MarkBERT: Marking Word Boundaries Improves Chinese BERT
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Abstract
We present a Chinese BERT model dubbed MarkBERT that uses word information. Existing word-based BERT models regard words as basic units, however, due to the vocabulary limit of BERT, they only cover high-frequency words and fall back to character level when encountering out-of-vocabulary (OOV) words. Different from existing works, MarkBERT keeps the vocabulary being Chinese characters and inserts boundary markers between contiguous words. Such design enables the model to handle any words in the same way, no matter they are OOV words or not. Besides, our model has two additional benefits: first, it is convenient to add word-level learning objectives over markers, which is complementary to traditional character and sentence-level pre-training tasks; second, it can easily incorporate richer semantics such as POS tags of words by replacing generic markers with POS tag-specific markers. MarkBERT pushes the state-of-the-art of Chinese named entity recognition from 95.4\% to 96.5\% on the MSRA dataset and from 82.8\% to 84.2\% on the OntoNotes dataset, respectively. Compared to previous word-based BERT models, MarkBERT achieves better accuracy on text classification, keyword recognition, and semantic similarity tasks.

1 Introduction
Chinese words can be composed of multiple Chinese characters. For instance, the word 地球 (earth) is made up of two characters 地 (ground) and 球 (ball). However, there are no delimiters (i.e., space) between words in written Chinese sentences. Traditionally, word segmentation is an important first step for Chinese natural language processing tasks (Chang et al., 2008). Instead, with the rise of pre-trained models (Devlin et al., 2018), Chinese BERT models are dominated by character-based ones (Cui et al., 2019a; Sun et al., 2019; Cui et al., 2020; Sun et al., 2021b,a), where a sentence is represented as a sequence of characters. There are several attempts at building Chinese BERT models where word information is considered. Existing studies tokenize a word as a basic unit (Su, 2020), as multiple characters (Cui et al., 2019a) or a combination of both (Zhang and Li, 2020; Lai et al., 2021; Guo et al., 2021). However, due to the limit of the vocabulary size of BERT, these models only learn for a limited number (e.g., 40K) of words with high frequency. Rare words below the frequency threshold will be tokenized as separate characters so that the word information is neglected.

In this work, we present a simple framework, MarkBERT, that considers Chinese word information. Instead of regarding words as basic units, we use character-level tokenizations and inject word information via inserting special markers between contiguous words. The occurrence of a marker gives the model a hint that its previous character is the end of a word and the following character is the beginning of another word. Such a simple model design has the following advantages. First, it avoids the problem of OOV words since it deals with common words and rare words (even the words never seen in the pre-training data) in the same way. Second, the introduction of marker allows us to design word-level pre-training tasks (such as replaced word detection illustrated in section 2), which are complementary to traditional character-level pre-training tasks like masked language modeling and sentence-level pre-training tasks like next sentence prediction. Third, the model is easy to be extended to inject richer semantics of words.

In the pre-training stage, we train our model with two pre-training tasks. The first task is masked language modeling. We also mask markers such that word boundary knowledge can be learned. The second task is replaced word detection. We replace

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Figure 1: An illustrative example of our model. Box (a) gives the original input written in Chinese, its translation in English, word segmentation results given by an off-the-shell text analyzer, and the POS tags of words. Box (b) shows a traditional character-level Chinese BERT. Box (c) shows the base model of MarkBERT, in which generic word boundary markers $[S]$ are inserted between words. In box (d), the POS tag version of MarkBERT replaces the generic markers $[S]$ with POS tag specific ones such as $[S_{NN}]$ and $[S_{VV}]$.

2 MarkBERT Pre-training

2.1 MarkBERT Model

In Chinese language model pre-training, the encoding unit is different from the widely used BPE encoding in English: Chinese pre-trained models are usually character-level and word level information is typically neglected.

To make better use of word-level information in Chinese pre-training, we introduce a simple framework called MarkBERT. We insert markers between word spans to give explicit boundary information for the model pre-training. As seen in Figure 1, we first use a segmentation tool to obtain word segmentations, then we insert special markers between word spans as separators between characters. These markers are treated as normal characters so they take positions in the transformers structure. Plus, they can also be masked for the mask language modeling task to predict, therefore the encoding process needs to be aware of predicting word boundaries rather than simply filling in masks from the context. The mask prediction task becomes more challenging since predicting the masks correctly requires a better understanding of the word boundaries. In this way, the model is still character-level encoded while it is aware of word boundaries since word-level information is given explicitly.

2.2 Replaced Word Detection

To further strengthen the model, we adopt a replaced word detection task. Specially, when a word span is replaced by a confusion word, the marker is supposed to make a "replaced" prediction labeled as "False", otherwise labeled as "True". Formally, suppose the representation of the $i$th marker is $x^i$ with label $y^{true}$ and $y^{false}$, the replaced word detection loss is:

$$L = -\sum_i [y^{true} \cdot \log(x^i_y) + y^{false} \cdot \log(x^i_y)]$$

(1)
We add this loss term to the masked language modeling loss as a multi task training process.

We construct confusion words can come from synonyms or phonetics similar words. Through this task, the markers can be more sensitive to the word span in the context since these markers are assigned to discriminate the representation type of the word spans before them. This process is similar to an ELECTRA (Clark et al., 2020) framework.

In addition, we can improve the MarkBERT model by using richer-semantic markers instead of simply a special token. For example, we can use part-of-speech tags as markers to insert between word spans to construct a richer-semantic model called MarkBERT-POS. More details can be found in Appendix B.

2.3 Pre-Training
In our MarkBERT pre-training, the mask ratio is still 15% of the total characters. For 30% of the time, we do not insert any markers so that the model can also be used in a no-marker setting which is the vanilla BERT-style model. For 50% of the time we run a whole-word-mask prediction and for the rest we run a traditional masked language model prediction. In the marker insertion, for 30% of the time, we replace the word span with a phonetic(pinyin)-based confusion or a synonym-based confusion word and the marker will predict a phonetic(pinyin)-confusion marker or a synonym-confusion marker; for the rest of the time, the marker will predict a normal-word marker. To avoid imbalance labels of the marker learning process, we only calculate 15% percent of loss on normal markers. We give implementation details in the Appendix C.

3 Experiments
To test the performance of our proposed MarkBERT, we conduct experiments on the NER. Other experiments and analysis on natural language understanding tasks can be found in the Appendix D.

### Table 1: NER results on the MSRA and OntoNotes dataset.

| Model                                      | MSRA(Test) | OntoNotes(Dev) | OntoNotes(Test) |
|--------------------------------------------|------------|----------------|-----------------|
| BERT (Devlin et al., 2018)                 | 94.9       | 74.8           | 78.0            |
| RoBERTa (Cui et al., 2019a)                | 95.3       | 76.8           | 77.6            |
| FLAT-BERT (Li et al., 2020)                | -          | -              | -               |
| Soft-Lexicon (Ma et al., 2019)             | 95.8       | 80.3           | 83.4            |
| RoBERTa (ours)                             | 95.7       | 80.3           | 83.4            |
| MarkBERT (ours)                           | 96.5       | 84.1           | 85.4            |

Table 2: Ablation Studies with development set F1 score results.

|                      | MSRA | Ontonotes | Ours w/o syn | w/o pho | MLM w/o marker |
|----------------------|------|----------|--------------|---------|---------------|
|                      | 96.5 | 83.8     | 96.2         | 96.0    | 95.5          |

3.1 NER Task and Implementations
In the NER task, we use the MSRA (Levow, 2006) and Ontonotes (Weischedel et al., 2013) datasets with the same data-split as in Ma et al. (2019) and Li et al. (2020). We compare with FLAT-BERT (Li et al., 2020) and Soft-Lexicon (Ma et al., 2019) which are state-of-the-art models on the NER task which incorporate lexicons in the transformers/LSTM structure. We use the Huggingface Transformers (Wolf et al., 2020) to implement all experiments and follow the implementation details given in the Transformers toolkit. ①

### Table 2: Ablation Studies with development set F1 score results.

3.2 Results on NER Task
In Table 1, our proposed boundary-aware MarkBERT outperforms all baseline models including pre-trained models and lexicon-enhanced models.

Compared with the baseline methods, our proposed MarkBERT with markers inserted between words can lift performances by a large margin. When we insert markers using the same tokenization process used in pre-training MarkBERT in fine-tuning the MarkBERT in the NER task, we obtain a considerable performance improvement compared with SOTA methods, indicating that the inserted markers catch some important fine-grained information that helps improve entity understanding. The improvement proves the effectiveness of inserting markers for better understanding word

①https://github.com/huggingface/transformers
Figure 2: Visualization of attentions of the markers selected from a random layer. We use [unused1] in the BERT vocabulary as the inserted marker.

3.3 Model Analysis

We conduct ablation experiments to explore the effectiveness of each part in our MarkBERT framework in different tasks:

- MarkBERT-MLM only considers the MLM task without the replaced word detection task.
- MarkBERT-rwd is a version that removes phonetics words or synonyms separately in the replaced word detection process.
- MarkBERT-w/o marker is a version that removed markers during downstream task finetuning which is the same as the vanilla BERT model.

From the ablation results represented in Table 2, we can make conclusions as follows. (1) the MarkBERT-MLM model gains significant boost in the NER task, indicating that word boundary information is important in the fine-grained task. (2) without inserting markers, MarkBERT-w/o marker can still achieve similar performances with the baseline methods in the language modeling tasks, indicating that MarkBERT can also be used as a vanilla BERT model for easy usage in language understanding tasks. As for the NER task, inserting markers is still important, indicating that MarkBERT structure is effective in learning word boundaries for tasks that requires such fine-grained representations.

3.3.1 Visualization of Marker Attentions

To further explore how the markers work in the encoding process, we use the attention visualization tool to show the attention weights of the inserted markers. We explore the attention weights on the pre-trained MarkBERT and the fine-tuned model based on the Ontonotes NER task. As seen in Figure 2, the pre-trained representations of the markers are focusing on the local semantics of the word-level information. These markers are also connected to other special tokens indicating that the markers play important roles in learning the context representations.

4 Related Work

Pre-trained models exemplified by BERT (Devlin et al., 2018) and RoBERTa (Cui et al., 2019a) have been proved successful in various Chinese NLP tasks (Xu et al., 2020; Cui et al., 2019b). Existing Chinese BERT models that incorporate word information can be divided into two categories. The first category uses word information in the pre-training stage but represents a text as a sequence of characters when the pretrained model is applied to downstream tasks (Cui et al., 2019a; Lai et al., 2021). The second category uses word information when the pretrained model is used in downstream tasks (Su, 2020; Zhang and Li, 2020; Guo et al., 2021). In this paper, MarkBERT incorporate the boundary information in the training process latent.

The idea of inserting markers is explored in entity-related natural language understanding tasks, especially in relation classification. Given a subject entity and an object entity as the input, existing work inject untyped markers (Sun et al., 2019; Soares et al., 2019) or entity-specific markers (Zhong and Chen, 2020) around the entities, and make better predictions of the relations of the entities.

5 Conclusion and Future Work

In this paper, we have introduced MarkBERT, a simple framework for Chinese language model pre-training. We insert special markers between word spans in the character-level encodings in pretraining and fine-tuning to make use of word-level information in Chinese. We test our proposed model on the NER tasks as well as natural language understanding tasks. Experiments show that MarkBERT makes significant improvements over baseline models. In the future, we are hoping to incorporate more information to the markers based on the simple structure of MarkBERT.
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Appendix

A Word-level Chinese BERT models

We provide an illustration of word-level Chinese BERT models.

• Word-Level BERT: Su (2020) uses a word-level vocabulary. The vocabulary size is limited therefore may face out-of-vocabulary problems.

• Lattice BERT: Lai et al. (2021) uses lexicons to enhance the character-level encodings (left side of the encoder in Figure 3 (b) ). It uses the parallel structure in the transformers to discriminate characters and additional lexicons.

• LICHEE: Guo et al. (2021) uses both character and word level embeddings before passing that into the BERT encoder to incorporate word-level information.

B MarkBERT Implementation Details

In addition, we can improve the MarkBERT model by using richer-semantic markers instead of simply a special token. Similar to the MarkBERT model, we use part-of-speech tags as markers to insert between word spans to construct a richer-semantic model called MarkBERT-POS. In this way, the model can be given clearer information for understanding the context. As seen in Figure 1(d), these special markers can be replaced by POS-tags acquired externally. These POS-tag markers can also be masked as well, so the mask language modeling task also needs to predict correct POS-tags.

The idea of using pos-tags is a naive usage of expanding markers. Our model can be further expanded with more helpful information as the inserted special markers.

To obtain the synonyms, we use an external word embedding provided by Zhang and Yang (2018). We calculate the cosine similarity between words and use the most similar ones as the synonyms confusions. To obtain the phonetic-based confusions, as seen in Figure 4, we use an external tool to get the phonetics of the word and select a word that share the same phonetics as its confusions.

In the masked language modeling task, we employ both the masked language modeling strategy and the whole-word-masking strategy. In the replaced word detection task, as seen in Figure 4, when the word span is replaced by confusion words, the model is supposed to correct the confusions. This correction process is similar to MacBERT (Cui et al., 2020). For the confusion generation, we use synonyms and pinyin-based confusions. The synonyms are obtained by a synonym dictionary based on calculating the cosine similarity between
the Chinese word-embeddings provided by Zhang and Yang (2018).

We need to notice that most of the time the marker is a normal marker if the normal markers are not POS-tag enhanced. Therefore, we only calculate 15% percent of loss on these normal markers to avoid imbalance labels of the marker learning process. During fine-tuning on downstream tasks, we use the markers in the input texts. Also, we can save the markers and downgrade the model to a vanilla BERT-style model for easier usage.

C Pre-training Implementation Details

C.1 Pre-training Dataset Usage

We use a collection of raw Chinese texts containing Chinese wikipedia, Chinese novels, news. The entire data size is around 80B characters. We use a simple word segmentation tool Texsmart (Zhang et al., 2020) to tokenize the raw data and obtain pos-tags. We use the same data preprocess framework used in BERT (Devlin et al., 2018) which constructs documents containing multiple sentences with the length of the maximum token limit and randomly pick another document to train the next sentence prediction task.

C.2 Pre-Training Settings

We initialize our model from the Roberta whole-word-mask model checkpoint provided by Cui et al. (2019a). Therefore, we use the same character-level vocabulary in training our boundary-aware model. We use both whole-word-mask and normal character mask strategies in the language model training since we aim to learn inner connections between characters in the given word which cannot be achieved by whole-word-masking alone.

We train the model with a maximum sequence length of 512 for the entire training time. With the markers inserted, the actual maximum sequence length is smaller but we maintain the length as 512 to keep coordinated with previous pre-trained models. We use the ADAM optimizer (Kingma and Ba, 2014) used in BERT with a batch size 8,192 on 64x Tesla V100 GPUs. We set the learning rate to 1e-4 with a linear warmup scheduler. We run the warmup process for 10k steps and train 100k steps in total.

D Experiments on Language Understanding Task

We also conduct experiments on language understanding tasks. We use various types of tasks from the CLUE benchmark (Xu et al., 2020). We use classification tasks such as TNEWS, IFLYTEK;
### D.1 Results on Language Understanding

Table 3 shows that comparing with the RoBERTa model that uses the same pre-training data, MarkBERT is superior in all tasks. This indicates that the learned representations contain more useful information for the downstream task fine-tuning. The word-level model WoBERT (ours) trained with the same data used in MarkBERT only achieves a slightly higher accuracy in the IFLYTEK dataset which might because the IFLYTEK dataset contains very long texts where word-level model is superior since it can process more contexts while the total sequence lengths of character level and word level model are both 512.

When comparing with previous works that focus on word-level information, MarkBERT achieves higher performances than the multi-grained encoding method AMBERT as well as LICHEE which incorporates word information as an additional embedding. We can assume that adding word-level information through **horizontal** markers is more effective than **vertically** concatenating word-level information. When comparing with the LatticeBERT model, our method can still reach a competitive level of performance, meanwhile the relative improvements of our model is larger than the improvements of the LatticeBERT model. Please note that the lexicons used in LatticeBERT training actually contains more segmentation possibilities which can significantly increase the downstream task performance over the word segmentation based methods (Zhang and Yang, 2018). The basic idea of incorpor-
Datasets
MSRA Ontonotes TNEWS IFLYTEK AFQMC

| DEVELOPMENT | F1 | F1 | Acc. | Acc. | Acc. |
|-------------|----|----|------|------|------|
| MarkBERT    | 96.5 | 83.8 | 58.4 | 60.6 | 74.8 |
| MarkBERT-rwd-pho | 96.2 | 83.4 | 58.0 | 60.8 | 74.3 |
| MarkBERT-rwd-syn | 96.2 | 83.5 | 58.0 | 60.9 | 74.5 |
| MarkBERT-MLM | 96.0 | 83.3 | 58.0 | 60.7 | 74.6 |
| MarkBERT-w/o marker | 95.5 | 79.2 | 58.2 | 61.0 | 74.5 |
| RoBERTa (ours) | 95.1 | 78.2 | 57.9 | 60.8 | 74.5 |

Table 4: Ablation Studies on the NER and the language understanding tasks using dev set results.

Figure 5: Results on different MarkBERT versions.

rating lexicons is parallel with the marker insertion framework. MarkBERT makes use of word-level information in a different perspective.

D.2 Influence of Different Sementation Tools in MarkBERT

The quality of the pre-processed segmentation results may play a vital role, therefore, we use a different version of segmentation in the Texsmart toolkit (Zhang et al., 2020) where the segmentations are more fine-grained to train a MarkBERT-seg-v2 model as a comparison.

As seen in figure 5, segmentation quality is trivial to MarkBERT. The performances of MarkBERT (seg-v1) is similar to a variant MarkBERT-seg-v2 using a different segmentation tool, which indicates that the training framework helps rather than the information from an external segmentation tool.

Combined with results in Table 4, we can conclude that introducing segmentation tools and use mark-style encoding is important while the quality of the segmentation is trivial.

We establish several strong baselines to explore the effectiveness of our MarkBERT. In language understanding tasks, we compare with the RoBERTa-wwm-ext (Cui et al., 2019a) baseline, which is a whole-word-mask trained Chinese pre-trained models. We also further pre-train the RoBERTa model denoted as RoBERTa (ours) and the WoBERT model denoted as WoBERT (ours) based on our collected data which is the same data used in pre-training MarkBERT to make fair comparisons with our model.

For the language understanding tasks, we follow the implementation details used in the CLUE benchmark official website and the fine-tuning hyper-parameters used in Lattice-BERT (Lai et al., 2021).

In the CLUE benchmark, the situation becomes different: in the IFLYTEK task, inserting markers will hurt the model performance which is because the sequence length exceeds the maximum length of the pre-trained model. Therefore, inserting markers will results in a lost of contexts.