End-to-End Chinese Parsing Exploiting Lexicons

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Abstract

Chinese parsing has traditionally been solved by three pipeline systems including wordsegmentation, part-of-speech tagging and dependency parsing modules. In this paper, we propose an end-to-end Chinese parsing model based on *character inputs* which jointly learns to output word segmentation, part-of-speech tags and dependency structures. In particular, our parsing model relies on word-char graph attention networks, which can enrich the character inputs with *external word knowledge*. Experiments on three Chinese parsing benchmark datasets show the effectiveness of our models, achieving the state-of-the-art results on end-toend Chinese parsing.

1 Introduction

As a fundamental task in syntactic analysis, dependent parsing has received constant research attention (Dozat and Manning, 2016; Dozat et al., 2017; Strubell et al., 2018; Ma et al., 2018; Li et al., 2019). It offers useful information to a range of downstream tasks, such as relation extraction (Gamallo et al., 2012; Miwa and Bansal, 2016; Guo et al., 2019; Zhang et al., 2018) and semantic parsing (Hajič et al., 2009; Poon and Domingos, 2009; Sun et al., 2018). As shown in Figure 1, the goal of syntactic dependency parsing is to build a dependency tree for a given sentence, where each arc represents a head-dependent relationship between two words.

Traditionally, Chinese dependency parsing takes word segmentation and POS tagging as preprocessing steps (Zhou, 2000; Ma and Zhao, 2012; Zhang and McDonald, 2014). The pipeline method, however, suffers from error propagation as incorrect word boundaries and POS tags lead to decreases in parsing performance. End-to-end models, which take character sequences as input and jointly perform the three task, have been investigated to address the problem (Hatori et al., 2012; Zhang et al.,



Figure 1: End-to-end parsing exploiting lexicons.

2013; Kurita et al., 2017; Li et al., 2018).

While most existing work takes a transitionbased method (Nivre, 2008; Zhang and Nivre, 2011; Bohnet, 2010; Chen and Manning, 2014; Andor et al., 2016), we consider a graph-based method for end-to-end parsing, adopting the biaffine framework of Dozat and Manning (2016). In particular, our model takes a character sequence as input, using a sequence representation network to find the representation of each character. Word segmentation, POS-tagging and parsing are performed jointly over the character representation by multi-task learning. More specifically, both word segmentation and POS-tagging are performed as character sequence labeling tasks, where a local classifier is built on top of each character representation. Dependency parsing follows a bi-affine scoring function between characters, so that the head of each character can be found. Both bidirectional long short-term memory networks (BiL-STMs) and self attention networks (SANs; Vaswani et al., 2017) are considered as the encoder network.

One salient difference of neural graph-based parsing, as compared with its transition-based counterpart, is that the representation of input is calculated first, before local outputs such as sequence labels and bi-word relation tags are predicted. In contrast, a transition-based parser builds a joint output structure using a state-transition process, the representation of which contains mixed input and output information. As a result, one advantage of neural graph-based parsing is that the representation calculation can be more parallelizable, allowing faster running speed. However, for our joint parser, since word segmentation and dependency parsing are performed jointly on characters, word information cannot be used directly to benefit parser disambiguation.

To solve this issue, we consider integrating lexicon knowledge for enriching the character sequence representation, by jointly encoding the characters and all the words in the input that match a dictionary. To this end, we use lattice LSTM (Zhang et al., 2019) for extending a BiLSTM character encoder, and make a novel extension to the Transformer architecture for the SAN counterpart. The latter runs over a order of magnitude faster than the former thanks to strong parallelization. In particular, the Transformer (Vaswani et al., 2017) architecture is adopted, which can be regarded as a graph-attentional neural network (Veličković et al., 2017) with a fully-connected character graph. We integrate information from lexicon words into this graph attentional neural network by taking them as additional vertices in the graph, adding wordcharacter edges and word-word edges to the input graph. The standard self-attention function is further extended into a novel combination of a semantic channel and a structural channel, the former using semantic similarity for weight calculation, and the latter taking paths in the graph into consideration.

Experiments on three Chinese parsing datasets show that integrating lexicon word information is useful for improving character-level end-to-end parsing. Our graph-based parser, enriched with word-level features, outperforms all existing methods in all the datasets, achieving the best results on segmentation, POS tagging and parsing in the literature. To our knowledge, we are the first to investigate an end-to-end Chinese parser exploiting lexicon knowledge.

2 Related Work

End-to-End Chinese Parsing. Hatori et al. (2012) pioneer research on the joint model of word segmentation, POS tagging, and dependency parsing for Chinese using transition-based methods. Zhang et al. (2014) exploit the manually annotated

intra-character dependencies. Zhang et al. (2015) consider transition-based joint word segmentation, POS tagging and dependency reranking using randomized greedy inference. Kurita et al. (2017) first investigate transition-based models for joint Chinese lexical and syntactic analysis with neural models. We investigate the same task, but our end-to-end models are built on graph-based parsers.

Very recently, Yan et al. (2020) consider using a BiLSTM and BERT encoder for representing character sequences for end-to-end Chinese parsing. Our work is similar in being a graph-based parser, but differs in three aspects. First, we investigate the effectiveness of word information for the task by considering a novel graph attention network with semantic and structural channels. Second, we compare BiLSTM encoding with Transformer encoding with BERT. Third, while they consider joint segmentation and parsing, we consider joint segmentation, POS-tagging and parsing.

Word-character Lattice Neural Networks. Chen et al. (2017) and Zhang and Yang (2018) use lattice LSTM to deal with mixed word and character inputs. Ding et al. (2019) use graph convolutional networks (Kipf and Welling, 2016) for entity lattice inputs. Their lattice requires named entities and their entity types as inputs. More closely related to our work, Sperber et al. (2019) adapt Transformer (Vaswani et al., 2017) for lattice inputs. Our models are different from them in three aspects. First, their lattice is built from compressing speech hypothesis, while we build the lattice by lexicon matching. Second, there is no concept of word in their models, while we explicitly model word inputs and exploit pretrained word embeddings. Third, we differentiate semantic and structural information according to the edge types in lattice by taking inspirations from graph Transformers (Veličković et al., 2017; Zhu et al., 2019). Existing work can be regarded as a variant of our models, which only captures semantic features.

3 Task Description

Formally, as shown in Figure 1, given a sequence of characters $s = c_1, ..., c_n$, the target of end-to-end parsing is to obtain a dependency tree T = (V, E) together with segmented word sequence $s_w = w_1, ..., w_k$ and a POS tag sequence $s_t = t_1, ..., t_k$, where c_i is the *i*-th Chinese character in the sentence, w_j is the *j*-th segmented word and t_j is the

POS tag for w_j . The node set V contains all segmented words and an additional root dummy node. The arc set $E = \{(i_k, j_k)\}$, where the tuple (i_k, j_k) represents w_{i_k} is the head of w_{j_k} .

4 LSTM Encoder

The overall framework of our method is shown in Figure 2. In particular, we adopt graph-based parsing and use biaffine transformation for dependency arc prediction. For word segmentation and POS tagging, a CRF is used for predicting label sequences. We use recurrent neural networks for input representations, following Dozat and Manning (2016), Kiperwasser and Goldberg (2016) and Wang and Chang (2016). Specifically, we obtain character embeddings through BERT: $\mathbf{e}_{c_i} = \operatorname{emb}(c_i)$.

A multi-layer bi-directional LSTM structure is used to calculate the character sequence representations. In particular, the initial character embedding \mathbf{e}_{c_i} are denoted as $\mathbf{h}_{c_i}^0$. Subsequently, for the k-th layer, $\mathbf{h}_{c_1}^k, \dots, \mathbf{h}_{c_n}^k$ are calculated from $\mathbf{h}_{c_1}^{k-1}, \dots, \mathbf{h}_{c_n}^{k-1}$ as follows:

$$\begin{split} \overrightarrow{\mathbf{h}_{i}^{k}}, \overrightarrow{\mathbf{c}_{i}^{k}} &= \overrightarrow{\textit{LSTM}^{k}}(\overrightarrow{\mathbf{h}_{i}^{k-1}}, \overrightarrow{\mathbf{h}_{i-1}^{k}}, \overrightarrow{\mathbf{c}_{i-1}^{k}}), \\ \overleftarrow{\mathbf{h}_{i}^{k}}, \overleftarrow{\mathbf{c}_{i}^{k}} &= \overleftarrow{\textit{LSTM}^{k}}(\overleftarrow{\mathbf{h}_{i}^{k-1}}, \overleftarrow{\mathbf{h}_{i+1}^{k}}, \overrightarrow{\mathbf{c}_{i+1}^{k}}), \\ \mathbf{h}_{i}^{k} &= \langle \overleftarrow{\mathbf{h}_{i}^{k}}, \overrightarrow{\mathbf{h}_{i}^{k}} \rangle, \quad \mathbf{c}_{i}^{k} &= \langle \overleftarrow{\mathbf{c}_{i}^{k}}, \overrightarrow{\mathbf{c}_{i}^{k}} \rangle, \end{split}$$

where $LSTM^k$ is the LSTM network for the k-th layer, \mathbf{h}_i^k and \mathbf{c}_i^k are the hidden output and the internal cell state of the *i*-th character. \rightarrow and \leftarrow indicate the left and right composition directions of LSTM networks respectively. The final representation of the *i*-th character c_i is the output hidden vector of the K-th layer: $\mathbf{h}_{c_i} = \mathbf{h}_{c_i}^K$.

We follow the lattice LSTM extension (Zhang et al., 2019) for integrating word features from a dictionary. Formally, the hidden states are calculated as follows:

$$\overrightarrow{\mathbf{h}_{i}^{k}}, \overrightarrow{\mathbf{c}_{i}^{k}} = \overrightarrow{LatticeLSTM^{k}} (\overrightarrow{\mathbf{h}_{i}^{k-1}}, \overrightarrow{\mathbf{h}_{i-1}^{k}}, \overrightarrow{\mathbf{c}_{i-1}^{k}}, \mathbf{E}_{w_{\cdot i}}), \\ \overrightarrow{\mathbf{h}_{i}^{k}}, \overrightarrow{\mathbf{c}_{i}^{k}} = \overleftarrow{LatticeLSTM^{k}} (\overrightarrow{\mathbf{h}_{i}^{k-1}}, \overleftarrow{\mathbf{h}_{i+1}^{k}}, \overrightarrow{\mathbf{c}_{i+1}^{k}}, \mathbf{E}_{w_{i\cdot}}), \\ \mathbf{h}_{i}^{k} = \langle \overleftarrow{\mathbf{h}_{i}^{k}}, \overrightarrow{\mathbf{h}_{i}^{k}} \rangle, \quad \mathbf{c}_{i}^{k} = \langle \overleftarrow{\mathbf{c}_{i}^{k}}, \overrightarrow{\mathbf{c}_{i}^{k}} \rangle,$$

where *LatticeLSTM*^k is the Lattice-LSTM network for the k-th layer. $\mathbf{E}_{w_{\cdot i}}$ and $\mathbf{E}_{w_{i}}$ are the sets of word embeddings for words ending and starting with the *i*-th character, respectively.

Block		Relation	Example
A (char)	1 2 3 4 5	word \rightarrow char char \leftarrow word char \rightarrow char char \leftarrow char self-to-self	- 成果(result):华(China) 访(visit):华(China) 成(become):华(China) 华(China):华(China)
B (word)	6 7 8	$char \rightarrow word$ word $\leftarrow char$ self-to-self	华(China):成果(result) 表(table):成果(result) 成果(result):成果(result)

Table 1: Relation definitions of word-character interaction. Relation expression "A \rightarrow B" indicates a relation from A (left) to B (right). Block A (to a character) and Block B (to a word) take the character "华(China)" and word "成果(Result)" as examples, respectively.

5 Word-Character GAT Encoder

We extend the standard transformer (Vaswani et al., 2017). As shown in Figure 2, the word-character GAT encoder is used as one alternative encoder for the LSTM encoder component in the earlier section to model a word-char mixed sequence. The model consists of a multi-layer encoder. Each layer consists of two sub-layers, including a multi-head selfattention sublayer and a position-wise feed-forward network sublayer. Layer normalization and residual network are used for each sublayer. Formally, denote the input character-word mixed sequence as $t = [c_1, ..., c_n, w_1, ..., w_k]$, where $c_1, ..., c_n$ represent the input character sequence and $w_1, ..., w_k$ represent the words in the input that match a lexicon. For the convenience of notation, we represent each token in the input as $t_i (i \in [1, n+k])$, regardless of whether it is a character (i < n+1) or word (i > n).

Position Embedding We use static position embeddings to encode the input following Vaswani et al. (2017). $e^p(i)$ represents the position embedding for the *i*-th position. We inject position embedding to characters and word input as follows:

$$\mathbf{e}_{c_i}' = \mathbf{e}_{c_i} + \mathbf{e}^p(i); \mathbf{e}_{w_i}' = \mathbf{e}_{w_i}' + \mathbf{e}^p(b_{w_i}).$$

We take the position of the first character b_{w_i} of the word w_i in the original sentence to represent the position of the word.

Information Integration For the convenience of describing both word and characters, we unify them as nodes in a graph represented using a graph attention network (Veličković et al., 2017). We define two channels for capturing semantic and structural features in the graph, respectively. In particular, the semantic channel captures interac-



Figure 2: End-to-end Chinese parsing. The input is a part of the sentence in Figure 1 with character index $i \in [7, 11]$. The output sequences are the gold labels accordingly. The output structure for the entire sentence is shown in Figure 1.

tion between characters and words in the sentence without differentiating their types, and the structural channel adds the type and relative position when considering node interaction. The detailed definitions are given later. As shown in Figure 2, a graph neural network works by iteratively updating the representation of each node through layers. In each layer, each node receives information from its neighbors in the input graph structure so that its representation vector can be updated. The naive transformer structure (Vaswani et al., 2017) can be viewed as a graph attentional neural network, where each input character is a node and there is a graph edge between every two nodes.

Formally, denote the input of each layer as $x = [x_1, ..., x_n, x_{n+1}, ..., x_{n+k}]$, where x_i is the input representation of c_i for $1 \le i \le n$ and x_i is the input representation of w_{i-n} for $n+1 \le i \le n+k$. The input for the first encoder layer is the embedding sequence $[\mathbf{e}'_{c_1}, ..., \mathbf{e}'_{c_n}, \mathbf{e}'_{w_1}, ..., \mathbf{e}'_{w_k}]$. For the *m*-th attention head, the similarity between two tokens \mathbf{x}_i and \mathbf{x}_j can be calculated by a vector inner product:

$$s_{ji}^{sem,m} = \left(\mathbf{x}_i \mathbf{W}^{K,m}\right) \cdot \left(\mathbf{x}_j \mathbf{W}^{Q,m}\right)$$

where $\mathbf{W}^{K,m}$ and $\mathbf{W}^{Q,m}$ are the model parameters for the *m*-th attention head.

The similarity $s_{ji}^{sem,m}$ can control how much information t_i can receive from t_j . The key in the above information exchange process is a characterword mixed self-attention mechanism, where a weight score s_{ji}^{sem} is calculated by the similarity of

token t_j and t_i . To this end, s_{ji}^{sem} can be regarded as a **semantic channel**.

We further introduce a **structural channel** by taking path structure into consideration. As shown in Table 1, we differentiate edges according to both the word/character difference and the relative position, resulting in 7 types of edges. For example, "word \rightarrow character" represents an edge from a word to a character at its right. "self-to-self" represents a self-loop over a character or a word.

We make use of rich edge types by defining structural channels. Each token t_i can receive the information from all the input according to the edges defined in Table 1. Taking the character "华(China)" as an example, it can receive information from "成 果(result)", "访(visit)", "成(become)", "华(China)" through the edges r_2 , r_3 , r_4 and r_5 in the table, respectively. In addition, we define a special edge "others" for each other relation type so that "华(China)" can receive information from all characters and words.

Formally, denote the relation from node o to node i as r_{ji} . We can obtain the embedding of each relation r_{ji} through an embedding lookup table:

$$\mathbf{e}_{ji} = \operatorname{emb}(r_{ji}).$$

We further calculate contextualized relation embeddings \mathbf{e}_{oi}^{ct} , which is sensitive to the representations of the two nodes \mathbf{x}_i and \mathbf{x}_o for r_{oi} :

$$\mathbf{e}_{ji}^{ct,m} = \sigma(\mathbf{e}_{ji}\mathbf{W}^{E,m} + \mathbf{e}_{x_i}\mathbf{W}^{S,m} + \mathbf{e}_{x_j}\mathbf{W}^{T,m}),$$

where $\mathbf{W}^{E,m}$, $\mathbf{W}^{S,m}$ and $\mathbf{W}^{T,m}$ are parameters.

The structural similarity score is calculated as:

$$s_{ji}^{str,m} = \mathbf{w}^m \cdot \mathbf{e}_{ji}^{ct,m},$$

where vector \mathbf{w}^m is a model parameter for the *m*-th attention head.

The final similarity score s_{oi} between token $j \in [1, n + k]$ and token $i \in [1, n + k]$ is the combined scores from semantic channels and structural channels:

$$s_{ji}^m = s_{ji}^{sem,m} + s_{ji}^{str,m}.$$

The hidden state of t_i for the *m*-th head is:

$$\mathbf{h}_{i}^{m} = \sum \operatorname{softmax}_{j}(\mathbf{s}_{ji}^{m}) \cdot \left(\mathbf{x}_{j}\mathbf{W}^{V,m}\right)$$

where \mathbf{x}_j is the input of token t_j for the current encoder layer, and $\mathbf{W}^{V,m}$ is a model parameter.

The final output h_i is the concatenation of outputs from all the M attention heads:

$$\mathbf{h}_i = [\mathbf{h}_i^1, ..., \mathbf{h}_i^M].$$

6 Decoding and Training

For word segmentation and POS tagging, we use a joint tag scheme t_{ws} - t_{pos} , where $t_{ws} \in \{B, M, E, S\}$ denotes segmentation labels (Xue and Shen, 2003), and t_{pos} denotes POS. The probability $segpos_{ij}$ for the joint tag $\{t_{ws}$ - $t_{pos}\}_i$ is:

$$\mathbf{t}_i = \mathrm{MLP}_t(\mathbf{h}_{c_i}); \ posseg_{ij} = \mathrm{softmax}_j(\mathbf{W}_t \mathbf{t}_i)$$

For dependency parsing, following Dozat and Manning (2016), we use two representations of each character, which can distinguish between dependents and heads in dependency relations. In particular, for the *i*-th character c_i , a head representation \mathbf{h}_{c_i} and a dependent representation \mathbf{d}_{c_i} are obtained through two multi-layered perceptrons:

$$\mathbf{h}_i = \mathrm{MLP}_h(\mathbf{h}_{c_i}); \ \mathbf{d}_i = \mathrm{MLP}_d(\mathbf{h}_{c_i})$$

The dependency confidence score dep_{ij} of the dependency relation $j \rightarrow i$ is obtained by using a biaffine transformation:

$$dep_{ij} = \operatorname{softmax}_i \left(\mathbf{h}_j^T \mathbf{A} \mathbf{d}_i + \mathbf{b}_1^T \mathbf{h}_j + \mathbf{b}_2^T \mathbf{d}_i \right)$$

where A, b_1 and b_2 are the model parameters.

Training A negative log-likelihood loss value \mathcal{L} is computed on each character c_i over the head

probability dep_{ij} locally and accumulated along the sentence,

$$\mathcal{L} = -\sum_{i=1}^{N} \left(\log dep_{i,head_i} + \log segpos_{i,tag_i} \right),$$

where $head_i$ and tag_i denotes the head index and the joint segmentation-POS tag of the *i*-th character, respectively. During training, we minimize \mathcal{L} to train the model parameters.

Decoding Hierarchical decoding is used for dependency parsing: we first perform decoding to parse the internal structure of a word and find the root character, and then perform decoding for all root character for all root character in the sentence to obtain a word-level parsing results. Given the confidence score of all potential dependency arcs dep_{ij} , the decoding process can be formulated as a max spanning tree (MST) problem. Specifically, we use the Tarjan implementation (Tarjan, 1977) of the Chu-Liu-Edmonds algorithm (Chu, 1965; Edmonds, 1967) to find the MST derivation.

7 Experiments

We investigate the effect of word information and our GAT encoder to character-level graph-based Chinese parsing.

7.1 Settings

We use three releases of the Chinese Penn Treebank (i.e., 5.0, 6.0 and 7.0) (Xue et al., 2005), splitting the corpora into training, development and test sets according to previous work. CTB 5.0 is split by following Zhang and Clark (2010), CTB 6.0 by following the official documentation, and CTB 7.0 by following Wang et al. (2011).

We use the head rules of Zhang and Clark (2008) to convert phrase structures in CTB into dependency structures. Following Hatori et al. (2012), the standard measures of word-level precision, recall and F1 score are used to evaluate word segmentation, POS-tagging and dependency parsing, respectively. For a given word $w = c_1c_2...c_k$, we simply use the right branching tree $c_1 \rightarrow c_2 \rightarrow$ $... \rightarrow c_k$ as the intra-word dependency structure. Following Zhang and Yang (2018), we take the external Chinese lexicon dictionary from Song et al. (2018). The experiments are conducted under the same hardware environment: Geforce GTX 2080Ti graph card and i7-7900 CPU.

Hyper-parameters We initialize character embeddings using BERT (Devlin et al., 2018), and

Parameter	SEG	POS	DEP
1 head	98.5	96.4	91.0
4 heads	98.8	96.5	91.4
8 heads	98.6	96.4	91.3
16 heads	98.7	96.5	90.9
1 layer	98.5	96.2	90.0
2 layers	98.5	96.3	91.1
3 layers	98.8	96.5	91.4

Table 2: Dev experiments for word-character graph attention model.

word embeddings with the average pooling result of BERT character embeddings. Neither character nor word embeddings are fine-tuned due to limitation of GPU memory. The size of hidden states is set to 400 for all models (The hidden size of each direction in biLSTM is 200).

Training is done on mini-baches via Adagrad (Duchi et al., 2011) with a learning rate of 0.002, $\beta_1 = 0.9, \beta_2 = 0.9$ and $\epsilon = 1e - 12$. We adopt gradient clipping with a threshold of 5.0. Dropout (Hinton et al., 2012) is used on each layer, with a rate of 0.2.

7.2 Development Experiments

We conduct development experiments on the CTB 5.0 dev set to decide the final hyper-parameters of the two mixed model. Below we show the details of three important factors.

Effect of Encoder Layers We investigate the effect of the number of encoder layers for the word-character graph attention model. The results are shown in Table 2. As the number of encoder layer increases from 1 to 3, performance improves for parsing, as well as word segmentation and POS tagging. We do not conduct experiments on more layers because of memory limitation. The number of encoder layers is set to 3 in the remaining experiments.

Effect of Attention Heads We further investigate the effect of attention head number for the word-character graph attention model, as shown in Table 2. We observe performance increases as the number of attention heads increases from 1 to 4, but adding more attention heads does not lead a further performance improvement. We thus fix the number of attention heads to 4 accordingly.

Effect of Word Information and Model Architectures We conduct a set of development experiments to verify the influence of model architecture and word information on each architecture.

The results are shown in Table 3. In particular, a

Model	SEG	POS	DEP
Character-level LSTM	98.4	96.1	90.3
Character-level transformer	98.7 98.7	96.4 96.5	90.8 90.9
Word-char graph attention	98.8	96.5	91.4

Table 3: Dev experiments on different models.

character-level LSTM model gives a parsing accuracy of 90.3%. With word-character lattice, the results are improved to 90.8% Using GAT, the model gives a 90.9% development accuracy for parsing, which is improved to 91.4% by using word information additionally. This shows that word information is beneficial to both the LSTM architecture and the GAT architecture. In addition to dependency structures, the results for both word segmentation and POS-tagging are also improved.

In addition, LSTM models underperform their SAN counterparts regardless whether word information is combined into the character encoder. The lattice LSTM system is much slower to train (nearly half an hour for training one epoch on CTB 5, and the total training takes several days) compared with the chracter-level BiLSTM model (145 seconds for one epoch) and SAN models (421 seconds for one epoch).

7.3 Final Results

Table 4 shows the overall performances of end-toend Chinese dependency parsing where our model is compared with the state-of-the-art methods in the literature. We report the performances on Chinese word segmentation, POS tagging and parsing, respectively. First, we can find that BERT pretrained models outperform neural models using traditional embeddings (Kurita et al., 2017; Li et al., 2018) and statistical models (Hatori et al., 2012; Zhang et al., 2014, 2015) by a large margin. Compared with Joint Multi BERT (Yan et al., 2020), the word-char graph attention model achieves better performance especially on parsing. Note that we do not leverage on additional syntactic and lexical annotation within a word as Zhang et al. (2014) and Li et al. (2018) do. This demonstrates the advantage of our word-character graph attention model.

The final results on parsing of the lattice-LSTM BERT end-to-end model are 88.1%, 83.6% and 84.9% on the CTB 5, 6 and 7 datasets, respectively, and the final results of the GAT model are 91.3%, 87.2% and 86.2% on the three datasets, respectively. The improvements are statistically significant at

Model	CTB 5.0			CTB 6.0			CTB 7.0		
	SEG	POS	DEP	SEG	POS	DEP	SEG	POS	DEP
Incremental Joint (Hatori et al., 2012)	96.9	93.0	76.0	96.2	92.0	75.8	96.1	91.3	74.6
Char STD (Zhang et al., 2014)	97.8	94.6	82.1	95.6	91.4	77.1	95.5	90.8	75.7
Char EAG Zhang et al. (2014)	97.8	94.4	82.1	95.7	91.5	77.0	95.5	90.7	75.8
Joint Annotated (Zhang et al., 2015)	98.0	94.5	82.0	-	-	-	-	-	-
NN transition (Kurita et al., 2017)	98.4	94.8	81.4	-	-	-	96.4	91.3	75.3
NN char-level (Li et al., 2018)	96.6	92.9	79.4*	-	-	-	-	-	-
Joint Multi BERT (Yan et al., 2020)	98.5	-	89.6	-	-	-	97.1	-	85.1
Lattice-LSTM E2E BERT Word-char Graph Attention	98.4 98.7	96.2 96.5	88.1 91.3	97.3 97.3	94.6 94.8	83.6 87.2	96.9 97.3	93.9 94.4	84.9 86.2

Table 4: Final Results. * indicate performance on CTB 5.1.

p < 0.05 using t-test. Overall, the GAT architecture gives better segmentation, POS-tagging and parsing results compared with the LSTM model on all datasets, while running much faster. This shows the advantage of our semantic and structural channels for integrating word information. Compared with the existing methods for joint Chinese parsing, our final GAT model gives better results on all the three datasets, achieving the best reported accuracies on dependency parsing in the literature.

Segmentation Results According to Table 4, word information brings the most improvements on parsing accuracies, followed by tagging accuracies. Segmentation benefits relatively less. However, as a fully end-to-end model, POS tagging and dependency parsing information can also benefit word segmentation. Thus our joint model can be a competitive choice for the segmentation task alone. We compare the performance of different models with BERT pretraining on the CTB6 word segmentation task in Table 5 (previous work mostly uses the CTB6 version).

The first 4 items are the segmentation models trained on the single segmentation task. BiLSTM-CRF-BERT (Gan and Zhang, 2019) uses a BiL-STM network followed by CRF network with pretrained BERT as input. LSAN-CRF (Gan and Zhang, 2019) uses a local self-attention network instead of BiLSTM. DP-BERT (Huang et al., 2019) and Unified-BERT (Ke et al., 2020) are both multicriteria Chinese word segmentation models, which are trained on a range of extra training sets to enhance the segmentor. DP-BERT (Huang et al., 2019) uses a domain projection for multi-criteria learning while unified BERT (Ke et al., 2020) employs a fully shared model for all criteria.

Our model gives better performance on segmentation BiLSTM-CRF-BERT and a bit worse result than LSAN-CRF-BERT, which is optimised

Model	F1-score
BiLSTM-CRF-BERT (Gan and Zhang, 2019)	97.2
LSAN-CRF-BERT (Gan and Zhang, 2019)	97.4
DP-BERT (Huang et al., 2019)	97.6
Unified BERT (Ke et al., 2020)	97.2
Word-char Graph Attention	97.3

Table 5: Word Segmentation results. All results are based on BERT pretraining.



Figure 3: Performance against sentence length. The F1 score for each length l is calculated on the test set sentences length in the bin [l, l + 15].

for segmentation. In addition, our model gives comparable results in segmentation compared with DP-BERT and Unified-BERT, which shows the advantage of joint parsing as compared to external segmentation datasets. Compared with Yan et al. (2020), our model can give better segmentation.

7.4 Analysis

In this section, we focus on the word-character GAT model to thoroughly investigate the effect of word information.

OOV Table 6 shows the recall of out-of-vocabulary words on the CTB 5.0 test set. A word-character graph attention model enriched with word information achieves 0.9%, 2.1% and 4.1% abso-

Sentence	以菲律宾前总统名字命名的拉蒙·麦格赛赛奖 Ramon Magsaysay Award named after ex-president of the Philippines	Sentence	费孝通被授予麦格赛赛奖 Fei Xiaotong was awarded the Magsaysay Prize
Words	菲律宾(Ramon) 前总统(ex-president) 总统(president) 拉蒙·麦格赛赛奖(Ramon Magsaysay Award) 拉蒙(Ramon) 麦格赛赛(Ramon Magsaysay) 麦格(Mag) 格赛(Gsay)	Words	费孝通(Fei Xiaotong) 孝通(Xiaotong) 授予(awarded) 麦格赛赛(Ramon Magsaysay) 麦格(Mag) 格赛(Gsay)
Character	以菲律宾前总统名字命名的拉蒙麦格赛赛奖	Character	费孝通 被 授予 麦格赛 赛奖
-level	after Philippines ex- president name name -ed Ramon Magsaysay Award	-level	Fei Xiaotong was awarded Magsay Say-Prize
baseline	P NR H _{DT} NN NN VV DEC NR NN	baseline	NR SB VV NR NN
Word-char	以 菲律宾 前 总统 名字 命名 的 拉蒙麦格赛赛 奖	Word-char	费孝通 被 授予 麦格赛赛 奖
graph	after Philippines ex- president name name -ed Ramon Magsaysay Award	graph	Fei Xaotong was awarded Magsaysay Prize
attention	P NR H NN NN VV DEC NR NN	attention	NR SB VV NR NN

Figure 4: Sample outputs. Errors are in red.

Task	Char M.	Word-char M.	Diff.
SEG	87.4	88.3	+0.9
POS	81.7	83.8	+2.1
DEP	76.6	80.7	+4.1
DEP'	87.6	91.4	+3.8

Table 6: Recalls of OOV words. DEP' indicates the parsing recall rate when the dependent word is correctly segmented.

lute improvement over the character-level model on word segmentation, POS tagging and parsing, respectively. It shows that the word-character attention model benefits transfer learning and generalization. This is likely because lexicons help to learn better representation for OOV words. In particular, the word-char attention model shows significant improvement on parsing. The improvement of parsing results from better segmentation (+ 0.9%) and better head inference (+3.8\%).

Performance Against the Sentence Length We further analyze the performance with respect to different sentence lengths. Figure 3 shows the results. The performance of word segmentation and POS tagging are relatively stable against sentence length as these two tasks rely more on the local context. There is a tendency of decreasing F1 scores for parsing when the sentence length increases. Compared with the the Transformer model without using word information, the word-character GAT model gives about the same improvements on parsing across different sentence lengths. In addition, the use of word information also makes the curve more smooth across different sentence lengths, which shows the benefit of lexicon features in enhancing the model robustness.

Configuration	F1 score	Diff.
Word-char graph attention	91.3	0
- structural channel	90.8	-0.5
- semantic channel	90.6	-0.7
- all word information	90.5	-0.8

Table 7: Ablation test of the word-character graph attention model.

Ablation Study We conduct ablation experiments to investigate the effect of different channels of the word-char graph attention model showing three important factors on the CTB 5.0 test set in Table 7. Compared with the word-char graph attention model, removing the structural channel leads to a parsing F1 score decrease by 0.6%. In contrast, excluding the semantic channel decreases the parsing F1 score by 0.8%. Compared with the structural channel, the semantic channel contains important position information besides semantic similarity, which can be the reason for its better performance. However, the best result is achieved using both channels, from which it can be inferred that the channels can interact with and complement each other on the final performance. We can also observe that using word information through either channel or both channels combined can improve the parsing performance compared to a characterlevel attention model ("- all word info" in the table), showing the effectiveness of word information.

Case Study Figure 4 shows samples of endto-end Chinese parsing on CTB 5.0. In the first sentence, the head word of token "菲律宾(the Philippines)" is incorrectly recognized as "名 字(name)" in the vanilla LSTM model, while the word-char graph attention model identifies its correct head "总统(president)". The vanilla LSTM model suffers from polysemous characters "菲(commonly used character in names)", "律(law)" and "宾(commonly used character in names)". In contrast, the word-character graph attention model taking additional word information "菲律宾(the Philippines)" can better understand the sentence and thus gives a correct syntactic parsing result.

In the second sentence, the expression "麦格 赛赛奖(Magsaysay Award)" (Gold segmentation: "麦格赛赛(Magsaysay)", "奖(Award)") is incorrectly segmented into tokens "麦格赛(Magsay)" and "赛奖(Competition Award)" by the vanilla LSTM model, which results in errors in the POS tagging and parsing result. It shows that word features can help better identify word boundaries, which is important to POS tagging and parsing. The word-char graph attention model segments the sentence correctly, and thus gives the correct result in all three tasks. In summary, the word-character graph attention model performs better in identifying dependency heads in addition to word boundaries, thanks to the lexicon input.

8 Conclusion

We investigated the effectiveness of word information for end-to-end graph-based Chinese parsing by extending a character-level transformer encoder. Compared with LSTM-based representation learning models, our method is more feasible due to better parallelization between characters and convenience to batching. Results on the three datasets show that word information benefits all the three tasks, and our word-char graph attention model outperforms the lattice-LSTM model, and achieving the best results on segmentation, POS tagging and parsing in the literature. To our knowledge, we are the first to investigate an end-to-end Chinese parser exploiting lexicon knowledge.

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