Pre-trained Model for Chinese Word Segmentation with Meta Learning

Zhen Ke\(^1\), Liang Shi\(^1\), Erli Meng\(^1\), Bin Wang\(^1\), Xipeng Qiu\(^2\)

Xiaomi AI Lab, Xiaomi Inc., Beijing, China\(^1\)
Shanghai Key Laboratory of Intelligent Information Processing, Fudan University\(^2\)
kezhen,shiliang1,mengerli,wangbin11\}@xiaomi.com
xpqiu\}@fudan.edu.cn

Abstract

Recent researches show that pre-trained models such as BERT (Devlin et al., 2019) are beneficial for Chinese Word Segmentation tasks. However, existing approaches usually fine-tune pre-trained models directly on a separate downstream Chinese Word Segmentation corpus. These recent methods don’t fully utilize the prior knowledge of existing segmentation corpora, and don’t regard the discrepancy between the pre-training tasks and the downstream Chinese Word Segmentation tasks. In this work, we propose a Pre-Trained Model for Chinese Word Segmentation, which can be abbreviated as PTM-CWS. PTM-CWS model employs a unified architecture for different segmentation criteria, and is pre-trained on a joint multi-criteria corpus with meta learning algorithm. Empirical results show that our PTM-CWS model can utilize the existing prior segmentation knowledge, reduce the discrepancy between the pre-training tasks and the downstream Chinese Word Segmentation tasks, and achieve new state-of-the-art performance on twelve Chinese Word Segmentation corpora.

1 Introduction

Chinese Word Segmentation (CWS) is a fundamental task for Chinese natural language processing, which aims at identifying word boundaries in a sentence composed of continuous Chinese characters. Most existing approaches convert the CWS task into a character-based sequence labeling task (Xue, 2003; Zheng et al., 2013; Chen et al., 2015; Ma et al., 2018; Qiu et al., 2019).

Recently, pre-trained models such as BERT (Devlin et al., 2019) have been introduced into CWS tasks, which can leverage prior linguistic knowledge and boost the performance of CWS systems. Yang (2019) directly fine-tunes BERT model on CWS tasks. Huang et al. (2019) fine-tunes BERT in a multi-criteria learning framework, where each criterion shares a common BERT-based feature extraction layer and owns a private projection layer. Meng et al. (2019) enriches Chinese character representations with glyce information and combines it with the pre-trained BERT representations. However, BERT is pre-trained with the Masked Language Modeling task and then fine-tuned on downstream CWS tasks. Thus, pre-trained models like BERT can not make full use of the prior knowledge of existing segmentation resource. Furthermore, due to the discrepancy between pre-training tasks and downstream CWS tasks, pre-trained models may not provide suitable initialization for downstream tasks.

To utilize the prior segmentation knowledge and alleviate the discrepancy between pre-training tasks and downstream CWS tasks, we propose a Pre-Trained Model for Chinese Word Segmentation, namely PTM-CWS. PTM-CWS employs a unified architecture for different criteria in Chinese Word Segmentation, and is pre-trained on a joint multi-criteria corpus with meta learning algorithm (Finn et al., 2017). The pre-trained PTM-CWS model can utilize fully the prior segmentation knowledge, reduce the discrepancy between the pre-training tasks and the downstream Chinese Word Segmentation tasks, thus provide a better initialization for the downstream CWS tasks.

Experiments show that our PTM-CWS model can outperform the original pre-trained BERT model when fine-tuned on downstream CWS tasks, and achieve new state-of-the-art results on twelve CWS datasets. Further experiments show that PTM-CWS can generalize better on the unseen criteria with fewer data in low-resource setting, and improve the Out-Of-Vocabulary (OOV) recalls in comparison with BERT. To the best of
our knowledge, our proposed PTM-CWS model is the first pre-trained model especially for the Chinese Word Segmentation task.

2 Approach

In this section, we will describe PTM-CWS model in three parts. First we present the joint multi-criteria corpus for pre-training. Second, we introduce the unified architecture for different criteria. Finally, we elaborate on the meta learning algorithm used for pre-training optimization.

2.1 Joint Multi-Criteria Corpus

As shown in Table 1, different CWS criteria usually share a large proportion of common prior segmentation knowledge and may overlap on most words.

| Criteria | Li | Na | entered | the semi-final |
|----------|----|----|---------|---------------|
| CTB6     | 李娜 | 进入 | 半决赛 |
| PKU      | 李娜 | 进入 | 半决赛 |
| MSRA     | 李娜 | 进入 | 半决赛 |

Table 1: An example of CWS on different criteria.

We propose a joint multi-criteria corpus for pre-training of PTM-CWS, to make full use of the prior segmentation knowledge of existing CWS resources. Nine CWS datasets of different criteria are used as our joint multi-criteria corpus.

The sentence under each criterion is augmented with criterion, and then merged into a joint multi-criteria corpus. To represent criterion information, we add a specific criterion token to the front of the input sentence, such as [pku] for PKU criterion (Emerson, 2005). Then we add [CLS] and [SEP] token to the sentence head and tail like BERT (Devlin et al., 2019). The augmented input sentence represents both criterion and text information.

We randomly pick 10% sentences from the joint multi-criteria corpus and replace their criterion tokens with a special token [unc], which means undefined criterion. The undefined criterion is used to learn criterion-independent segmentation knowledge and helps to transfer prior segmentation knowledge to downstream CWS tasks.

2.2 The Unified Architecture

In traditional Chinese Word Segmentation system (Ma et al., 2018), the CWS model adopts a separate architecture for each segmentation criterion. Thus, an instance of such model can only serve one segmentation criterion, without sharing any knowledge between different criteria.

To better leverage the prior segmentation knowledge, our PTM-CWS employs a unified architecture with shared encoder and decoder for different criteria. We utilize a BERT-like (Devlin et al., 2019) shared encoder for all criteria, encoding the augmented input sentence into hidden text representations. Then a shared linear classifier with softmax is followed to map hidden representations to the distribution over the segmentation labels, which consist of \{B, M, E, S\}. It should be noted that the unified architecture of PTM-CWS is similar to BERT’s architecture, instead of using the pre-trained parameters of BERT directly.

Given the augmented input sentence \(X\), our unified architecture predicts its segmentation sequence labels \(Y\) of corresponding criterion. We use the normal supervised cross-entropy loss function as objective for pre-training on corpus \(D\):

\[
L(\theta; D) = -\sum_{X,Y \in D} \log P_\theta(Y|X)
\]

(1)

2.3 Meta Learning

The objective of normal pre-training is to maximize its performance on pre-training tasks, which may lead to the discrepancy between the pre-trained model and downstream tasks. To alleviate the above task discrepancy, we utilize the meta learning (Lv et al., 2020) algorithm for pre-training optimization of our PTM-CWS model. The main objective of meta learning is to maximize generalization performance on downstream tasks, preventing it from overfitting on pre-training tasks.

The meta-learning algorithm (Finn et al., 2017) treats the pre-training task \(T\) as one of the downstream tasks, instead of a special task. It tries to optimize the meta parameters \(\theta_0\), from which we can get the task-specific model parameters \(\theta_k\) by \(k\) gradient descent steps over the training data \(D_{T,\text{train}}^{\text{train}}\),

\[
\theta_k = \theta_0 - \alpha \nabla_{\theta_0} L_T(\theta_0; D_{T,\text{train}}^{\text{train}}),
\]

\[
\ldots
\]

\[
\theta_k = \theta_{k-1} - \alpha \nabla_{\theta_{k-1}} L_T(\theta_{k-1}; D_{T,k}^{\text{train}}),
\]

(2)
in which $\alpha$ is learning rate, $D_{T,i}^{train}$ is the $i$-th batch of training data. The task specific parameters $\theta_k$ can be denoted as a function of meta parameters $\theta_0$ as follows: $\theta_k = f_k(\theta_0)$.

To optimize the generalization performance on task $T$, we should optimize meta parameters $\theta_0$ on the batch of test data $D_{T}^{test}$ such that,

$$
\theta_0^* = \arg \min_{\theta_0} L_T(\theta_k; D_{T}^{test})
$$

$$
= \arg \min_{\theta_0} L_T(f_k(\theta_0); D_{T}^{test})
$$

The above optimization could be achieved by gradient descent, so the update rule for meta parameters $\theta_0$ is as follows:

$$
\theta_0 = \theta_0 - \beta \nabla_{\theta_0} L_T(\theta_k; D_{T}^{test})
$$

$$
L_T(\theta_k; D_{T}^{test}) = \nabla_{\theta_k} L_T(\theta_k; D_{T}^{train}) \times \nabla_{\theta_k} \theta_k \times \cdots \nabla_{\theta_k} \theta_k
$$

$$
= \nabla_{\theta_k} L_T(\theta_k; D_{T}^{train}) \prod_{j=1}^{k} \left( I - \alpha \nabla_{\theta_j} L_T(\theta_j; D_{T,j}^{train}) \right)
$$

$$
\approx \theta_0 - \beta \nabla_{\theta_0} L_T(\theta_k; D_{T}^{test})
$$

where $\beta$ is the meta learning rate, and the last step in Equation 4 adopts first-order approximation for computational simplification.

**Algorithm 1 Meta Learning for Pre-training Optimization**

**Require**: Distribution over pre-training task $p(T)$, initial meta parameters $\theta_0$, objective function $L$

**Require**: Learning rate $\alpha$, meta learning rate $\beta$, meta train steps $k$

1: for $t = 1, 2, \ldots$ do
2: Sample $k$ training data batches $D_{T}^{train}$ from $p(T)$
3: for $j = 1, 2, \ldots, k$ do
4: $\theta_j \leftarrow \theta_{j-1} - \alpha \nabla_{\theta_{j-1}} L_T(\theta_{j-1}; D_{T,j}^{train})$
5: end for
6: Sample test data batch $D_{T}^{test}$ from $p(T)$
7: $\theta_0 \leftarrow \theta_0 - \beta \nabla_{\theta_0} L_T(\theta_k; D_{T}^{test})$
8: end for
9: return Meta parameters $\theta_0$

The meta learning algorithm for pre-training optimization is described in Algorithm 1. It can be divided into two main steps: i) meta train step, which updates task specific parameters by $k$ gradient descent steps over training data; ii) meta test step, which updates meta parameters by one gradient step over test data. Hyper-parameter $k$ is the meta train steps. The meta learning algorithm degrades to normal gradient descent algorithm when $k = 0$. The returned meta parameters $\theta_0$ are used as the pre-trained parameters for our PTM-CWS model.

### 3 Experiment

#### 3.1 Datasets

We collect twelve CWS datasets to evaluate performance of CWS models. Each dataset corresponds to a CWS criterion. Among these twelve datasets, PKU, MSRA, CITYU, AS datasets are from SIGHAN2005 (Emerson, 2005), with CKIP, NCC, SXU from SIGHAN2008 (Jin and Chen, 2008), CTB6 from Xue et al. (2005), WTB from Wang et al. (2014), UD from Zeman et al. (2017), ZX from Zhang et al. (2014) and CNC dataset.

For CTB6, WTB, UD, ZX and CNC datasets, we use the official data split of training, development, and test set. For the other seven datasets, we use the official test set and randomly pick 10% samples from the training data as the development set.

We pre-process all the datasets following four procedures: i) convert traditional Chinese datasets into simplified, such as CITYU, AS and CKIP; ii) convert full-width tokens into half-width; iii) replace continuous English letters and digits with a unique token; iv) split sentences into shorter clauses by punctuation. The statistics of all processed datasets are displayed in Table 2.

Among all datasets, WTB, UD, ZX datasets are used as unseen criteria, while the other nine datasets are used as pre-training criteria. The training sets of pre-training criteria are merged into the pre-training corpus, amounting to nearly 18M words.

#### 3.2 Hyper-Parameters

We employ the same architecture of BERT-Base (Devlin et al., 2019) as the unified architecture of our proposed PTM-CWS model, which has 12 transformer layers, 768 hidden sizes and 12 attention heads.

For pre-training, we initialize our PTM-CWS model with the released parameters of Chinese BERT-Base model and then pre-trained on the joint multi-criteria corpus. The maximum sentence length is set to 64, and longer sentence

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1. [http://corpus.zhonghuayuwen.org/](http://corpus.zhonghuayuwen.org/)
2. [https://github.com/google-research/bert](https://github.com/google-research/bert)
Corpus | #Train Words | #Dev Words | #Test Words | OOV Rate | Avg. Length
--- | --- | --- | --- | --- | ---
PKU | 999,823 | 110,124 | 104,372 | 3.30% | 10.6
MSRA | 2,133,674 | 234,717 | 106,873 | 2.11% | 11.3
CITYU | 1,308,774 | 146,856 | 40,936 | 6.36% | 11.0
AS | 4,902,887 | 546,694 | 122,610 | 3.75% | 9.7
CKIP | 649,215 | 72,334 | 90,678 | 7.12% | 10.5
NCC | 823,948 | 89,898 | 152,367 | 4.82% | 10.0
SXU | 475,489 | 52,749 | 113,527 | 4.81% | 11.1
CTB6 | 678,811 | 51,229 | 52,861 | 5.17% | 12.5
CNC | 5,841,239 | 727,765 | 726,029 | 0.75% | 9.8
WTB | 14,774 | 1,843 | 1,860 | 15.05% | 28.2
UD | 98,607 | 12,663 | 12,012 | 11.04% | 11.4
ZX | 67,648 | 20,393 | 67,648 | 6.48% | 8.2

Table 2: Statistics of datasets. The first block corresponds to the pre-training criteria, which are used for pre-training of PTM-CWS. The second block corresponds to downstream criteria, which are not visible during the pre-training phase.

will be truncated. Pre-training batch size is set to 64, and dropout rate is 0.1. The pre-trained model is optimized using AdamW optimizer (Loshchilov and Hutter, 2019) with $\beta_1 = 0.9$, $\beta_2 = 0.999$ and weight decay rate of 0.01. The optimizer is implemented by the meta learning algorithm, where both learning rate $\alpha$ and meta learning rate $\beta$ are set to 2e-5 with a linear warm-up proportion of 0.1. The meta train steps are selected to $k = 1$ according to the downstream performance. The pre-training procedure is run for nearly 127,000 meta test steps, amounting to $(k + 1) \times 127,000$ total pre-training steps. The pre-training process takes about 21 hours on one NVIDIA Tesla V100 32GB GPU card.

For downstream adaptation, we just fine-tune our PTM-CWS model on the criterion-specific corpus. The maximum sentence length for all criteria is 64 except that it’s 128 for WTB. Batch size for fine-tuning is 64. We fine-tune the PTM-CWS model with AdamW optimizer of the same setting as pre-training without meta learning. All fine-tuned models are optimized for 5 epochs. The criterion tokens of downstream criteria are set to [unc], for the downstream criteria don’t exist in pre-training.

For low-resource settings, the criterion is set to WTB and the maximum sentence length is 128. We test on sampling rates of 1%, 5%, 10%, 20%, 50%, 80%. Batch size is 1 for sampling rate of 1% and 8 for other rates. Other hyper-parameters are the same as those of fine-tuning.

The standard average F1 scores are used to evaluate the performance of Chinese Word Segmentation models.

3.3 Results on Pre-training Criteria

After pre-training, we fine-tune PTM-CWS model on each pre-training criterion. Table 3 shows F1 scores on test sets of nine pre-training criteria in two blocks. The first block displays the performance of previous works. The second block displays three models implemented by us: BERT-Base is the fine-tuned model initialized with official BERT-Base parameters. PTM-CWS (w/o fine-tune) is the pre-trained PTM-CWS model directly used for inference without fine-tuning. PTM-CWS is the fine-tuned model initialized with pre-trained PTM-CWS parameters.

From the second block, we observe that fine-tuned PTM-CWS could outperform fine-tuned BERT-Base on each criterion, with 0.26% improvement on average. This shows that PTM-CWS can learn better representations for CWS tasks. Even without fine-tuning, PTM-CWS still behaves better than fine-tuned BERT-Base model, showing that our pre-training method is the key factor for the effectiveness of PTM-CWS. Fine-tuned PTM-CWS performs better than that of no fine-tuning, showing that criterion fine-tuning is still necessary. Furthermore, PTM-CWS can achieve state-of-the-art results on all nine pre-training criteria, demonstrating the effectiveness of our proposed methods.
3.4 Results on Downstream Criteria

To evaluate the generalization ability of PTM-CWS, we perform experiments on three downstream criteria which do not exist in pre-training phase. Table 4 shows F1 scores on test sets of downstream criteria. The first block displays recent works on these downstream criteria. The second block displays three models implemented by us (see Section 3.3 for details).

Table 4: F1 scores on test sets of downstream criteria.

| Models          | WTB  | UD   | ZX   | Avg.  |
|-----------------|------|------|------|-------|
| Ma et al. (2018) | 93.10 | 97.30 | 97.00 | 95.80 |
| Huang et al. (2019) | -    | 96.90 | -    | -     |
| BERT-Base (ours) | 93.00 | 98.32 | 97.06 | 96.13 |
| PTM-CWS (w/o fine-tune) | 89.53 | 83.84 | 88.48 | 87.28 |
| PTM-CWS         | 93.97 | 98.49 | 97.22 | 96.56 |

Results show that PTM-CWS outperforms the previous best model by 0.76% on average, achieving new state-of-the-art performance on these downstream criteria. Moreover, PTM-CWS without fine-tuning actually performs zero-shot inference on the downstream criteria and still achieves 87.28% average F1 score. This shows that our PTM-CWS model does learn some prior segmentation knowledge shared by different criteria in pre-training phase, even if it doesn’t see these downstream criteria before.

3.5 Ablation Studies

We perform further ablation studies on the effects of meta learning and pre-training, by removing them consecutively from the complete PTM-CWS model. After removing both of them, PTM-CWS degrades into the normal BERT-Base model. F1 scores for ablation study on three unseen criteria are illustrated in Table 5.

Table 5: F1 scores for ablation studies on downstream criteria.

| Models          | WTB  | UD   | ZX   | Avg.  |
|-----------------|------|------|------|-------|
| PTM-CWS         | 93.97 | 98.49 | 97.22 | 96.56 |
| - meta learning | 93.71 | 98.49 | 97.22 | 96.47 |
| - pre-training  | 93.00 | 98.32 | 97.06 | 96.13 |

We observe that the average F1 score drops by 0.09% when removing the meta learning algorithm, and continues to drop by 0.34% when removing the pre-training phase of PTM-CWS. It demonstrates that meta learning and task-specific pre-training are both significant for the performance of PTM-CWS model.

3.6 Low-Resource Settings

To better explore the downstream generalization ability of PTM-CWS, we perform experiments on the downstream WTB criterion in low-resource settings. Specifically, we randomly sample a given rate of instances from the training set and fine-tune PTM-CWS on the down-sampled low-resource training set. The performance of models at different sampling rates is evaluated on the same test set and reported in Table 6.

Table 6: F1 scores on test sets of downstream criteria in low-resource settings.

| Models          | WTB  | UD   | ZX   | Avg.  |
|-----------------|------|------|------|-------|
| PTM-CWS         | 93.97 | 98.49 | 97.22 | 96.56 |
| - meta learning | 93.71 | 98.49 | 97.22 | 96.47 |
| - pre-training  | 93.00 | 98.32 | 97.06 | 96.13 |
### Table 6: F1 scores on WTB test set in low-resource settings.

| Models    | PKU | MSRA | CITYU | AS | CKIP | NCC | SXU | CTB6 | CNC | WTB | UD | ZX | Avg. |
|-----------|-----|------|-------|----|------|-----|-----|------|-----|-----|----|----|------|
| BERT-Base | 80.15 | 81.03 | 90.62 | 79.60 | 84.48 | 79.64 | 84.75 | 89.10 | 61.18 | 83.57 | 93.36 | 87.69 | 82.93 |
| PTM-CWS   | 80.90 | 83.03 | 90.66 | 80.89 | 84.42 | 84.14 | 85.98 | 89.21 | 61.90 | 85.00 | 93.59 | 87.33 | 83.92 |

Results show that PTM-CWS outperforms BERT-Base at every sampling rate. The margin is larger when the sampling rate is lower and reaches 6.20% on 1% sampling rate. This demonstrates that PTM-CWS can generalize better on the new criterion in the low-resource settings.

When the sampling rate drops from 100% to 1%, F1 score of BERT-Base decreases by 7.60% while that of PTM-CWS only decreases by 2.37%. The performance of PTM-CWS at 1% sampling rate still reaches 91.60% with only 8 instances, comparable with performance of BERT-Base at 20% sampling rate. This indicates that our PTM-CWS can make better use of prior segmentation knowledge, learn from less amount of data, and decrease the need of human annotation significantly.

### 3.7 Out-of-Vocabulary Recall

Out-of-Vocabulary (OOV) words denote the words which exist in inference phase but don’t exist in training phase. OOV words are a critical cause of errors on CWS tasks. We evaluate the recalls of OOV words on test sets of all twelve criteria in Table 7.

Results show that our PTM-CWS outperforms BERT-Base on 10/12 criteria and improves OOV recall by 0.99% on average. This indicates that PTM-CWS can benefit from our proposed pre-training methodology and recognize more OOV words in the test phase.

### 4 Conclusion

In this work, we propose a pre-trained model for Chinese Word Segmentation task, which is named as PTM-CWS. PTM-CWS employs a unified architecture for different criteria, which is pre-trained on a joint multi-criteria corpus with meta learning algorithm. Experiments from different aspects show that PTM-CWS can make use of the prior segmentation knowledge, and alleviate the discrepancy between pre-training tasks and downstream CWS tasks. PTM-CWS can also display better generalization abilities on downstream CWS tasks, especially in low-resource settings, and achieve new state-of-the-art performance on twelve CWS datasets.

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