracle F1 scores of N-best lists and forests on test set are listed in Table 2, where ‘Berkeley(50)’ means the performance of 50-best lists from Berkeley parser; ‘Charniak(50)’ means the performance of 50-best list from Charniak parser; ‘Comb(100)’ means the performance of 100-best lists by combining the two 50-best lists; “Nbest” means the oracle F1 of N-best lists; and “Forest” means the oracle F1 of forests which are evaluated through the Forest Oracle Algorithm proposed in Huang (2008). In Table 2, we can see that the oracle F1 scores of forests are much better than associated N-best lists. This result clearly demonstrates that the approach of obtaining forests by recombining N-best lists is effective.

6.2 Parameter Tuning on Development Set

We tuned some parameters manually for our models in the sub-section, including the number of iterations in the training algorithm, and the beam size k in the forest reranking algorithm. Models are trained with training set’s 100-best lists and evaluated on development set’s 100-best lists.

The F1 score curves varying with iteration times are shown in Figure 5. Although there are some fluctuations, we can see that the F1 score tends to improve with the incremental iteration times, and that the average model yields additional improvement. To avoid the problem of overfitting to the training set, we fix the iteration times at 10 in the following experiments. Figure 6 shows F1 score curves varying with beam size. We see that when the beam size exceeds 5, the performance fluctuates slightly, so we fix the beam size at 5 in our experiments. In Figure 6, we can also see that the model trained with the early updating strategy can obtain better performance than with the perceptron updating strategy.

6.3 Evaluation on Test Set

In this sub-section, we build three parsing systems using the methods described in the previous sections. For brevity, we annotate the N-best reranking system trained with the perceptron updating strategy as “NbestRerank”; the forest reranking system trained with the perceptron updating strategy as “ForestRerank”; and the forest reranking system trained with the early updating strategy as “EarlyUpdate”. We also employ the Charniak parser (Charniak) and the Berkeley

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3 http://nlp.cs.nyu.edu/evalb/
4 http://code.google.com/p/berkeleyparser/
5 http://bllip.cs.brown.edu/download/reranking-parserAug06.tar.gz
Using the parameter configuration tuned on development set, we have evaluated all the systems on test set. The $F_1$ scores are shown in Table 3. We can find that the $F_1$ scores are improved enormously when we make use of higher-order lexical dependencies. No matter which $N$-best list is used, EarlyUpdate system gets the highest $F_1$. However, the improved ranges vary with $N$-best list. The improvement is 1.93% for Berkeley parser’s 50-best list, while it is 0.91% for Charniak parser’s 50-best list. In our opinion, the reason is that Charniak parser has made use of headword information during parsing, so it is less sensitive to lexical dependencies than Berkeley parser. When we use the combined 100-best lists for training and testing, all the three systems are improved. NbestRerank gets 1.55% improvements than Berkeley does, ForestRerank gets 1.04% improvements further than NbestRerank does, and EarlyUpdate makes the final performance up to 85.74%.

Intuitively, since they benefit from the higher-order lexical dependencies, the generated constituent trees should show better dependency accuracy as well. So we convert the generated constituent trees into dependency trees and calculate their unlabeled dependency accuracy (UA)\(^6\).

### Table 3. $F_1$ (%) scores on Test Set. The column headed by “Berkeley” is trained and tested with Berkeley parser’s 50-best list; the column headed by “Charniak” is trained and tested with Charniak parser’s 50-best list; the column headed by “Combine” is trained and tested with 100-best list generated by Berkeley parser and Charniak parser.

| Parsers          | UA(%) | Berkelev | Charniak | Combine |
|------------------|------|----------|----------|---------|
| Baseline         | 83.13| 82.41    | -----    |         |
| NbestRerank      | 84.68| 83.29    | 84.68    |         |
| ForestRerank     | 84.31| 83.11    | 85.72    |         |
| EarlyUpdate      | **85.06**| **83.32**| 85.74    |         |

### Table 4. Unlabeled dependency accuracy (UA). NbestRerank, ForestRerank and EarlyUpdate are trained and tested with combined 100-best lists parser (Berkeley) as our baselines.

| Parsers          | UA(%) |
|------------------|------|
| Charniak         | 82.31|
| Berkeley         | 84.05|
| NbestRerank      | 85.89|
| ForestRerank     | 85.69|
| EarlyUpdate      | 86.26|
| MST 1-ord (automatic POS) | 79.62 |
| MST 2-ord (automatic POS) | 80.24 |
| MST 1-ord (gold-standard POS) | 85.23 |
| MST 2-ord (gold-standard POS) | 86.66 |

Table 5. $F_1$ (%) score on development set of the EarlyUpdate system using different lexical dependency types.

| Parsers          | $F_1$(%) |
|------------------|----------|
| Baseline         | 84.59    |
| +dependency      | 85.46    |
| (first-order)    |          |
| +sibling & grandchild | 86.20 |
| (second-order)   |          |
| +grand-sibling & tri-sibling | 86.37 |
| (third-order)    |          |

To demonstrate the effectiveness of our systems, we also train a 1-order MSTParser\(^7\) (MST 1-ord) and a 2-order MSTParser (MST 2-ord), and then use them to parse the test set with gold-standard POS tags and automatically annotated POS tags (accuracy is 95.17%). All of the results are shown in Table 4. We see that the UAs of our systems are much better than those of Charniak and Berkeley. Although our systems employ no gold-standard POS tags during parsing, their UAs exceed those of MST 1-ord, which does employ such tags; and the UA of EarlyUpdate is even comparable with those of MST 2-ord, which also employs such tags.

The figures shown in Table 3 and Table 4 clearly reveal that our parsing approach obtains constituent trees with both better $F_1$ scores and better UAs.

### 6.4 Ablation studies

The experimental results above have shown that reranking parses based on higher-order lexical dependencies is effective. To verify the contributions of different lexical dependency types, we further evaluate the development set using the EarlyUpdate system trained with combined forests. First, we reranked forests with first-order (dependency) lexical dependencies. Then we added the second-order (sibling and grandchild) lexical dependencies into our system. Finally, we added the third-order (grand-sibling and tri-sibling) lexical dependencies. All of the parsing results are shown in Table 5. It is clear that all of the lexical dependency types are helpful for constituent tree evaluation.

### 6.5 Comparison with State-of-the-art Results

Table 6 compares our best results with that of state-of-the-art parsers. Compared to the dependency arc labels are different from ours, we simply calculate the UAs.

\(^6\) To compare with dependency parsing systems whose dependency arc labels are different from ours, we simply calculate the UAs.

\(^7\) http://sourceforge.net/projects/mstparser/
“Charniak & Johnson Reranker” \(^8\) which is a parse reranking system and exploits various sorts of features including 1-order lexical dependencies (Charniak and Johnson, 2005), our NbestRerank parser, which uses higher-order lexical dependency features, gets a higher F1. Comparing with the parsers combination system (Zhang et al., 2009) which combines scores evaluated by Berkeley parser and Charniak parser to evaluate a parse tree, our EarlyUpdate system haven’t used scores evaluated by first stage parsers and still gets a higher F1 score. Although our EarlyUpdate system uses no resources other than CTB, it still obtains better results than other parsers which have employed extra resources (Burkett and Klein, 2008; Huang and Harper, 2009; Niu et al., 2009). These comparisons allow us to confidently conclude that exploitation of higher-order lexical dependencies is highly beneficial for constituent parsing.

### Table 6. F1 (%) scores of state-of-the-art methods compared with ours on the Chinese Treebank.

|                          | Individual System | N-best Reranking | Parsers Combination | Using Extra Resource | Reranking with Lexical Dependencies |
|--------------------------|-------------------|------------------|---------------------|---------------------|------------------------------------|
| (Petrov and Klein, 2007) | 83.32             |                  |                     |                     |                                    |
| (Huang and Harper, 2009) | 84.15             |                  |                     |                     |                                    |
| Charniak & Johnson Reranker | 83.30            |                  |                     |                     |                                    |
| Our NbestRerank System   | 84.68             |                  |                     |                     |                                    |
| (Zhang et al., 2009)     | 85.45             |                  |                     |                     |                                    |
| (Burkett and Klein, 2008)| 84.24             |                  |                     |                     |                                    |
| (Huang and Harper, 2009) | 85.18             |                  |                     |                     |                                    |
| (Niu et al., 2009)       | 85.20             |                  |                     |                     |                                    |
| Our EarlyUpdate System   | **85.74**         |                  |                     |                     |                                    |

8 The F1 score of Charniak & Johnson Reranker on CTB was reported in Niu et al. (2009).

### Conclusion and Future Work

We have presented a method for evaluating constituent trees using higher-order lexical dependencies. Within a parse reranking framework, our models rerank N-best lists and forests based on dependency features. Experimental results show that higher-order lexical dependencies can yield greater improvements in constituent parsing performance than commonly used first-order lexical dependencies. The best results of our models outperformed all previous results on the CTB, and the dependency accuracy of generated constituent trees is significantly improved as well. All of the results demonstrate that exploitation of higher-order lexical dependencies provides significant benefits for constituent tree evaluation.

Although all of our experiments were carried out only on the Chinese Treebank, our method is language independent. It can be adapted to any languages which can represent constituent trees with labeled dependency trees. We will apply our methods to other languages in the future.

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