Exploiting Word Semantics to Enrich Character Representations of Chinese Pre-trained Models

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Abstract. Most of the Chinese pre-trained models adopt characters as basic units for downstream tasks. However, these models ignore the information carried by words and thus lead to the loss of some important semantics. In this paper, we propose a new method to exploit word structure and integrate lexical semantics into character representations of pre-trained models. Specifically, we project a word’s embedding into its internal characters’ embeddings according to the similarity weight. To strengthen the word boundary information, we mix the representations of the internal characters within a word. After that, we apply a word-to-character alignment attention mechanism to emphasize important characters by masking unimportant ones. Moreover, in order to reduce the error propagation caused by word segmentation, we present an ensemble approach to combine segmentation results given by different tokenizers. The experimental results show that our approach achieves superior performance over the basic pre-trained models BERT, BERT-wwm and ERNIE on different Chinese NLP tasks: sentiment classification, sentence pair matching, natural language inference and machine reading comprehension. We make further analysis to prove the effectiveness of each component of our model.

Keywords: word semantics · character representation · pre-trained models

1 Introduction

Pre-trained language models (PLMs) such as BERT [3], RoBERTa [10] and XLNet [20] have shown great power on a variety of natural language processing (NLP) tasks, such as natural language understanding, text classification and automatic question answering. In addition to English, pre-trained models also prove their effectiveness on Chinese NLP tasks [19,2].

Pre-trained models were originally designed for English, where spaces are considered as natural delimiters between words. But in Chinese, since there is no explicit word boundary, it is intuitive to utilize characters directly to build pre-trained models, such as BERT for Chinese [3], BERT-wwm [2] and ERNIE [19]. In Chinese, words instead of characters are the basic semantic units that have
specific meanings and can behave independently [22] to build a sentence. The meaning of a single Chinese character is always ambiguous. For example, “足” has four meanings specified in the Chinese dictionary: foot, attain, satisfy and enough. Therefore, one single character cannot express the meaning precisely. In contrast, the Chinese word which is constructed by combining several characters can accurately express semantic meaning. For example, if the character “足” is combined with the character “不” (no), we get the Chinese word “不足” (insufficient). If the character “足” is combined with the character “球” (ball), we get the Chinese word “足球” (soccer). Therefore, to understand Chinese text, the knowledge of words can greatly avoid ambiguity caused by single characters.

Previous ways to integrate word information into the pre-trained model can be categorized into two ways, as shown in Figure 1. The first way (shown as 1(a)) is to splice character information and word information, and merge them through the self-attention mechanism [14,7,6]. This type of method increases the length of the input sequence, and because the self-attention mechanism is position-insensitive, the model needs to be specified with the positional relation between characters and their corresponding words. The other way (shown as 1(b)) is to add word information into their internal characters’ information, which can either use one encoder to operate [8], or use two encoders to encode characters and words separately [4]. Previous work tends to integrate multiple words’ information into a character representation, which might introduce redundant information and bring noises. Our work is in line with Method (b), but we design a more comprehensive strategy to exploit word semantics and enrich character representation.

In this paper, we propose a new method, Hidden Representation Mix and Fusion (HRMF), exploiting word semantics to enrich character representations of Chinese pre-trained models in the fine-tuning stage. Firstly, the importance of each character in a word is calculated based on the cosine similarity between the character’s representation and its paired word’s representation. Then we integrate the word embedding into the representation of each internal character according to the importance weight. After that, we apply a mixing mechanism to enable characters within a word exchange information with each other to further enhance the character representation. In addition, we apply a multi-
head attention and a masked multi-head attention which masks the unimportant characters, and the final representation is obtained by fusing the representations given by the two attention mechanisms, which is then applied in downstream tasks. Moreover, in order to minimize the impact of word segmentation errors, we adopt a multi-tokenizer voting mechanism to obtain the final word segmentation result.

We conduct extensive experiments on several NLP tasks, including sentiment classification, sentence pair matching, natural language inference and machine reading comprehension. Experimental results show that our proposed method consistently improves the performance of BERT, BERT-wwm and ERNIE on different NLP tasks, and the ablation study shows that each component of our model yields improvement over the basic pre-trained models. Our code are made available at https://github.com/liwb1219/HRMF.

To sum, the contributions of this paper are as follows:

– We define the character’s importance in a word, which enables our model to lay particular emphasis on important characters in a word.
– We apply a mixing mechanism to facilitate information exchange between characters, which further enriches our character representation.
– We present a masked multi-head attention mechanism to discard the semantics of unimportant characters in a word, which provides a supplement to the original sentence representation.
– Our proposed method outperforms the main-stream Chinese pre-trained models on a variety of NLP tasks.

2 Related Work

To exploit word information and help the model extract a enhanced representation of Chinese characters, the related work can be roughly divided into traditional methods and transformer-based methods.

In traditional methods, Su et al. [18] propose a word-lattice based Recurrent Neural Network (RNN) encoder for NMT, which generalizes the standard RNN to a word lattice topology. Zhang et al. [21] propose a word-lattice based LSTM network to integrate latent word information into the character-based LSTM-CRF model, which uses gated cells to dynamically route information from different paths to each character. Ma et al. [13] propose a simple but effective method for incorporating lexicon information into the character representations, which requires only a subtle adjustment of the character representation layer to introduce the lexicon information.

As for the transformer-based pre-trained method, there are two main approaches: Splice and Add, as illustrated in Figure 1.

**Splice.** Pre-trained models are mostly constructed through the multi-head self-attention mechanism, which is not sensitive to location, the location information needs to be clearly specified in the model. Xue et al. [14] propose PLTE, which models all the characters and matched lexical words in parallel with batch processing. Lai et al. [6] propose a novel pre-training paradigm
for Chinese—Lattice-BERT, which explicitly incorporates word representations along with characters, thus can model a sentence in a multi-granularity manner. Li et al. [7] propose FLAT: Flat-LAttice Transformer for Chinese NER, which converts the lattice structure into a flat structure consisting of spans. Each span corresponds to a character or latent word and its position in the original lattice.

Add. The Splice method not only increases the complexity of sequence modeling, but also needs to be specified with the positional relation between characters and words. The Add method is relatively flexible, where the word information can be added to its corresponding character representation based on word boundary. The model can use one encoder or two. By using one encoder, the encoder can be used to simultaneously encode character information and word information. As for two encoders, they can be used to encode character information and word information separately. Diao et al. [4] propose ZEN, a BERT-based Chinese text encoder enhanced by N-gram representations. They use one encoder to encode character and the other encoder to encode N-gram, and combine the two lines of information at each layer of the model. Liu et al. [8] propose Lexicon Enhanced BERT (LEBERT) to integrate lexicon information between Transformer layers of BERT directly, where a lexicon adapter is designed to dynamically extract the most relevant matched words for each character using a char-to-word bilinear attention mechanism, and then is applied between adjacent layers.

3 Multiple Word Segmentation Aggregation

In the experiment, we use three tokenizers to vote, namely PKUSEG [12], LAC [5] and snownlp\footnote{https://github.com/isnowfy/snownlp}. With the segmentation results given by the tokenizers, we select the final segmentation result following two rules, the majority rule and the granularity rule. Firstly, with the beginning character $c_s$, we extract the segmented word starts with $c_s$ from the segmentation results of different tokenizers. We get $\{T^{A}_{c_s}, T^{B}_{c_s}, T^{C}_{c_s}\}$, which means the set of segmented words from different tokenizers starting with $c_s$. Then, following the majority rule, we select the one appears the most in $\{T^{A}_{c_s}, T^{B}_{c_s}, T^{C}_{c_s}\}$ as the first part of the segmentation result. If there are two words having the same time of occurrence, we choose the one with larger granularity. After determining the first segmented word $T_{c_s}$, we set the character after $T_{c_s}$ as the next beginning character and repeat this process until we get the final segmentation result. For a clear understanding, Figure 2 shows an example.

4 Projecting Word Semantics to Character Representation

The overall structure of our model is shown in Figure 3. We employ the pre-trained model BERT and its updated variants (BERT-wwm, ERNIE) to obtain
Fig. 2. Example of voting segmentation plan. Firstly, with the character “重” as the beginning character, “重庆” appears twice, and “重庆人” appears once. Following the majority rule, we choose “重庆” as the first part of the segmentation result. Then, we choose “人” as the beginning character. “人和” appears once, and “人和中学” appears once, which has the same time of occurrence. Following the granularity rule, the word with larger granularity is preferred, so we choose “人和中学”. Finally, the word segmentation result is “重庆/人和中学”.

the original character representation, and a parallel multi-head attention module is applied to facilitate the fusion of character representation and word semantics.

4.1 Integrating Word Embedding to Character Representation

At present, the mainstream Chinese pre-trained models usually use character-level features. In order to make use of lexical semantics, we integrate word knowledge into character representation. Specifically, we first calculate the cosine similarity between the character and its corresponding word. And then, we assign the word information to its internal characters based on the similarity score.

The input text is denoted as $S = (c_1, c_2, ..., c_n)$, and the hidden layer representation after BERT encoding is expressed as $H = \text{BERT}(S) = (h_1, h_2, ..., h_n)$. The $t$-th word in the text is $w_t = (c_i, ..., c_j)$. We first obtain word embedding by:

$$x_t = e^w(w_t) \quad (1)$$

where $e^w$ is a pre-trained word embedding lookup table [17].

We use two linear layers to transform dimensions and learn the difference between two different sets of vector spaces.

$$v_t = (\tanh(x_t W_1 + b_1)) W_2 + b_2 \quad (2)$$

where $W_1 \in \mathbb{R}^{d_w \times d_h}$, $W_2 \in \mathbb{R}^{d_h \times d_h}$, $b_1$ and $b_2$ are scalar bias. $d_w$ and $d_h$ denote the dimension of word embedding and the hidden size of BERT respectively.

To measure the semantic weight of each character within a word, we compute the cosine similarity:
Fig. 3. The architecture of our proposed model. The color shades of squares in the hidden representation mix layer indicate the importance weights of different characters. The masked multi-head attention means that unimportant characters are masked when calculating the attention score.

\[
\text{score}_k = \cos(h_k, v_t), k = i, ..., j
\]  

where \( \text{score}_k \) represents the cosine similarity between the word and its \( k \)-th character.

We integrate word information into character embeddings based on the similarity score:

\[
h_k^w = h_k + \frac{\text{score}_k}{\sum_{m \neq k} \text{score}_m} v_t, k = i, ..., j
\]  

where \( h_k^w \) denotes the updated hidden representation of character \( k \).

### 4.2 Mixing Character Representations within a Word

In order to enrich the representations of characters, we mix the embeddings of characters within a word, that is, we let the characters in one word exchange information with each other. First, we define the key character as the one that has the highest similarity score with the corresponding word:

\[
p = \arg\max(\text{score}_k), k = i, ..., j
\]  

where \( p \) denotes the index of the key character in a word.

Accordingly, the key character collects information from all other characters, and at the same time, the key character also passes its own information to all other characters.
Specifically, for single-character words, they keep the original representations. For two-character words, we let the key character passes a small amount of information to the non-important character, and the non-important character gives a small amount of information to the key character. For multi-character words (larger than or equal to three), we let the key character passes a small amount of information to all non-important characters, and all non-important characters give a small amount of information to the key character, while there is no information exchange among non-important characters.

We set a parameter $\lambda$ as the retention ratio of the key character information. We introduce a non-linear function to degrade its reduction rate. The hidden representation of characters in non-single-character words is calculated as follows:

$$\tilde{h}_k^w = \begin{cases} 
  f(\lambda)h_k^w + g(\lambda) \sum_{i \leq m \leq j} h_m^w, & k = p \\
  g(\lambda)h_p^w + (1 - g(\lambda))h_k^w, & k \neq p 
\end{cases}$$  \quad (6)

$$f(\lambda) = e^{\lambda - 1}$$  \quad (7)

$$g(\lambda) = \frac{1 - f(\lambda)}{j - i}$$  \quad (8)

where $\tilde{h}_k^w$ is the mixed hidden representation of character $k$.

Therefore, the new sequence is represented as:

$$\tilde{H} = (\tilde{h}_1^w, \tilde{h}_2^w, ..., \tilde{h}_n^w)$$  \quad (9)

### 4.3 Fusing New Character Embedding to Sentence Representation

We apply the self-attention mechanism on the mixed hidden representation obtained in the previous step to get a new hidden representation $H^1$:

$$H^1 = \text{softmax}(\frac{(QW_1^q)(KW_1^k)}{\sqrt{d_h}})(VW_1^v)$$  \quad (10)

where $Q$, $K$ and $V$ are all equal to the collective representation $\tilde{H}$ obtained in the previous step. $W_1^q$, $W_1^k$, $W_1^v$ are trainable parameter matrices.

Taking into account that the non-important characters’ information has been integrated into the key character’s representation, when calculating the attention score, those non-important characters can be masked. In this way, a new hidden representation $H^2$ is obtained by a masked self-attention:

$$H^2 = \text{softmax}(\frac{(QW_2^q)(KW_2^k)}{\sqrt{d_h}} + \text{mask})(VW_2^v)$$  \quad (11)
\[
    \text{mask}_{ij} = \begin{cases} 
    0, & j \in \Omega \\
    -\infty, & j \notin \Omega 
    \end{cases} 
\]

where \( W^2_q, W^2_k, W^2_v \) are trainable parameter matrices, \( \text{mask} \in \mathbb{R}^{n \times n} \), \( \Omega \) is the set of subscripts corresponding to important words.

The final representation is obtained by fusing two sorts of embeddings:

\[
    \hat{H} = \mu H^1 + (1 - \mu) H^2 
\]

where \( \hat{H} \) is the final hidden representation, which will be applied to downstream tasks.

5 Experimental Setup

5.1 Tasks and Datasets

In order to prove the effectiveness of our proposed method, we conduct experiments on the following four public datasets with several NLP tasks. For data statistics of these datasets, please refer to Table 1.

Sentiment Classification (SC): ChnSentiCorp is a Chinese sentiment analysis data set, containing online shopping reviews of hotels, laptops and books.

Sentence Pair Matching (SPM): LCQMC [9] is a large Chinese question matching corpus, aiming to identify whether two sentences have the same meaning.

Natural Language Inference (NLI): XNLI [1] is a cross-lingual natural language inference corpus, which is a crowdsourced collection of multilingual corpora. We only use the Chinese part.

Machine Reading Comprehension (MRC): DRCD [16] is a span-extraction MRC dataset written in Traditional Chinese.

| Dataset       | Task      | MaxLen | Batch | Epoch | Blr* | ERNIE lr* | Train | Dev | Test | Domain     |
|---------------|-----------|--------|-------|-------|------|-----------|-------|-----|-----|------------|
| ChnSentiCorp  | SC        | 256    | 64    | 4     | 3e-5 | 3e-5      | 9.6K  | 1.2K | 1.2K | various    |
| LCQMC         | SPM       | 128    | 64    | 3     | 2e-5 | 3e-5      | 239K  | 8.8K | 12.5K | Zhidao     |
| XNLI          | NLI       | 128    | 64    | 2     | 3e-5 | 5e-5      | 393K  | 2.5K | 5K  | various    |
| DRCD          | MRC       | 512    | 16    | 2     | 3e-5 | 5e-5      | 27K   | 3.5K | 3.5K | Wikipedia  |

Table 1. Hyper-parameter settings and data statistics in different tasks. Blr* represents the initial learning rate of BERT/BERT-wwm model for the AdamW optimizer.

5 https://github.com/pengming617/bert_classification
5.2 Baseline Models

We adopt the pre-trained models BERT [3], BERT-wwm [2] and ERNIE [19] as our base architectures.

5.3 Training Details

In order to ensure the fairness and robustness of the experiment, for the same dataset and encoder, we use the same parameters, such as maximum length, warm-up ratio, initial learning rate, optimizer, etc. We repeated each experiment five times and reported the average score.

We do experiments using the Pytorch [15] framework, and all the baseline weight files were converted to the Pytorch version. At training time, we fix the pretrained word embeddings, using the AdamW optimizer [11], the weight decay is 0.02, and the warm-up ratio is 0.1. The proportion of the key character information retention $\lambda$ is set to 0.9. The fusion coefficient $\mu$ is set to 0.5. For detailed hyper-parameter settings, please see Table 1.

6 Results and Analysis

6.1 Overall Results

Table 2 shows the experimental results on four public data sets with different NLP tasks, which demonstrates that our method obtains an obvious improvement compared with the baseline pre-trained models.

| Task | SC | SPM | NLI | MRC | avg. |
|------|----|-----|-----|-----|------|
| Dataset | ChnSentiCorp | LCQMC | XNLI | DRCD | cls | all |
| BERT | 94.72 | 86.61 | 77.85 | 85.48 | 91.36 | 86.39 | 87.20 |
| +HRMF | 95.48 | 87.24 | 78.44 | 86.32 | 91.76 | 87.05 | 87.85 |
| BERT-wwm | 94.82 | 86.67 | 78.02 | 85.79 | 91.66 | 86.50 | 87.39 |
| +HRMF | 95.36 | 86.96 | 78.21 | 86.55 | 92.11 | 86.84 | 87.84 |
| ERNIE | 95.32 | 87.26 | 78.26 | 87.78 | 93.20 | 86.95 | 88.36 |
| +HRMF | **96.12** | **88.29** | **78.87** | **88.59** | **93.70** | **87.76** | **89.11** |

Specifically, in the classification task, our method yields the most obvious improvement in sentiment analysis, with an improvement of 0.76 over BERT, 0.54 over BERT-wwm and 0.80 over ERNIE. We believe that this is because the emotional polarity of a sentence is more sensitive to word semantics. In other words, the emotional tendency of a sentence is likely to be determined by some of the words. Similarly, in sentence meaning matching and natural
language inference, our method also achieves an average improvement of 0.65 and 0.46 compared with three baseline models. As for the task of machine reading comprehension, our method significantly improves the EM index with an average improvement of 0.80, which shows that after incorporating word knowledge, the model judges the boundary of answers more accurately. The baseline models already achieve a relatively high F1 score, and our method still obtains an average improvement of 0.45 on F1.

6.2 Ablation Study

In order to verify the effectiveness of our method, we strip off different parts of the model to conduct experiments, as shown in Table 3.

Table 3. Ablation study of different components. As shown in Figure 2, HRMF is the complete model of this paper. -HRML is to remove the hidden representation of mix layer; -MMHA means to remove the masked multi-head attention module.

| Task   | SC       | SPM     | NLI     | MRC      |
|--------|----------|---------|---------|----------|
| Dataset | ChnSentiCorp | LCQMC | XNLI | DRCD | EM / F1 |
| BERT   | 94.72    | 86.61   | 77.85   | 85.48 / 91.36 |
| BERT+HRMF | 95.48    | 87.24   | 78.44   | 86.32 / 91.76 |
| BERT+HRMF-HRML | 95.30    | 86.92   | 78.18   | 86.00 / 91.73 |
| BERT+HRMF-MMHA | 95.40    | 87.14   | 78.16   | 86.09 / 91.77 |

After stripping off the hidden representation mix layer, the model has an obvious drop in the performance. It decreases by 0.18, 0.32, 0.26, 0.32 respectively on the four data sets. The performance of the model declines the most compared with other stripped off models on three data sets, which shows that mixing the representation of the characters within a word greatly enhances the representation of the original character representation. Besides, after stripping off the masked multi-head attention module, the model also gets a drop in the performance, which demonstrates that downstream tasks benefit from the additional representation of masked multi-head attention module that masks unimportant characters.

6.3 Case Study

To better demonstrate our model’s improvement on the understanding of semantics, we conduct case studies on several specific instances, as shown in Figure 4 for classification tasks.

Compared with BERT, our proposed model obtains better performance on several tasks. On the Sentiment Classification (SC) task, our model has a better understanding on the sentences that have a emotional semantic transition. For example, in Case 1, the sentences’ emotional tendencies change from negative to positive through the word ”不过(However)”, which is accurately understood
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Fig. 4. Some examples of classification tasks.

by our model. On the Sentence Pair Matching (SPM) task, our proposed model shows a better understanding on the relation between sentences’ semantic information. For example, our model can accurately understand that "胎儿(fetus)" has the same meaning from "宝宝(baby)" in Case 2. On the Natural Language Inference (NLI) task, our model can accurately identify the relation between semantic information and make correct inference. For example, in case 3, our model recognizes that "不是个好人(not a good man)" has the same meaning with "是个混蛋(an asshole)". One possible reason that our model outperforms BERT is that our model integrates word semantic information.

7 Conclusion

In this paper, we propose a method HRMF to improve character-based Chinese pre-trained models by integrating lexical semantics into character representations. We enrich the representations by mixing the intra-word characters’ embeddings, and add a masked multi-head attention module by masking unimportant characters to provide a supplement to the original sentence representation. We conduct extensive experiments on four different NLP tasks. Based on the main-stream Chinese pre-trained models BERT, BERT-wwm, and ERNIE, our proposed method achieves obvious improvements, which proves its effectiveness and universality. In future work, we will combine more knowledge with Chinese characteristics to further improve Chinese pre-trained models for downstream tasks.

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