

# CAN-NER: Convolutional Attention Network for Chinese Named Entity Recognition

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**Abstract**—Named entity recognition (NER) in Chinese is essential but difficult because of the lack of natural delimiters. Therefore, Chinese Word Segmentation (CWS) is usually considered as the first step for Chinese NER. However, models based on word-level embeddings and lexicon features often suffer from segmentation errors and out-of-vocabulary (OOV) words. In this paper, we investigate a Convolutional Attention Network called CAN for Chinese NER, which consists of a character-based convolutional neural network (CNN) with local-attention layer and a gated recurrent unit (GRU) with global self-attention layer to capture the information from adjacent characters and sentence contexts. Also, compared to other models, not depending on any external resources like lexicons and employing small size of char embeddings make our model more practical. Extensive experimental results show that our approach outperforms state-of-the-art methods without word embedding and external lexicon resources on different domain datasets including Weibo, MSRA and Chinese Resume NER dataset.

## I. INTRODUCTION

Named Entity Recognition (NER) aims at identifying text spans which are associated with a specific semantic entity type such as person (PER), organization (ORG), location (LOC), and geopolitical entity (GPE). NER receives constant research attention as it is the first step in a wide range of downstream Natural Language Processing (NLP) tasks, e.g., entity linking [1], relation extraction [2], event extraction [3], and co-reference resolution [4].

The standard method of existing state-of-the-art models for English NER treats it as a word-by-word sequence labeling task and makes full use of the Recurrent Neural Network (RNN) and Conditional Random Field (CRF) to capture context information at the word level [5], [6], [7], [8]. These models for English NER predict a tag for each word assuming that words can be separated clearly by explicit word separators, e.g., blank space. Therefore, for Chinese language without natural delimiters, it is intuitive to apply Chinese Word Segmentation (CWS) first to get word boundaries and then use a word-level sequence labeling model similar to the English NER models. However, in Chinese language, word boundaries can be ambiguous, which leads the possibility that entity boundaries does not match word boundaries. For example, in a sentence, “西藏自治区 (Tibet Autonomous Region)” is a GPE type in NER task while can be segmented

<b>Sentence:</b> 南京市长江大桥
<b>Segmentation 1:</b> 南京市   长江大桥 Nanjing City, Yangtze River Bridge Location, Location
<b>Segmentation 2:</b> 南京   市长   江大桥 Nanjing, Mayor, Jiang Daqiao Location, Title, Person

Fig. 1: Entity Ambiguity with Word Segmentation.

as one single word or as two words “西藏 (Tibet)” and “自治区 (autonomous region)” separately, depending on different granularity of segmentation tools. But most of the time, it is hard to determine or unify the granularity of word segmentation. Also, as shown in Figure 1, different segmentation sometimes leads different sentence meaning in Chinese, which can even result in different named entities. Obviously, it is impossible to make the right extraction with word-based NER model if the boundaries are mistakenly detected at the first time. Most recent neural network based Chinese NER models rely heavily on the word-level embeddings and external lexicon sets [9], [10]. The quality of those models would potentially be affected by different word embedding representations and lexicon features. Moreover, word-based models will suffer from OOV issues for Chinese words can be enormous and named entities are important source of OOV words. We also list other potential problems as follows: (1) Word embeddings dependency increases the model size and makes the fine-tuning process harder in the training step; (2) It is hard to learn word representation correctly without enough labeled utterances for named entities are usually the proper nouns. (3) Large lexicons are much expensive for real NER system because it will spend large memories and long matching time to obtain the features, that makes the model inefficient. (4) It is barely impossible to clean noise words in the large lexicon. Both of word embeddings and lexicon are hard to be updated after trained.

Moreover, character embedding can only carry limited information for losing word and word sequence information. For instance, the character “拍” in word “球拍” (bat) and “拍卖” (auction) has entirely different meanings. How to better integrate the segmentation information and exploit local context information is the key in the character-based model. [10] leverage lexicons to add all the embeddings of candidate

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word segmentation to their last character embeddings as soft features and construct a convolutional neural network (CNN) to encode characters as word-level information. [11] propose a multi-task architecture to learn NER tagging and Chinese word segmentation together with each part using a character-based Bi-LSTM. We propose a convolutional attention layer to extract the implicit local context features from character sequence. With the segmentation vector softly concatenating into character embedding, the convolutional attention layer is able to group implicitly meaning-related characters and reduce the impact of segmentation errors. Results show that our model outperforms other Chinese NER models without external resources.

The main contributions of this paper can be summarized as follows:

- We first combine the CNN with the local-attention mechanism to enhance the ability of the model to capture implicitly local context relations among character sequence. Compared with experimental results of baseline with normal CNN layer, our Convolutional Attention layer leads a remarkable improvement of F1 performance.
- We introduce a character-based Chinese NER model that consists of CNN with local attention and Bi-GRU with global self-attention layers. Our model achieve state-of-the-art F1-scores without using any external word embeddings and lexicon resources, which is more practical for real NER system.

## II. METHODOLOGY

We utilize BiGRU-CRF as our basic structure. Our model considers multi-level context features using convolutional attention layer, GRU layer and global attention layer. The whole architecture of our proposed model is illustrated in Figure 2.

### A. Formulation

In the Chinese NER task, we denote an input sentence as  $\mathbf{X}_i = \{x_{i,1}, x_{i,2}, x_{i,3}, \dots, x_{i,\tau}\}$ , where  $x_{i,\tau} \in \mathbb{R}^{d_e}$  represents the  $\tau$ -th character in sentence  $\mathbf{X}_i$  and  $d_e$  is the dimension of the input embeddings. Correspondingly, we denote the sentence label sequence as  $\mathbf{Y}_i = \{y_{i,1}, y_{i,2}, y_{i,3}, \dots, y_{i,\tau}\}$ , where  $y_{i,\tau} \in \mathcal{Y}$  belongs to the set of all possible labels. The objective is learning a function  $f_\theta : \mathbf{X} \mapsto \mathbf{Y}$  to obtain the entity types including the ‘O’ type for all the characters in the input text. In the following text, we take one instance as the example and therefore omitting subindex  $i$  in the formula.

### B. Convolutional Attention Layer

The convolutional attention layer aims to encode the sequence of input characters and implicitly group meaning-related characters in the local context.

The input representation for each character is constructed as  $x = [x_{ch}; x_{seg}]$ , where  $x_{ch} \in \mathbb{R}^{d_{ch}}$  and  $x_{seg} \in \mathbb{R}^{d_{seg}}$  are character embedding and segmentation mask, respectively. The segmentation information is encoded by BMES scheme [12].

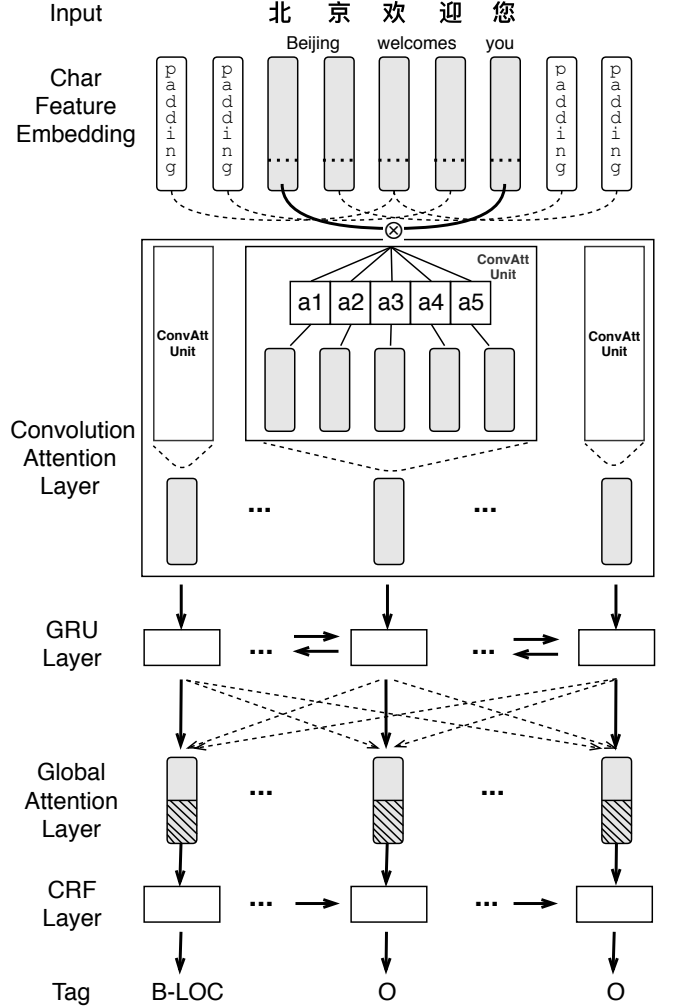


Fig. 2: The Whole Architecture. A convolutional attention layer is constructed to encode both character- and word-level information. The BiGRU-CRF layer is extended by a global self-attention layer to capture long sequential sentence-level relations.

For every window in CNN, whose window size is  $k$ , we first concatenate a position embedding to each character embedding, helping to keep the sequential relations in the local window context. The dimension of the position embedding equals to the window size  $k$  with the initial values of 1 at the position where the character lies in the window and 0 at other positions. So, the dimension of the concatenated embedding is  $d_e = d_{ch} + d_{pos} + d_{seg}$ . Then we apply a local attention inside the window to capture the relations between the center character and each context token, followed by a CNN with sum pooling layer. We set the hidden dimension as  $d_h$ . For the  $j$ -th character, the local attention takes all the concatenated embeddings  $x_{j-\frac{k-1}{2}}, \dots, x_j, \dots, x_{j+\frac{k-1}{2}}$  in the window as the input and outputs  $k$  hidden vectors  $h_{j-\frac{k-1}{2}}, \dots, h_j, \dots, h_{j+\frac{k-1}{2}}$ . The hidden vectors are calculated as follows:

$$h_m = \alpha_m x_m, \quad (1)$$

where  $m \in \{j - \frac{k-1}{2}, \dots, j + \frac{k-1}{2}\}$  and  $\alpha_m$  is the attention weight, which is calculated as:

$$\alpha_m = \frac{\exp s(x_j, x_m)}{\sum_{n \in \{j - \frac{k-1}{2}, \dots, j + \frac{k-1}{2}\}} \exp s(x_j, x_n)}. \quad (2)$$

The score function  $s$  is defined as follows:

$$s(x_j, x_k) = v^\top \tanh(W_1 x_j + W_2 x_k), \quad (3)$$

where  $v \in \mathbb{R}^{d_h}$  and  $W_1, W_2 \in \mathbb{R}^{d_h, d_e}$ .

The CNN layer contains  $d_h$  kernels on a context window of  $k$  tokens as:

$$h_j^c = \sum_k [W^c * h_{j - \frac{k-1}{2} : j + \frac{k-1}{2}} + b^c], \quad (4)$$

where  $W^c \in \mathbb{R}^{k \times d_h \times d_e}$  and  $b^c \in \mathbb{R}^{k \times d_h}$ . The operation  $*$  denotes element-wise product and  $h_{j - \frac{k-1}{2} : j + \frac{k-1}{2}}$  means a concatenation of the hidden states  $h_{j - \frac{k-1}{2}}, \dots, h_{j + \frac{k-1}{2}}$ , both of which are calculated at the first dimension. Finally a sum-pooling is also conducted on the first dimension.

### C. BiGRU-CRF with Global Attention

After extracting the local context features by convolutional attention layer, we feed them into a BiGRU-CRF based model to predict final label for each character.

The BiGRU layer is to model the sequential sentence information and calculated as follows:

$$h_j^r = \text{BiGRU}(h_{j-1}^r, h_j^c; W^r, U^r), \quad (5)$$

where  $h_j^c$  is the output of convolutional attention layer,  $h_{j-1}^r$  is the previous hidden state for the BiGRU layer, and  $W^r, U^r \in \mathbb{R}^{d_h \times d_h}$  are the parameters.

Then we apply a global self-attention layer to better handle the sentence-level information as:

$$h_j^g = \sum_{s=1}^n \alpha_{j,s}^g h_s^r \quad (6)$$

where  $j = 1, \dots, \tau$  denotes all the characters in a sentence instance and  $\alpha_{j,s}^g$  is calculated as:

$$\alpha_{j,s}^g = \frac{\exp s(h_j^r, h_s^r)}{\sum_{n \in \{1, \dots, \tau\}} \exp s(h_j^r, h_n^r)}. \quad (7)$$

The score function  $s$  is similar to Equation 3 with different parameters  $v^g \in \mathbb{R}^{d_h}$  and  $W_1^g, W_2^g \in \mathbb{R}^{d_h, d_h}$  instead.

Finally, a standard CRF layer is used on the top of the concatenation of the output of BiGRU layer and global attention layer, which is denoted as  $H_\tau = [h_\tau^r; h_\tau^g]$ . Given the predicted tag sequence  $\mathbf{Y} = \{y_1, y_2, y_3, \dots, y_\tau\}$ , the probability of the ground-truth label sequence is computed by:

$$P(\mathbf{Y}|\mathbf{X}) = \frac{\exp(\sum_i (\mathbf{W}_{\text{CRF}}^{y_i} H_i + b_{\text{CRF}}^{(y_{i-1}, y_i)}))}{\sum_{y'} \exp(\sum_i (\mathbf{W}_{\text{CRF}}^{y'_i} H_i + b_{\text{CRF}}^{(y'_{i-1}, y'_i)}))}, \quad (8)$$

where  $y'$  denotes an arbitrary label sequence,  $\mathbf{W}_{\text{CRF}}^{y_i}$  and  $b_{\text{CRF}}^{(y_{i-1}, y_i)}$  are trainable parameters. In decoding, we use Viterbi algorithm to get the predicted tag sequence.

Till now we get the whole architecture which contains character-based, word-based, and sentence-based information altogether using multi-feature embeddings, CNN featurizers with local attention, and global self-attention mechanism.

Dataset	Type	Train	Test	Dev
OntoNotes	Sentences	15.7k	4.3k	4.3k
	Char	491.9k	208.1k	200.5k
	Entities	13.4k	7.7k	6.95k
MSRA	Sentences	46.4k	4.4k	-
	Char	2169.9k	172.6k	-
	Entities	74.8k	6.2k	-
Weibo	Sentences	1.4k	0.27k	0.27k
	Char	73.8k	14.8k	14.5k
	Entities	1.89k	0.42k	0.39k
Resume	Sentences	3.8k	0.48k	0.46k
	Char	124.1k	15.1k	13.9k
	Entities	1.34k	0.15k	0.16k

TABLE I: Statistics of datasets

### D. Training

For training, we exploit log-likelihood objective as the loss function. Given a set of training examples  $\{(\mathbf{X}_i, \mathbf{Y}_i)\}_{i=1}^K$ , the loss function  $L$  can be defined as follows:

$$L = \sum_{i=1}^K \log P(\mathbf{Y}_i | \mathbf{X}_i) \quad (9)$$

In the training phase, at each iteration, we first shuffle all the training instances, and then feed them to the model with batch updates. We use AdaDelta [13] algorithm to optimize the final objective with all the parameters as described in Section III-A.

## III. EXPERIMENTS

To demonstrate the effectiveness of our proposed model, we did some experiments on Chinese NER datasets of different domains. We will describe the details of datasets, setting and results in our experiments. Standard precision (P), recall (R) and F1-score (F1) are used as evaluation metrics.

### A. Experimental Settings

**Data** We use four datasets in our experiments. For news domain, we experiment on OntoNotes 4 [14] and MSRA NER dataset of SIGHAN Bakeoff 2006 [15]. For the social media domain, we adopt the same annotated Weibo corpus as [16] which is extracted from Sina Weibo<sup>1</sup>. For more variety in test domains, we also use Chinese Resume dataset [10] collected from Sina Finance<sup>2</sup>.

Weibo dataset is annotated with four entity types: PER (Person), ORG (Organization), LOC (Location) and GPE (Geo-Political Entity), including named and nominal mentions. Weibo corpus is already divided into training, development and test sets. Chinese Resume dataset is annotated with eight types of named entities: CONT (Country), EDU

<sup>1</sup><http://www.weibo.com/>

<sup>2</sup><http://finance.sina.com.cn/stock/index.html>

(Educational Institution), LOC, PER, ORG, PRO (Profession), RACE (Ethnicity Background) and TITLE (Job Title). OntoNotes 4 dataset is annotated with four named entity categories: PER, ORG, LOC and GPE. We follow the same data split method of [17] on OntoNotes. For MSRA dataset, it only contains three annotated named entities: ORG, PER and LOC. The development subset is not available in MSRA dataset. The detail statistic information of our datasets is

Models	NE	NM	Overall
[16, Peng and Dredze 2015]	51.96	61.05	56.05
[18, Peng and Dredze 2016]	55.28	62.97	58.99
[19, He and Sun 2017]	50.60	59.32	54.82
[20, He and Sun 2017]	54.50	62.17	58.23
[11, Cao et al. 2018]	54.34	57.35	58.70
[10, Zhang and Yang 2018]	53.04	62.25	58.79
Baseline	49.02	58.80	53.80
Baseline + CNN	53.86	58.05	55.91
CAN Model	<b>55.38</b>	<b>62.98</b>	<b>59.31</b>

TABLE II: Weibo NER results

shown in Table I.

Gold segmentation is unavailable for Weibo dataset, Chinese Resume datasets and MSRA test sections. We followed [10] to automatically segment Weibo dataset, Chinese Resume dataset and MSRA test sections using the model of [21]. We treat NER as a sequential labeling problem and adopt BIOES tagging style in this paper since it has been shown that models using BIOES are remarkably better than BIO [22].

**Hyper-parameter settings** For hyper-parameter configuration, we adjust them according to the performance on the development set of Chinese NER task. We set the character embedding size, hidden sizes of CNN and Bi-GRU to 300 dims. After comparing to experimental results with different window sizes of CNN, we set the window size as 5. Adadelta is used for optimization, with an initial learning rate of 0.005. The character embeddings used in our experiments are from [23], which is trained by Skip-Gram with Negative Sampling (SGNS) on Baidu Encyclopedia.

### B. Experimental Results

In this section, we will give the experimental results of our proposed model and previous state-of-the-art methods on Weibo dataset, Chinese Resume dataset, OntoNotes 4 dataset and MSRA dataset, respectively. We propose two baselines and a CAN model. In the experiment results table, we use Baseline to represent the BiGRU + CRF model and Baseline + CNN to indicate CNN + BiGRU + CRF.

1) *Weibo Dataset*: We compare our proposed model with the latest models on Weibo dataset. Table II shows the F1-scores for named entities (NE), nominal entities (NM, excluding named entities) and both (Overall). We observe that our proposed model achieves state-of-the-art performance.

Existing state-of-the-art systems include [18], [20], [11] and [10], who leverage rich external data like cross-domain data, semi-supervised data and lexicon or joint train NER task with Chinese Word Segmentation (CWS) task.<sup>3</sup> In the

<sup>3</sup>The results of [16], [18] are taken from [24]

first block of Table II, we report the performance of the latest models. The model that jointly train embeddings with NER task proposed by [16] achieves F1-score of 56.05% on overall performance. The model [18] that jointly train CWS task improves the F1-score to 58.99%. [20] propose a unified model to exploit cross-domain and semi-supervised data, which improves the F1-score from 54.82% to 58.23% compared with the model proposed by [19]. [11] use an adversarial transfer learning framework to incorporate task-shared word boundary information from CWS task and achieves F1-score of 58.70%. [10] leverage a lattice structure to integrate lexicon information into their model and achieve F1-score of 58.79%.

In the second block of Table II, we give the results of our baselines and proposed models. Our baseline Bi-GRU + CRF achieves a F1-score of 53.80% and adding a normal CNN layer as featurizer improve F1-score to 55.91%. Replacing normal CNN with our convolutional attention layer will significantly improve the F1-score to 59.31%, which is the highest result among existing models. The improvement demonstrates the effectiveness of our proposed model.

Models	P	R	F1
[10, Zhang and Yang 2018] <sup>1</sup>	94.53	94.29	94.41
[10, Zhang and Yang 2018] <sup>2</sup>	94.07	94.42	94.24
[10, Zhang and Yang 2018] <sup>3</sup>	94.81	94.11	94.46
Baseline	93.71	93.74	93.73
Baseline + CNN	94.36	<b>94.85</b>	94.60
CAN Model	<b>95.05</b>	94.82	<b>94.94</b>

TABLE III: Results on Chinese Resume Dataset. For models proposed by [10], 1 represents the char-based LSTM model, 2 indicates the word-based LSTM model and 3 is the Lattice model.

2) *Chinese Resume Dataset*: The Chinese Resume test results are shown in Table III. [10] release Chinese Resume dataset and achieve F1-score of 94.46% with lattice structure incorporating additional lexicon information. It can be seen that our proposed baseline (CNN + Bi-GRU + CRF) outperforms [10] with F1-score of 94.60%. Adding our convolutional attention leads a further improvement and achieves state-of-the-art F1-score of 94.94%, which demonstrates the effectiveness of our proposed model.

3) *OntoNotes Dataset*: Table IV shows the comparisons on OntoNotes 4 dataset.<sup>4</sup> In the first block, we list the performance of previous methods for Chinese NER task on OntoNotes 4 dataset. [25] propose a model combining neural and discrete feature, e.g., POS tagging features, CWS features and orthographic features, improving the F1-score from 68.57% to 76.40%. Leveraging bilingual data, [17] and [26] achieves F1-score of 74.32% and 73.88% respectively. [10]<sup>‡</sup> is the character-based model with bichar and softword.

In the second block of Table IV, we give the results of our baselines and proposed models. Consistent with observations

<sup>4</sup>In Table IV and V, we use \* to denote a model with external labeled data for semi-supervised learning. † denotes that the model use external lexicon data. [10] with ‡ is the char-based model in the paper.

Models	P	R	F1
[25, Yang et al. 2016]	65.59	71.84	68.57
[25, Yang et al. 2016]*	72.98	<b>80.15</b>	<b>76.40</b>
[17, Che et al. 2013]*	<b>77.71</b>	72.51	75.02
[26, Wang et al. 2013]*	76.43	72.32	74.32
[10, Zhang and Yang 2018]†	76.35	71.56	73.88
[10, Zhang and Yang 2018]‡	74.36	69.43	71.81
Baseline	70.67	71.64	71.15
Baseline + CNN	72.69	71.51	72.10
CAN Model	75.05	72.29	73.64

TABLE IV: Results on OntoNotes

Models	P	R	F1
[27, Chen et al. 2006]	91.22	81.71	86.20
[28, Zhang et al.2006]*	92.20	90.18	91.18
[29, Zhou et al.2013]	91.86	88.75	90.28
[30, Lu et al. 2016]	-	-	87.94
[31, Dong et al. 2016]	91.28	90.62	90.95
[11, Cao et al. 2018]	91.30	89.58	90.64
[32, Zhou et al. 2018 ]	92.04	91.31	91.67
[10, Zhang and Yang 2018]	<b>93.57</b>	<b>92.79</b>	<b>93.18</b>
Baseline	92.54	88.20	90.32
Baseline + CNN	92.57	92.11	92.34
CAN Model	<b>93.53</b>	92.42	<b>92.97</b>

TABLE V: Results on MSRA dataset

on the Weibo and Resume datasets, our Convolutional Attention layer leads an increment of F1-score and our proposed model achieves a competitive F1-score of 73.64% among character-based model without using external data.

4) *MSRA Dataset*: Table V shows comparisons on MSRA dataset. In the first block, we give the performance of previous methods for Chinese NER task on MSRA dataset. [27], [28] and [29] leverage rich hand-crafted features and [30] exploit multi-prototype embeddings features for Chinese NER task. [31] introduce radical features into LSTM-CRF. [11] make use of Adversarial Transfer Learning and global self-attention to improve performance. [32] propose a character-based CNN-BiLSTM-CRF model to incorporate stroke embeddings and generate n-gram features. [10] introduce a lattice structure to incorporate lexicon information into the neural network, which actually includes word embedding information. Although the model achieves state-of-the-art F1-score of 93.18%, it leverages external lexicon data and the result is dependent on the quality of the lexicon.

In the second block, we list baselines and proposed model. It can be seen that our Baseline + CNN is already outperform most previous methods. Compared with the state-of-the-art model proposed by [10], our char-based method achieves competitive F1-score of 92.97% without additional lexicon data and word embedding information. Our CAN model achieves state-of-the-art result among the character-based models.

### C. Discussion

1) *Effectiveness of Convolutional Attention and Global Self-Attention*: Shown by Table II, III and V, the performance of our proposed model demonstrates the effectiveness of the Convolutional Attention Network. To better evaluate the effect of the Attention Mechanism, we visualize the

normalized attention weights  $\alpha_m^l$  for each window from Eq. 2, as in Figure 3a. Each row of the matrix represents location attention weights in each window. For example, the third row indicates that the relationship between center character “总” and contexts “美国总统克”. We can see from the Figure 3a that the word-level features can be extracted through the local attention. In the context, the center character “美” tends to have a stronger connection with its related character “国”, which means they have a higher possibility of consisting of a Chinese word “美国 (American)”. Also for characters “克”, “林” and “顿” tend to have a strong connection because “克林顿” means “Clinton”. Character “欧” and “洲” have strong connection seen from the Figure 3a because “欧洲” represents “Europe” in Chinese. Therefore, both experiments results and visualization verifies that the Convolutional Attention is effective for obtaining the phrase information between adjacent characters.

In Figure 3b, we visualize the global self-attention matrix. From the picture, we can find that global self-attention can capture the sentence context information from the long-distance relationship of words to overcome the limitation of Recurrent Neural Network. For the word “克林顿 (Clinton)”, the global self-attention learns the dependencies with “前往 (leave for)” and “1号 (on the 1st)”. Distinguished by the color, “克林顿 (Clinton)” has a stronger connection with “前往 (leave for)” than with “1号 (on the 1st)”, which accords with the expectation that the predicate in the sentence provides more information to the subject than the adverbial of time.

2) *Results Analysis*: Our proposed model outperforms previous work on Weibo and Chinese Resume dataset and gains competitive results on MSRA and OntoNotes 4 datasets without using any external resources. The experiments results demonstrate the effectiveness of our proposed model, especially among the char-based model. The performance improvement after adding Convolutional Attention Layer and Global Attention Layer verifies that our model can capture the relationship between character and its local context, as well as the relationship between word and global context. However, although we can obtain comparable results compared with other models without external resources, we find that our model performs relatively unsatisfying in the OntoNotes 4 dataset. It may be explained by the reason that discrete features and external resources like other labeled data or lexicons have a more positive influence on this dataset when the model cannot learn enough information from the training set.

## IV. RELATED WORK

### A. Neural Network Models

It has been shown that neural networks, such as LSTM and CNN, can outperform conventional machine learning methods without requiring handcrafted features. [33] applied a CNN-CRF model and gained competitive results to the best statistical models. More recently, the LSTM-CRF architecture has been used on NER tasks. [34] employed BiLSTM to

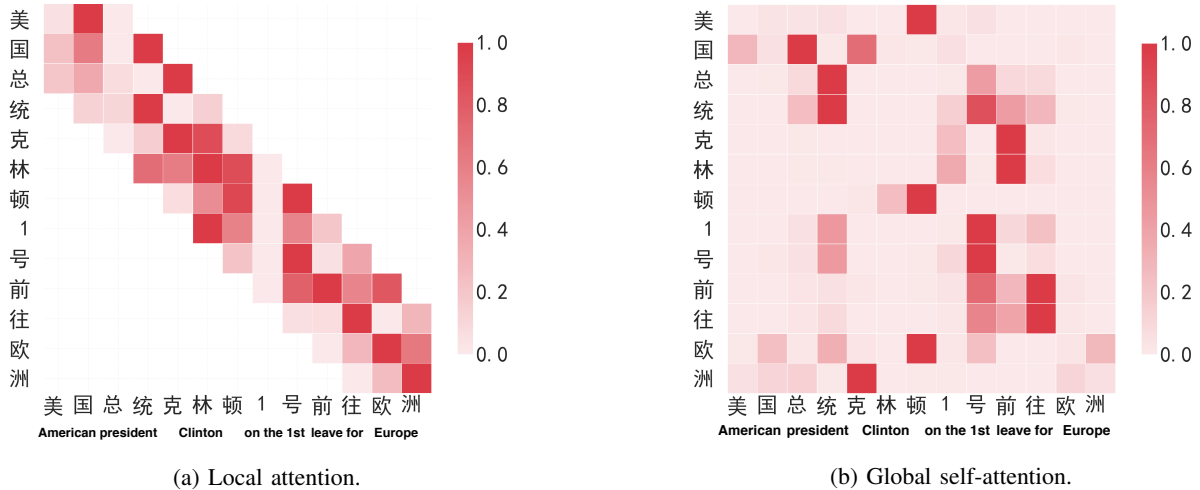


Fig. 3: Attention visualization. The left part shows the normalized Convolutional Attention weights in each window in a sentence. The right part indicates the global self-attention weights among the whole sentence. For both pictures, the x-axis represents the context while the y-axis on behalf of the query in the attention mechanism.

extract word-level context information and [5] further introduced hierarchy structure by incorporating BiLSTM-based character embeddings. Many works integrating word-level information and character-level information have been found to achieve good performance [35], [7], [6], [5]. External knowledge has also been exploited for NER tasks. To utilize character-level knowledge, character-level pre-trained [36] and co-trained [8] neural language models were introduced. Recently, many works exploit learning pre-trained language representations with deep language models to improve the performance of downstream NLP tasks, such as ELMo [37] and BERT [38].

### B. Attention Mechanism related Models

Recently, Attention Mechanism has shown a very good performance on a variety of tasks including machine translation, machine comprehension and related NLP tasks [39], [40], [41]. In language understanding task, [42] exploit self-attention to learn long range dependencies. [43] proposed the model employing an attention mechanism to combine the character-based representation with the word embedding instead of simply concatenating them. This method allows the model to dynamically decide which source of information to use for each word, and therefore outperforming the concatenation method used in previous work. [44] use pictures in Tweets as external information through an adaptive co-attention network to decide whether and how to integrate the images into the model. The method can only apply to websites like Tweets which has text-related images, but the resources like that are insufficient. [45] and [11] employ self-attention to directly capture the global dependencies of the inputs for NER task and demonstrate the effectiveness of self-attention in Chinese NER task.

### C. Chinese NER

Multiple previous works tried to address the problems that the Chinese language doesn't have explicit word boundaries. Traditional models depended on hand-crafted features and CRFs-based models [46], [47]. Character-based LSTM-CRF model was applied to Chinese NER to utilize both character-level and radical-level representations [31]. [16] applied character positional embeddings and proposed a jointly trained model for embeddings and NER. To better integrate word boundary information into Chinese NER model, [18] co-trained NER and word segmentation to improve both tasks. [20] unified cross-domain learning and semi-supervised learning to obtain information from out-of-domain corpora and in-domain unannotated texts. Instead of performing word segmentation first, [10] constructed a word-character lattice by matching words in texts with a lexicon to avoid segmentation errors. [11] used the adversarial network to jointly train Chinese NER task and Chinese Word Segmentation task to extract task-shared word boundary information. [48] leveraged character-level BiLSTM to extract higher-level features from crowd-annotations.

## V. CONCLUSION

In this paper, we propose a Convolutional Attention Network model to improve Chinese NER model performance and preclude word embedding and additional lexicon dependencies, that makes the model more efficient and robust. In our model, we implement local-attention CNN and Bi-GRU with the global self-attention structure to capture word-level features and context information with char-level features. Experiments show that our model outperforms the state-of-art systems on the different domain datasets.

For future works, we would like to study how to joint learning word segmentation and NER tasks to further reduce

constraints.

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