GlyphCRM: Bidirectional Encoder Representation for Chinese Character with its Glyph

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ABSTRACT
Previous works indicate that the glyph of Chinese characters contains rich semantic information and has the potential to enhance the representation of Chinese characters. The typical method to utilize the glyph features is by incorporating them into the character embedding space. Inspired by previous methods, we innovatively propose a Chinese pre-trained representation model named as GlyphCRM, which abandons the ID-based character embedding method yet solely based on the sequential character images. We render each character into a binary grayscale image and design two-channel position feature maps for it. Formally, we first design a two-layer residual convolutional neural network, namely HanGlyph to generate the initial glyph representation of Chinese characters, and subsequently adopt multiple bidirectional encoder Transformer blocks as the superstructure to capture the context-sensitive information. Meanwhile, we feed the glyph features extracted from each layer of the HanGlyph module into the underlying Transformer blocks by skip-connection method to fully exploit the glyph features of Chinese characters. As the HanGlyph module can obtain a sufficient glyph representation of any Chinese character, the long-standing out-of-vocabulary problem could be effectively solved. Extensive experimental results indicate that GlyphCRM substantially outperforms the previous BERT-based state-of-the-art model on 9 fine-tuning tasks, and it has strong transferability and generalization on specialized fields and low-resource tasks. We hope this work could spark further research beyond the realms of well-established representation of Chinese texts.

CCS CONCEPTS
• Computing methodologies → Artificial intelligence; Natural language processing; Lexical semantics.

KEYWORDS
Chinese characters, glyph representation, pre-trained model

1 INTRODUCTION
Pre-trained neural language models, e.g., BERT [9], BART [21], and XLNET [44], have achieved extraordinary success in many natural language processing (NLP) tasks, such as Information Retrieval [8], Semantic Matching [10, 35], Question Answering [4, 42] and Text Classification [28]. In these models, each word is usually converted into a discrete vector representation by looking up the word embedding table, and then the context-sensitive word representation is learned by certain structures. However, for Chinese texts, these routine methods ignore that the static glyph of Chinese characters contains rich semantic information. For instance, Pictographs: the shape of ‘山’ (mountain), ‘日’ (sun) and ‘马’ (horse) is inextricably related to the shape of natural objects as shown in Figure 1; Radicals: ‘崎’ (rough) and ‘岖’ (rugged), which have the same radical ‘山’ (mountain), are usually used to describe things related to mountains (e.g., mountain road) together. Hence, the glyphs of Chinese characters can convey some meanings in many cases, and Chinese characters with similar structures have intrinsic links. They
intuitively indicate that the glyph features of Chinese characters have the potential to enhance their representations.

Based on the above observations, some methods [6, 26, 38] incorporate the glyph features to enhance the Chinese character representation already covered into character embeddings (character ID-based), e.g., Meng et al. [26] combine the glyph features extracted from various forms of Chinese characters with the BERT embeddings. They demonstrate that the glyph features of Chinese characters are authentically helpful to improve the performance of models. However, previous methods only use glyphs of Chinese characters as the additional features, and there is no pre-trained Chinese text representation framework based on glyphs. In this paper, as shown in Figure 2, instead of using the ID-based character embedding method, we propose to only use the glyph vectors of Chinese characters as the representations, obtained by the HanGlyph module. To capture the contextual information, we further adopt the bidirectional encoder Transformer [41] as the superstructure and finally propose the Chinese pre-trained representation model named GlyphCRM, based entirely on glyphs.

Concretely, we design two residual convolutional blocks in the HanGlyph module to obtain the glyph representation of any Chinese character, which is converted into the grayscale image. Each block has similar sub-layer architectures, including convolutional neural networks (CNN) and ReLU [1] activation function. Furthermore, we design two-channel position maps for the character image to reinforce the capture of the spatial structure of Chinese characters’ glyphs. Meanwhile, to fully exploit the glyph features of Chinese characters, we incorporate the glyph features extracted by the HanGlyph module into the underlying two Transformer blocks by the skip-connection method. From the whole architecture of GlyphCRM, it does not use the ID-based word/character embedding method and can be fine-tuned for specific NLU tasks. As the whole architecture of GlyphCRM, it is the novel design of GlyphCRM that can address the out-of-vocabulary problem by the HanGlyph module, which can generate the glyph representation of any character already converted into the grayscale image when fine-tuned on specific tasks.

Previous state-of-the-art pre-trained representation model BERT on a wide range of Chinese tasks. The in-depth analysis indicates that it converges faster than BERT during pre-training and has strong transferability and generalization on specialized fields and low-resource tasks.

The contributions of our paper are three-fold:

- We propose a Chinese pre-trained representation model GlyphCRM based entirely on glyphs for the first time, where it replaces the ID-based word/character embedding method with the convolutional representation of Chinese glyphs.

- GlyphCRM addresses the out-of-vocabulary problem by the HanGlyph module, which can generate the glyph representation of any character already converted into the grayscale image when fine-tuned on specific tasks.

- Extensive experiments demonstrate that our proposed model achieves better performance on a wide range of Chinese NLU tasks, especially on sequence labeling, compared to BERT with similar Transformer depth.

2 RELATED WORK

Pre-trained Language Representation Models: As the distributional representation of words is proved more efficient and practical than independent representation that ignores the contextual information [36], how to obtain the rich context-sensitive representation of words has been attracting promising attention of many researchers. Early methods such as Word2Vec [27] and GloVe [29] learn the word embeddings with fixed dimensions through the co-occurrence of words in fixed windows on large-scale corpora. Recently, to alleviate the problem of insufficient representation of the above methods, some researchers study how to learn the word embeddings that contain more comprehensive contextual information and long-distance dependency information between words. Peters et al. [30, 31] proposed ELMo and its successors that learn the word embeddings with fixed dimensions through the co-occurrence of words in fixed windows on large-scale corpora. Recently, to alleviate the problem of insufficient representation of the above methods, some researchers study how to learn the word embeddings that contain more comprehensive contextual information and long-distance dependency information between words. Peters et al. [30, 31] proposed ELMo and its successors that utilize the language models to capture the contextual features with left-to-right and right-to-left methods.

As the simple yet efficient Transformer [41] architecture emerged, recently proposed pre-trained language models adopt it as the main architecture and have achieved significant performances on many NLU tasks. For instance, GPT and its successors [5, 32, 33]...
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utilize the Transformer decoder-based architecture with the self-supervised left-to-right pre-training method to obtain the context-sensitive representation of words. Different from GPT, BERT [9] utilizes the self-attention mechanism-based Transformer architecture and adopts the Masked Language Model pre-training object and Next Sentence Prediction task to obtain the bidirectional representation of words. Moreover, sequence-to-sequence pre-trained models such as T5 [34] and BART [21], and BERT-based representation models such as RoBERTa [24], XLNET [44], DeBERT [37], also achieve promising gains on NLP tasks.

Many researchers also proposed pre-trained language models for different languages such as CamemBERT for French [25], BERT-wmm [7] and ERNIE [46] for Chinese. Multi-language pre-trained models such as mT5 [43] are also proposed to handle the compounded language tasks such as machine translation expeditiously. To summarize, the language models pre-trained on large-scale corpora are extremely useful for the development of natural language processing. In this paper, we also adopt the popular directional encoder Transformer as the superstructure of our model, which uses the cross attention mechanism to capture the context-sensitive information. We pre-train it on large-scale Chinese corpora.

**Glyph Vector:** Generally, to represent the discrete symbolic texts, researchers proposed to encode various symbols into the corresponding word embedding space, such as one-hot encoding and distributed representation, making a remarkable progress in the field of natural language processing. However, from the perspective of symbolic evolution, Chinese symbols have always possessed their unique structural features and peculiarities, developing from the initial hieroglyphics to their present forms as the Chinese characters. As shown in Figure 1, recent researches [6, 38] also demonstrate that the glyphs of Chinese characters contain rich semantic information and have the potential to enhance the word representation of them. Meng et al. [26] first apply the glyph features of Chinese characters into the pre-trained model BERT and achieve significant performance on many Chinese NLU tasks, such as Named Entity Recognition [20], News Text Classification [22] and Sentiment Analysis [40]. Among them, the typical method is to use the deep convolutional neural networks to extract the glyph features of Chinese characters after converting them into images. Then, the glyph features of Chinese characters and corresponding character embeddings are integrated to enrich the representation of Chinese characters. We argue that the full glyph of Chinese characters is expressive enough, and further propose the Chinese pre-trained representation model GlyphCRM, based entirely on glyphs.

### 3 OUR METHODOLOGY

In what follows, we first introduce the data preprocessing and then mainly introduce the overall architecture of GlyphCRM, presented in Figure 4, containing the HanGlyph module and bidirectional encoder layer. Finally, we introduce the two-stage pre-training and fine-tuning methods of our model in detail.

#### 3.1 Data Preprocessing

For the input text, we render each Chinese character into a single-channel $48 \times 48$ grayscale image. As the instance shown in Figure 3, the position on each character feature map (i.e. grayscale image) is set to ‘1’ where the stroke of Chinese character passes, otherwise, the position is set to ‘0’. After obtaining the sequential feature maps of character-level input text, we apply a special token [CLS] as the start symbol for all inputs. We also apply another special token [SEP] to separate sentences and as the ending symbol of input for pre-training and specific NLU tasks. The two special tokens are also converted to the grayscale image to obtain the corresponding feature maps. Hence, the input and output sequence can be separately denoted to $X = (x_{cls}, x_1, x_2, ..., x_{N}, x_{sep})$, and $H = (h_{cls}, h_1, h_2, ..., h_n, h_{sep})$.

To further capture the spatial structure of Chinese characters, we design the identical two-channel position maps for each character image, which have the same size as the feature maps of Chinese characters. As shown in Figure 3, we set the coordinate axis with the center point of the Chinese character image as the origin, and the value range of the horizontal and vertical axis is between $-0.2$ and $0.2$. Hence, the two-channel position maps separately represent the abscissa and ordinate values of each pixel after being projected, respectively.

#### 3.2 HanGlyph

After obtaining the three-channel representation of each Chinese input character as shown in Figure 3, we adopt two residual convolutional blocks to extract its glyph feature, namely HanGlyph. As the orange box shown in Figure 4, for each residual convolutional block, the sequential input feature maps pass one convolutional layer with $3 \times 3$ kernel size, three-layer CNN and $2 \times 2$ max-pooling layer in turn. We take the second residual convolutional block for instance, which can be calculated by the equation as Eq.1.

$$
\begin{align*}
  z^2_1 &= \text{ReLU}(w^2z^1 + b^2) \\
  z^2_2 &= \text{ReLU}(\text{Max}_{3\times3}(z^2_1) + \mathcal{F}(z^2_1, W_r^2)) \\
  z^2 &= \text{Max}_{3\times3}(z^2_2)
\end{align*}
$$

where $z^1$ is the output of ResBlock 1 and $\text{ReLU}$ [1] is the activation function widely used for deep convolutional neural networks (DCNN). $w^2$ and $b^2$ are the parameters for the first convolutional sub-layer where the padding width and stride length both are 1.

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1. We use Python’s fontTools and PIL library to set the font of Chinese characters and render Chinese characters into images.
for each residual block. The output of the first sub-layer passes the three-layer CNN denoted as $\mathcal{F}(x_2^r, W_2^r)$. Note that the core three-layer convolutional networks of ResBlock 1 have a large kernel window $9 \times 9$ to alleviate the issue of sparse image features, which is caused by the strokes of most Chinese characters occupying only a small number of pixels. Finally, one $2 \times 2$ max-pooling layer is used to obtain the final output for each residual block.

Besides entering the next layer, we convert the final output of each residual block into one hidden state with the same dimensions as the upper bidirectional encoder layer through the linear layer. We denote the hidden state to be $g = (g_1, g_2, ..., g_n)$, which can be directly fed into the Transformer block as shown in Figure 4. ResBlock 2 is followed by one linear function to convert the output of each Chinese character into the glyph vector with fixed dimensions. It allows us to obtain the sequential glyph vectors of Chinese text, denoted as $r = (r_1, ..., r_l, ..., r_n)$, where $r_j$ is the single Chinese character representation and $n$ is the length of input.

### 3.3 Bidirectional Encoder Layer

After obtaining the glyph vector of each Chinese character through the HanGlyph module, we use the bidirectional encoder layer based on Transformer[41] to obtain the context-sensitive representation of Chinese characters. Before $R$ is input into the superstructure, we sum the sequential glyph vectors, position embeddings, and segment embeddings to construct the more reasonable input; otherwise, characters in all input positions are regarded as equally important by the attention mechanism. Yet Chinese characters in different positions usually play different roles for understanding sentences.

We adopt the popular Transformer structure as the backbone of the bidirectional encoder layer due to its capability to capture long-distance dependency information between words [9, 34, 37]. Concretely, each Transformer block, shown in Figure 4, includes the multi-head attention mechanism and feed-forward neural networks. We take the $l$ th Transformer block as an instance and the computation process can be presented by the following equations.

$$h_l^M = \text{LayerNorm}(h_{l-1} + \text{MultiHeadAttention}(h_{l-1}))$$
$$h_l = \text{LayerNorm}(h_l^M + \text{FFN}(h_l^M))$$

(2)

where $h_{l-1}$ is the output of the $l-1$ th Transformer block. LayerNorm [2] is one way to reduce the training time by performing normalization on the feature dimension of input. FFN is the feed-forward neural network, which is similar to Multi-Layer Perceptrons [11]. MultiHeadAttention is the core structure of each Transformer block, which is used to update the contextual representation of characters by way of calculating the similarity with aspect to other characters. Specifically, the process can be denoted as Eq.3.

$$\text{MultiHeadAttention} = \text{Concat}(\text{head}_1, \text{head}_2, \ldots, \text{head}_h)W^h$$
$$\text{head}_i = \text{Attention}(QW_i^Q, KW_i^K, VW_i^V)$$

(3)

where $h$ is the number of heads. $W_i^Q$, $W_i^K$ and $W_i^V$ are the projection parameters, and their dimensions are $d_{\text{model}} \times d_h$, $W^h \in \mathbb{R}^{h \times d_h \times d_h}$, where $d_{\text{model}}$ is the hidden size. In our work, we set $d_h = d_{\text{model}}/h$ for each Transformer block. The dimension of each head is reduced, so the total computational cost is almost identical to the single head attention with full dimensionality. For the dot-product Attention, the computational method is denoted as Eq.4.

$$\text{Attention}(Q, K, V) = \text{softmax}(\frac{QK^T}{\sqrt{d_k}})V$$

(4)

In practice, the queries $Q$, keys $K$ and values $V$ present the whole input sequence in each block. However, when updating the representation of any character, the query vector is itself, and the keys and values are the hidden states of the whole input sequence.

In order to make full use of the glyph features of Chinese characters, we incorporate the glyph representation obtained in each residual block of the HanGlyph module into the Transformer Block of the first two layers. As the gray box shown in Figure 4, the output of the FFN of the underlying two Transformer blocks is not only integrated with the output of the multi-head attention module, but also with the output of the residual blocks of HanGlyph. The detailed process is presented in Figure 5. Concretely, we take the simple addition of the three input vectors because an overly complex integration method will significantly increase the computation cost of GlyphCRM, and this method is also proved effective [14].

From the overall architecture of GlyphCRM, the underlying four-layer networks are a symmetrical structure, which can have a stable information interaction way to capture and exploit glyph features. To summarize, GlyphCRM contains the glyph features of Chinese characters extracted from images and the contextual information of input text, which can be regarded as a pre-trained multi-modal model but is different from general cross-modality models such as VisualBERT [23], LXMERT [39] and ERNIE-ViL [45]. Without using the ID-based word embedding method, GlyphCRM will not
be restricted by the unseen (out of fixed vocab) Chinese characters when fine-tuned on specific downstream tasks which contain unseen characters. Furthermore, the glyph features of Chinese characters can be used to infer the meaning of previously unseen or sparse Chinese characters by glyph similarity, compared to directly converting them into word vector according to word/character ID having no such inference information.

### 3.4 Training

In this section, we introduce the detailed two-stage training process of our model, containing pre-training and fine-tuning.

#### 3.4.1 Pre-training

To avoid overfitting, models with huge parameters usually need large-scale corpus to train, but manual labeling will cost copious resources. Yet like BERT, the large neural language models are usually pre-trained on large-scale corpora with an unsupervised method to enable them to have a detailed understanding of texts on specific languages, i.e., pre-trained language models have good initial parameters when used for specific tasks again. Hence, training on large-scale corpora with unsupervised methods is a relatively efficient approach for training large-param-eter models due to the unnecessary to spend enormous manpower and material resources, thereby achieving a remarkable success in natural language processing.

In this paper, we first pre-train our proposed model GlyphCRM with two unsupervised tasks, identical to those in BERT [9]. The first one is the Masked LM task where we randomly choose 15% of all Chinese characters for each input text to be replaced with one special token [MASK] 80% of the time, a random character 10% of the time, and the unchanged character 10% of the time. It exploits other Chinese characters to predict the corrupted characters. For predicting the masked characters, we count the number of Chinese characters in the pre-training corpora and construct the corresponding vocabulary used for classification. We select the universally used Chinese characters which can be presented by Song typeface, monofont, or boldface. The sparse characters are replaced by another special token [UNK]. The final vocab size is about 18,612, less than that of BERT. Specifically, for any input sequence X, we first construct the corrupted input version \( \hat{x} \) by the above randomly masked method. We define the masked characters as \( \hat{x} \), and the training object of masked prediction can be presented as the following:

\[
\mathcal{L}_{mp} = \max_\theta \log p(x | \hat{x}) = \sum_{t=1}^{n} m_t \log (H_\theta(x_t) e(x_t))
\]

where \( m_t = 1 \) represents \( x_t \) is masked, and \( H_\theta \) is the top hidden state of our model. Thus, the final hidden states of the input text can be denoted as \( H_\theta(x) = (H_\theta(x_1), H_\theta(x_2), ..., H_\theta(x_n)) \). \( e(x) \) indicates the final projection matrix that maps the final hidden state of masked characters to the vocabulary size.

Besides, we adopt the next sentence prediction (NSP) pre-training task to impel our model to understand the relationship between sentences, which is instrumental for being fine-tuned on some downstream tasks such as Question Answering [4, 42] and Sentence Matching [12, 15]. Concretely, when the training example is the composition of sentence A and B, we formulate that 50% of the time B is the general next sentence that follows A (regarded as the IsNext), 50% of the time B is from the other training data (regarded as the NotNext). While training, the top hidden state of the start token [CLS] is used to predict the relationship between two sentences as the blue arrow shown in Figure 6.

#### 3.4.2 Fine-tuning

Compared to pre-training, fine-tuning expends relatively fewer resources. In this paper, we fine-tune our proposed model on general natural language processing tasks, including single sentence classification, text classification, sequence labeling and sentence matching. For single sentence classification, sentence matching, and multi-sentence text classification tasks, we feed the final output of the start token [CLS] to one task-specific output layer to predict the correct label. For sequence labeling, the final output of each Chinese character is fed into an output layer for classification. Notably, the self-attention mechanism in the Transform block of GlyphCRM ensures the almost seamless connection of the two stages of pre-training and fine-tuning, making the application of our model direct and effective in specific tasks. The detailed analyses and comparison with BERT will be presented in the following experiment section.
Figure 7: The pre-training loss curves of BERT and GlyphCRM in the first 6 epochs. Each point in the curve represents the average loss of current epoch. Epoch ‘0’ represents the starting point of training.

4 EXPERIMENT

In this section, we first introduce the detailed experimental settings and the pre-training performance of our model. Secondly, we in-detail analyze the performance of GlyphCRM on 9 Chinese natural language understanding (NLU) datasets.

4.1 Experimental settings

4.1.1 Model Architecture. The architecture of GlyphCRM and the baseline model BERT-Base we adopt both have 12 Transformer blocks. Each layer of them has 12 attention heads, and the size of hidden states is 768. The total parameters of BERT-Base are 110 million, yet GlyphCRM only has 95 million parameters. In the case of the same number of Transformer blocks, the proposed model has fewer parameters. We separately pre-train BERT and GlyphCRM for 15 and 6 epochs on the same processed 3 million pre-trained Chinese corpora. From the downward trend of the two pre-training losses shown in Figure 7, we can observe that the representation model based entirely on glyphs of Chinese characters has a stronger learning ability than BERT.

4.1.2 Datasets for Evaluation. We first compare GlyphCRM and BERT on the following Chinese NLU datasets.

ChnSentiCorp: ChnSentiCorp [40] is the Chinese sentiment analysis dataset, including three-domain documents: education, movie, and house. Each domain contains two classification labels: positive and negative. We divide the data in each domain into training, validation, and test sets at the ratio of 0.8:0.1:0.1.

Hotel Review Sentiment Analysis: Hotel Review Sentiment Analysis dataset3 is collected from the Ctrip website, including 10k texts and two positive and negative classification labels. It is an unbalanced sentiment classification dataset, having 7k positive samples. We divide the data of each label into training, validation, and test sets at the ratio of 0.8:0.1:0.1.

Chinese Natural Language Inference: The Chinese Natural Language Inference (CNLI) is from the public evaluation tasks of the Seventeenth China National Conference on Computational Linguistics4 (CCL2018). We split the whole dataset into 90,000, 10,000, 10,000 as the train, validation and test set. Each example contains two sentences, where the relationship between them is entailment, contradiction, or neutral.

THUCNews: THUCNews [22] is a long document classification dataset. After processing the long document dataset, we retain 65k documents. We randomly select 10k samples as the test set, 5k samples as the validation set, and 50k samples as the training set.

 TouTiaoCNews: TouTiaoCNews5 is the short news text classification dataset. It contains 382, 688 examples, and all documents are divided into 15 categories according to their content. We randomly divide the total data with a ratio of 0.8:0.1:0.1, separately as the train, validation, and test set.

MSRA-NER: MSRA-NER [17, 20] dataset is the sequence labeling task proposed by Microsoft Research Asia in 2006. It contains 7 tagging labels: O, B-PER, I-PER, B-ORG, I-ORG, B-LOC, and I-LOC. Hence, it can be regarded as the 7 classification task.

People-NER: The data of People-NER comes from the article of the People’s Daily in 20146. It contains approximately 28k data, and has the same 7 tagging labels as MSRA-NER. We split it into train, validation, and test set, separately with 20, 864, 2, 318, and 4,636 samples.

Unknown character Statistics: We count the distribution of unknown characters in the above 7 datasets according to the vocab of BERT. As the results shown in Table 1, despite the vocab of BERT has 21, 128 tokens, there are still many unknown characters in the long Chinese texts. Even for fine-grained classification tasks such as MSRA-NER and People-NER, there are usually many unknown characters in the dataset, so it is meaningful and valuable to solve the out-of-vocabulary problem.

4.1.3 Experimental Details. We use 2 Tesla V100 GPUs to pre-train BERT and GlyphCRM on the processed 3 million Chinese texts with Adam [18] optimizer with the initial learning rate to 0.0001, $\beta_1 = 0.9$, $\beta_2 = 0.999$, The pre-training Chinese texts comes from the Chinese Wikipedia7, and the preprocessing way is identical to BERT. We set the weight decay to 0.01 and set the linear decay of learning rate, and the learning rate warmup over the first 10k steps. We set the batch size and maximum input length to 256 and 512. The pre-training loss is the sum of the mean Masked LM likelihood and the mean NSP likelihood. Furthermore, we fine-tune GlyphCRM and BERT on the specific tasks with the same hyperparameter settings. We set up different learning rates for different tasks, which are presented in the following experiment analyses.

4.2 Results and Analysis

In this section, we will represent the comparison results between the previous state-of-the-art pre-trained model BERT and our designed model GlyphCRM. Note that we use the validation set to select the model with the best performance.
4.2.1 Single Sentence Classification. ChnSentiCorp and Hotel Review Sentiment Analysis are coarse-grained sentiment classification datasets, where models are trained to perform sentence-level binary classification task. The evaluation metrics for all datasets are the prediction accuracy. For classification, we enable the last hidden state of [CLS] pass a fully connected linear layer followed by a softmax activation function to classify the input sentence. The experimental results are shown in Table 2.

The above experimental results show that whether it is from the validation set or the test set, the classification accuracy of our model significantly exceeds BERT on the two sentiment classification dataset, especially on the test set. For instance, 93.08 vs 91.25 on the test set of ChnSentiCorp and 92.70 vs 91.40 for Hotel Review Sentiment Analysis. It demonstrates that GlyphCRM has a stronger ability to understand the semantics of whole sentences compared to BERT. Moreover, the experimental results in Table 2 and loss curves in Figure 7 indicate that our model can learn the contextual information of the overall sentence better and faster. It may be attributed to the fact that the glyph features extracted by the HanGlyph module can sufficiently express the structure of Chinese characters, which has the easily distinguishable features. In addition, GlyphCRM could distinguish the contextual semantics of positive and negative words according to the glyph features of them. Overall, the above analyses and the experimental results of comparison models further indicate that glyph features of Chinese characters are practical when used in the sentiment analysis task.

4.2.2 Chinese Text Classification. After evaluating the performance of models on the single sentence classification task, we tested them on two multi-sentence document classification datasets THUCNews and TouTiaoCNews to evaluate their ability to understand Chinese long documents. Formally, we still take a fully connected linear layer followed by a softmax activation function to map the classification labels. The experimental results on validation and test sets are shown in Table 3. From the experimental results, we observe that the performance of GlyphCRM is still better than BERT, yet the gap between two models is smaller compared to being evaluated on the single sentence classification task. Specifically, the performance of our model separately exceeds BERT by about 0.5% and 0.7% on the validation and test sets, yet GlyphCRM outperforms BERT by about 1.5% gains on two test sets as shown in Table 2. It indicates that the performance of our model based entirely on glyphs is comparable to and even surpasses BERT when dealing with long Chinese documents. Furthermore, whether from short text (at least one sentence) or long text, the pre-trained representation model based entirely on Chinese glyphs is simple and effective for Chinese multi-label classification tasks.

### Table 1: The detailed statistics of unknown characters (chars) in different datasets.

| Dataset            | Unknown Chars | Total Chars | Ratio (%) |
|--------------------|--------------|------------|-----------|
| # ChnSentidev      | 798          | 123,568    | 0.65      |
| # CNLI             | 722          | 288,534    | 0.25      |
| # HRSA             | 358          | 123,690    | 0.29      |
| # THUCNews         | 34,604       | 2,004,771  | 1.72      |
| # TouTiaoCNews     | 26,750       | 1,384,652  | 1.93      |
| # MSRA-NER         | 1,508        | 142,095    | 1.06      |
| # People-NER       | 1,061        | 107,894    | 0.98      |

### Table 2: Automatic evaluation results on the validation and test sets of ChnSentiCorp and Hotel Review Sentiment Analysis. The leftmost column represents the model and their pre-training degree. LR represents the learning rate of a specific task (Unless otherwise stated, the instruction LR in the following table are the same). 15e and 6e separately represent the pre-training epochs of BERT and GlyphCRM.

| Model             | LR  | Dev ACC(%) | Test ACC(%) |
|-------------------|-----|------------|-------------|
| ChnSentiCorp      |     |            |             |
| # BERT15e         | 2e  | 92.66      | 91.25       |
| # GlyphCRM6e      | 2e  | 93.17      | 93.08       |

| Hotel Review Sentiment Analysis |
|---------------------------------|
| # BERT15e          | 2e  | 92.88      | 91.40       |
| # GlyphCRM6e       | 2e  | 93.80      | 92.70       |

### Table 3: Automatic evaluation results on the validation and test sets of THUCNews and TouTiaoCNews.

| Model             | LR  | Dev ACC(%) | Test ACC(%) |
|-------------------|-----|------------|-------------|
| THUCNews          |     |            |             |
| # BERT15e         | 3e  | 96.28      | 95.41       |
| # GlyphCRM6e      | 3e  | 96.60      | 96.32       |

| TouTiaoCNews      |
|-------------------|
| # BERT15e         | 3e  | 88.85      | 88.84       |
| # GlyphCRM6e      | 3e  | 89.60      | 89.45       |
Table 4: Automatic evaluation results on the validation and test sets of Chinese natural language inference (CNLI).

| Model       | LR  | Dev ACC(%) | Test ACC(%) |
|-------------|-----|------------|-------------|
| # BERT15e   | 3e−5| 71.04      | 69.74       |
| # GlyphCRM5e | 3e−5| 72.28      | 71.80       |

Table 5: Two instances of the test set of CNLI.

- **Sentence A**: 一位黑发女子在舞台上用相机拍下了一张乐队的照片. (A black-haired woman took a photo of the band with a camera on the stage.)
  - Label: Entailment
  - BERT: Neural
  - GlyphCRM: Entailment

- **Sentence B**: 这位女士正在一场音乐会上. (A lady is at a concert.)
  - Label: Contradiction
  - BERT: Neural
  - GlyphCRM: Contradiction

Table 6: Automatic evaluation results on the validation and test sets of Chinese named entity recognition tasks, including MSRA-NER and People-NER. F1, P, and R represent F1-score, Precision, and Recall.

| Model       | LR  | F1(%) | P(%) | R(%) |
|-------------|-----|-------|------|------|
| **MSRA-NER (validation)** |     |       |      |      |
| # BERT15e   | 3e−5| 83.55 | 81.69| 85.48|
| # GlyphCRM5e | 3e−5| 90.15 | 89.32| 91.00|
| **MSRA-NER (test)** |     |       |      |      |
| # BERT15e   | 3e−5| 77.78 | 75.84| 79.81|
| # GlyphCRM5e | 3e−5| 86.04 | 85.53| 86.57|
| **People-NER (validation)** |     |       |      |      |
| # BERT15e   | 3e−5| 80.40 | 78.61| 82.27|
| # GlyphCRM5e | 3e−5| 85.62 | 85.34| 85.90|
| **People-NER (test)** |     |       |      |      |
| # BERT15e   | 3e−5| 79.20 | 76.91| 81.64|
| # GlyphCRM5e | 3e−5| 84.05 | 82.80| 85.35|

Table 4 shows that our model separately surpasses the benchmark model BERT by about 1.2%, 2% on the validation and test set, demonstrating that full glyphs of Chinese characters are expressive enough to be used for their representations. The excellent performance may be attributed to two facts: 1) GlyphCRM can further capture sentence-level semantic according to the glyph features of consecutive Chinese characters. 2) Compared to directly converting the character into a vector, each Chinese character representation incorporating its glyph is more distinguishable in the semantic space.

Moreover, we select two examples from the test set to verify the performance of models, presented in Table 5. For the first instance, we observe that the first sentence can deduce the second sentence according to the keywords of the first sentence: '女子' (women), '舞台' (stage), '乐队' (band) and keywords of the second sentence: '女士' (lady), '音乐会' (concert). For the second instance, the semantics of keywords in the sentence B such as '购物中心' (shopping center), '售货亭' (kiosk) and '工作' (working), are different from '伞' (umbrella) and '画漫画' (drawing comic) in sentence A. Judging from the inference results of models, BERT usually cannot infer the relationship between two sentences in many cases, thus determining that the two sentences are neutral. However, our model incorporating glyphs has a great advantage in inferring the semantic relevance between sentences.

4.2.4 Sequence Labeling. Compared to text classification tasks that focus on the overall understanding of input content, sequence labeling, e.g., word segmentation, part-of-speech tagging, named entity recognition, and relationship extraction, is more fine-grained classification tasks. It can be used to evaluate the ability of Chinese pre-trained representation models to represent Chinese characters, which is directly related to the fine-grained classification accuracy. Different from previous methods of adding CRF [19] network based on the pre-trained representation model, we just add a fully connected layer to the final output hidden states of models. So the whole architecture mainly relies on representation models. Notably, the final fully connected layer is exactly identical for GlyphCRM and BERT in order to compare them fairly. The performance of the whole network can directly evaluate the ability of the Chinese pre-trained representation model to express Chinese characters. We adopt the frequently used Chinese NER datasets MSRA-NER and People-NER to evaluate the fine-grained representation capability of GlyphCRM and BERT. The experimental results are shown in Table 6. Firstly, compared to the experimental results on Chinese text classification tasks, the performance of GlyphCRM and BERT has a greater gap in NER, e.g., F1-score: 90.15 vs 83.55 on MSRA validation, 86.04 vs 77.78 on MSRA test. Precision: 85.53 vs 75.84 on MSRA test, 82.80 vs 76.91 on People-NER test. Recall: 91.00 vs 85.48 on MSRA test, 85.35 vs 81.64 on People-NER test. It indicates that our model has a strong ability to understand the overall semantics of Chinese texts and excellent representation for the fine-grained (a single Chinese character) character semantics. Secondly, Table 6 shows that the performance of our model is significantly higher than BERT in Precision and Recall, and the performance on the two indicators is not much different. It indicates that GlyphCRM has high overall recognition accuracy on sequence labeling tasks.

Specifically, we select two typical examples from the test sets, presented in Table 7. BERT usually has inferior accuracy when predicting the ending position of location phrases. Yet, the glyph-based method can alleviate this problem by effectively learning the difference between phrases, e.g., the meaning conveyed by ‘民
Table 7: Two typical recognition instances of MSRA-NER and People-NER. ‘O’ represents that the character has no specific label as a category, ‘B-LOC’ and ‘I-LOC’ separately represent the start and inside of location words. Red-colored words are the error predictions. PER represents the name of Chinese people.

| MSRA-NER (test) | True Label | BERT | GlyphCRM |
|-----------------|------------|------|----------|
| Sentence        | 加泰罗尼亚 | B-LOC I-LOC I-LOC I-LOC I-LOC | 加泰罗尼亚 | B-LOC I-LOC I-LOC I-LOC I-LOC |
| Others: O       |            | O    | O        |

| People-NER (test) | True Label | BERT | GlyphCRM |
|-------------------|------------|------|----------|
| Sentence          | 崔剑平 | B-PER I-PER I-PER | 崔剑平 | B-PER I-PER I-PER |
| Others: O         |            | O    | O        |

The transferability evaluation of pre-trained models has been attracting attention of many researchers because the high transferability means that models can adapt to a wide range of application scenarios. In this section, we first evaluate the two pre-trained models on the Chinese sentence semantic matching dataset in the medical field (CMSSM), related to COVID-19. It is provided by More Health technology company. CMSSM is a fine-grained semantic matching task that mainly involves 10 diseases such as pneumonia, mycoplasma pneumonia, bronchitis, and so on. The length of each sentence is less than 20 words. Its training, validation and test set include 8, 747, 2, 002 and 7, 032 samples, respectively.

Table 8: Automatic evaluation results on the validation and test sets of CMSM.

| Model           | LR     | Dev ACC(%) | Test ACC(%) |
|-----------------|--------|------------|-------------|
| # BERT05e       | 3e−5   | 89.41      | 89.79       |
| # GlyphCRM5e    | 3e−5   | 90.71      | 90.84       |

Table 9: Automatic evaluation results on the validation and test sets of low-resource E-commerce Product Review Dataset for Sentiment Analysis task.

| Model           | LR     | Dev ACC(%) | Test ACC(%) |
|-----------------|--------|------------|-------------|
| # BERT05e       | 3e−5   | 79.35      | 73.61       |
| # GlyphCRM5e    | 3e−5   | 81.25      | 76.07       |

5 TRANSFERABILITY ASSESSMENT ON SPECIALIZED FIELDS AND LOW-RESOURCE TASKS

Medical Field: The transferability evaluation of pre-trained models has been attracting attention of many researchers because the high transferability means that models can adapt to a wide range of application scenarios. In this section, we first evaluate the two pre-trained models on the Chinese sentence semantic matching dataset in Woodstock '18, June 03–05, 2018, Woodstock, NY
To summarize, GlyphCRM can quickly adapt to various Chinese natural language understanding tasks and achieve promising performances. It is mainly attributed to the glyphs of Chinese characters conveying vivid and significant meanings. Meanwhile, the pre-trained model we design makes full use of the glyph features of Chinese characters and their contextual information. What is important is that our proposed approach can solve the out-of-vocabulary problem, which can be reflected by the improvement on some tests and high transferability on medical fields.

6 CONCLUSION

In this paper, inspired by glyphs of Chinese characters could enhance the representation of Chinese characters, we propose the Chinese pre-trained representation model named as GlyphCRM, based entirely on glyphs. To verify its effectiveness, we conduct extensive experiments on a wide range of Chinese NLU tasks. The surprising performance of GlyphCRM is that it outperforms previous state-of-the-art model BERT in 9 Chinese NLU tasks. The pre-training process and the fine-tuning results indicate that our pre-trained model we design makes full use of the glyph features of Chinese characters conveying vivid and significant meanings. Meanwhile, the performances are mainly attributed to the glyphs of Chinese characters conveying vivid and significant meanings.

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*We will open the codes and pre-trained checkpoints soon.*
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