

# FGN: Fusion Glyph Network for Chinese Named Entity Recognition

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## Abstract

Chinese NER is a challenging task. As pictographs, Chinese characters contain latent glyph information, which is often overlooked. In this paper, we propose the FGN<sup>1</sup>, Fusion Glyph Network for Chinese NER. Except for adding glyph information, this method may also add extra interactive information with the fusion mechanism. The major innovations of FGN include: (1) a novel CNN structure called CGS-CNN is proposed to capture both glyph information and interactive information between glyphs from neighboring characters. (2) we provide a method with sliding window and Slice-Attention to fuse the BERT representation and glyph representation for a character, which may capture potential interactive knowledge between context and glyph. Experiments are conducted on four NER datasets, showing that FGN with LSTM-CRF as tagger achieves new state-of-the-arts performance for Chinese NER. Further, more experiments are conducted to investigate the influences of various components and settings in FGN.

## Introduction

Named entity recognition (NER) is generally treated as sequence tagging problem and solved by statistical methods or neural networks. Character-based tagging method is the main strategy in the field of Chinese NER [Lu et al., 2016, Meng et al., 2019]. Actually, some researches [Liu et al., 2010; Li et al., 2014] have explicitly compared character-based methods and word-based methods, confirming that the former are the better one. Therefore, representation learning toward character-level is essential for Chinese NER and this field has been explored widely.

Currently, distributed representation learning has become the mainstream method to represent Chinese characters, especially after the raise of BERT [Devlin et al., 2019], which raised the baselines for almost all fields of NLP. However, these methods overlooked the information inside words or characters. Actually, there have been studies, focusing on internal components of words or characters. In English field, researchers [Ma and Hovy, 2016] used Convolutional Neural Network (CNN) to encode the spelling of words as representation for NER task. This method is not suitable for Chinese

NER, as Chinese is not alphabetical language but hieroglyphic language. Fortunately, Chinese characters can be further segmented into radicals. For example, character of “抓”(grasp) is consisted of “扌”(hand) and “爪”(claw). Study on radical-based character embedding [Sun et al., 2014] has confirmed the effectiveness of these components in Chinese characters.

Further, researchers have turned attention to regard Chinese characters as graphs for encoding. Some researches [Dai and Cai, 2017; Shao et al., 2017] tried running CNNs to encode the character graph, which got unobvious improvement in experiments. Avoiding the shortcomings of previous works, a glyph representation call Glyce [Meng et al., 2019] was proposed. Being concatenated with BERT representation in the final layer, Glyce achieved SOTA performances in various NLP tasks including NER. Meng proposed the Tianzige-CNN to encode each Chinese character with seven historical and contemporary scripts. Tianzige is a traditional form of Chinese calligraphy which conforms the radical distribution inside a Chinese character. Then Transformer [Vaswani et al., 2017] was used as tagger in Glyce. Further, Sehanobish and Song [2019] proposed a glyph-based NER model which simplified the Glyce using only the Hei Ti font of each character. Also, representation of non-Chinese characters was took into consideration carefully in there works. Comparing with Glyce, this glyph-based NER method achieved comparable performance in multiple NER datasets.

Although current researches have successfully added glyph information into character representation for Chinese NER, these researches was unable to capture interactive knowledge between glyphs and contexts. Actually, the meaning of a single Chinese character is not complete. for example, the character “朝” not only have the meaning “morning” but also the meaning “dynasty”. If we encode the “朝” independently to obtain glyph information, we may only obtain the relevant information of “morning”, as “朝” contains radicals “日”(sun) and “月”(moon). In addition, interactive knowledge between the glyphs of neighboring characters may also benefit NER tasks. For example, characters in tree names like “杨树”(aspen), “柏树”(cypress) and “松树”(pine tree) have the same radical “木”(wood), but characters of an algorithm name “决策树”(decision tree) have no such pattern. In fact, there are many similar patterns in Chinese language, which can be differentiated by the interactive knowledge between the glyphs of neighboring characters.

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<sup>1</sup> <https://github.com/AidenHuen/FGN-NER>

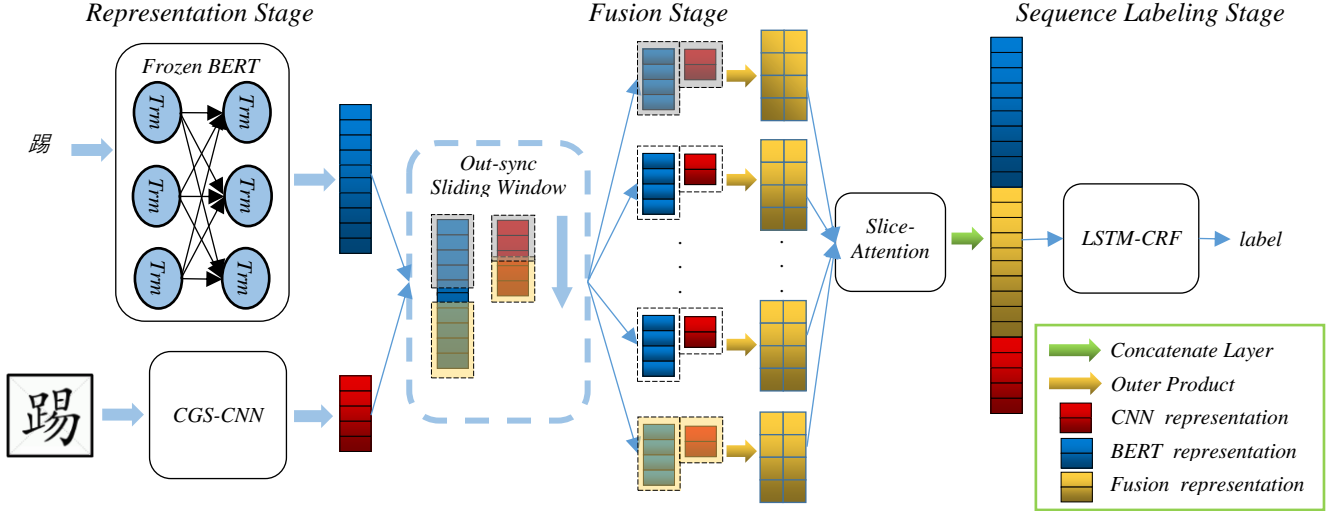


Figure 1: Architecture of the FGN for named entity recognition

Therefore, we propose the FGN, Fusion Glyph Network for Chinese NER. The major innovations in FGN include: (1) a novel CNN structure called CGS-CNN, Character Graph Sequence CNN is offered for glyph encoding which may capture potential information between the glyphs of neighboring characters. (2) We provide a fusion method with out-of-sync sliding window and Slice-Attention to extract interactive knowledge between glyph representation and character representation.

FGN is found to improve the performance of NER, which outperforms other SOTA models on four NER datasets (Section 4.2). We also encode radicals of characters to further enhance the performance of FGN, which tries confirming the complementation between glyph and radical representation. In addition, we verify and discuss the influence of various proposed settings in FGN (Section 4.3).

## 2 Related Work

Our work is related to neural network for NER. CNN-CRF model [Collobert et al., 2011] is a neural NER model, obtaining competitive result to various best statistical models. LSTM-CRF [Huang Z et al., 2015] has been widely used in current sequence labeling tasks, being the mainstream component in subsequent NER models. To obtain more word-level information, LSTM-CNN-CRF [Ma and Hovy, 2016] is proposed, using CNNs to encode the spelling of each English word. Further, a coreference aware representation learning method [Dai et al., 2019] was used and combined with LSTM-CNN-CRF for NER. In Chinese field, researches [Dong et al., 2016] organized radicals in each character as sequence and used LSTM to encode them on Chinese NER task. A novel NER method call lattice-LSTM [Zhang and Yang, 2018] was proposed, which skillfully encoded Chinese characters as well as all potential words that match a lexicon. Similar to Lattice-LSTM, Word-Character LSTM (WC-LSTM) [Liu et al., 2019] was proposed, outperforming other

SOTA NER models without BERT. WC-LSTM added word information into the start and the end characters of a word, alleviating the influence of word segmentation errors.

Currently, knowledge from vision has been widely-used leveraged in NLP. We simply divide these relative researches into two categories according to the source of vision knowledge: glyph representation learning and multimodal language modeling. The Former is scarce as mentioned earlier. To our knowledge, we are the first to run 3D convolution to encode character graphs in sentence-level. Actually, 3D convolution is mostly provided to encode video information. Similar to video preprocessing, we transform text sentences to graph sequences. The latter is current hotspot in various NLP fields. Researchers [Zhang et al., 2018] proposed an adaptive co-attention network for tweets NER, which adaptively balanced the fusion proportions of image representation and text representation from a tweet. With reference of BERT, a multimodal BERT [Jiang et al., 2019] was proposed for target-oriented sentiment classification. Multiple self-attention layers [Vaswani et al., 2017] were used in the model to capture interactive information after concatenating BERT and visual representation. Further, Researchers [Mai et al., 2019] proposed a fusion network with local and global perspective for multimodal affective computing. They provided a sliding window to slice multimodal vectors and fused each slice pair by outer product. Also, Attentive Bi-directional Skip-connected LSTM was used to combine slice pairs. Our method borrows the ideas of above-mentioned methods for multimodal fusion. Different from theirs that fused the sentence-level representation, we focus on character-level fusion for Chinese NER.

## 3 Model

In this section, we introduce the FGN for NER task in detail. As shown in Figure 1, FGN can be divided into three stages:

representation stage, fusion stage and tagging stage. We follow the strategy of character-based sequence tagging for Chinese NER.

### 3.1 Representation Stage

We mainly use character representation and glyph representation, which are separately encoded by BERT and CGS-CNN. In addition, we encode radicals of each character for further experiment between glyph representation and radical representation. Detail of these representations are as followed.

#### Frozen BERT

BERT is a multi-layer Transformer encoder in nature, which offers distributed representations for words or characters. We use the pre-trained character-based BERT to encode each character in sentence. Different from the normal fine-tuning strategy, we first fine-tune BERT in training set with a CRF layer as tagger. Then freeze the BERT parameters and transfer them to another BERT structure, which is a part of the FGN. The reason to follow this strategy is that fine-tuning BERT only requires minimal learning rate but initialized parameters of FGN need a hundred times larger learning rate to adjust. Subsequent experiment shows the effectiveness of this strategy.

#### CGS-CNN

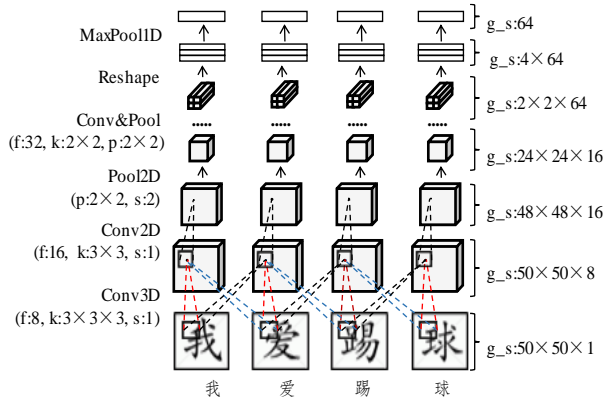


Figure 2: Architecture of CRS-CNN with an input sample “我爱踢球”(I love playing football). “f”, “k”, “s”, “p” stand for kernel number, kernel size, stride, and pooling window size. “g\_s” represents the tensor size of output from each layer.

Figure 2 depicts the architecture of CGS-CNN. Different from Glyce using seven types of character script, we only choose the simple Chinese script to generate glyph vectors. The input format of CGS-CNN is sentence but not single character. We first convert sentences to graph sequences, in which characters are replaced with  $50 \times 50$  gray-scale graphs. Characters that are not Chinese are given corresponding random matrices with values between 0 and 1. Then, we provide two  $3 \times 3 \times 3$  3D convolution layers to encode graph sequence and output each  $50 \times 50$  graph with 8 channels. 3D convolution can extract feature from both spatial and temporal dimensions, which means each glyph vector may obtain additional

glyph information from the neighboring graphs. Using padding on the dimension of graph sequence, we may keep the length of graph sequence constant after passing through 3D convolution, which is necessary for character-based tagging. Then the output of 3D convolution passes through several groups of 2D convolution and 2D max pooling to compress each graph to  $2 \times 2$  Tianzige-structure with 64 channel. In order to filter noises and blank pixels, we then flatten the  $2 \times 2$  structures and adopt a 1D max pooling to extract glyph vector for each character. The size of glyph vectors is 64 that is much smaller than the size of Tianzige-CNN output (1024 dimension).

Different from Glyce that sets image classification task to learn glyph representation, we learn the parameters of CGS-CNN while training whole NER model in domain datasets. As we only use the simple Chinese script, setting task to predict the character IDs of this script seems meaningless.

#### Radical Representation

We organized Chinese character as radical sequence. For example, character “朝”(morning) can be divided into {“十”(ten), “日”(sun), “十”, “月”(moon)}. Radical embedding for a character can be defined as  $r = \{r_1, r_2, \dots, r_{l-1}, r_l\}$ . Where  $l$  represents the number of radicals in character and  $r_1$  represents the embedding of the 1th radical. Then self-attention [Vaswani et al., 2017] is adopted to encode this radical embedding:

$$r' = \text{softmax}\left(\frac{rW^Q W^K^T r^T}{\sqrt{d^T}}\right) rW^V \quad (1)$$

Where  $W^Q$ ,  $W^K$ ,  $W^V$  represent the initialized weights for the input vectors. After that, pass through a max pooling layer to extract radical features and obtain the radical vector  $r_v$  for a character:

$$r_v = \text{pool}(r') \quad (2)$$

### 3.2 Fusion Stage

We provide a sliding window to slide through both character and glyph vectors. After the sliding window, we obtain slice pairs and compute outer product among these pairs to obtain local interactive features. Then Slice-Attention is adopted to balance the importance of each slice pair and combine them to output fusion vector.

#### Out-of-sync Sliding Window

Sliding window has been applied in multimodal affective computing [Mai et al., 2019] as mentioned above. The reason for using sliding windows is that directly fusing vectors with outer product would exponentially expand vector size, which increases space and time complexity for subsequent network. However, this method requires the multimodal representations to have the same size, which is not suitable to slide through both BERT vector and glyph vector. Because character representations of BERT have richer semantic information than glyph representations, requiring a bigger vector size. Here we provide an out-of-sync sliding window that can satisfy different vector sizes while keeping the same number of slices.

Assume that we have one Chinese character with character vector defined as  $c_v \in \mathbb{R}^{d^c}$  and glyph vector defined as  $g_v \in \mathbb{R}^{d^g}$ . Here  $d^c$  and  $d^g$  stand for the sizes of two vectors. To keep the same number of the slices of these two vectors after passing through the sliding window, the setting of sliding window needs to meet the following limitation:

$$n = \frac{d^c - k^c}{s^c} + 1 = \frac{d^g - k^g}{s^g} + 1, n \in \mathbb{N}^* \quad (3)$$

Where  $n$  is a positive integer, standing for slice number of two vectors;  $k^c$  and  $s^c$  respectively stand for window size and stride of character vector.  $k^g$  and  $s^g$  respectively represent window size and stride for glyph vector. The strategy we use to satisfy this condition is to limit the hyper-parameters of sliding window such that  $d^c$ ,  $k^c$  and  $s^c$  are respectively an integral multiple of  $d^g$ ,  $k^g$  and  $s^g$ .

To get slice pairs, we first calculate the left border index of sliding window at each stride:

$$i \in \{1, 2, 3, \dots, n\} \quad (4)$$

$$p_{(i)}^c = s^c(i - 1) \quad (5)$$

$$p_{(i)}^g = s^g(i - 1) \quad (6)$$

Where  $p_{(i)}^c$  and  $p_{(i)}^g$  represent the boundary index of sliding window respectively for character and glyph vector at the  $i$ th stride. Then we can obtain each slice during the following formula:

$$c_{-S(i)} = \{c_{-v(p_{(i)}^c+1)}, c_{-v(p_{(i)}^c+2)}, \dots, c_{-v(p_{(i)}^g+k^c)}\} \quad (7)$$

$$g_{-S(i)} = \{g_{-v(p_{(i)}^g+1)}, g_{-v(p_{(i)}^g+2)}, \dots, g_{-v(p_{(i)}^g+k^g)}\} \quad (8)$$

Where  $c_{-S(i)}$  and  $g_{-S(i)}$  represent the  $i$ th slices respectively from two vectors;  $c_{-v(p_{(i)}^c+1)}$  stands for the value at  $(p_{(i)}^c + 1)$ th dimension of  $c_v$ .

In order to fuse the two slice in a local perspective, outer product is adopted to generate an interactive tensor, as shown in the formula:

$$m_i = \text{Outer}(c_{-S(i)}, g_{-S(i)}) \\ = \begin{bmatrix} c_{-v(p_{(i)}^c+1)}g_{-v(p_{(i)}^g+1)}, \dots, c_{-v(p_{(i)}^c+1)}g_{-v(p_{(i)}^g+k^g)} \\ \vdots \\ c_{-v(p_{(i)}^g+k^c)}g_{-v(p_{(i)}^g+1)}, \dots, c_{-v(p_{(i)}^g+k^c)}g_{-v(p_{(i)}^g+k^g)} \end{bmatrix} \quad (9)$$

Where  $m_i \in \mathbb{R}^{d^c \times d^g}$  stands for fusion tensor of the  $i$ th slice pair;  $c_{-v(p_{(i)}^c+1)}g_{-v(p_{(i)}^g+1)}$  represent product result between the  $p_{(i)}^c + 1$ th value in  $c_v$  and the  $p_{(i)}^g + 1$ th value in  $g_v$ . During outer product, we may obtain all product result among elements from two vectors.

Then we flatten tensor  $m_i$  to vector  $m'_i \in \mathbb{R}^{d^c d^g}$ . Representation of slices for one character can be represented as:

$$m' = \{m'_1, m'_2, \dots, m'_{n-1}, m'_n\}, m' \in \mathbb{R}^{n \times (k^c k^g)} \quad (10)$$

Where  $m'$  contains  $n$  fusion vectors of slice pairs. The size of each vector is  $k^c k^g$ .

### Slice-Attention

Outer product enriches the interactive information for characters at the same time generates more noises, as many features are irrelevant. With reference to attention mechanism, we propose the Slice-Attention, which can adaptively quantify the importance of each slice pair and combined them to represent a character. Importance of slice pair can be quantified as:

$$a_i = \frac{\exp(\sigma(v) \odot \sigma(W^{\text{slice}} \odot m'_i + b^{\text{slice}}))}{\sum_{i=1}^n \exp(\sigma(v) \odot \sigma(W^{\text{slice}} \odot m'_i + b^{\text{slice}})) + \varepsilon} \quad (11)$$

Where  $a_i$  stands for importance value of the  $i$ th slice pair;  $\sigma$  is Sigmoid function and  $\odot$  is dot product. Sigmoid function here may limit the value range in vectors between 0 and 1, which ensures subsequent dot product computing meaningful.  $W^{\text{slice}} \in \mathbb{R}^{(k^c k^g) \times (k^c k^g)}$  and  $b^{\text{slice}} \in \mathbb{R}^{k^c k^g}$  stand for initialized weight and bias.  $v \in \mathbb{R}^{(k^c k^g)}$  is similar to the query in self-attention [Vaswani et al., 2017], which is another initialized weight we provide.  $\varepsilon$  represents a fuzz factor with the value of  $1e-7$ .

Finally, we fuse the vectors of slice pairs by weighted average computation and obtain fusion vector  $f_v$  for a character:

$$f_v = \sum_{i=1}^n a_i m'_i \quad (12)$$

### 3.3 Tagging Stage

We concatenate each vector in character-level before tagging. As the need of experiment, two groups of representation are set to represent each character. One is without radical representation defined as  $\text{concat}(f_v, g_v, c_v)$ , another is with radical vector defined as  $\text{concat}(f_v, g_v, c_v, r_v)$ . Representation of a sentence can be defined as  $x = \{x_1, x_2, \dots, x_\tau\}$ , where  $\tau$  stands for the length of sentence.

### BiLSTM

LSTM (Long Short Terms Memory) units contain three specially designed gates to control information transmission along a sequence. To encode sequence information of  $x$ , we use a forward LSTM network to obtain forward hidden state and a backward LSTM network to obtain backward hidden state. Then the two hidden states are combined as:

$$h = \overrightarrow{LSTM}(x) \oplus \overleftarrow{LSTM}(x) \quad (13)$$

Where  $h = \{h_1, h_2, \dots, h_\tau\}$  is the hidden representation of characters and  $\oplus$  represents sum operation of corresponding values between two hidden states.

### CRF

A standard CRF layer is used to decode the hidden representation above. Here CRF may enhance the binding among the neighboring tagging results. Assume that we have a sentence represented as  $s$ . The probability of tagging result  $y = \{l_1, l_2, \dots, l_\tau\}$  for  $s$  is computed as:

$$P(y|s) = \frac{\exp(\sum_{i=1}^{\tau} (W_{l_i}^{\text{crf}} h_i + b_{(l_{i-1}, l_i)}^{\text{crf}}))}{\sum_{y'} \exp(\sum_{i=1}^{\tau} (W_{l'_i}^{\text{crf}} h_i + b_{(l'_{i-1}, l'_i)}^{\text{crf}}))} \quad (14)$$

Model	Weibo			MSRA			Resume			OntoNote 4		
	P	R	F1	P	R	F1	P	R	F1	P	R	F1
Lattice-LSTM	53.04	62.25	58.79	93.57	92.79	93.18	93.57	92.79	93.18	76.35	71.56	73.88
WC-LSTM	52.55	67.41	59.84	94.58	92.91	93.74	95.27	95.15	95.21	76.09	72.85	74.43
BERT	66.88	67.33	67.12	94.97	94.62	94.80	96.12	95.45	95.78	78.01	80.35	79.16
Glyce	67.68	67.71	67.70	95.57	95.51	95.07	96.62	96.48	96.54	80.87	80.40	80.62
GlyNN	N/A	N/A	69.20	N/A	N/A	95.21	N/A	N/A	95.66	N/A	N/A	N/A
FGN	68.00	<b>72.61</b>	<b>70.23</b>	95.45	<b>95.81</b>	95.64	96.49	97.08	96.79	<b>82.61</b>	81.48	82.04
FGN-Radical	<b>69.21</b>	70.60	69.90	<b>95.79</b>	95.48	<b>95.73</b>	<b>96.67</b>	<b>97.09</b>	<b>96.88</b>	81.43	<b>83.46</b>	<b>82.39</b>

Table 1: Detailed statistics of FGN compared with various SOTA models

Where  $y'$  represents a possible label sequence;  $W_{l_i}^{crf}$  is the weight for  $l_i$ ; and  $b_{(l_{i-1}, l_i)}^{crf}$  is the bias from  $l_{i-1}$  to  $l_i$ .

After CRF decoding, we use first-order Viterbi algorithm to find the most probable label sequence for a sentence. Assume that there is a labeled set  $\{(s_i, y_i)\}_{i=1}^N$ , we can maximize the below log-likelihood function to train the whole model:

$$L = \sum_{i=1}^N \log(P(y_i | s_i)) \quad (15)$$

## 4 Experiments

In Section 4.1 and Section 4.2, we introduce the situation of datasets we use and some setting of the follow-up experiments. The main experiment result can be found in Section 4.2, where we set a comparison of our model and various SOAT models. The models we proposed are tested for 10 times in each dataset to compute the average Precision (P), Recall (R), F1-score (F1). In Section 4.3, we test some main components in FGN and each component is test for 5 times to compute the average metrics. Both the best and the worst results we obtained are eliminated to get precise results in both section 4.2 and section 4.3.

### 4.1 Experimental Settings

#### Dataset

Four widely-used NER datasets are chosen for experiments, including OntoNotes 4, MSRA, Weibo and Resume. All of these Dataset is annotated with a BMES tagging scheme. Among them, OntoNotes 4 and MSRA are in news domain; Weibo is annotated from Sina Weibo, a social media in China. These three datasets only contain traditional name entities, such as location, personal name and organization. Resume was annotated from personal resumes with 8 types of named entities.

#### Character Embedding

Character-based BERT we use has been pre-trained by Google<sup>2</sup>. Following the default configuration, output vector size of each character is set to 764. Character graphs we used are collected from *Xinhua Dictionaries*<sup>3</sup> with the number of 8630. We covert these graphs to  $50 \times 50$  gray-scale graph. Radicals for each character are collected according to the work [Dong et al., 2016]. Max length of radicals for each

character is set to 7 and the size of radical embedding is set to 32.

#### Hyper-Parameter Setting

We use dropout for both character graphs and radical embedding. Dropout rate for graph is set to 0.2 and the radical one is set to 0.3. The hidden size of LSTM is set to 764 and the dropout rate of LSTM is set to 0.5. As mentioned in Section 3.2, window size and stride in sliding window of character vector are respectively an integer multiple of the ones for glyph vectors. Thus, we set size and stride of the former to 96 and 8, and the later to 12 and 1 according to empirical study. Adam is adopted as optimizer for both BERT fine-tuning and NER model training. Learning rates for fine-tuning condition and training condition are different. The former one is set to 0.00002, and the latter one is set to 0.002.

### 4.2 Main Result

Table 1 shows some detailed statistics of FGN, compared with other SOTA model on four NER datasets. Here FGN represents the proposed model without extra radical representation; FGN-Radical represents the proposed model with extra radical representation as mentioned in Section 3.1. Both FGN and FGN-radical apply BiLSTM-CRF as tagger. Lattice LSTM [Zhang and Yang, 2018] and WC-LSTM [Liu et al., 2019] are the SOTA model without BERT, combining both word embedding and character embedding. Glyce [Meng et al., 2019] is the SOTA BERT-based glyph network as mentioned earlier. GlyNN is another SOTA BERT-based glyph network proposed by Sehanobish and Song [2019]. Especially, we select the average F1 of GlyNN for comparison as we also adopt the average F1 as metric. Other baselines had not shown that whether they have testing their model for multiple times. So we select the best result from their reports for comparison.

As can be seen, FGN and FGN-Radical outperform other SOTA models in all four datasets. Compared with BERT, the F1 of FGN obtains obvious boosts of 2.90%, 0.84%, 1.01% and 2.88% respectively on four datasets. Improvement of FGN is obvious on datasets with high recognition difficulty like Weibo and OntoNote 4, which shows that glyph information may enhance the representation of characters as additional semantic information for Chinese NER tasks. Further, FGN outperforms the SOTA glyph networks like Glyce and

<sup>2</sup> <http://zidian.aies.cn/>

GlyNN on all four datasets. FGN-Radical slightly outperforms FGN in three datasets, except for Weibo, which is less formal in expression. It seems that glyph representation and radical representation are complementary in some cases. One probable cause is that CGS-CNN mainly encodes the information of overall glyph for characters, which inevitably leaves out some knowledge from radical-level.

### 4.3 Ablation Study

Here we discuss the influences of various settings and components in FGN. The components we investigate contain: CNN structure, named entity tagger and fusion method.

CNN-type	P	R	F
CGS-CNN <sup>2d</sup>	67.56	70.45	69.01
CGS-CNN <sup>avg</sup>	68.13	70.35	69.22
2D-CNN	66.75	71.45	68.93
Tianzige-CNN	<b>69.94</b>	69.24	69.59
CGS-CNN	68.00	<b>72.61</b>	<b>70.23</b>

Table 2: Performances of various CNN structures on Weibo dataset

Weibo dataset is used for these illustrations. In addition, we investigate the performance of vision-based NER method without any distributed representation.

#### Effect of CNN structure

As shown in Table 2, we investigate the performances of various CNN structures while keep other settings of FGN constant. In this table, “2d” represents the CGS-CNN with no 3D convolution layer. “avg” represents that 1D max pooling in CGS-CNN is replaced by 1D average pooling. 2D CNN represents the CNN structure with only 2D convolution and 2D pooling layers. Tianzige-CNN is proposed from Glyce.

tagger-type	P	R	F
CRF	69.44	69.10	69.26
LSTM-CRF	69.77	69.60	69.69
BiLSTM-CRF	68.00	<b>72.61</b>	<b>70.23</b>
Transformer	<b>72.14</b>	66.08	68.98

Table 3: Performances of various taggers on Weibo dataset

As can be seen, the common 2D-CNN structure obtains the worse result, as it completely overlooks the information of Tianzige structure and neighbor character glyph. Comparing with Tianzige-CNN, using CGS-CNN introduces a boost of 0.64% in F1. Using 3D convolution in CGS-CNN introduces a boost of 1.11% in F1. Further, max pooling works better than average pooling when capture feature in Tianzige structure. As mentioned earlier, max pooling may better filter some blank pixels and noises in character graph.

#### Effect of Named Entity Tagger

Some widely-used sequence taggers are chosen to replace BiLSTM-CRF in FGN for discussion. Table 3 shows the performances of various chosen taggers. As can be seen, methods that based on LSTM and CRF outperform Transformer [Vaswani et al., 2017] encoder in NER task. Compared with

only CRF, LSTM introduces a boost of 0.43% in F1. In addition, bidirectional LSTM introduces a further boost of 0.54% in F1.

#### Effect of Fusion Method

We investigate the performances of different setting in fusion stage as shown in Table 4. In this table, “concat” represents concatenating glyph and BERT representation without any fusion; no freeze represents FGN with trainable BERT; “avg pool” and “max pool” represent that Slice-Attention in FGN is respectively replaced by pooling or max pooling; “outer-fc” represents the FGN without sliding windows, applying outer product and a fully connected layer with 128 units to directly fuse the output of BERT and CGS-CNN. In addition, we reset the window size to (196, 16), (48, 4) and the stride to (24, 2) in sliding window respectively for character and glyph representations.

fusion-type	P	R	F
concat	68.13	70.35	69.43
no freeze	65.92	<b>73.87</b>	69.67
avg pool	68.00	72.61	69.11
max pool	68.60	70.40	69.64
outer-fc	67.90	72.36	69.81
w(196, 16)	<b>69.58</b>	70.10	69.84
w(48, 4)	69.25	70.22	69.73
s(24, 2)	68.17	72.10	70.08
FGN	68.00	72.61	<b>70.23</b>

Table 4: Performances of different fusion settings on Weibo dataset

Compared to directly concatenating vectors from glyph and BERT, FGN introduces a boost of 0.80% in F1, confirming the effectiveness of our fusion strategy. FGN with the strategy of fine-tuning and freezing BERT in different stages outperforms the FGN with a trainable BERT. Using Slice-Attention outperforms using average pooling or max pooling in FGN, as Slice-Attention adaptively balances information of each slices but pooling layer only filter information statically. Using sliding window outperforms directly computing outer product of two vectors with a boost of 0.42% in F1. It confirms that sliding window not only reduces the dimension of output vector from outer product, but also enhances the performance of interactive information extraction. Further, Sliding window with the default setting (Section 4.1) slightly outperforms other hyper-parameter settings.

## 5 Conclusion

In this paper, we focus on extracting Chinese glyph information and fusing it into character representation. Analyzing and reforming some existing works of both multimodal representation learning and glyph representation learning, we propose the FGN for Chinese NER. In FGN, a novel CNN structure called CGS-CNN was applied to encode glyph information from both character graph itself and neighboring graphs of this character. Then a fusion method with out-of-sync sliding window and Slice-Attention is used to fuse two output vectors from BERT and CGS-CNN, which may offer extra interactive information for NER tasks. Experiments are

conducted on four NER datasets, showing that FGN with LSTM-CRF as tagger obtained SOTA performance on all four datasets. Further, influences of various settings and components in FGN are discussed during ablation study.

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