Higher-order methods for dependency parsing can partially but not fully address the issue that edges in dependency tree should be constructed at the text span/subtree level rather than word level. In this paper, we propose a new method for dependency parsing to address this issue. The proposed method constructs dependency trees by directly modeling span-span (in other words, subtree-subtree) relations. It consists of two modules: the text span proposal module which proposes candidate text spans, each of which represents a subtree in the dependency tree denoted by (root, start, end); and the span linking module, which constructs links between proposed spans. We use the machine reading comprehension (MRC) framework as the backbone to formalize the span linking module in an MRC setup, where one span is used as a query to extract the text span/subtree it should be linked to.

The proposed method comes with the following merits: (1) it addresses the fundamental problem that edges in a dependency tree should be constructed between subtrees; (2) the MRC framework allows the method to retrieve missing spans in the span proposal stage, which leads to higher recall for eligible spans. Extensive experiments on the PTB, CTB and Universal Dependencies (UD) benchmarks demonstrate the effectiveness of the proposed method. We are able to achieve new SOTA performances on PTB and UD benchmarks, and competitive performances to previous SOTA models on the CTB dataset. Code is available at https://github.com/ShannonAI/mrc-for-dependency-parsing.1

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1Leilei Gan and Yuxian Meng contribute equally to this work.
address the issue. In nature, the token-token strategy can be viewed as a coarse simplification of the span-span (subtree-subtree) strategy, where the root token in the token-token strategy can be viewed as the average of all spans covering it. We would like an approach that directly models span-span relations using exact subtrees behind tokens, rather than the average of all spans covering it.

To address this challenge, in this work, we propose a model for dependency parsing that directly operates at the span-span relation level. The proposed model consists of two modules: (1) the text span proposal module which proposes eligible candidate text spans, each of which represents a subtree in the dependency tree denoted by (root, start, end); (2) and the span linking module, which constructs links between proposed spans to form the final dependency tree. We use the machine reading comprehension (MRC) framework as the backbone to formalize the span linking module in an MRC setup, where one span is used as a query to extract the text span/subtree it should be linked to. In this way, the proposed model is able to directly model span-span relations and build the complete dependency tree in a bottom-up recursive manner.

The proposed model provides benefits in the following three aspects: (1) firstly, it naturally addresses the shortcoming of word-word modeling in vanilla graph-based approaches and directly performs at the span level; (2) with the MRC framework, the left-out spans in the span proposal stage can still be retrieved at the span linking stage, and thus the negative effect of unextracted spans can be alleviated; and (3) the MRC formalization allows us to take advantage of existing state-of-the-art MRC models, with which the model expressivity can be enhanced, leading to better performances.

Extensive experiments on the widely used dependency parsing benchmarks PTB and Universal Dependencies (UD) demonstrate the effectiveness of the proposed method. We are able to achieve new SOTA performances on PTB and UD benchmarks, and competitive performances to previous SOTA models on the CTB dataset.

2 Related Work

2.1 Dependency Parsing

Transition-based dependency parsing incrementally constructs a dependency tree from input words through a sequence of shift-reduce actions (Zhang and Nivre, 2011; Chen and Manning, 2014; Zhou et al., 2015; Dyer et al., 2015; Yuan et al., 2019; Han et al., 2019; Mohammadshahi and Henderson, 2020). Graph-based dependency parsing searches through the space of all possible dependency trees for a tree that maximizes the score (Pei et al., 2015; Wang et al., 2018; Zhang et al., 2019).

Graph-based dependency parsing is first introduced by McDonald et al. (2005a,b). They formalized the task of dependency parsing as finding the maximum spanning tree (MST) in directed graphs and used the large margin objective (Crammer et al., 2006) to efficiently train the model. Zhang et al. (2016) introduced a probabilistic convolutional neural network (CNN) for graph-based dependency parsing to model third-order dependency information Wang and Chang (2016); Kiperwasser and Goldberg (2016) proposed to employ LSTMs as an encoder to extract features, which are then used to score dependencies between words. Zhang and Zhao (2015); Zhang et al. (2019); Wang and Tu (2020) integrated higher-order features across adjacent dependency edges to build the dependency tree. Ji et al. (2019) captured high-order dependency information by using graph neural networks. The biaffine approach (Dozat and Manning, 2016) is a particular kind of graph-based methods improving upon vanilla scoring functions in graph-based dependency parsing. Ma et al. (2018) combined biaffine classifiers and pointer networks to build dependency trees in a top-down manner. Jia et al. (2020); Zhang et al. (2020a) extended the biaffine approach to the conditional random field (CRF) framework, improving both efficiency and effectiveness of CRF models for dependency parsing. Mrini et al. (2020) incorporated label information into the self-attention structure (Vaswani et al., 2017) for biaffine dependency parsing and achieved state-of-the-art performances.

2.2 MRC for NLP Tasks

Machine reading comprehension (MRC) takes the form of (context, question, answer) triplets, by extracting an answer to the question from the context. Recent years has witnessed a trend of extending the MRC framework to different types of NLP tasks. (McCann et al., 2018; Gardner et al., 2019; Zhang et al., 2020b). Levy et al. (2017) casted relation extraction in an MRC fashion, where each relation type \( r(\mathbf{x}, \mathbf{y}) \) is characterized as a question \( q(\mathbf{x}) \).
whose answer is \( y \). Li et al. (2019b) proposed to extract relations by progressively asking questions defined by question templates. Li et al. (2019a) introduced a QA framework for named entity recognition, where each type of entity corresponds to a specific question. Wu et al. (2019) formalized coreference resolution as an MRC task. Other applications of MRC include entity linking (Gu et al., 2021), text classification (Chai et al., 2020), dialog state tracking (Gao et al., 2019, 2020), SQL generation (Yan et al., 2020) and event extraction (Du and Cardie, 2020; Liu et al., 2020).

### 3 Method

#### 3.1 Notations

Given a sequence of input tokens \( s = (w_0, w_1, \ldots, w_n) \), where \( n \) denotes the length of the sentence and \( w_0 \) is a dummy token representing the root of the sentence, we formalize the task of dependency parsing as finding the tree with the highest score among all possible trees rooted at \( w_0 \).

\[
\hat{T} = \arg \max_{T_{w_0}} \text{score}(T_{w_0}) \tag{1}
\]

Each token \( w_i \) in the input sentence corresponds to a subtree \( T_{w_i} \) within the full tree \( T \) rooted at \( w_j \), and the subtree can be characterized by a text span, with the index of its leftmost token being \( T_{w_i}.s \) in the original sequence, and the index of its rightmost token being \( T_{w_i}.e \) in the original sequence. As shown in the first example of Figure 1, the span covered by the subtree \( T_{\text{love}} \) is the full sentence “I love Tim’s cat”, and the span covered by the subtree \( T_{\text{cat}} \) is “Tim’s cat”. Each directional arc \( w_i \rightarrow w_j \) in \( T \) represents a parent-child relation between \( T_{w_i} \) and \( T_{w_j} \), where \( T_{w_j} \) is a subtree of \( T_{w_i} \). This implies that the text span covered by \( T_{w_j} \) is fully contained by the text span covered by \( T_{w_i} \).

It is worth-noting that the currently proposed paradigm can only handle the projective situation. We will get back to how to adjust the current paradigm to non-projective situation in Section 3.5.

#### 3.2 Scoring Function

With notations defined in previous section, we now illustrate how to compute the score \( \text{score}(T_{w_i}) \) in Eq.(1).

Since we want to model the span-span relations inside a dependency tree, where the tree is composed by spans and the links between them, we formalize the scoring function as:

\[
\text{score}(T_{w_0}) = \sum_{i=1}^{n} \text{score}_{\text{span}}(T_{w_i}) + \lambda \sum_{(w_i \rightarrow w_j) \in T_{w_0}} \text{score}_{\text{link}}(T_{w_i}, T_{w_j}) \tag{2}
\]

where \( \text{score}_{\text{span}}(T_{w_i}) \) represents how likely the subtree rooted at \( w_i \) covers the text span from \( T_{w_i}.s \) to \( T_{w_i}.e \). \( \text{score}_{\text{link}}(T_{w_i}, T_{w_j}) \) represents how likely tree \( T_{w_j} \) is a subtree of \( T_{w_i} \), i.e. there is an arc from \( w_i \) to \( w_j \), and \( \lambda \) is a hyper-parameter to balance \( \text{score}_{\text{span}} \) and \( \text{score}_{\text{link}} \). We will illustrate the details how to score \( \text{span}(T) \) and \( \text{score}_{\text{link}}(T_1, T_2) \) in the following sections. Table 1 shows all the spans and links for the left tree in Figure 1.

| Sentence: root I love Tim’s cat |
|---|
| **Spans** | **Links** |
| \( T_{\text{root}} \): root I love Tim’s cat | \( T_{\text{root}} \rightarrow T_{\text{love}} \) |
| \( T_{\text{I}} \): I | \( T_{\text{love}} \rightarrow T_{\text{I}} \) |
| \( T_{\text{love}} \): I love Tim’s cat | \( T_{\text{love}} \rightarrow T_{\text{cat}} \) |
| \( T_{\text{Tim’s}} \): Tim’s | \( T_{\text{cat}} \rightarrow T_{\text{Tim’s}} \) |
| \( T_{\text{cat}} \): Tim’s cat |

Table 1: Spans and links for the left tree in Figure 1.

3.3 Span Proposal Module

In this section, we introduce the span proposal module. This module gives each tree \( T_{w_i} \) a score \( \text{score}_{\text{span}}(T_{w_i}) \) in Eq.(2), which represents how likely the subtree rooted at \( w_i \) covers the text span from \( T_{w_i}.s \) to \( T_{w_i}.e \). The score can be decomposed into two components – the score for the left half span from \( w_i \) to \( T_{w_i}.s \), and the score for the right half span from \( w_i \) to \( T_{w_i}.e \), given by:

\[
\text{score}_{\text{span}}(T_{w_i}) = \text{score}_{\text{start}}(T_{w_i}.s | w_i) + \text{score}_{\text{end}}(T_{w_i}.e | w_i) \tag{3}
\]

We propose to formalize \( \text{score}_{\text{start}}(T_{w_i}.s | w_i) \) as the score for the text span starting at \( T_{w_i}.s \), ending at \( w_i \), transforming the task to a text span extraction problem. Concretely, we use the biaffine function Dozat and Manning (2016) to score the text span by computing \( \text{score}_{\text{start}}(j | i) \) – the score of the tree rooted at \( w_i \) and staring at \( w_j \):

\[
\text{score}_{\text{start}}(j | i) = x_i^T U_{\text{start}} x_j + w_{\text{start}}^T x_j \tag{4}
\]

where \( U \in \mathbb{R}^{d \times d} \) and \( w \in \mathbb{R}^d \) are trainable parameters, \( x_i \in \mathbb{R}^d \) and \( x_j \in \mathbb{R}^d \) are token representations of \( w_i \) and \( w_j \) respectively. To obtain \( x_i \) and
\( \mathbf{x}_j \), we pass the sentence \( s \) to BERT. \( \mathbf{x}_i \) and \( \mathbf{x}_j \) are the last-layer representations output from BERT for \( w_i \) and \( w_j \). We use the following loss to optimize the left-half span proposal module:

\[
L_{\text{span}}^{\text{start}} = -\sum_{i=1}^{n} \frac{\exp(\text{score}_{\text{start}}(T_{w_i}, s|i))}{\sum_{j=1}^{n} \exp(\text{score}_{\text{start}}(j|i))}
\]  
(5)

This objective enforces the model to find the correct span start \( T_{w_i}, s \) for each word \( w_i \). We ignore loss for \( w_0 \), the dummy root token, since its span is covers \( 0 \sim n \).

\( \text{score}_{\text{end}}(T_{w_i}, e|w_i) \) can be computed in the similar way, where the model extracts the text span rooted at index \( w_i \) and ending at \( T_{w_i}, e \):

\[
\text{score}_{\text{end}}(j|i) = \mathbf{x}_i^T U_{\text{end}} \mathbf{x}_j + w_{\text{end}} \mathbf{x}_j
\]  
(6)

The loss to optimize the right-half span proposal module

\[
L_{\text{span}}^{\text{end}} = -\sum_{i=1}^{n} \frac{\exp(\text{score}_{\text{end}}(T_{w_i}, e|i))}{\sum_{j=1}^{n} \exp(\text{score}_{\text{end}}(j|i))}
\]  
(7)

Using the left-half span score in Eq.(4) and the right-half span score in Eq.(6) to compute the full span score in Eq.(3), we are able to compute the score for any subtree, with text span starting at \( T_{w_i}, s \), ending at \( T_{w_i}, e \) and rooted at \( w_i \).

### 3.4 Span Linking Module

Given two subtrees \( T_{w_i} \) and \( T_{w_j} \), the span linking module gives a score \(- \text{score}_{\text{link}}(T_{w_i}, T_{w_j})\) to represent the probability of \( T_{w_j} \) being a subtree of \( T_{w_i} \). This means that \( T_{w_i} \) is the parent of \( T_{w_j} \), and that the span associated with \( T_{w_j} \), i.e., \( (T_{w_j}, s, T_{w_j}, e) \) is fully contained in the span associated with \( T_{w_i} \), i.e., \( (T_{w_i}, s, T_{w_i}, e) \).

We propose to use the machine reading comprehension framework as the backbone to compute this score. It operates on the triplet \{context \( X \), query \( q \), and answer \( a \)\}. The context \( X \) is the original sentence \( s \). The query \( q \) is the child span \( (T_{w_j}, s, T_{w_j}, e) \). And we wish to extract the answer, which is the parent span \( (T_{w_i}, s, T_{w_i}, e) \) from the context input sentence \( s \).

**Constructing Query** In the query, we should consider both the span and its root. The query is thus formalized as follows:

\[
<sos>, T_{w_j}, s, T_{w_j}, s + 1, ..., T_{w_j} - 1, <\text{eor}>, T_{w_j}, <\text{eor}>, T_{w_j} + 1, ..., T_{w_j}, e - 1, T_{w_j}, e, <\text{eos}>
\]  
(8)

where \( <\text{sos}>, <\text{eor}>, <\text{eor}>, \) and \( <\text{eos}> \) are special tokens, which respectively denote the start of span, the start of root, the end of root, and the end of span. One issue with the the way above to construct query is that the position information of \( T_{w_j} \) is not included in the query. In practice, we turn to a more convenient strategy where the query is the original sentence, with special tokens \( <\text{sos}>, <\text{eor}>, <\text{eor}>, <\text{eos}> \) used to denote the position of the child. In this way, position information for child \( T_{w_j} \) can be naturally considered.

**Answer Extraction** The answer is the parent, with the span \( T_{w_j}, s, T_{w_j}, e \) rooted at \( T_{w_i} \). We can directly take the framework from the MRC model by identifying the start and end of the answer span, respectively denoted by \( \text{score}_{\text{parent}}(T_{w_i}, s|T_{w_j}) \) and \( \text{score}_{\text{parent}}(T_{w_i}, e|T_{w_j}) \). We also wish to identify the root \( T_{w_i} \) from the answer, which is characterized by the score of \( w_i \), being the root of the span, denoted by \( \text{score}_{\text{parent}}(w_i|T_{w_j}) \). Furthermore, since we also want to identify the relation category between the parent and the child, the score signifying the relation label needed to be added, denoted by \( \text{score}_{\text{parent}}(l|T_{w_j}, w_i) \).

For quadruple \( (T_{w_i}, s, T_{w_i}, e, T_{w_j}, l) \), which denotes the span \( T_{w_i}, s, T_{w_i}, e \) rooted at \( T_{w_j} \), the final score for it being the answer to \( T_{w_j} \), and the relation between the subtrees is \( l \), is given by:

\[
\begin{align*}
\text{score}_{\text{parent}}(T_{w_i}|T_{w_j}) = \\
\text{score}_{\text{parent}}(w_i|T_{w_j}) + \text{score}_{\text{parent}}(T_{w_i}, s|T_{w_j}) + \\
\text{score}_{\text{parent}}(T_{w_i}, e|T_{w_j}) + \text{score}_{\text{parent}}(l|T_{w_j}, T_{w_i})
\end{align*}
\]  
(9)

In the MRC setup for QA, the input is the concatenation of the query and the context, denoted by \{[cls], query, [sep], context\}, where \{[cls] and [sep] are special tokens. The input is fed to BERT, and we obtain representations for each input token. Let \( h_t \) denote the representation for the token with index \( t \) output from BERT. The probability of \( t \)th token being the root of the answer, which is denoted by \( \text{score}_{\text{parent}}(w_t|T_{w_j}) \) is the softmax function over all constituent tokens in the context:

\[
\text{score}_{\text{parent}}(w_t|T_{w_j}) = \frac{\exp(h_{\text{root}}^T \times h_t)}{\sum_{t' \in \text{context}} \exp(h_{\text{root}}^T \times h_{t'})}
\]  
(10)

where \( h_{\text{root}}^T \) is the trainable parameter. \( \text{score}_{\text{parent}} \) and \( \text{score}_{\text{parent}}^e \) can be computed in the similar way:
where $h^{start}_i$ and $h^{end}_i$ are trainable parameters. For score$^e_{parent}(l|T_{w_j}, T_{w_i})$, which denotes the relation label between $T_{w_j}$ and $T_{w_i}$, we can compute it in a simple way. Since $h_{w_i}$ already encodes information for $h_{w_j}$ through self-attentions, the representation $h_{w_i}$ for $w_i$ is directly fed to the softmax function over all labels in the label set $L$:

$$\text{score}_{\text{parent}}^e(w_i|T_{w_j}) = \frac{\exp(h^{T}_{end} \times h_{w_i})}{\sum_{t' \in \text{context}} \exp(h^{T}_{end} \times h_{t'})} \tag{11}$$

where $h^{start}_i$ and $h^{end}_i$ are trainable parameters. For score$^e_{parent}(l|T_{w_j}, T_{w_i})$, which denotes the relation label between $T_{w_j}$ and $T_{w_i}$, we can compute it in a simple way. Since $h_{w_i}$ already encodes information for $h_{w_j}$ through self-attentions, the representation $h_{w_i}$ for $w_i$ is directly fed to the softmax function over all labels in the label set $L$:

$$\text{score}_{\text{parent}}^e(w_i|T_{w_j}, T_{w_i}) = \frac{\exp(h^{T}_{end} \times h_{w_i})}{\sum_{t' \in \text{context}} \exp(h^{T}_{end} \times h_{w_i})} \tag{12}$$

**Mutual Dependency** A closer look at Eq.(9) reveals that it only models the uni-directional dependency relation that $T_{w_i}$ is the parent of $T_{w_j}$. This is suboptimal since if $T_{w_i}$ is a parent answer of $T_{w_j}$, $T_{w_i}$ should be a child answer of $T_{w_j}$. We thus propose to use $T_{w_j}$ as the query $q$ and $T_{w_i}$ as the answer $a$.

$$\text{score}_{\text{child}}(T_{w_j}|T_{w_i}) = \text{score}_{\text{child}}^e(w_j|T_{w_i}) + \text{score}_{\text{child}}^a(T_{w_i}, s|T_{w_i}) + \text{score}_{\text{child}}^e(T_{w_j}, c|T_{w_i}) + \text{score}_{\text{parent}}^l(l|T_{w_i}, T_{w_j}) \tag{13}$$

The final score $\text{score}_{\text{link}}$ is thus given by:

$$\text{score}_{\text{link}}(T_{w_j}, T_{w_i}) = \text{score}_{\text{child}}(T_{w_j}|T_{w_i}) + \text{score}_{\text{parent}}(T_{w_i}|T_{w_j}) \tag{14}$$

Since one tree may have multiple children but can only have one parent, we use the multi-label cross entropy loss $L_{\text{parent}}$ for scoreparent$(T_{w_i}|T_{w_j})$ and use the binary cross entropy loss $L_{\text{child}}$ for scorechild$(T_{w_j}|T_{w_i})$. We jointly optimize these two losses $L_{\text{link}} = L_{\text{parent}} + L_{\text{child}}$ for the span linking module.

### 3.5 Inference

Given an input sentence $s = (w_0, w_1, w_2, ..., w_n)$, the number of all possible subtree spans $(w_1, T_{w_1}, s, T_{w_1}, e)$ is $O(n^3)$, thus running MRC procedure for every candidate span is computationally prohibitive. A naive solution is to use the span proposal module to extract top-k scored spans rooted at each token. This gives rise to a set of span candidates $\mathcal{T}$ with size $1+n \times k$ (the root token $w_0$ produces only one span), where each candidate span is associated with its subtree span score $\text{score}_{\text{span}}(\cdot)$. Then we construct the optimal dependency tree based only on these extracted spans by linking them. This strategy obtains a local optimum for Eq.(2), because we want to compute the optimal solution for the first part $\sum_{i=1}^{n} \text{score}_{\text{span}}(T_{w_i})$ depending on the second part of Eq.(2), i.e., $\sum_{(w_i \rightarrow w_j) \in T_{w_0}} \text{score}_{\text{link}}(T_{w_i}, T_{w_j})$. But in this naive strategy, the second part is computed after the first part.

It is worth noting that the naive solution of using only the top-k scored spans has another severe issue: spans left out at the span proposal stage can never be a part of the final prediction, since the span linking module only operates on the proposed spans. This would not be a big issue if top-k is large enough to recall almost every span in ground-truth. However, span proposal is intrinsically harder than span linking because the span proposal module lacks the triplet span information that is used by the span linking module. Therefore, we propose to use the span linking module to retrieve more correct spans.

Concretely, for every span $T_{w_j}$ proposed by the span proposal module, we use $\text{argmax}_{T_{w_j}} \text{score}_{\text{parent}}(T_{w_i}|T_{w_j})$ to retrieve its parent with the highest score as additional span candidates. Recall that span proposal proposed $1+n \times k$ spans. Added by spans proposed by the span linking module, the maximum number of candidate spans is $1+2n \times k$, since there might be a large overlap between spans proposed by the span linking module and spans proposed by the span proposal module.

**Projective Decoding** Given retrieved spans harvested in the proposal stage, we use a CKY-style bottom-up dynamic programming algorithm to find the projective tree with the highest score based on Eq.(2). The algorithm is present in Algorithm 1. The key idea is that we can generalize the definition of score$(T_{w_i})$ in Eq.(2) to any $w$ by the following definition:

$$\text{score}(T_w) = \sum_{T_{w_i} \subseteq T_w} \text{score}_{\text{span}}(T_{w_i}) + \lambda \sum_{(w_i \rightarrow w_j) \in T_w} \text{score}_{\text{link}}(T_{w_i}, T_{w_j}) \tag{15}$$
Algorithm 1: Projective Inference

Input: Input sentence $s$, span candidates $T$, span scores $\text{score}_{\text{span}}(T)$, $\forall T \in T$

Output: Highest score of every span $\text{score}(T)$, $\forall T \in T$

/* Compute linking scores based on Eq. (14) */

$\text{score}_{\text{link}}(T_1, T_2) \leftarrow \text{score}_{\text{parent}}(T_1[T_2]) + \text{score}_{\text{child}}(T_2[T_1], T_1, T_2) \in T$

/* Compute score for each pair of tokens */

for $\text{len} \gets 0$ to $\text{len}_n$

for $T \gets T$ do

if $T.e - T.s = \text{len}$ then

/* $T$ covers a single word */

if $\text{len} = 0$ then

$\text{score}(T) \leftarrow \text{score}_{\text{span}}(T)$

else

/* $C$ is a set of direct subtrees composing $T$ */

$\text{score}(T) \leftarrow \text{score}_{\text{span}}(T) + \max_{T \in C(T)} (\sum_{T \in C(T)} \text{score}(T) + \lambda \text{score}_{\text{link}}(T, T_i))$

end

end

end

end

where $\{T_{w_i} \mid T_{w_i} \subseteq T_w, i = 0, 1, ..., n\}$ is all subtrees inside $T_w$, i.e. there is a path in $T_w$ like $w \rightarrow w_{i_1} \rightarrow \cdots \rightarrow w_i$

Using this definition, we can rewrite $\text{score}(T_w)$ in a recursive manner:

$$\text{score}(T_w) = \text{score}_{\text{span}}(T_w) + \sum_{T_{w_j} \in C(T_w)} \text{score}(T_{w_j}) + \lambda \text{score}_{\text{link}}(T_{w_i}, T_{w_j})$$

(16)

where $C(T_w) = \{T_{w_i} \mid (w \rightarrow w_i) \in T_w, i = 0, 1, 2, ..., n\}$ is the set of all direct subtrees of $T_w$.

Non-Projective Decoding It is noteworthy that effectively finding a set of subtrees composing a tree $T$ in Algorithm 1 requires trees to be projective (the projective property guarantees every subtree is a continuous span in text), and experiments in Section 4 shows that this algorithm performs well on datasets where most trees are projective, but performs worse when a number of trees are non-projective. To address this issue, we adapt the proposed strategy to the MST (Maximum Spanning Tree) algorithm (McDonald et al., 2005b). The key point of MST is obtaining the score for each pair of tokens $w_i$ and $w_j$ (rather than spans), denoted by $\text{score}_{\text{edge}}(w_i, w_j)$. We propose that the score to link $w_i$ and $w_j$ is the highest score achieved by two spans respectively rooted at $w_i$ and $w_j$:

$$\text{score}_{\text{edge}}(w_i, w_j) = \max_{T_{w_i}, T_{w_j}} \text{score}_{\text{span}}(T_{w_i}) + \text{score}_{\text{span}}(T_{w_j}) + \lambda \text{score}_{\text{link}}(T_{w_i}, T_{w_j})$$

(17)

The final score for tree $T$ is given by:

$$\text{score}(T) = \sum_{(w_i \rightarrow w_j) \in T} \text{score}_{\text{edge}}(w_i, w_j)$$

(18)

Under this definition, MST can be readily used for decoding.

4 Experiments

4.1 Datasets and Metrics

We carry out experiments on three widely used dependency parsing benchmarks: the English Penn Treebank v3.0 (PTB) dataset (Marcus et al., 1993), the Chinese Treebank v5.1 (CTB) dataset (Xue et al., 2002) and the Universal Dependency Treebanks v2.2 (UD) (Nivre et al., 2016) where we select 12 languages for evaluation. We follow Ma et al. (2018) to process all datasets. The PTB dataset contains 39832 sentences for training and 2416 sentences for test. The CTB dataset contains 16091 sentences for training and 1910 sentences for test. The statistics for 12 languages in UD dataset are the same with Ma et al. (2018).

We use the unlabeled attachment score (UAS) and labeled attachment score (LAS) for evaluation. Punctuations are ignored in all datasets during evaluation.

Training Details For all experiments, we concatenate 100d POS tag embedding with 1024d pretrained token embeddings, then project them to 1024d using a linear layer. Following Mrini et al. (2020), we further add 1-3 additional encoder layers on top to let POS embeddings well interact with pretrained token embeddings. We tried two different types of additional encoders: Bi-LSTM (?) and Transformer (?). For Bi-LSTM, the number of hidden size is 1024d. For Transformer, the number of attention heads and hidden size remain the same as pretrained models (16 for attention heads and 1024d for hidden size). We use 0.1 dropout rate for pretrained models and 0.3 dropout rate for additional layers. We use Adam (?) as optimizer and linear rate decay for scheduler. The weight parameter $\lambda$ is tuned on the development set from 0.1 to 10.0, with the best $\lambda$ used for test.
4.2 Baselines

- **Biaffine**: Dozat and Manning (2016) fed pairs of words into a biaffine classifier to determine the dependency relations between them.
- **StackPTR**: Ma et al. (2018) combined pointer network with transition-based method to make it benefits from the information of whole sentence and all previously derived subtree structures.
- **GNN**: Ji et al. (2019) used graph neural networks (GNN) to learn token representations for graph-based dependency parsing.
- **MP2O**: Wang and Tu (2020) used message passing to integrate second-order information to biaffine backbone.
- **CVT**: Clark et al. (2018) proposed Cross-View Training, a semi-supervised approach to improve model performance.
- **HPSG**: Zhou and Zhao (2019) used head-driven phrase structure grammar to jointly train constituency and dependency parsing.
- **HPSG+LA**: Mrini et al. (2020) added a label attention layer to HPSG to improve model performance. HPSG+LA also relies on the additional constituency parsing dataset.

We implement our proposed model and the Biaffine model based on RoBERTa_{large} (Liu et al., 2019), RoBERTa-wwm_{large} (Cui et al., 2019), XLM-RoBERTa_{large} (Lample and Conneau, 2019) respectively for PTB, CTB and UD. We apply both projective decoding and non-projective MST decoding for all datasets.

4.3 Main Results

Table 2 compares our model to existing state-of-the-art models on PTB/CTB test sets. On PTB, the proposed model achieves a new SOTA performance of 97.17% UAS and 95.45% LAS. On CTB, our best model is comparable to other SOTA performances. As PTB and CTB contain almost only projective trees, the projective decoding strategy significantly outperforms the non-projective MST algorithm. It is worth noting that, since HPSG and HPSG+LDA rely on additional labeled data of constituency parsing, results for HPSG are not comparable to ours. We list them here for reference purposes.

Table 3 compares our model with existing state-of-the-art methods on UD test sets. Other than es, where the proposed model slightly underperforms the SOTA model by 0.02, the proposed model achieves SOTA performances on all other 11 languages, with the average performance boost of 0.3. As many languages in UD have a notable portion of non-projective trees, MST decoding significantly outperforms projective decoding, achieving SOTA performances in almost all language sets.

5 Ablation Study and Analysis

We use PTB to perform comprehensive ablation studies to understand behaviors of the proposed model. As projective decoding works best for PTB, scores reported in this section are all from projective decoding.

5.1 Effect of Candidate Span Number

We would like to study the effect of the number of candidate spans proposed by the span proposal module, i.e., the value of $k$. We vary the value of $k$ from 1 to 25. As shown in Table 4, increasing values of $k$ leads to higher UAS, and the performance stops increasing once $k$ is large enough ($k > 15$).

5.2 Effect of Span Retrieval by Span Linking

As shown in Table 5, span recall significantly improves with the presence of the span linking stage. This is in line with our expectation, since spans missing at the proposal module can be retrieved by QA model in the span linking stage. Recall boost narrows down when $k$ becomes large, which is expected as more candidates are proposed at the
Table 3: LAS for different model on UD. We use ISO 639-1 codes to represent languages from UD.

| Model        | bg     | ca     | cs     | de     | en     | es     | fr     | it     | nl     | no     | ro     | ru     | Avg.   |
|--------------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|
| GNN          | 90.33  | 92.39  | 90.95  | 79.73  | 88.43  | 91.56  | 87.23  | 92.44  | 88.57  | 89.38  | 85.26  | 91.20  | 89.47  |
| MP2O         | 91.30  | 93.60  | 92.09  | 82.00  | 90.75  | 92.62  | 89.32  | 93.66  | 91.21  | 91.74  | 86.40  | 92.61  | 91.02  |
| Biaffine     | 91.04  | 94.15  | 93.57  | 84.84  | 91.93  | 92.64  | 91.64  | 94.07  | 92.78  | 94.17  | 88.66  | 94.91  | 92.15  |
| Ours-Proj    | 93.61  | 94.04  | 93.1   | 84.97  | 91.92  | 92.32  | 91.69  | 94.86  | 92.51  | 94.07  | 88.76  | 94.66  | 92.21  |
| Ours-NProj   | 93.76  | 94.38  | 93.72  | 85.23  | 91.95  | 92.62  | 91.76  | 94.79  | 92.97  | 94.50  | 88.67  | 95.00  | 92.45  |

Table 4: Effect of number of span candidates

| k  | 1     | 2     | 5     | 10    | 15    | 20    |
|----|-------|-------|-------|-------|-------|-------|
| UAS| 96.94 | 97.10 | 97.22 | 97.23 | 97.24 | 97.23 |

Table 5: Span recall with/without span linking module

(4) Removing the Mutual Dependency module which only uses child → parent relation and ignores parent → child relation also leads to performance decrease.

5.4 Analysis

Following Ma et al. (2018); Ji et al. (2019), we analyze performances of the Biaffine parser and the proposed method with respective to sentence length, dependency length, and subtree span length, respectively. Results are shown in Figure 2.

Sentence Length. As shown in Figure 2(a), the proposed parser achieves better performances on long sentences compared with Biaffine. Specially, when sentence length is greater than 50, the performance of the Biaffine parser decreases significantly, while the proposed parser has a much smaller drop (from 0.97 to 0.964).

Dependency Length. Figure 2(b) shows the results with respect to dependency length. The proposed parser shows its advantages on long-range dependencies. We suppose span-level information is beneficial for long-range Dependencies.

Subtree Span Length. We further conduct experiments on subtree span length. We divide the average lengths of the two spans in the span linking module into seven buckets. We suppose our parser should show advantages on long subtree span, and the results in Figure 2(c) verify our conjecture.
In summary, the span-span strategy works significantly better than the token-token strategy, especially for long sequences. This explanation is as follows: the token-token strategy can be viewed as a coarse simplification of the span-span strategy, where the root token in the token-token strategy can be viewed as the average of all spans covering it, while in the span-span strategy, it represents the exact span, rather than the average. The deviation from the average is relatively small from the extract when sequences are short, but becomes larger as sequence length grows, since the number of spans covering the token exponentially grows with length. This makes the token-token strategy work significantly worse for long sequences.

6 Conclusion
In this paper, we propose to construct dependency trees by directly modeling span-span instead of word-word relations. We use the machine reading comprehension framework to formalize the span linking module, where one span is used as a query to extract the text span/subtree it should be linked to. Extensive experiments on the PTB, CTB and UD benchmarks show the effectiveness of the proposed method.

References
Duo Chai, Wei Wu, Qinghong Han, Fei Wu, and Jiwei Li. 2020. Description based text classification with reinforcement learning. In International Conference on Machine Learning, pages 1371–1382. PMLR.

Danqi Chen and Christopher D Manning. 2014. A fast and accurate dependency parser using neural networks. In Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP), pages 740–750.

Kevin Clark, Minh-Thang Luong, Christopher D. Manning, and Quoc Le. 2018. Semi-supervised sequence modeling with cross-view training. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 1914–1925, Brussels, Belgium. Association for Computational Linguistics.

Koby Crammer, Ofer Dekel, Joseph Keshet, Shai Shalev-Shwartz, and Yoram Singer. 2006. Online passive-aggressive algorithms. J. Mach. Learn. Res., 7:551–585.

Yiming Cui, Wanxiang Che, Ting Liu, Bing Qin, Ziqing Yang, Shijin Wang, and Guoping Hu. 2019. Pre-training with whole word masking for chinese bert. arXiv preprint arXiv:1906.08101.

Timothy Dozat and Christopher D Manning. 2016. Deep biaffine attention for neural dependency parsing. arXiv preprint arXiv:1611.01734.

Xinya Du and Claire Cardie. 2020. Event extraction by answering (almost) natural questions. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 671–683, Online. Association for Computational Linguistics.

Chris Dyer, Miguel Ballesteros, Wang Ling, Austin Matthews, and Noah A Smith. 2015. Transition-based dependency parsing with stack long short-term memory. arXiv preprint arXiv:1505.08075.

Jason Eisner. 1997. Three new probabilistic mod-
els for dependency parsing: An exploration. *arXiv preprint cmp-lg/9706003*.

Shuyang Gao, Sanchit Agarwal, Tagyoung Chung, Di Jin, and Dilek Hakkani-Tur. 2020. From machine reading comprehension to dialogue state tracking: Bridging the gap. *arXiv preprint arXiv:2004.05827*.

Shuyang Gao, Abhishek Sethi, Sanchit Agarwal, Tagyoung Chung, and Dilek Hakkani-Tur. 2019. Dialog state tracking: A neural reading comprehension approach. *arXiv preprint arXiv:1908.01946*.

Matt Gardner, Jonathan Berant, Hannaneh Hajishirzi, Alon Talmor, and Sewon Min. 2019. Question answering is a format; when is it useful? *Transactions of the Association for Computational Linguistics*, 4:313–327.

Guillaume Lample and Alexis Conneau. 2019. Cross-lingual language model pretraining. *arXiv preprint arXiv:1901.07291*.

Omer Levy, Minjoon Seo, Eunsol Choi, and Luke Zettlemoyer. 2017. Zero-shot relation extraction via reading comprehension. In *Proceedings of the 21st Conference on Computational Natural Language Learning (CoNLL 2017)*, pages 333–342, Vancouver, Canada. Association for Computational Linguistics.

Xiaoya Li, Jinfeng Feng, Yuxian Meng, Qinghong Han, Fei Wu, and Jiwei Li. 2019a. A unified mrc framework for named entity recognition. *arXiv preprint arXiv:1910.11476*.

Xiaoya Li, Fan Yin, Zijun Sun, Xiayu Li, Arianna Yuan, Duo Chai, Mingxin Zhou, and Jiwei Li. 2019b. Entity-relation extraction as multi-turn question answering. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 1340–1350, Florence, Italy. Association for Computational Linguistics.

Jian Liu, Yubo Chen, Kang Liu, Wei Bi, and Xiaojian Liu. 2020. Event extraction as machine reading comprehension. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 1641–1651, Online. Association for Computational Linguistics.

Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Roberta: A robustly optimized bert pretraining approach. *arXiv preprint arXiv:1907.11692*.

Xuezhe Ma, Zecong Hu, Jingzhou Liu, Nanyun Peng, Graham Neubig, and Eduard Hovy. 2018. Stack-pointer networks for dependency parsing. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1403–1414, Melbourne, Australia. Association for Computational Linguistics.

Mitchell P. Marcus, Beatrice Santorini, and Mary Ann Marcinkiewicz. 1993. Building a large annotated corpus of English: The Penn Treebank. *Computational Linguistics*, 19(2):313–330.

Bryan McCann, Nitish Shirish Keskar, Caiming Xiong, and Richard Socher. 2018. The natural language decathlon: Multitask learning as question answering. *arXiv preprint arXiv:1806.08730*.

Ryan McDonald, Koby Crammer, and Fernando Pereira. 2005a. Online large-margin training of dependency parsers. In *Proceedings of the 43rd
Annual Meeting of the Association for Computational Linguistics (ACL’05), pages 91–98.

Ryan McDonald, Fernando Pereira, Kiril Ribarov, and Jan Hajic. 2005b. Non-projective dependency parsing using spanning tree algorithms. In Proceedings of human language technology conference and conference on empirical methods in natural language processing, pages 523–530.

Alireza Mohammadshahi and James Henderson. 2020. Graph-to-graph transformer for transition-based dependency parsing. In Findings of the Association for Computational Linguistics: EMNLP 2020, pages 3278–3289, Online. Association for Computational Linguistics.

Khalil Mrini, Franck Dernoncourt, Quan Hung Tran, Trung Bui, Walter Chang, and Ndapa Nakashole. 2020. Rethinking self-attention: Towards interpretability in neural parsing. In Findings of the Association for Computational Linguistics: EMNLP 2020, pages 731–742, Online. Association for Computational Linguistics.

Joakim Nivre. 2003. An efficient algorithm for projective dependency parsing. In Proceedings of the Eighth International Conference on Parsing Technologies, pages 149–160.

Joakim Nivre, Marie-Catherine de Marneffe, Filip Ginter, Yoav Goldberg, Jan Hajič, Christopher D. Manning, Ryan McDonald, Slav Petrov, Sampo Pyysalo, Natalia Silveira, Reut Tsarfaty, and Daniel Zeman. 2016. Universal Dependencies v1: A multilingual treebank collection. In Proceedings of the Tenth International Conference on Language Resources and Evaluation (LREC’16), pages 1659–1666, Portorož, Slovenia, European Language Resources Association (ELRA).

Wenhui Wang and Baobao Chang. 2016. Graph-based dependency parsing with bidirectional LSTM. In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 2306–2315, Berlin, Germany. Association for Computational Linguistics.

Wenhui Wang, Baobao Chang, and Maigup Mansur. 2018. Improved dependency parsing using implicit word connections learned from unlabeled data. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 2857–2863, Brussels, Belgium. Association for Computational Linguistics.

Xinyu Wang and Kewei Tu. 2020. Second-order neural dependency parsing with message passing and end-to-end training. In Proceedings of the 1st Conference of the Asia-Pacific Chapter of the Association for Computational Linguistics and the 10th International Joint Conference on Natural Language Processing, pages 93–99, Suzhou, China. Association for Computational Linguistics.

Wei Wu, Fei Wang, Arianna Yuan, Fei Wu, and Jiwei Li. 2019. Coreference resolution as query-based span prediction. ArXiv.

Nianwen Xue, Fu-Dong Chiou, and Martha Palmer. 2002. Building a large-scale annotated Chinese corpus. In COLING 2002: The 19th International Conference on Computational Linguistics.

Zeyu Yan, Jianqiang Ma, Yang Zhang, and Jianping Shen. 2020. SQL generation via machine reading comprehension. In Proceedings of the 28th International Conference on Computational Linguistics, pages 350–356, Barcelona, Spain (Online). International Committee on Computational Linguistics.

Yunzhe Yuan, Yong Jiang, and Kewei Tu. 2019. Bidirectional transition-based dependency parsing. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 33, pages 7434–7441.

Yu Zhang, Zhenghua Li, and Min Zhang. 2020a. Efficient second-order TreeCRF for neural dependency parsing. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 3295–3305, Online. Association for Computational Linguistics.

Yue Zhang and Joakim Nivre. 2011. Transition-based dependency parsing with rich non-local fea-
tures. In Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies, pages 188–193, Portland, Oregon, USA. Association for Computational Linguistics.

Zhisong Zhang, Xuezhe Ma, and Eduard Hovy. 2019. An empirical investigation of structured output modeling for graph-based neural dependency parsing. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 5592–5598, Florence, Italy. Association for Computational Linguistics.

Zhisong Zhang and Hai Zhao. 2015. High-order graph-based neural dependency parsing. In Proceedings of the 29th Pacific Asia Conference on Language, Information and Computation, pages 114–123.

Zhisong Zhang, Hai Zhao, and Lianhui Qin. 2016. Probabilistic graph-based dependency parsing with convolutional neural network. In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 1382–1392, Berlin, Germany. Association for Computational Linguistics.

Zhuosheng Zhang, Hai Zhao, and Rui Wang. 2020b. Machine reading comprehension: The role of contextualized language models and beyond. arXiv preprint arXiv:2005.06249.

Hao Zhou, Yue Zhang, Shujian Huang, and Jiajun Chen. 2015. A neural probabilistic structured-prediction model for transition-based dependency parsing. In Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing (Volume 1: Long Papers), pages 1213–1222.

Junru Zhou and Hai Zhao. 2019. Head-Driven Phrase Structure Grammar parsing on Penn Treebank. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 2396–2408, Florence, Italy. Association for Computational Linguistics.