

# SLK-NER: Exploiting Second-order Lexicon Knowledge for Chinese NER

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**Abstract**—Although character-based models using lexicon have achieved promising results for Chinese named entity recognition (NER) task, some lexical words would introduce erroneous information due to wrongly matched words. Existing researches proposed many strategies to integrate lexicon knowledge. However, they performed with simple first-order lexicon knowledge, which provided insufficient word information and still faced the challenge of matched word boundary conflicts; or explored the lexicon knowledge with graph where higher-order information introducing negative words may disturb the identification.

To alleviate the above limitations, we present new insight into second-order lexicon knowledge (SLK) of each character in the sentence to provide more lexical word information including semantic and word boundary features. Based on these, we propose a SLK-based model with a novel strategy to integrate the above lexicon knowledge. The proposed model can exploit more discernible lexical words information with the help of global context. Experimental results on three public datasets demonstrate the validity of SLK. The proposed model achieves more excellent performance than the state-of-the-art comparison methods.

**Index Terms**—lexicon knowledge, attention mechanism, Chinese named entity recognition

## I. INTRODUCTION

Named Entity Recognition (NER) aims to locate and classify named entities into predefined entity categories in the corpus, which is a fundamental task for various downstream applications such as information retrieval [1], question answering [2], machine translation [3], etc. Word boundaries in Chinese are ambiguities and word segmentation errors have a negative impact on identifying Name Entity (NE) [4], which would make Chinese NER more difficult to identify. Explicit discussions have approved that character-based taggers can outperform word-based counterparts [5].

Because entity boundaries usually coincide with some word boundaries, integrating external lexicon knowledge into character-based models has attracted research attention [5]. Although lexicon can be useful, in practice the lexical words may introduce erroneous information and suffer from word boundary conflicts, which easily lead to wrongly matched entities and limit system the performance [6]. To address the above issues, many sequence-based efforts have been devoted to incorporated lexicon knowledge into sentences [7, 8].

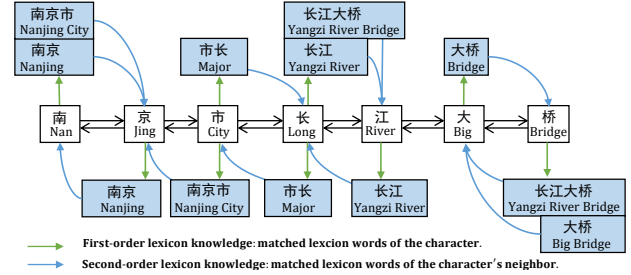


Fig. 1. An example of a word character lattice. The top is that predicting the label uses from left to right sequence and the bottom is using from right to left sequence. The green arrow line represents that the character (start) can match with the lexical word (end). The blue arrow line represents the lexical word (start) information would be integrated into the character (end).

However, these strategies explore simple *first-order lexicon knowledge* (FLK) of each character as shown in the green arrow line in Fig.1. FLK only contains the lexical features of the characters itself, which cannot offer adequate word information. For example, the character “京(Jing)” only introduces “南京(Nanjing)” based on FLK. The wrongly matched word information would misidentify as “南京(Nanjing)” instead of “南京市(Nanjing City)”. As a result, they continue to suffer from boundary conflicts between potential words being incorporating in the lexicon. The conflict caused by this deficiency mainly comes from the middle of the named entity, such as “大(Big)” and “江(River)” in “长江大桥(Yangtze River Bridge)”.

Recently, some models attempted to aggregate rich higher-order lexicon knowledge, such as graph structure [9–11]. This higher-order information probably introduces irrelevant words with the character, limiting the performance to some extent. In addition, the existence of shortcut paths may cause the model degeneration into a partially word-based model, which would suffer from segmentation errors.

To address the above issue, we introduce the *second-order lexicon knowledge* (SLK) to each character in the input sentence, that is the neighbor’s lexicon knowledge of the character, as elaborated in Fig.1 with the blue arrow lines. The SLK of “京(Jing)” contains both “南京市(Nanjing City)” and “南京(Nanjing)” from its left neighbor “南(Nan)”, and “南京市(Nanjing City)” from its right neighbor “市(City)”. With regard to global semantics of the sentence, “南京

市(Nanjing City)” is more likely to be the named entity than “南京(Nanjing)” due to higher semantic similarity of “南京市(Nanjing City)”. Similarly, the SLK of “江(River)” is the potential words “长江大桥(Yangtze River Bridge)” and “长江(Yangtze River)”, and the SLK of “大(Big)” is “长江大桥(Yangtze River Bridge)” and “大桥(Big Bridge)”. By synthesizing global considerations, these lexicon knowledge guides the character subsequence “长江大桥(Yangtze River Bridge)” to be recognized as the named entity.

To take advantage of this insight, we proposed a SLK-based model with a novel strategy named SLK-NER, to integrate more informative lexicon words into the character-based model. Specifically, we assign SLK to each character and ensure no shortcut paths between characters. Furthermore, we utilize global contextual information to fuse the lexicon knowledge via attention mechanism. The model enables capture more useful lexical word features automatically and relieves the word boundary conflicts problem for better Chinese NER performance.

The main contributions can be summarized as follows:

- **Insight.** We present a new insight about second-order lexicon knowledge (SLK) of the character. SLK can provide sufficient lexicon knowledge into characters in sentences and is capable of relieving the challenge of word boundary conflicts.
- **Method.** To properly leverage SLK, we propose a Chinese NER model named SLK-NER with a novel strategy to integrate lexicon knowledge into the character-based model. SLK-NER can enable to capture more beneficial word features with the help of global context information via attention mechanism.
- **Evaluation.** Experimental results demonstrate the efficiency of SLK and our model significantly outperforms pervious methods, achieving state-of-the-art over three public Chinese NER datasets. The source code and dataset are available<sup>1</sup>.

## II. RELATED WORKS

Early character-based methods for NER considered few word information in character sequence [4, 12–14]. To tackle this limitation, many works generally use lexicon as extra word information for Chinese NER.

### A. Sequence-based Methods

Zhang et al. [5] introduced a lattice LSTM to model all potential words matching a sentence to exploit explicit word information and achieved state-of-the-art results. Lattice LSTM enlightened various approaches for the useage of lexicon knowledge. Chain-structured LSTM [8] integrated word boundary features into input character vector via four strategies. Gui et al. [7] extended rethinking mechanism to relieve word boundary conflicts.

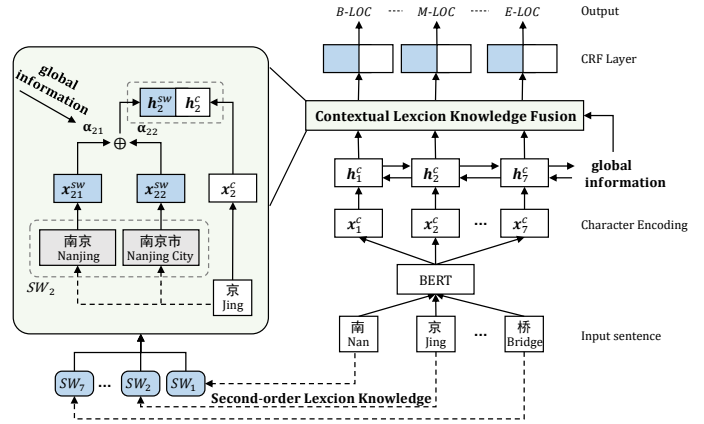


Fig. 2. The whole architecture of SLK-NER. It is comprised of character encoding layer, lexicon knowledge encoding layer, contextual lexicon knowledge fusion and a CRF decoding layer.

### B. Graph-based Methods

With the development of graph, there are some studies improved by graph neural networks. For instance, Gui et al. [9] proposed a GNN-based method to explore multiple graph-based interactions among characters, potential words, and the whole-sentence semantics and effectively alleviated the word ambiguity. Sui et al. [10] propose a collaborative graph network to assign both self-matched and the nearest contextual lexical words. Ding et al. [11] proposed a multi-digraph structure to learn the contextual information of the characters and the lexicon.

## III. METHOD

### A. Overview

The overall architecture of our proposed model is illustrated in Fig.2. First, we encode character-based sentences to explicitly capture the contextual features of the sentence via character encoding layer. Second, to integrate more lexicon knowledge, we construct the second-order lexicon knowledge (SLK) for each character. Third, a fusion layer with the global attention information is used for fusing different SLK to alleviate the impact of word boundary conflicts. Finally, a standard CRF model [15] is employed for decoding labels.

Formally, we denote an input sentence as  $s = \{c_1, c_2, \dots, c_n\}$ , where  $c_i$  means the  $i$ th character. The lexicon  $\mathcal{D}$  is the same as [5], which is built by using automatically segmented large raw text. For  $i$ th character, we use  $\overrightarrow{\mathcal{FW}}_i$  to denote a set of words obtained by matching all possible forward subsequences in lexicon  $\mathcal{D}$  [8]. Similarly, we use  $\overleftarrow{\mathcal{FW}}_i$  to denote the words for  $i$ th character in backward process. The knowledge involved in these sets represents the FLK corresponding to the  $i$ th character, i.e.,  $\overline{\mathcal{FW}}_i = \overrightarrow{\mathcal{FW}}_i \cup \overleftarrow{\mathcal{FW}}_i$ . Based on FLK, SLK of  $i$ th character can be defined as:

$$SW_i = \overrightarrow{\mathcal{FW}}_{i-1} \cup \overleftarrow{\mathcal{FW}}_{i+1}, i \in [1, n]. \quad (1)$$

As the example shows in Fig.2, SLK of the character “京(Jing)” is the word set including “南京(Nanjing)” and “南

<sup>1</sup><https://github.com/zerohd4869/SLK-NER>

京市(Nanjing City)”. SLK can mitigate the negative impact of word boundary conflicts. Therefore, we utilize SLK in our proposed model.

### B. Character Encoding Layer

Given the sentence  $s$ , a pre-trained model BERT [12] encodes each character  $c_i$  in the sentence to a vector.

$$\mathbf{x}_i^c = BERT(c_i). \quad (2)$$

To capture more contextual information, we apply bi-directional Gate Recurrent Unit:

$$\mathbf{h}_i^c = GRU(\mathbf{x}_i^c), i \in [1, n]. \quad (3)$$

The hidden state of last character contains the global features of the input sentence, i.e.,  $\mathbf{g} = \mathbf{h}_n^c$ .

### C. Lexicon Knowledge Encoding Layer

To represent the semantic information of SLK of  $i$ th character, we embed  $j$ th lexical word  $sw_{ij}$  in  $S\mathcal{W}_i$  to distributional space as a semantic vector:

$$\mathbf{x}_{ij}^{sw} = \mathbf{e}^w(sw_{ij}), \quad (4)$$

where  $\mathbf{e}^w$  is a pre-trained word embedding lookup table.

### D. Contextual Lexicon Knowledge Fusion

Not all lexical words contribute equally to the representation of the character meaning. Hence, we introduce a global contextual information to extract such SLK that are important to the meaning of the character and aggregate them to refine a character vector. Specifically, for the  $j$ th word in the matching set  $S\mathcal{W}_i$  of the  $i$ th character, we can obtain a hidden representation  $\mathbf{u}_{ij}$  for word embedding  $\mathbf{x}_{ij}^{sw}$ :

$$\mathbf{u}_{ij} = \mathbf{W}_u \mathbf{x}_{ij}^{sw} + \mathbf{b}_u, \quad (5)$$

where  $\mathbf{W}_u$  and  $\mathbf{b}_u$  are update parameters. We measure the importance of lexical word as the similarity and get a normalized importance weight  $\alpha_{ij}$ . Then, the SLK of  $i$ th character can be computed as a weighted sum of the word information.

$$\alpha_{ij} = \frac{\exp(\mathbf{u}_{ij}^T \mathbf{g})}{\sum_j \exp(\mathbf{u}_{ij}^T \mathbf{g})}, \quad (6)$$

$$\mathbf{h}_i^{sw} = \sum_j \alpha_{ij} \mathbf{x}_{ij}^{sw}. \quad (7)$$

Finally, the final representation of  $i$ th character is denoted as  $\mathbf{r}_i = [\mathbf{h}_i^{sw}; \mathbf{h}_i^c]$ .

### E. Decoding and Training

To formulate the dependencies between successive labels, a standard CRF layer is used to make sequence tagging. We define matrix  $\mathbf{O}$  to be scores calculated based on the final representations  $\mathbf{R} = \{\mathbf{r}_1, \dots, \mathbf{r}_n\}$ :

$$\mathbf{O} = \mathbf{W}_o \mathbf{R} + \mathbf{b}_o, \quad (8)$$

where  $\mathbf{W}_o$  and  $\mathbf{b}_o$  are trainable parameters. Then, the probability of tag sequence  $y = \{y_1, \dots, y_n\}$  is:

$$p(y|s) = \frac{\exp(\sum_i (\mathbf{O}_{i,y_i} + \mathbf{T}_{y_{i-1},y_i}))}{\sum_{\hat{y}} \exp(\sum_i (\mathbf{O}_{i,\hat{y}_i} + \mathbf{T}_{\hat{y}_{i-1},\hat{y}_i}))}, \quad (9)$$

where  $\mathbf{T}$  is a transition score matrix, and  $\hat{y}$  denotes all possible tag sequences. While decoding, we apply the Viterbi [16] algorithm to get label sequence with the highest score.

Given training examples  $\{(s_j, y_j)\}_{j=1}^N$ , we optimize the model by minimizing the negative log-likelihood loss:

$$L = - \sum_j \log(p(y_j|s_j)). \quad (10)$$

## IV. EXPERIMENTS

### A. Experimental Settings

1) *Datasets*: As shown in Table I, we evaluate our model on three datasets, **OntoNotes4**, **Weibo** and **Resume**. OntoNotes4 is a multilingual corpus in the news domain that contains four types of named entities. Weibo dataset consists of annotated NER messages drawn from Sina Weibo<sup>2</sup>. The corpus contains PER, ORG, GEP, and LOC for both named entity and nominal mention. Resume dataset is composed of resumes collected from Sina Finance<sup>3</sup>. It is annotated with 8 types of named entities. For OntoNotes4, we use the same training, validating and testing splits as [17]. Since other datasets have already been split, we don't change them.

TABLE I  
THE STATISTICS OF THE DATASETS.

Dataset	Training	Validation	Testing
OntoNotes4	15724	4301	4346
Weibo	1350	270	270
Resume	3821	463	477

2) *Comparisons*: The methods evaluated are as follows. **BiLSTM-CRF** [13] was a sequence labeling model consisting of BiLSTM layer and CRF layer. **BERT** [12] was a pre-trained model with deep bidirectional transformer. **CAN** [14] investigated CNN-based model with attention layers to capture features of the character and its contexts. **Lattice-LSTM** [5] encoded characters in a sequence and all potential words that match a lexicon. **LGN** [9] used lexicon to construct the graph and provide word-level features. The literature [11] applied a multi-digraph structure to incorporate gazetteer information, and we denote **MG-GNN** for convenience. **WC-LSTM** [8] was used to add word information into the start or the end character of the word. **LR-CNN** [7] extended the rethinking mechanism when using lexicon. **CGN** [10] investigated collaborative graph network (CGN) to leverage lexical knowledge.

3) *Implementation Details*: We use lexicon and word embeddings provided by [18], which is pretrained on Chinese Giga-Word using word2vec model. For character embeddings, we apply the bert-base Chinese model<sup>4</sup> (12-layer, 768-hidden,

<sup>2</sup><https://www.weibo.com>

<sup>3</sup><https://finance.sina.com.cn/stock/>

<sup>4</sup><https://github.com/google-research/bert>

TABLE II  
EXPERIMENTAL RESULTS(%) ON THREE DATASETS.

Models	OntoNotes4			Weibo			Resume		
	P	R	F1	P	R	F1	P	R	F1
BiLSTM-CRF[13]	72.0	75.1	73.5	60.8	52.9	56.6	93.7	93.3	93.5
BERT[12]	<b>78.0</b>	80.4	79.2	61.2	63.9	62.5	94.2	95.8	95.0
CAN[14]	75.1	72.3	73.6	55.4	63.0	59.3.	95.1	94.8	94.9
LGN[9]	76.1	73.7	74.9	-	-	60.2	95.3	95.5	95.4
MG-GNN[11]	74.3	76.2	75.2	<b>63.1</b>	56.3	59.5	-	-	-
CGN[10]	75.1	74.5	74.8	-	-	63.1	-	-	-
LatticeLSTM[5]	76.4	71.6	73.9	53.0	62.3	58.8	94.8	94.1	94.1
WC-LSTM[8]	76.1	72.9	74.4	52.6	<b>67.4</b>	59.8	95.3	95.2	95.2
LR-CNN[7]	76.4	72.6	74.5	-	-	59.9	<b>95.4</b>	94.8	95.1
<b>SLK-NER</b>	77.9	<b>82.2</b>	<b>80.2</b>	61.8	66.3	<b>64.0</b>	95.2	<b>96.4</b>	<b>95.8</b>

TABLE III  
EXPERIMENTAL RESULTS (%) OF DIFFERENT ENCODING STRATEGIES ON THREE DATASETS.

Encoding Strategy	OntoNotes4			Weibo			Resume		
	P	R	F1	P	R	F1	P	R	F1
using SLK	<b>77.9</b>	82.2	<b>80.2</b>	<b>61.8</b>	66.3	<b>64.0</b>	<b>95.2</b>	<b>96.4</b>	<b>95.8</b>
using FLK	76.6	<b>82.9</b>	79.8	<b>61.8</b>	64.6	63.2	95.1	96.2	95.6
using SLK and FLK	76.4	82.7	79.6	60.6	63.6	62.1	94.9	96.2	95.5
no lexicon	77.7	81.3	79.6	56.7	<b>66.5</b>	61.2	94.2	96.1	95.1

TABLE IV  
EXPERIMENTAL RESULTS (%) OF DIFFERENT FUSION STRATEGIES ON THREE DATASETS.

Fusion Strategy	OntoNotes4			Weibo			Resume		
	P	R	F1	P	R	F1	P	R	F1
<b>Global-Attention</b>	77.9	<b>82.2</b>	<b>80.2</b>	<b>61.8</b>	<b>66.3</b>	<b>64.0</b>	<b>95.2</b>	<b>96.4</b>	<b>95.8</b>
Self-Attention	77.2	81.2	79.1	55.9	60.1	57.9	94.2	96.3	95.2
Shortest Word First	77.1	81.5	79.2	55.8	57.7	56.7	93.9	96.1	95.0
Longest Word First	77.1	81.6	79.3	57.6	56.9	57.3	94.7	96.1	95.4
Average	<b>78.6</b>	80.8	79.7	56.4	58.4	57.3	94.3	96.3	95.3

12-heads). For characters and words that do not appear in the pretrained embeddings, we initialize them with a uniform distribution<sup>5</sup>. When training, character embeddings and word embeddings are updated along with other parameters. For hyper-parameter configuration, we set max length of sentences to 250, word embedding size to 50, the dimensionality of Bi-GRU to 512, the number of Bi-GRU layer to 1, the dropout to 0.1, the batch size to 32. We use Adam to optimize all the trainable parameters with learning rate  $5e-5$ . For evaluation, we use the Precision(P), Recall(R) and F1 score(F1) as metrics in our experiments.

### B. Experimental Results

Firstly, we compare SLK-NER with three general sequence labeling model for NER. All of them performed without any lexicon knowledge. The results in the first block in Table II, show that our proposed model achieves best F1 and R, which proves the efficiency of SLK-NER.

Next, the second block in Table II shows the performance of graph-based models. SLK-NER gives better F1 and R than LGN, MG-GNN and CGN. Although these baselines explore lexicon knowledge via the graph structure, they performed without the consideration of contextual information. Hence,

<sup>5</sup>The range is  $[-\sqrt{\frac{3}{dim}}, +\sqrt{\frac{3}{dim}}]$ , where  $dim$  denotes the size of embedding.

we attribute the benefits to the efficiency of global context-aware in SLK-NER.

Furthermore, the third block in Table II shows results of state-of-the-art sequence-based models. We can observe that our proposed model achieves a remarkably improvement on F1 over three datasets. The results strongly verify the integrating SLK into character-based model enables to boost the performance. By leveraging the SLK properly, our model is capable of improving NER in various domains, such as social network, news and Chinese resume.

### C. Strategies Analysis

In this part, we explore the effects of strategies about lexicon knowledge.

1) *Lexicon Knowledge Types*: We conduct comparative experiments on different kinds of lexicon knowledge. The results are illustrated in Table III. We can clearly see that the character-based model performs poorly without lexicon knowledge, demonstrating the usefulness of lexicon. Besides, adding FLK makes a small improvement on F1. While adding SLK outperforms significantly on F1 in all datasets. The fact demonstrates the efficiency of SLK, and reveals that leveraging second-order lexicon knowledge can indeed alleviate the word boundary conflicts. Interestingly, when using both FLK and SLK, the F1 declines over three datasets. We conjecture

the reason is there may be some negative word conflicts simultaneously for a character which limit the performance.

2) *Lexicon Knowledge Encoding*: We analyze the difference between the strategy in our model (Global-Attention) with four strategies proposed by [8] for encoding word information, including Self-Attention, Shortest Word First, Longest Word First and Average. The results in Table IV show that global attention in our model achieves best performance on F1 score. This demonstrates that our model can combine more informative features to determine the word boundary and effectively alleviate the negative influence of word boundary conflicts.

#### D. Sentence Length Analysis

Fig.3 shows the F1 score of several baselines and SLK-NER against sentence length on OntoNotes4 dataset. BERT and SLK-NER outperform significantly than other baselines, which indicates the ability to capture long dependencies. However, BERT ignores the word information among the sentence. SLK-NER obtains a higher F1 over different sentence lengths compared to BERT, which proves the SLK and global context-aware can capture more useful contextual information.

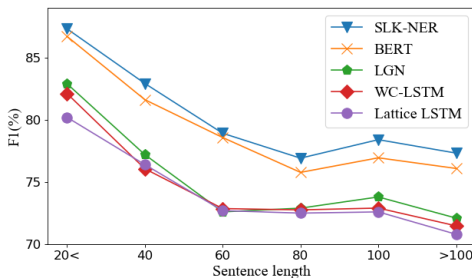


Fig. 3. F1 against sentence length on OntoNotes4 dataset. We split samples into six parts according to the sentence length.

## V. CONCLUSION

In this paper, we have investigated a lexicon-based model in Chinese NER task. We present a new insight about second-order lexicon knowledge to incorporate informative lexicon into character-based model. Based on this insight, SLK-NER is proposed to integrate more contextual word information into each character utilizing the global context. SLK-NER can effectively alleviate the impact of word boundary conflicts and word segmentation errors. Extensive experiments on three public datasets have demonstrated the superior performance of SLK-NER than state-of-the-art models.

## REFERENCES

- [1] Jiafeng Guo, Gu Xu, Xueqi Cheng, and Hang Li. Named entity recognition in query. In *SIGIR*, pages 267–274, 2009.
- [2] Dennis Diefenbach, Vanessa Lopez, Kamal Singh, and Pierre Maret. Core techniques of question answering systems over knowledge bases: a survey. *Knowledge and Information systems*, 55(3):529–569, 2018.

- [3] Sandipan Dandapat and Andy Way. Improved named entity recognition using machine translation-based cross-lingual information. *Computación y Sistemas*, 20(3):495–504, 2016.
- [4] Nanyun Peng and Mark Dredze. Named entity recognition for chinese social media with jointly trained embeddings. In *EMNLP*, pages 548–554, 2015.
- [5] Yue Zhang and Jie Yang. Chinese NER using lattice LSTM. In *ACL*, pages 1554–1564, 2018.
- [6] Jason PC Chiu and Eric Nichols. Named entity recognition with bidirectional lstm-cnns. *TACL*, 4:357–370, 2016.
- [7] Tao Gui, Ruotian Ma, Qi Zhang, Lujun Zhao, Yu-Gang Jiang, and Xuanjing Huang. Cnn-based chinese ner with lexicon rethinking. In *28th IJCAI*, pages 4982–4988. AAAI Press, 2019.
- [8] Wei Liu, Tongge Xu, Qinghua Xu, Jiayu Song, and Yueran Zu. An encoding strategy based word-character lstm for chinese ner. In *NAACL*, pages 2379–2389, 2019.
- [9] Tao Gui, Yicheng Zou, Qi Zhang, Minlong Peng, Jinlan Fu, Zhongyu Wei, and Xuan-Jing Huang. A lexicon-based graph neural network for chinese ner. In *EMNLP-IJCNLP*, pages 1039–1049, 2019.
- [10] Dianbo Sui, Yubo Chen, Kang Liu, Jun Zhao, and Shengping Liu. Leverage lexical knowledge for chinese named entity recognition via collaborative graph network. In *EMNLP-IJCNLP*, pages 3821–3831, 2019.
- [11] Ruixue Ding, Pengjun Xie, Xiaoyan Zhang, Wei Lu, Linlin Li, and Luo Si. A neural multi-digraph model for chinese ner with gazetteers. In *ACL*, pages 1462–1467, 2019.
- [12] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. BERT: Pre-training of deep bidirectional transformers for language understanding. In *NAACL*, pages 4171–4186, Minneapolis, June 2019.
- [13] Zhiheng Huang, Wei Xu, and Kai Yu. Bidirectional lstm-crf models for sequence tagging. *arXiv preprint arXiv:1508.01991*, 2015.
- [14] Yuying Zhu and Guoxin Wang. Can-ner: Convolutional attention network for chinese named entity recognition. In *NAACL*, pages 3384–3393, 2019.
- [15] John Lafferty, Andrew McCallum, and Fernando CN Pereira. Conditional random fields: Probabilistic models for segmenting and labeling sequence data. 2001.
- [16] Andrew Viterbi. Error bounds for convolutional codes and an asymptotically optimum decoding algorithm. *IEEE transactions on Information Theory*, 13(2):260–269, 1967.
- [17] Wanxiang Che, Mengqiu Wang, Christopher D. Manning, and Ting Liu. Named entity recognition with bilingual constraints. In *HLT-NAACL*, pages 52–62. ACL, 2013.
- [18] Shen Li, Zhe Zhao, Renfen Hu, Wensi Li, Tao Liu, and Xiaoyong Du. Analogical reasoning on Chinese morphological and semantic relations. In *ACL*, pages 138–143, Australia, July 2018.