Two Local Models for Neural Constituent Parsing

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Non-local features have been exploited by syntactic parsers for capturing dependencies between sub output structures. Such features have been a key to the success of state-of-the-art statistical parsers. With the rise of deep learning, however, it has been shown that local output decisions can give highly competitive accuracies, thanks to the power of dense neural input representations that embody global syntactic information. We investigate two conceptually simple local neural models for constituent parsing, which make local decisions to constituent spans and CFG rules, respectively. Consistent with previous findings along the line, our best model gives highly competitive results, achieving the labeled bracketing F1 scores of 92.4% on PTB and 87.3% on CTB 5.1.

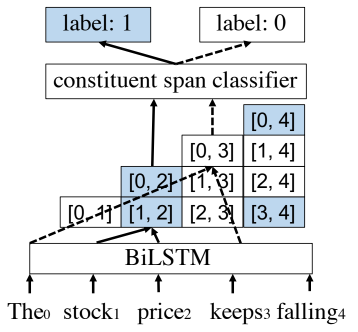
1 Introduction

Non-local features have been shown crucial for statistical parsing (Huang, 2008a; Zhang and Nivre, 2011). For dependency parsing, High-order dynamic programs (Koo and Collins, 2010), integer linear programming (Martins et al., 2010) and dual decomposition (Koo et al., 2010) techniques have been exploited by graph-based parser to integrate non-local features. Transition-based parsers (Nivre, 2003; Nivre, 2008; Zhang and Nivre, 2011; Bohnet, 2010; Huang et al., 2012) are also known for leveraging non-local features for achieving high accuracies. For most state-of-the-art statistical parsers, a global training objective over the entire parse tree has been defined to avoid label bias (Lafferty et al., 2001).

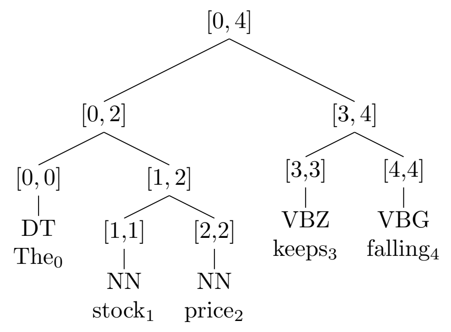
For neural parsing, on the other hand, local models have been shown to give highly competitive accuracies (Cross and Huang, 2016b; Stern et al., 2017) as compared to those that employ long-range features (Watanabe and Sumita, 2015; Zhou et al., 2015; Andor et al., 2016; Durrett and Klein, 2015). Highly local features have been used in recent state-of-the-art models (Stern et al., 2017; Dozat and Manning, 2016; Shi et al., 2017). In particular, Dozat and Manning (2016) show that a locally trained arc-factored model can give the best reported accuracies on dependency parsing. The surprising result has been largely attributed to the representation power of long short-term memory (LSTM) encoders (Kiperwasser and Goldberg, 2016b).

An interesting research question is to what extent the encoding power can be leveraged for constituent parsing. We investigate the problem by building a chart-based model that is local to unlabeled constituent spans (Abney, 1991) and CFG-rules, which have been explored by early PCFG models (Collins, 2003; Klein and Manning, 2003). In particular, our models first predict unlabeled CFG trees leveraging biaffine modelling (Dozat and Manning, 2016). Then, constituent labels are assigned on unlabeled trees by using a tree-LSTM to encode the syntactic structure, and a LSTM decoder for yielding label sequences on each node, which can include unary rules.

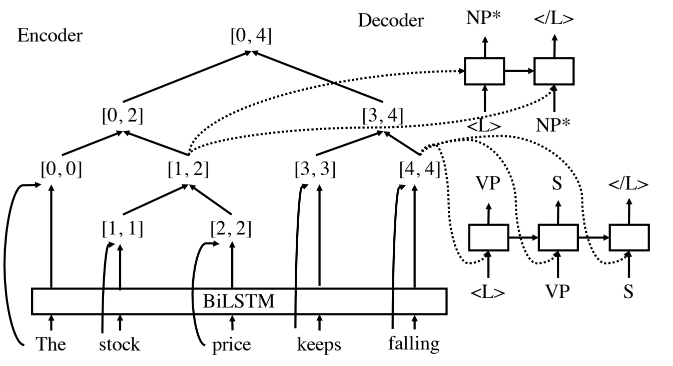
Experiments show that our conceptually simple models give highly competitive performances compared with the state-of-the-art. Our best models give labeled bracketing F1 scores of 92.4% on PTB and 87.3% on CTB 5.1 test sets, without reranking, ensembling and external parses. We release our code at



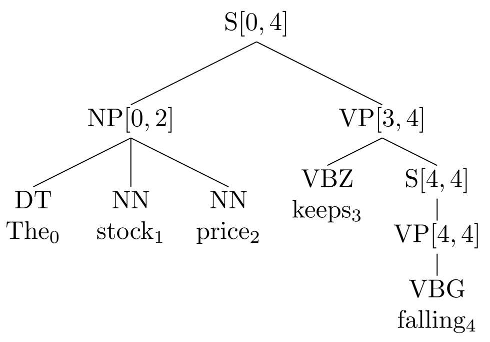
(a) BiLSTM based constituent span classifier.



(b) unlabeled binarized parse tree.



(c) Label generator for two example spans. **NP*** is an intermediate constituent label.



(d) Final example parse tree.

Figure 1: An example workflow of our parsers for the sentence "The stock price keeps falling". We annotate every non-terminal span with its covered span range. Figure 1a shows constituent span classifiers making 0/1 decisions for all possible spans. Based on the local classification probabilities, we obtain an unlabeled binarized parse tree (Figure 1b) using binary CKY parsing algorithms. We then hierarchically generate labels for each span (Figure 1c) using encoder-decoder models. Figure 1d shows the final output parse tree after debinarization.

`https://github.com/zeeeyang/two-local-neural-conparsers.`

2 Model

Our models consist of an unlabeled binarized tree parser and a label generator. Figure 1 shows a running example of our parsing model. The unlabeled parser (Figure 1a, 1b) learns an unlabeled parse tree using simple BiLSTM encoders (Hochreiter and Schmidhuber, 1997). The label generator (Figure 1c, 1d) predicts constituent labels for each span in the unlabeled tree using tree-LSTM models.

In particular, we design two different classification models for unlabeled parsing: the **span model** (Section 2.1) and the **rule model** (Section 2.2). The span model identifies the probability of an arbitrary span being a constituent span. For example, the span $[1, 2]$ in Figure 1a belongs to the correct parse tree (Figure 1d). Ideally, our model assigns a high probability to this span. In contrast, the span $[0, 3]$ is not a valid constituent span and our model labels it with 0. Different from the span model, the rule model considers the probability $P([i, j] \to [i, k][k + 1, j]|S)$ for the production rule that the span $[i, j]$ is composed by two children spans $[i, k]$ and $[k + 1, j]$, where $i \leq k < j$. For example, in Figure 1a, the rule model assigns high probability to the rule $[0, 2] \to [0, 0][1, 2]$ instead of the rule $[0, 2] \to [0, 1][2, 2]$. Given the local probabilities, we use CKY algorithm to find the unlabeled binarized parses.

The label generator encodes a binarized unlabeled tree and to predict constituent labels for every span. The encoder is a binary tree-LSTM (Tai et al., 2015; Zhu et al., 2015), which recursively composes the representation vectors for tree nodes bottom-up. Based on the representation vector of a constituent span, a LSTM decoder (Cho et al., 2014; Sutskever et al., 2014) generates chains of constituent labels, which can represent unary rules. For example, the decoder outputs "VP $\rightarrow$S$\rightarrow$ </L>" for the span [4, 4] and "NP$\rightarrow$ </L>" for the span [0,2] in Figure 1c where </L> is a stopping symbol.

2.1 Span Model

Given an unlabeled binarized tree T_{ub} for the sentence S, $S = w_0, w_1 \dots w_{n-1}$, the span model trains a neural network model $P(Y_{[i,j]}|S, \Theta)$ to distinguish constituent spans from non-constituent spans, where $0 \le i \le n-2$, $1 \le j < n$, $i < j$. $Y_{[i,j]} = 1$ indicates the span [i, j] is a constituent span ($[i, j] \in T_{ub}$), and $Y_{[i,j]} = 0$ for otherwise, Θ are model parameters. We do not model spans with length 1 since the span $[i, i]$ always belongs to T_{ub}.

Network Structure. Figure 2a shows the neural network structures for the binary classification model. In the bottom, a bidirectional LSTM layer encodes the input sentence to extract non-local features. In particular, we append a starting symbol <s> and an ending symbol </s> to the left-to-right LSTM and the right-to-left LSTM, respectively. We denote the output hidden vectors of the left-to-right LSTM and the right-to-left LSTM for $w_0, w_1, \dots, w_{n-1}$ is $\mathbf{f}_1, \mathbf{f}_2, \dots, \mathbf{f}_n$ and $\mathbf{r}_0, \mathbf{r}_1, \dots, \mathbf{r}_{n-1}$, respectively. We obtain the representation vector $\mathbf{v}[i, j]$ of the span $[i, j]$ by simply concatenating the bidirectional output vectors at the input word i and the input word j,

$$\mathbf{v}[i, j] = [\mathbf{f}_{i+1}; \mathbf{r}_i; \mathbf{f}_{j+1}; \mathbf{r}_j]. \tag{1}$$

$\mathbf{v}[i, j]$ is then passed through a nonlinear transformation layer and the probability distribution $P(Y_{[i,j]}|S, \Theta)$ is given by

$$\mathbf{o}[i, j] = \tanh(\mathbf{W}_o\mathbf{v}[i, j] + \mathbf{b}_o), \ \ \mathbf{u}[i, j] = \mathbf{W}_u\mathbf{o}[i, j] + \mathbf{b}_u, \ \ P(Y_{[i,j]}|S, \Theta) = \text{softmax}(\mathbf{u}[i, j]), \tag{2}$$

where $\mathbf{W}_o, \mathbf{b}_o, \mathbf{W}_u$ and $\mathbf{b}_u$ are model parameters.

Input Representation. Words and part-of-speech (POS) tags are integrated to obtain the input representation vectors. Given a word w, its corresponding characters $c_0, \dots, c_{|w|-1}$ and POS tag t, first, we obtain the word embedding $\mathbf{E}^{w}_{word}$, character embeddings $\mathbf{E}^{c_0}_{char}, \dots, \mathbf{E}^{c_{|w|-1}}_{char}$, and POS tag embedding $\mathbf{E}^{t}_{pos}$ using lookup operations. Then a bidirectional LSTM is used to extract character-level features. Suppose that the last output vectors of the left-to-right and right-to-left LSTMs are $\mathbf{h}^{f}_{char}$ and $\mathbf{h}^{r}_{char}$, respectively. The final input vector $\mathbf{x}_{input}$ is given by

$$\mathbf{x}_{char} = \tanh(\mathbf{W}^{l}_{char}\mathbf{h}^{l}_{char} + \mathbf{W}^{r}_{char}\mathbf{h}^{r}_{char} + \mathbf{b}_{char}), \ \ \mathbf{x}_{input} = [\mathbf{E}^{w}_{word} + \mathbf{x}_{char}; \mathbf{E}^{t}_{pos}], \tag{3}$$

where $\mathbf{W}^{l}_{char}$, $\mathbf{W}^{r}_{char}$ and $\mathbf{b}_{char}$ are model parameters.

Training objective. The training objective is to maximize the probabilities of $P(Y_{[i,j]} = 1|S, \Theta)$ for spans $[i, j] \in T_{ub}$ and minimize the probabilities of $P(Y_{[i,j]} = 1|S, \Theta)$ for spans $[i, j] \notin T_{ub}$ at the same time. Formally, the training loss for binary span classification $\mathcal{L}_{\text{binary}}$ is given by

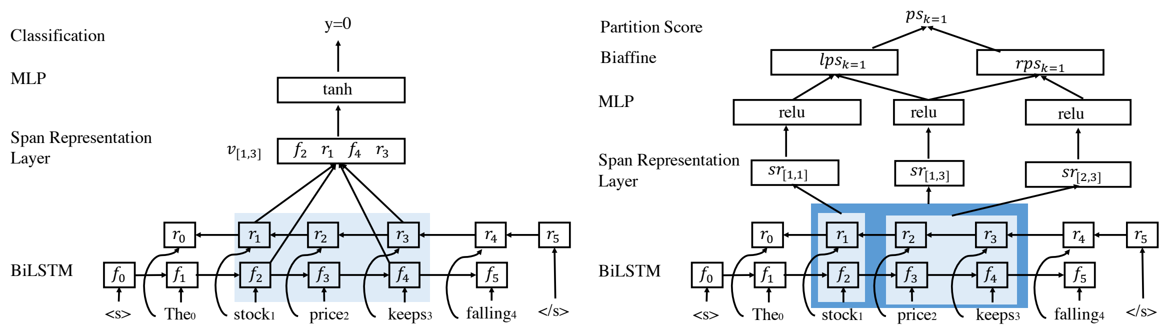
$$\mathcal{L}_{\text{binary}} = -\sum_{[i,j]\in T_{ub}} \log P(Y_{[i,j]} = 1|S, \Theta) - \sum_{[i,j]\notin T_{ub}} \log P(Y_{[i,j]} = 0|S, \Theta), \\ (0 \le i \le n-2, 1 \le j < n, i < j) \tag{4}$$

For a sentence with length n, there are $\frac{n(n-1)}{2}$ terms in total in Eq 4.

Neural CKY algorithm. The unlabeled production probability for the rule $r : [i, j] \rightarrow [i, k][k+1, j]$ given by the binary classification model is,

$$P(r|S, \Theta) = P(Y_{[i,k]} = 1|S, \Theta)P(Y_{[k+1,j]} = 1|S, \Theta).$$

During decoding, we find the optimal parse tree T^{*}_{ub} using the CKY algorithm. Note that our CKY algorithm is different from the standard CKY algorithm mainly in that there is no explicit phrase rule probabilities being involved. Hence our model can be regarded as a zero-order constituent tree model, which is the most *local*. All structural relations in a constituent tree must be implicitly captured by the BiLSTM encoder over the sentence alone.


Classification
MLP
Span Representation Layer
BiLSTM
y=0
tanh
$v_{[1,3]}$
f_2 r_1 f_4 r_3
r_0 r_1 r_2 r_3 r_4 r_5
f_0 f_1 f_2 f_3 f_4 f_5
<s> The0 stock1 price2 keeps3 falling4 </s>
Partition Score
Biaffine
MLP
Span Representation Layer
BiLSTM
$ps_{k=1}$
$lps_{k=1}$
$rps_{k=1}$
relu
relu
relu
$sr_{[1,1]}$
$sr_{[1,3]}$
$sr_{[2,3]}$
r_0 r_1 r_2 r_3 r_4 r_5
f_0 f_1 f_2 f_3 f_4 f_5
<s> The0 stock1 price2 keeps3 falling4 </s>

(a) Span model.

(b) Rule model.

Figure 2: Neural network structures for span and rule models using BiLSTM encoders.

Multi-class Span Classification Model. The previous model preforms binary classifications to identify constituent spans. In this way, the classification model only captures the existence of constituent labels but does not leverage constituent label type information. In order to incorporate the syntactic label information into the span model, we use a multi-class classification model $P(Y_{[i,j]} = c|S, \Theta)$ to describe the probability that c is a constituent label for span $[i, j]$. The network structure is the same as the binary span classification model except the last layer. For the last layer, given $\mathbf{o}_{[i,j]}$ in Eq 2, $P(Y_{[i,j]} = c|S, \Theta)$ is calculated by,

$$\mathbf{m}[i,j] = \mathbf{W}_m \mathbf{o}[i,j] + \mathbf{b}_m,\ P(Y_{[i,j]} = c|S,\Theta) = \text{softmax}(\mathbf{m}[i,j])_{[c]}. \tag{5}$$

Here $\mathbf{W}_m, \mathbf{b}_m, \mathbf{W}_m$ and $\mathbf{b}_m$ are model parameters. The subscript $[c]$ is to pick the probability for the label c. The training loss is,

$$\mathcal{L}_{\text{multi}} = -\sum_{[i,j]\in T_{ub}} \sum_{c\in \textsc{Gen}[i,j], c\neq </L>} \log P(Y_{[i,j]} = c|S,\Theta) - \sum_{[i,j]\notin T_{ub}} \log P(Y_{[i,j]} = </L>|S,\Theta), \tag{6}$$
$$(0 \le i \le n-2, 1 \le j < n, i < j)$$

Note that there is an additional sum inside the first term in Eq 6, which is different from the first term in Eq 4. $\textsc{Gen}[i, j]$ denotes the label set of span $[i, j]$. This is to say that we treat all constituent labels equally of a unary chain. For example, suppose there is a unary chain S→VP in span [4,4]. For this span, we hypothesize that both labels are plausible answers and pay equal attentions to VP and S during training. For the second term in Eq 6, we maximize the probability of the ending label for non-constituent spans.

For decoding, we transform the multi-class probability distribution into a binary probability distribution by using,

$$P(Y_{[i,j]} = 1|S,\Theta) = \sum_{c, c\neq </L>} P(Y_{[i,j]} = c|S,\Theta),\ \ P(Y_{[i,j]} = 0|S,\Theta) = P(Y_{[i,j]} = </L>|S,\Theta)$$

In this way, the probability of a span being a constituent span takes all possible syntactic labels into considerations.

2.2 Rule Model

The rule model directly calculates the probabilities of all possible splitting points k $(i \le k < j)$ for the span $[i, j]$. Suppose the partition score of splitting point k is ps_k. The unlabeled production probability for the rule $r : [i, j] \to [i, k][k + 1, j]$ is given by a softmax distribution,

$$P([i,j] \to [i,k][k+1,j]|S,\Theta) = \frac{\exp(ps_k)}{\sum_{k'=i}^{j-1} \exp(ps_{k'})}.$$

The training objective is to minimize the log probability loss of all unlabeled production rules.

$$\mathcal{L}_{\text{rule}} = -\sum_{r \in T_{ub}} \log P(r : [i,j] \rightarrow [i,k][k+1,j] | S, \Theta)$$

The decoding algorithm is the standard CKY algorithm, which we omit here. The rule model can be regarded as a first-order constituent model, with the probability of each phrase rule being modeled. However, unlike structured learning algorithms (Finkel et al., 2008; Carreras et al., 2008), which use a global score for each tree, our model learns each production rule probability individually. Such local learning has traditionally been found subjective to label bias (Lafferty et al., 2001). Our model relies on input representations solely for resolving this issue.

Span Representation. Figure 2b shows one possible network architecture for the rule model by taking the partition point $k = 1$ for the span $[1, 3]$ as an example. The BiLSTM encoder layer in the bottom is the same as that of the previous span classification model. We obtain the span representation vectors using difference vectors (Wang and Chang, 2016; Cross and Huang, 2016b). Formally, the span representation vector $\mathbf{sr}[i, j]$ is given by,

$$\begin{aligned} \mathbf{s}[i,j] &= [\mathbf{f}_{j+1} - \mathbf{f}_i; \mathbf{r}_i - \mathbf{r}_{j+1}], \\ \mathbf{sr}[i,j] &= [\mathbf{s}[0, i-1]; \mathbf{s}[i,j]; \mathbf{s}[j+1, n-1]]. \end{aligned} \tag{7}$$

We first combine the difference vectors $(\mathbf{f}_{j+1} - \mathbf{f}_i)$ and $(\mathbf{r}_i - \mathbf{r}_{j+1})$ to obtain a simple span representation vector $\mathbf{s}[i,j]$. In order to take more contextual information such as $\mathbf{f}_p$ where $p > j+1$ and $\mathbf{r}_q$ where $q < i$, we concatenate $\mathbf{s}[0, i-1]$, $\mathbf{s}[i,j]$, and $\mathbf{s}[j+1, n-1]$ to produce the final span representation vector $\mathbf{sr}[i,j]$. We then transform $\mathbf{sr}[i,j]$ to an output vector $\mathbf{r}[i,j]$ using an activation function ϕ,

$$\mathbf{r}[i,j] = \phi(\mathbf{W}_r^M \mathbf{sr}[i,j] + \mathbf{b}_r^M), \tag{8}$$

where $\mathbf{W}_r^M$ and $\mathbf{b}_r^M$ and model parameters, and M is a parameter set index. We use separate parameters for the nonlinear transforming layer. $M \in \{P, L, R\}$ are for the parent span $[i,j]$, the left child span $[i,k]$ and the right child span $[k+1,j]$, respectively.

After obtaining the span representation vectors, we use these vectors to calculate the partition score ps_k. In particular, we investigate two scoring methods.

Linear Model. In the linear model, the partition score is calculated by a linear affine transformation. For the splitting point k,

$$ps_k = \mathbf{w}_{ll,k}^T \mathbf{r}[i,k] + \mathbf{w}_{lr,k}^T \mathbf{r}[k+1,j] + b_{ll,k}$$

where $\mathbf{w}_{ll,k}^T$ and $\mathbf{w}_{ll,k}^T$ are two vectors, and $b_{ll,k}$ is a size 1 parameter.

Biaffine model. Since the possible splitting points for spans are varied with the length of span, we also try a biaffine scoring model (as shown in Figure 2b), which is good at handling variable-sized classification problems (Dozat and Manning, 2016; Ma and Hovy, 2017). The biaffine model produces the score lps_k between the parent span $[i,j]$ and the left child span $[i,k]$ using a biaffine scorer

$$lps_k = (\mathbf{r}[i,j] \oplus 1)^T \mathbf{W}_{pl} (\mathbf{r}[i,k] \oplus 1) \tag{9}$$

where $\mathbf{W}_{pl}$ is model parameters and $\oplus$ denotes vector concatenation. Similarly, we calculate the score rps_k between the parent span $[i,j]$ and the right child span $[k+1,j]$ using $\mathbf{W}_{pr}$ and $\mathbf{b}_{pr}$ as parameters. The overall partition score ps_k is therefore given by

$$ps_k = lps_k + rps_k.$$

2.3 Label Generator

Lexicalized Tree-LSTM Encoder. Shown in Figure 1c, we use lexicalized tree LSTM (Teng and Zhang, 2016) for encoding, which shows good representation abilities for unlabeled trees. The encoder first propagates lexical information from two children spans to their parent using a lexical gate, then it produces the representation vectors of the parent span by composing the vectors of children spans using a binarized tree-LSTM (Tai et al., 2015; Zhu et al., 2015). Formally, the lexical vector $\mathbf{tx}[i,j]$ for the span $[i,j]$ with the partition point at k is defined by:

$$\begin{aligned}\mathbf{i}^{lex}_{[i,j]} &= \sigma(\mathbf{W}^{lex}_{l}\mathbf{tx}[i,k] + \mathbf{W}^{lex}_{r}\mathbf{tx}[k+1,j] + \mathbf{W}^{lex}_{lh}\mathbf{h}_{[i,k]} + \mathbf{W}^{lex}_{rh}\mathbf{h}_{[k+1,j]} + \mathbf{b}_{lex})\\ \mathbf{tx}[i,j] &= \mathbf{i}^{lex}_{[i,j]} \odot \mathbf{tx}[i,k] + (\mathbf{1.0} - \mathbf{i}^{lex}_{[i,j]}) \odot \mathbf{tx}[k+1,j],\end{aligned}$$

where $\mathbf{W}^{lex}_{l}$, $\mathbf{W}^{lex}_{r}$ and $\mathbf{b}_{lex}$ are model parameters, $\odot$ is element-wise multiplication and σ is the logistic function. The lexical vector $\mathbf{tx}[i,i]$ for the leaf node i is the concatenate of the output vectors of the BiLSTM encoder and the input representation $\mathbf{x}_{\textbf{input}}[i]$ (Eq 3), as shown in Figure 1c.

The output state vector $\mathbf{h}[i,j]$ of the span $[i,j]$ given by a binary tree LSTM encoder is,

$$\begin{aligned}\mathbf{i}_p &= \sigma(\mathbf{W}_1\mathbf{tx}_p + \mathbf{W}_2\mathbf{h}_l + \mathbf{W}_3\mathbf{c}_l + \mathbf{W}_4\mathbf{h}_r + \mathbf{W}_5\mathbf{c}_r + \mathbf{b}_1),\\ \mathbf{f}^l_p &= \sigma(\mathbf{W}_6\mathbf{tx}_p + \mathbf{W}_7\mathbf{h}_l + \mathbf{W}_8\mathbf{c}_l + \mathbf{W}_9\mathbf{h}_r + \mathbf{W}_{10}\mathbf{c}_r + \mathbf{b}_2),\\ \mathbf{f}^r_p &= \sigma(\mathbf{W}_{11}\mathbf{tx}_p + \mathbf{W}_{12}\mathbf{h}_r + \mathbf{W}_{13}\mathbf{c}_l + \mathbf{W}_{14}\mathbf{h}_r + \mathbf{W}_{15}\mathbf{c}_r + \mathbf{b}_3),\\ \mathbf{g}_p &= \tanh(\mathbf{W}_{16}\mathbf{tx}_p + \mathbf{W}_{17}\mathbf{h}_l + \mathbf{W}_{18}\mathbf{h}_r + \mathbf{b}_4),\\ \mathbf{c}_p &= \mathbf{f}^l_p \odot \mathbf{c}_l + \mathbf{f}^r_p \odot \mathbf{c}_r + \mathbf{i}_p \odot \mathbf{g}_p,\\ \mathbf{o}_p &= \sigma(\mathbf{W}_{19}\mathbf{tx}_p + \mathbf{W}_{20}\mathbf{h}_p + \mathbf{W}_{21}\mathbf{h}_r + \mathbf{W}_{22}\mathbf{c}_p + \mathbf{b}_5),\ \ \mathbf{h}_p = \mathbf{o}_p \odot \tanh(\mathbf{c}_p).\end{aligned}$$

Here the subscripts p, l and r denote $[i,j]$, $[i,k]$ and $[k+1,j]$, respectively.

Label Decoder. Suppose that the constituent label chain for the span $[i,j]$ is $(\text{YL}^0_{[i,j]}, \text{YL}^1_{[i,j]}, \ldots, \text{YL}^m_{[i,j]})$. The decoder for the span $[i,j]$ learns a conditional language model depending on the output vector $\mathbf{h}[i,j]$ from the tree LSTM encoder. Formally, the probability distribution of generating the label at time step z is given by,

$$P(\text{YL}^z_{[i,j]}|T_{ub}, \text{YL}^{z<m}_{[i,j]}) = \text{softmax}\Big(g(\mathbf{h}[i,j], \mathbf{E}_{label}(\text{YL}^{z-1}_{[i,j]}), \mathbf{d}_{z-1})\Big),$$

where $\text{YL}^{z<m}_{[i,j]}$ is the decoding prefix, $\mathbf{d}_{z-1}$ is the state vector of the decoder LSTM and $\mathbf{E}_{label}(\text{YL}^{z-1}_{[i,j]})$ is the embedding of the previous output label.

The training objective is to minimize the negative log-likelihood of the label generation distribution,

$$\begin{aligned}\mathcal{L}_{\text{label}}[i,j] &= -\sum_{z=0}^{m} \log P(\text{YL}^z_{[i,j]}|T_{ub}, \text{YL}^{z<m}_{[i,j]}),\\ \mathcal{L}_{\text{label}} &= \sum_{[i,j]\in T_{ub}} \mathcal{L}_{\text{label}}[i,j].\end{aligned}$$

2.4 Joint training

In conclusion, each model contains an unlabeled structure predictor and a label generator. The latter is the same for all models. All the span models perform binary classification. The difference is that BinarySpan doesn't consider label information for unlabeled tree prediction. While MultiSpan guides unlabeled tree prediction with such information, simulating binary classifications. The unlabeled parser and the label generator share parts of the network components, such as word embeddings, char embeddings, POS embeddings and the BiLSTM encoding layer. We jointly train the unlabeled parser and the label generator for each model by minimizing the overall loss

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{parser}} + \mathcal{L}_{\text{label}} + \frac{\lambda}{2}||\Theta||^2,$$

where λ is a regularization hyper-parameter. We set $\mathcal{L}_{\text{parser}} = \mathcal{L}_{\text{binary}}$ or $\mathcal{L}_{\text{parser}} = \mathcal{L}_{\text{multi}}$ and $\mathcal{L}_{\text{parser}} = \mathcal{L}_{\text{rule}}$ when using the binary span classification model, the multi-class model and the rule model, respectively.

hyper-parameter	value	hyper-parameter	value
Word embeddings	English: 100 Chinese: 80	Word LSTM layers	2
Word LSTM hidden units	200	Character embeddings	20
Character LSTM layers	1	Character LSTM hidden units	25
Tree-LSTM hidden units	200	POS tag embeddings	32
Constituent label embeddings	32	Label LSTM layers	1
Label LSTM hidden units	200	Last output layer hidden units	128
Maximum training epochs	50	Dropout	English: 0.5, Chinese 0.3
Trainer	SGD	Initial learning rate	0.1
Per-epoch decay	0.05	ϕ	ELU (Clevert et al., 2015)

Table 1: Hyper-parameters for training.

3 Experiments

3.1 Experimental Settings

Data. We perform experiments for both English and Chinese. Following standard conventions, our English data are obtained from the Wall Street Journal (WSJ) of the Penn Treebank (PTB) (Marcus et al., 1993). Sections 02-21, section 22 and section 23 are used for training, development and test sets, respectively. Our Chinese data are the version 5.1 of the Penn Chinese Treebank (CTB) (Xue et al., 2005). The training set consists of articles 001-270 and 440-1151, the development set contains articles 301-325 and the test set includes articles 271-300. We use automatically reassigned POS tags in the same way as Cross and Huang (2016b) for English and Dyer et al. (2016) for Chinese.

We use ZPar (Zhang and Clark, 2011)[1] to binarize both English and Chinese data with the head rules of Collins (2003). The head directions of the binarization results are ignored during training. The types of English and Chinese constituent span labels after binarization are 52 and 56, respectively. The maximum number of greedy decoding steps for generating consecutive constituent labels is limited to 4 for both English and Chinese. We evaluate parsing performance in terms of both unlabeled bracketing metrics and labeled bracketing metrics including unlabeled F1 (UF)[2], labeled precision (LP), labeled recall (LR) and labeled bracketing F1 (LF) after debinarization using EVALB[3].

Unknown words. For English, we combine the methods of Dyer et al. (2016), Kiperwasser and Goldberg (2016a) and Cross and Huang (2016b) to handle unknown words. In particular, we first map all words (not just singleton words) in the training corpus into unknown word classes using the same rule as Dyer et al. (2016). During each training epoch, every word w in the training corpus is stochastically mapped into its corresponding unknown word class unk_w with probability $P(w \rightarrow unk_w) = \frac{\gamma}{\gamma + \#w}$, where $\#w$ is the frequency count and γ is a control parameter. Intuitively, the more times a word appears, the less opportunity it will be mapped into its unknown word type. There are 54 unknown word types for English. Following Cross and Huang (2016b), $\gamma = 0.8375$. For Chinese, we simply use one unknown word type to dynamically replace singletons words with a probability of 0.5.

Hyper-parameters. Table 1 shows all hyper-parameters. These values are tuned using the corresponding development sets. We optimize our models with stochastic gradient descent (SGD). The initial learning rate is 0.1. Our model are initialized with pretrained word embeddings both for English and Chinese. The pretrained word embeddings are the same as those used in Dyer et al. (2016). The other parameters are initialized according to the default settings of DyNet (Neubig et al., 2017). We apply dropout (Srivastava et al., 2014) to the inputs of every LSTM layer, including the word LSTM layers, the character LSTM layers, the tree-structured LSTM layers and the constituent label LSTM layers. For Chinese, we find that 0.3 is a good choice for the dropout probability. The number of training epochs is decided by the evaluation performances on development set. In particular, we perform evaluations on development set for every 10,000 examples. The training procedure stops when the results of next 20 evaluations do not become better than the previous best record.

[1]https://github.com/SUTDNLP/ZPar

[2]For UF, we exclude the sentence span [0,n-1] and all spans with length 1.

[3]http://nlp.cs.nyu.edu/evalb

Model	SpanVec	LP	LR	LF
BinarySpan	$\mathbf{v}[i,j]$	**92.16**	**92.19**	**92.17**
	$\mathbf{sr}[i,j]$	91.90	91.70	91.80
BiaffineRule	$\mathbf{v}[i,j]$	91.79	91.67	91.73
	$\mathbf{sr}[i,j]$	**92.49**	**92.23**	**92.36**

Table 2: Span representation methods.

Model	English			Chinese		
	LP	LR	LF	LP	LR	LF
BinarySpan	92.16	92.19	92.17	91.31	90.48	90.89
MultiSpan	92.47	**92.41**	**92.44**	**91.69**	90.91	**91.30**
LinearRule	92.03	92.03	92.03	91.03	89.19	90.10
BiaffineRule	**92.49**	92.23	92.36	91.31	**91.28**	91.29

Table 3: Main development results.

3.2 Development Results

We study the two span representation methods, namely the simple concatenating representation $\mathbf{v}[i,j]$ (Eq 1) and the combining of three difference vectors $\mathbf{sr}[i,j]$ (Eq 7), and the two representative models, i.e, the binary span classification model (**BinarySpan**) and the biaffine rule model (**BiaffineRule**). We investigate appropriate representations for different models on the English dev dataset. Table 2 shows the effects of different span representation methods, where $\mathbf{v}[i,j]$ is better for BinarySpan and $\mathbf{sr}[i,j]$ is better for BiaffineRule. When using $\mathbf{sr}[i,j]$ for BinarySpan, the performance drops greatly (92.17 $\rightarrow$ 91.80). Similar observations can be found when replacing $\mathbf{sr}[i,j]$ with $\mathbf{v}[i,j]$ for BiaffineRule. Therefore, we use $\mathbf{v}[i,j]$ for the span models and $\mathbf{sr}[i,j]$ for the rule models in latter experiments.

Table 3 shows the main results on the English and Chinese dev sets. For English, BinarySpan acheives 92.17 LF score. The multi-class span classifier (**MultiSpan**) is much better than BinarySpan due to the awareness of label information. Similar phenomenon can be observed on the Chinese dataset. We also test the linear rule (**LinearRule**) methods. For English, LinearRule obtains 92.03 LF score, which is much worse than BiaffineRule. In general, the performances of BiaffineRule and MultiSpan are quite close both for English and Chinese.

For MultiSpan, both the first stage (unlabeled tree prediction) and the second stage (label generation) exploit constituent types. We design three development experiments to answer what the accuracy would be like of the predicted labels of the first stage were directly used in the second stage. The first one doesn't include the label probabilities of the first stage for the second stage. For the second experiment, we directly use the model output from the first setting for decoding, summing up the label classification probabilities of the first stage and the label generation probabilities of the second stage in order to make label decisions. For the third setting, we do the sum-up of label probabilities for the second stage both during training and decoding. These settings give LF scores of 92.44, 92.49 and 92.44, respectively, which are very similar. We choose the first one due to its simplicity.

3.3 Main Results

English. Table 4 summarizes the performances of various constituent parsers on PTB test set. BinarySpan achieves 92.1 LF score, outperforming the neural CKY parsing models (Durrett and Klein, 2015) and the top-down neural parser (Stern et al., 2017). MultiSpan and BiaffineRule obtain similar performances. Both are better than BianrySpan. MultiSpan obtains 92.4 LF score, which is very close to the state-of-the-art result when no external parses are included. An interesting observation is that the model of Stern et al. (2017) show higher LP score than our models (93.2 v.s 92.6), while our model gives better LR scores (90.4 v.s. 93.2). This potentially suggests that the global constraints such as structured label loss used in (Stern et al., 2017) helps make careful decisions. Our local models are likely to gain a better balance between bold guesses and accurate scoring of constituent spans. Table 7 shows the unlabeled parsing accuracies on PTB test set. MultiSpan performs the best, showing 92.50 UF score. When the unlabeled parser is 100% correct, BiaffineRule are better than the other two, producing an oracle LF score of 97.12%, which shows the robustness of our label generator. The decoding speeds of BinarySpan and MutliSpan are similar, reaching about 21 sentences per second. BiaffineRule is much slower than the span models.

Chinese. Table 5 shows the parsing performance on CTB 5.1 test set. Under the same settings, all the three models outperform the state-of-the-art neural model (Dyer et al., 2016; Liu and Zhang, 2017a).

Parser	LR	LP	LF	Parser	LR	LP	LF
Zhu et al. (2013) (S)	91.1	91.5	91.3	Charniak (2000)	89.5	89.9	89.5
McClosky et al. (2006) (S)	92.1	92.5	92.3	Collins (2003)	88.1	88.3	88.2
Choe and Charniak (2016) (S,R,E)			93.8	Sagae and Lavie (2006)	87.8	88.1	87.9
Durrett and Klein (2015) (S)			91.1	Petrov and Klein (2007)	90.1	90.2	90.1
Vinyals et al. (2015) (S, E)			92.8	Carreras et al. (2008)	90.7	91.4	91.1
Charniak and Johnson (2005) (S, R)	91.2	91.8	91.5	Zhu et al. (2013)	90.2	90.7	90.4
Huang (2008b) (R)			91.7	Watanabe and Sumita (2015)			90.7
Huang and Harper (2009) (ST)	91.1	91.6	91.3	Fernández-González and Martins (2015)	89.9	90.4	90.2
Huang et al. (2010) (ST)	92.7	92.2	92.5	Cross and Huang (2016b)	90.5	92.1	91.3
Shindo et al. (2012) (E)			92.4	Kuncoro et al. (2017)			91.2
Socher et al. (2013) (R)			90.4	Liu and Zhang (2017b)	91.3	92.1	91.7
Dyer et al. (2016) (R)			93.3	Stern et al. (2017) top-down	90.4	93.2	91.8
Kuncoro et al. (2017) (R)			93.6	**BinarySpan**	91.9	92.2	92.1
Liu and Zhang (2017a) (R)			94.2	**MultiSpan**	92.2	92.5	**92.4**
Fried et al. (2017) (ES)			**94.7**	**BiaffineRule**	92.0	92.6	92.3

Table 4: Results on the PTB test set. *S* denotes parsers using auto parsed trees. *E*, *R* and *ST* denote ensembling, reranking and self-training systems, respectively.

Parser	LR	LP	LF	Parser	LR	LP	LF
Charniak and Johnson (2005) (R)	80.8	83.8	82.3	Petrov and Klein (2007)	81.9	84.8	83.3
Zhu et al. (2013) (S)	84.4	86.8	85.6	Zhang and Clark (2009)	78.6	78.0	78.3
Wang et al. (2015) (S)			86.6	Watanabe and Sumita (2015)			84.3
Huang and Harper (2009) (ST)			85.2	Dyer et al. (2016)			84.6
Dyer et al. (2016) (R)			86.9	**BinarySpan**	85.9	87.1	86.5
Liu and Zhang (2017b)	85.2	85.9	85.5	**MultiSpan**	86.6	88.0	**87.3**
Liu and Zhang (2017a)			86.1	**BiaffineRule**	87.1	87.5	**87.3**

Table 5: Results on the Chinese Treebank 5.1 test set.

Compared with the in-order transition-based parser, our best model improves the labeled F1 score by 1.2 (86.1 $\rightarrow$ 87.3). In addition, `MultiSpan` and `BiaffineRule` achieve better performance than the reranking system using recurrent neural network grammars (Dyer et al., 2016) and methods that do joint POS tagging and parsing (Wang and Xue, 2014; Wang et al., 2015).

4 Analysis

Constituent label. Table 6 shows the LF scores for eight major constituent labels on PTB test set. `BinarySpan` consistently underperforms to the other two models. The error distribution of `MultiSpan` and `BiaffineRule` are different. For constituent labels including SBAR, WHNP and QP, `BiaffineRule` is the winner. This is likely because the partition point distribution of these labels are less trivial than other labels. For NP, PP, ADVP and ADJP, `MultiSpan` obtains better scores than `BiaffineRule`, showing the importance of the explicit type information for correctly identifying these labels. In addition, the three models give similar performances of VP and S, indicating that simple local classifiers might be sufficient enough for these two labels.

LF v.s. Length. Figure 3 and Figure 4 show the LF score distributions against sentence length and span length on the PTB test set, respectively. We also include the output of the previous state-of-the-art top-down neural parser (Stern et al., 2017) and the reranking results of transition-based neural generative parser (RNNG) (Dyer et al., 2016), which represents models that can access more global information. For sentence length, the overall trends of the five models are similar. The LF score decreases as the length increases, but there is no salient difference in the downing rate (also true for span length $\leq$6), demonstrating our local models can alleviate the label bias problem. `BiaffineRule` outperforms the other three models (except RNNG) when the sentence length less than 30 or the span length less than 4. This suggests that when the length is short, the rule model can easily recognize the partition point. When the sentence length greater than 30 or the span length greater than 10, `MultiSpan` becomes the best option (except RNNG), showing that for long spans, the constituent label information are useful.

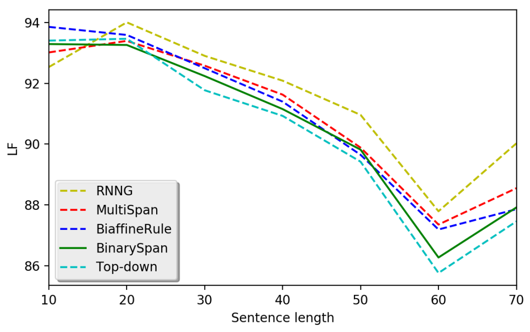


Figure 3: Sentence length v.s LF scores.

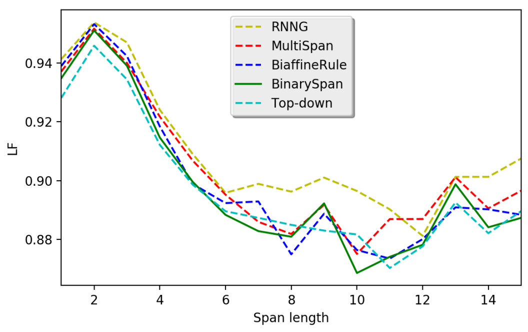


Figure 4: Span length v.s LF scores.

Model	NP	VP	S	PP	SBAR	ADVP	ADJP	WHNP	QP
BinarySpan	93.35	93.26	92.55	89.58	88.59	85.85	76.86	95.87	89.57
MultiSpan	**93.61**	93.41	92.76	**89.96**	89.16	**86.39**	**78.21**	95.98	89.51
BiaffineRule	93.53	**93.46**	**92.78**	89.30	**89.56**	85.89	77.47	**96.66**	**90.31**

Table 6: LF scores for major constituent labels.

Model	UF	LF	Speed(sents/s)
BinarySpan	92.16	96.79	22.12
MultiSpan	92.50	97.03	21.55
BiaffineRule	92.22	97.12	6.00

Table 7: UF, oralce LF and speed.

5 Related Work

Globally trained discriminative models have given highly competitive accuracies on graph-based constituent parsing. The key is to explicitly consider connections between output substructures in order to avoid label bias. State-of-the-art statistical methods use a single model to score a feature representation for all phrase-structure rules in a parse tree (Taskar et al., 2004; Finkel et al., 2008; Carreras et al., 2008). More sophisticated features that span over more than one rule have been used for reranking (Huang, 2008b). Durrett and Klein (2015) used neural networks to augment manual indicator features for CRF parsing. Structured learning has been used for transition-based constituent parsing also (Sagae and Lavie, 2005; Zhang and Clark, 2009; Zhang and Clark, 2011; Zhu et al., 2013), and neural network models have been used to substitute indicator features for transition-based parsing (Watanabe and Sumita, 2015; Dyer et al., 2016; Goldberg et al., 2014; Kiperwasser and Goldberg, 2016b; Cross and Huang, 2016a; Coavoux and Crabbé, 2016; Shi et al., 2017).

Compared to the above methods on constituent parsing, our method does not use global structured learning, but instead learns local constituent patterns, relying on a bi-directional LSTM encoder for capturing non-local structural relations in the input. Our work is inspired by the biaffine dependency parser of Dozat and Manning (2016). Similar to our work, Stern et al. (2017) show that a model that bi-partitions spans locally can give high accuracies under a highly-supervised setting. Compared to their model, we build direct local span classification and CFG rule classification models instead of using span labeling and splitting features to learn a margin-based objective. Our results are better although our models are simple. In addition, they collapse unary chains as fixed patterns while we handle them with an encoder-decoder model.

6 Conclusion

We investigated two locally trained span-level constituent parsers using BiLSTM encoders, demonstrating empirically the strength of the local models on learning syntactic structures. On standard evaluation, our models give the best results among existing neural constituent parsers without external parses.

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