Multi-Criteria Chinese Word Segmentation with Transformer

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Abstract

Different linguistic perspectives cause many diverse segmentation criteria for Chinese word segmentation (CWS). Most existing methods focus on improving the performance of single-criterion CWS. However, it is interesting to exploit these heterogeneous segmentation criteria and mine their common underlying knowledge. In this paper, we propose a concise and effective model for multi-criteria CWS, which utilizes a shared fully-connected self-attention model to segment the sentence according to a criterion indicator. Experiments on eight datasets with heterogeneous segmentation criteria show that the performance of each corpus obtains a significant improvement, compared to single-criterion learning.

Keywords: Chinese Word Segmentation, Multi-Criteria, Self-Attention, Transformer, Natural Language Processing, Deep Learning

1. Introduction

Unlike English, Chinese sentences consist of continuous characters and lack obvious boundaries between Chinese words. Since words are usually regarded as the minimum semantic units, therefore Chinese word segmentation (CWS) becomes a preliminary and important pre-processing step for the downstream Chinese natural language processing (NLP) tasks. Currently, CWS has been studied with considerable efforts in the NLP community, and the state-of-the-art CWS methods are based on supervised machine learning algorithms. Most of them regard CWS as a character-based sequence labeling problem [11], in which each character is assigned a label to indicate its boundary information. Recently, researchers have tended to explore neural network based approaches to reduce efforts of the feature engineering [2, 3, 4, 5, 6, 7, 8]. Although these methods have made great progress, they considerably rely on the large-scale high-quality annotated corpus. However, there are two main challenges to construct a high-quality annotated CWS corpus. The first is that annotating the segmentation
usually requires linguistic experts and its cost is extremely expensive. The second is that there are several inconsistent segmentation criteria from different linguistic perspectives. Therefore, although several CWS corpora have been built with great efforts, their segmentation criteria are different and their segmentations for one sentence are usually inconsistent.

Table 1: Illustration of the different segmentation criteria.

| Corpora | Lin Dan | won | the championship |
|---------|---------|-----|------------------|
| CTB     | 林丹    | 赢得| 总冠军           |
| PKU     | 林丹    | 赢得| 总冠军           |
| MSRA    | 林丹    | 赢得| 总冠军           |

As shown in Table 1, given a sentence “林丹赢得总冠军(Lin Dan won the championship)”, the three commonly-used corpora, PKU’s People’s Daily (PKU) [9], Penn Chinese Treebank (CTB) [10] and MSRA [11], use different segmentation criteria. Although these criteria are inconsistent, they share some common knowledge. The knowledge learned from a segmentation criterion can benefit other criteria.

Currently, most of CWS methods focus on improving the performance of each individual segmentation criterion. It is a waste of resources if we fail to fully exploit all the corpora with different criteria. Therefore, it remains to be a challenging problem on how to effectively utilize these resources.

In our previous work [12, 13], we consider a multi-criteria learning framework for CWS. Specifically, we regard each segmentation criterion as a single task under the framework of multi-task learning [14], where a shared layer is used to extract the criteria-invariant features, and a private layer is used to extract the criteria-specific features. However, it is unnecessary to use a specific private layer for each criterion. These different criteria often have partial overlaps. For the example in Table 1, the segmentation of “林丹(Lin Dan)” is the same as in PKU and MSRA criteria, and the segmentation of “总冠军(the championship)” is the same as in CTB and MSRA criteria. All these three criteria have same segmentation for the word “赢得(won)”.

In this work, we propose a concise model for multi-criteria Chinese word segmentation by integrating shared knowledge from multiple segmentation criteria. Inspired by the success of the Transformer [15], a fully-connected self-attention network, we design a fully shared architecture for multi-criteria CWS, where a shared encoder is used to extract the criteria-aware contextual features, and a shared decoder is used to predict the criteria-specific labels. Finally, we exploit the eight segmentation criteria on the five simplified Chinese and three traditional Chinese corpora. Experiments show that the proposed model is effective to improve the performance for multi-criteria CWS.

The contributions of this paper could be summarized as follows.

- Multi-criteria learning is formally introduced for CWS, which aims to make full use of the existing heterogeneous corpora. Although the segmentation criteria of these corpora are different, they share lots of common knowledge and could help each other.
• We proposed a concise model for multi-criteria CWS based on Transformer, which adopts a single shared model to predict the different criteria-specific labels. Due to the powerful ability of Transformer, we can use a simple control variable to determine the criterion-specific segmented output.

• It is a first attempt to train a Transformer from scratch for CWS task, which can effectively extract the non-local interactions and alleviate the long-term dependency problem of RNN and CNN.

2. Background

In this section, we first briefly describe the related background knowledge of our work.

2.1. Neural Architecture for CWS

Usually, CWS task could be viewed as a character-based sequence labeling problem. Specifically, each character in a sentence $X = \{x_1, \ldots, x_T\}$ is labelled as one of $y \in \mathcal{L} = \{B, M, E, S\}$, indicating the begin, middle, end of a word, or a word with single character. The aim of CWS task is to figure out the ground truth of labels $Y^* = \{y_1^*, \ldots, y_T^*\}$:

$$Y^* = \arg \max_{Y \in \mathcal{L}^T} p(Y|X).$$

(1)

Recently, deep learning methods have been widely used in segmenting Chinese words and can effectively reduce the efforts of feature engineering. The popular architecture of neural CWS could be characterized by three components: (1) a character embedding layer; (2) an encoding layer to extract the contextual features, which consists of several classical neural networks and (3) a decoding layer with conditional random fields (CRF) [17] layer or multi-layer perceptron (MLP).

**Embedding Layer:** In neural models, the first step is to map discrete language symbols into distributed embedding space. Formally, each character $x_t$ is mapped as $e_{x_t} \in \mathbb{R}^{d_e}$, where $d_e$ is a hyper-parameter indicating the size of character embedding.

**Encoding Layer:** The encoding layer is to extract the contextual features for each character. Usually, the recurrent neural network (RNN) or convolutional neural network (CNN) is adopted as the encoding layer.

For example, a prevalent choice for the encoding layer is the bi-directional LSTM (BiLSTM) [16], which could incorporate information from both sides of sequence.

$$h_t = \text{BiLSTM}(e_{x_t}, \overrightarrow{h}_{t-1}, \overleftarrow{h}_{t+1}, \theta_e),$$

(2)

where $\overrightarrow{h}_t$ and $\overleftarrow{h}_t$ are the hidden states at step $t$ of the forward and backward LSTMs respectively, $\theta_e$ denotes all the parameters in the BiLSTM layer.

Besides BiLSTM, CNN is also alternatively used to extract features.

**Decoding Layer:** The extracted features are then sent to conditional random fields (CRF) [17] layer or multi-layer perceptron (MLP) for tag inference.
Figure 1: Architectures of single-criterion and multi-criteria Chinese word segmentation. The red components are shared.

When using CRF as decoding layer, \( p(Y|X) \) in Eq (1) could be formalized as:

\[
p(Y|X) = \frac{\Psi(Y|X)}{\sum_{Y' \in \mathcal{L}^n} \Psi(Y'|X)}
\]

(3)

where \( \Psi(Y|X) \) is the potential function. In first order linear chain CRF, we have:

\[
\Psi(Y|X) = \prod_{t=2}^{n} \psi(X, t, y_{t-1}, y_t),
\]

(4)

\[
\psi(x, t, y', y) = \exp(\delta(X, t)_y + b_{y'y}),
\]

(5)

where \( b_{y'y} \in \mathbb{R} \) is trainable parameters respective to label pair \((y', y)\), score function \( \delta(X, t) \in \mathbb{R}^{|\mathcal{L}|} \) calculates scores of each label for tagging the \( t \)-th character:

\[
\delta(X, t) = W_{\delta}^\top h_t + b_\delta,
\]

(6)

where \( h_t \) is the hidden state of encoder at step \( t \), \( W_\delta \in \mathbb{R}^{d_h \times |\mathcal{L}|} \) and \( b_\delta \in \mathbb{R}^{|\mathcal{L}|} \) are trainable parameters.

When using MLP as decoding layer, \( p(Y|X) \) in Eq (1) is directly predicted by a MLP with softmax function as output layer:

\[
p(y_t|X) = \text{MLP}(h_t, \theta_d), \quad \forall t \in [1, T]
\]

(7)

where \( \theta_d \) denotes all the parameters in MLP layer.

2.2. Multi-Criteria CWS with Multi-Task Learning

Since annotations in Chinese word segmentation are valuable and expensive, it is important to jointly train Chinese word segmentation with multiple heterogeneous...
criteria to improve the performance. The multi-task learning framework is a suitable way to exploit the shared information among these different criteria.

Formally, assuming that there are $M$ corpora with heterogeneous segmentation criteria, we refer $D_m$ as corpus $m$ with $N_m$ samples:

$$D_m = \{ (X_n^{(m)}, Y_n^{(m)}) \}_{n=1}^{N_m},$$  \hspace{1cm} (8)$$

where $X_n^{(m)}$ and $Y_n^{(m)}$ denote the $i$-th sentence and the corresponding label in corpus $m$ respectively.

To exploit information across multiple corpora, the encoding layer additionally introduces a shared encoder, together with the original private encoder. The architecture of MTL-based multi-criteria CWS is shown in Figure 1b.

Concretely, for corpus $m$, a shared encoder and a private encoder are first used to extract the criterion-agnostic and criterion-specific features.

$$H^{(s)} = \text{enc}_s(eX; \theta_e^{(s)}),$$  \hspace{1cm} (9)$$

$$H^{(m)} = \text{enc}_m(eX; \theta_e^{(m)}), \quad \forall m \in [1, M]$$  \hspace{1cm} (10)$$

where $eX = \{ e_{x_1}, \cdots, e_{x_T} \}$ denotes the embeddings of the input characters $x_1, \cdots, x_T$, $\text{enc}_s(\cdot)$ represents the shared encoder and $\text{enc}_m(\cdot)$ represents the private encoder for corpus $m$; $\theta_e^{(s)}$ and $\theta_e^{(m)}$ are the shared and private parameters respectively. The shared and private encoders are usually implemented by the RNN or CNN network.

Then a private decoder is used to predict criterion-specific labels. For the $m$-th corpus, the probability of output labels is

$$p_m(Y | X) = \text{dec}_m([H^{(s)}; H^{(m)}]; \theta_d^{(m)}), \quad \forall m \in [1, M]$$  \hspace{1cm} (11)$$

where $\text{dec}_m(\cdot)$ is a private CRF or MLP decoder for corpus $m$, taking the shared and private features as inputs, and $\theta_d^{(m)}$ is the parameters of the $m$-th private decoder.

Objective. The objective is to maximize the log likelihood of true labels on all the corpora:

$$J_{seg}(\Theta^m, \Theta^s) = \sum_{m=1}^{M} \sum_{n=1}^{N_m} \log p(Y_n^{(m)} | X_n^{(m)}; \Theta^m, \Theta^s),$$  \hspace{1cm} (12)$$

where $\Theta^m = \{ \theta_e^{(m)}, \theta_d^{(m)} \}$ and $\Theta^s = \{ E, \theta_e^{(s)} \}$ denote all the private and shared parameters respectively; $E$ is the embedding matrix.

3. Proposed Model

In this work, we propose a more concise architecture for multi-criteria CWS, which adopts the Transformer encoder \cite{15} to extract the contextual features for each input character. In our proposed architecture, both the encoder and decoder are shared by all the criteria. The only difference is that a unique indicator is taken as input for each criterion. Figure 1 illustrates the difference between our proposed model and the previous models.

Figure 2 illustrates the proposed architecture for multi-criteria CWS. The detailed description is as follows.
3.1. Embedding Layer

Given a character sentence $X = \{x_1, \ldots, x_T\}$, we first map it into a vector sequence. Besides the standard character embeddings, we introduce three extra embeddings: criterion embedding, bigram embedding, and position embedding.

1) **Criterion Embedding**: The criterion embedding is used to indicate its expected output criterion. For the $m$-th criterion, we use $e_{[m]}$ to denote its embedding. To simplicity, we directly add a special token $[m]$ at the begin of $X$.

2) **Bigram Embedding**: Based on [5, 18, 19], bigram features can greatly benefit the task of CWS. Following their settings, we also introduce the bigram embedding to augment the character-level unigram embedding. The bigram representation of character $x_t$ is

$$e'_{x_t} = e_{x_t} \oplus e_{x_{t-1}},$$  \hspace{1cm} (13)

where $e$ denotes the embedding vector for the unigram and bigram, and $\oplus$ is the concatenation operator.

3) **Position Embedding**: To capture the order information of a sequence, a position embedding $PE$ is used for each position. The position embedding can be learnable parameters or pre-defined. In this work, we use the predefined position embedding following [15]. For the $t$-th character in a sentence, its position embedding is defined by

$$PE_{t, 2i} = \sin(t / 10000^{2i/d}),$$  \hspace{1cm} (14)

$$PE_{t, 2i+1} = \cos(t / 10000^{2i/d}),$$  \hspace{1cm} (15)

where $i$ denotes the dimensional index of position embedding and $d$ denotes the dimension of embedding vector.
Finally, the embedding matrix of the sequence $X = \{x_1, \cdots, x_T\}$ with criterion $m$ is formulated as

$$X = [e_{[m]} + PE_0; e'_{x_1} + PE_1; \cdots; e'_{x_T} + PE_T],$$

(16)

### 3.2. Encoding Layer

In sequence modeling, RNN and CNN often suffer from the long-term dependency problem and cannot effectively extract the non-local interactions in a sentence. Recently, the fully-connected self-attention architecture, such as Transformer [15], achieves great success in many NLP tasks, such as text classification, machine translation.

In this work, we adopt the Transformer encoder as our encoding layer, in which several multi-head self-attention layers are used to extract the contextual feature for each character.

In each multi-head self-attention layer, we use the scaled dot-product attention to model the intra-interactions of a sequence. Given a sequence of vectors $H \in \mathbb{R}^{(T+1) \times d_{model}}$, where $(T+1)$ and $d_{model}$ represent the length and the dimension of the input vector sequence, the self-attention projects $H$ into three different matrices: the query matrix $Q \in \mathbb{R}^{(T+1) \times d_k}$, the key matrix $K \in \mathbb{R}^{(T+1) \times d_k}$ and the value matrix vector $V \in \mathbb{R}^{(T+1) \times d_v}$, and uses scaled dot-product attention to get the output representation.

$$Q, K, V = HW_Q, HW_K, HW_V$$

(17)

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

(18)

where $W_Q \in \mathbb{R}^{d_{model} \times d_k}, W_K \in \mathbb{R}^{d_{model} \times d_k}, W_V \in \mathbb{R}^{d_{model} \times d_v}$ are learnable parameters and $\text{softmax}()$ is performed row-wise.

To enhance the ability of self-attention, multi-head self-attention is introduced as an extension of the single head self-attention, which jointly model the multiple interactions from different representation spaces,

$$\text{MultiHead}(H) = [\text{head}_1; \cdots; \text{head}_k]W^O,$$

where $\text{head}_i = \text{Attn}(HW^Q_i, HW^K_i, HW^V_i),$

(19)

(20)

where $W^Q_i, W^K_i, W^V_i (i \in [1,k])$ are learnable parameters.

Transformer encoder consists of several stacked multi-head self-attention layers and fully-connected layers. Assuming the input of the self-attention layer is $H$, its output $\tilde{H}$ is calculated by

$$Z = \text{layer-norm}\left(H + \text{MultiHead}(H)\right),$$

$$\tilde{H} = \text{layer-norm}\left(Z + \text{MLP}(Z)\right),$$

(21)

(22)

where $\text{layer-norm}(\cdot)$ represents the layer normalization [20].

All the tasks with the different criteria use the same encoder. But with the different criterion indicator $m$, the encoder can extract the criterion-aware representation for each character.
Table 2: Details of the eight datasets after preprocessing. “Word Types” represents the number of unique word. “Char Types” is the number of unique characters. “OOV Rate” is Out-Of-Vocabulary rate.

| Corpora | Words# | Chars# | Word Types | Char Types | OOV Rate |
|---------|--------|--------|------------|------------|----------|
| Sighan05 |        |        |            |            |          |
| MSRA    | 2.4M   | 4.0M   | 75.4K      | 5.1K       | 1.32%    |
|         | 0.1M   | 0.2M   | 11.9K      | 2.8K       |          |
| AS      | 5.4M   | 8.3M   | 128.8K     | 5.8K       | 2.20%    |
|         | 0.1M   | 0.2M   | 18.0K      | 3.4K       |          |
| PKU     | 1.1M   | 1.8M   | 51.2K      | 4.6K       | 2.06%    |
|         | 0.1M   | 0.2M   | 12.5K      | 2.9K       |          |
| CITYU   | 1.1M   | 1.8M   | 43.4K      | 4.2K       | 3.69%    |
|         | 0.2M   | 0.4M   | 23.2K      | 3.6K       |          |
| CTB     | 0.6M   | 1.0M   | 40.5K      | 4.2K       | 3.80%    |
|         | 0.1M   | 0.1M   | 11.9K      | 2.9K       |          |
| CKIP    | 0.7M   | 1.1M   | 44.7K      | 4.5K       | 4.29%    |
|         | 0.1M   | 0.1M   | 14.2K      | 3.1K       |          |
| NCC     | 0.9M   | 1.4M   | 53.3K      | 5.3K       | 3.31%    |
|         | 0.2M   | 0.2M   | 20.9K      | 3.9K       |          |
| SXU     | 0.5M   | 0.8M   | 29.8K      | 4.1K       | 2.60%    |
|         | 0.1M   | 0.2M   | 11.6K      | 2.8K       |          |

3.3. Decoding Layer
In the standard multi-task learning framework, each task has its own private decoder to predict the task-specific labels. Different from the previous work, we use a shared decoder for all the tasks since we have extracted the criterion-aware representation for each character. In this work, we attempt two kinds of decoders: CRF and MLP. We use the CRF as the default decoder since it is slightly better than MLP (see Sec. 4.4).

With the shared encoder and decoder, our model is more concise than the shared-private architectures [12, 30].

4. Experiments
4.1. Datasets
We experiment on eight CWS datasets from SIGHAN2005 [11] and SIGHAN2008 [21]. Among them, the AS, CITYU, and CKIP datasets are in traditional Chinese, while the MSRA, PKU, CTB, NCC, and SXU datasets are in simplified Chinese. Except otherwise stated, AS, CITYU and CKIP are translated into simplified Chinese as in [12, 13]. We randomly pick 10% instances from the training set as the development set for all datasets. Similar to the previous work [12, 8], we preprocess all the datasets by replacing the continuous Latin characters and digits with a unique token, and converting all digits, punctuation and Latin letters to half-width to deal with the full/half-width mismatch between training and test set. Table 2 gives the details of the eight datasets after preprocessing.
We use the standard measures of precision, recall and F1 scores to evaluate Chinese word segmentation [22]. The precision of Chinese word segmentation (denoted as $P$) is calculated by the number of correctly segmented words versus the total number of segmented words. The recall of Chinese word segmentation (denoted as $R$) is computed by the number of correctly segmented words versus the total number of golden words. Then we get $F1$ value by $F1 = 2 \times P \times R / (P + R)$.

4.2. Experimental Settings

**Pretrained Embedding.** Based on on [5, 18, 19], n-gram features are of great benefit to Chinese word segmentation and POS tagging tasks, thus we use unigram and bigram embeddings for our models. We first pretrain unigram and bigram embeddings on Chinese Wikipedia corpus by the method proposed in [23] which improves standard word2vec by incorporating token order information. For a sentence with characters “abcd...”, the unigram sequence is “a b c ...”; the bigram sequence is “ab bc cd ...”. In the training phase of CWS, all pretrained embeddings are fixed at the first 50 epochs and then updated during our experiments.

**Hyper-parameters.** The model is trained with Adam algorithm [24]. The development set is used for parameter tuning. We use the CRF as the default decoder since it is slightly better than MLP (see Sec. 4.4). All models are trained for 100 epochs, after each training epoch, we test the model on the dev set, and models with the highest $F1$ in dev set are tested in the test set and we report its outcomes. The detail hyperparameters can be found in Table 3.

| Hyper-Parameter Settings | Value |
|--------------------------|-------|
| Embedding Size           | 100   |
| Hidden State Size $d_{model}$ | 256   |
| Transformer Layers       | 6     |
| Attention Heads          | 4     |
| Gradients Clip           | 5     |
| Batch Size               | 128   |
| Embedding Dropout Ratio  | 0.33  |
| Initial Learning Rate    | 2e-3  |
| Annealing Rate           | .75t/5000 |
| Max epochs               | 100   |

Since the numbers of layers and attention heads are important, we list the performances with different settings in Table 4. Based on their performances, we use six layers of self-attention, each layer with four attention heads.
Table 4: Average F1 values with different number of Transformer layers and heads are used.

| # of Layer | # of head | avg F1 |
|------------|-----------|--------|
| 2          | 4         | 96.69  |
| 4          | 4         | 96.81  |
| 6          | 4         | 96.87  |
| 2          | 8         | 96.68  |
| 4          | 8         | 96.8   |
| 6          | 8         | 96.84  |

4.3. Overall Results

Table 5 shows the experiment results of the proposed model on test sets of eight CWS datasets.

We first compare our Transformer encoder with BiLSTM, Stacked Bi-LSTM and Switch-LSTMs from [12, 13] in the single-criterion learning scenario. The comparison is presented in the upper block of Table 5. As we can see, Transformer outpaces BiLSTMs, Stacked Bi-LSTM, and Switch-LSTMs both in F1 value and OOV. Quantitatively speaking, Transformer obtains 96.47 in average F1 value, while the previous state-of-the-art result is 94.76 [13], the absolute increase is 1.71. We argue that the capability of the Transformer is greater than conventional LSTM models, and this view can be consolidated by the 7.32 OOV improvement.

In the multi-criteria learning scenario, we compare Transformer with the multi-task learning framework (MTL) [12] and Switch-LSTMs [13]. The lower block of Table 5 displays the contrast. Firstly, although different criteria are trained together, most datasets (besides CTB) achieve better performance with respect to F1 value. Compared to the single-criterion scenario, 0.4 gain in average F1 value is obtained by multi-criteria scenario, which indicates the proposed criterion embedding is useful. Secondly, compare with previous multi-criteria learning models, the model proposed in this paper also achieves better average F1 value. This is a sign that the proposed Transformer-based multi-criteria CWS makes better use of different criteria datasets.

Figure 3 visualizes the 2D PCA projection of the learned embeddings of eight different criteria. Generally, the eight criteria are mapped into dispersed points in the embedding space, which indicates each criterion is different from others. Among them, MSRA is obviously different from others. A possible reason is that the named entity is regarded as a unique word in the MSRA criterion, which is significantly distinguishing with other criteria.

4.4. Ablation Study

To show the effectiveness of each component in our model, we also conduct an ablation study shown in Table 6.

The first ablation study is to verify the effectiveness of the CRF decoder, which is popular in most CWS models. The comparison between the first two lines indicates that with or without CRF does not make much difference since a model with CRF takes longer time to train and inference, we suggest not to use CRF in Transformer models.
Table 5: Results of the proposed model on the test sets of eight CWS datasets. Here, P, R, F, OOV indicate the precision, recall, $F_1$ value, and OOV recall rate respectively. The maximum $F_1$ value and OOV value are highlighted for each dataset. There are two blocks. The upper block consists of single-criterion learning models. Bi-LSTMs and stack-LSTMs are baselines and the results on them are reported in [12]. The lower block consists of multi-criteria learning models.

| Models            | MSRA  | AS    | PKU   | CTB   | CKIP  | CITYU | NCC   | SXU   | Avg.  |
|-------------------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| **Single-Criterion Learning** |       |       |       |       |       |       |       |       |       |
| Bi-LSTMs[12]      |       |       |       |       |       |       |       |       |       |
| P                 | 95.7  | 93.64 | 93.67 | 95.19 | 92.44 | 94    | 91.86 | 95.11 | 93.95 |
| R                 | 95.99 | 94.77 | 92.93 | 95.42 | 93.69 | 94.15 | 92.47 | 95.23 | 94.33 |
| F                 | 95.84 | 94.2  | 93.3  | 95.3  | 93.06 | 94.07 | 92.17 | 95.17 | 94.14 |
| OOV               | 66.28 | 70.07 | 66.09 | 76.47 | 72.12 | 65.79 | 59.11 | 71.27 | 68.4  |
| Stacked Bi-LSTM[12]|       |       |       |       |       |       |       |       |       |
| P                 | 95.69 | 93.89 | 94.1  | 95.2  | 92.4  | 94.13 | 91.81 | 94.99 | 94.03 |
| R                 | 95.81 | 94.54 | 92.66 | 95.4  | 93.39 | 93.99 | 92.62 | 95.37 | 94.22 |
| F                 | 95.75 | 94.22 | 93.37 | 95.3  | 92.89 | 94.06 | 92.21 | 95.18 | 94.12 |
| OOV               | 65.55 | 71.5  | 67.92 | 75.44 | 70.5  | 66.35 | 57.39 | 69.69 | 68.04 |
| Switch-LSTMs[13]  |       |       |       |       |       |       |       |       |       |
| P                 | 96.07 | 93.83 | 95.92 | 97.13 | 92.02 | 93.69 | 91.81 | 95.02 | 94.44 |
| R                 | 96.86 | 95.21 | 95.56 | 97.05 | 93.76 | 93.73 | 92.43 | 96.13 | 95.09 |
| F                 | 96.46 | 94.51 | 95.74 | 97.09 | 92.88 | 93.71 | 92.12 | 95.57 | 94.76 |
| OOV               | 69.9  | 77.8  | 72.7  | 81.8  | 71.6  | 59.8  | 55.5  | 67.3  | 69.55 |
| Transformer       |       |       |       |       |       |       |       |       |       |
| P                 | 98.14 | 96.61 | 96.06 | 96.26 | 95.97 | 96.44 | 95.56 | 97.08 | 96.52 |
| R                 | 98    | 95.51 | 96.73 | 96.57 | 95.35 | 96.2  | 96.59 | 97.09 | 96.51 |
| F                 | 98.07 | 96.26 | 96.39 | 96.43 | 95.66 | 96.32 | 95.57 | 97.08 | 96.47 |
| OOV               | 73.75 | 73.05 | 72.82 | 82.82 | 79.05 | 83.72 | 71.81 | 77.95 | 76.87 |
| **Multi-Criteria Learning** |       |       |       |       |       |       |       |       |       |
| MTL[12]           |       |       |       |       |       |       |       |       |       |
| P                 | 95.95 | 94.17 | 94.86 | 96.02 | 93.82 | 95.39 | 92.46 | 96.07 | 94.84 |
| R                 | 96.14 | 95.11 | 93.78 | 96.33 | 94.7  | 95.7  | 93.19 | 96.01 | 95.12 |
| F                 | 96.04 | 94.64 | 94.32 | 96.18 | 94.26 | 95.55 | 92.83 | 96.04 | 94.98 |
| OOV               | 71.6  | 73.5  | 72.67 | 82.48 | 77.59 | 81.4  | 63.31 | 77.1  | 74.96 |
| Switch-LSTMs[13]  |       |       |       |       |       |       |       |       |       |
| P                 | 97.69 | 94.42 | 96.24 | 97.09 | 94.53 | 95.85 | 94.07 | 96.88 | 95.85 |
| R                 | 97.87 | 96.03 | 96.05 | 97.43 | 95.45 | 95.69 | 94.17 | 97.62 | 96.84 |
| F                 | 97.78 | 95.22 | 96.15 | 97.26 | 94.99 | 96.22 | 94.12 | 97.25 | 96.12 |
| OOV               | 64.2  | 77.33 | 69.88 | 83.89 | 77.69 | 73.58 | 69.76 | 78.69 | 74.38 |
| Transformer       |       |       |       |       |       |       |       |       |       |
| P                 | 98.03 | 96.84 | 95.88 | 96.79 | 96.92 | 97.03 | 95.85 | 97.52 | 96.86 |
| R                 | 98.06 | 96.05 | 96.95 | 97.18 | 96.11 | 96.78 | 96.24 | 97.69 | 96.88 |
| F                 | 98.05 | 96.44 | 96.41 | 96.99 | 96.51 | 96.91 | 96.04 | 97.61 | 96.87 |
| OOV               | 78.92 | 76.39 | 78.91 | 87    | 82.89 | 86.91 | 79.3  | 85.08 | 81.92 |
Table 6: Ablation experiments. The first line presents the results of our full multi-criteria trained model. The following lines are results of separately removing a certain part.

| Models           | MSRA  | AS    | PKU   | CTB   | CKIP  | CITYU | NCC   | SXU   | Avg.  |
|------------------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| Full Model       | 98.05 | 96.44 | 96.41 | 96.99 | 96.51 | 96.91 | 96.04 | 97.61 | 96.87 |
| w/o CRF          | 98.02 | 96.42 | 96.41 | 96.9  | 96.59 | 96.87 | 95.96 | 97.5  | 96.83 |
| w/o bigram       | 97.41 | 96   | 96.25 | 96.71 | 96    | 96.31 | 94.62 | 96.84 | 96.27 |
| w/o pretrained emb. | 97.51 | 96.06 | 96.02 | 96.47 | 96.22 | 95.99 | 94.82 | 96.76 | 96.23 |

The other two ablation studies are to evaluate the effect of the bigram feature and pretrained embeddings. We can see that their effects vary in different datasets. Some datasets are more sensitive to the bigram feature, while others are more sensitive to pretrain embeddings. In terms of average performance, the bigram feature and pretrained embeddings are important and boost the performance greatly, but these two components do not have a clear winner.

### 4.5. Joint Training on both Simplified and Traditional Corpora

In the above experiments, the traditional Chinese corpora (AS, CITYU, and CKIP) are translated into simplified Chinese. However, the relation between simplified Chinese characters and traditional Chinese characters are not deterministic. For example, simplified word “代码” (“code” in simplified Chinese) is translated into its traditional version as “程式碼” (“code” in traditional Chinese). Even the number of characters is different. Therefore, it might be better if we can jointly train simplified and traditional Chinese word segmentation.
We study 4 different ways to train our model on Simplified and Traditional Chinese Corpora.

1. The first way (“8Simp”) is to translate all the corpora into Simplified Chinese. For the pretrained embeddings, we use the Simplified Chinese Wikipedia dump to pretrain the unigram and bigram embeddings. This way is the same as the previous experiments.

2. The second way (“8Trad”) is to translate all the corpora into Traditional Chinese. For the pretrained embeddings, we first convert the Wikipedia dump into traditional Chinese characters, then we use this converted corpus to pretrain unigram and bigram embeddings.

3. The third way (“5Simp, 3Trad”) is to keep the original characters of each corpus. The shared transformer encoder can take as input the Simplified or Traditional Chinese sentences. In this way, we pretrain the joint Simplified and Traditional Chinese embeddings in a joint embedding space. We merge the Wikipedia corpora used in “8Trad” and “8Simp” to form a mixed corpus, which contains both the Simplified and Traditional Chinese characters. The pretrained unigram and bigram embeddings are learned on this mixed corpus.

4. The last way (“8Simp, 8Trad”) is to simultaneously train our model on both the eight Simplified Chinese corpora in “8Simp” and the eight Traditional Chinese corpora in “8Trad”. The pretrained word embeddings are same to “5Simp, 3Trad”.

The results are shown in Table 7, which indicate that there does not exist too much difference between different logographs settings. Although in the setting “5Simp, 3Trad”, AS, CKIP and CITYU are in traditional Chinese, they also benefit from this multi-criteria scenario, since their performances are similar to “8Simp” and “8Trad”.

Table 7: This table presents the results of training simplified Chinese corpus and traditional Chinese corpus together. “8Simp”, “8Trad” means all corpus are converted into simplified Chinese or traditional Chinese respectively. “5Simp,3Trad” means 5 datasets are in simplified Chinese and 3 datasets(including AS, CITYU and CKIP, these datasets are given as traditional Chinese.) are in traditional Chinese.

| Models       | MSRA | AS  | PKU | CTB | CKIP | CITYU | NCC  | SXU | Avg. F1 |
|--------------|------|-----|-----|-----|------|-------|------|-----|--------|
| 8Simp        | 98.05| 96.44| 96.41| 96.99| 96.51| 96.91 | 96.04| 97.61| 96.87  |
| 8Trad        | 97.98| 96.39| 96.49| 96.99| 96.49| 96.86 | 95.98| 97.48| 96.83  |
| 5Simp, 3Trad | 98.03| 96.52| 96.6 | 96.94| 96.38| 96.8  | 96.02| 97.55| 96.86  |
| 8 Simp, 8 Trad | 98.04| 96.41| 96.43| 96.99| 96.54| 96.85 | 96.08| 97.52| 96.86  |

To better understand the quality of the learned joint embedding space of Simplified and Traditional Chinese, we conduct a qualitative analysis by doing some case studies in Table 8 to illustrate the most similar words for certain target words under different methods. Explicitly, we present the top 8 words that are most similar to our target word. Similar words are retrieved based on the cosine similarity calculated using the learned embeddings.

As we can see, the Traditional Chinese words are similar to their Simplified Chinese counterparts, and vice versa. The results shows that the Simplified and Traditional Chinese characters and bigrams are aligned well in the joint embedding space.
Table 8: Case study for qualitative analysis. Given the target word, we list its top 8 similar words. The word with red color indicates it is a Traditional Chinese word.

| 苹果 (apple) | 蘋果 (apple) | 热爱 (love) | 熱愛 (love) | 关心 (care) | 鬱心 (care) |
|------------|-------------|------------|------------|------------|------------|
| 坚果 (nut) | 微軟 (Microsoft) | 爱好 (hobby) | 愛好 (hobby) | 担心 (worry) | 擔心 (worry) |
| 谷歌 (Google) | 黃油 (butter) | 热爱 (love) | 熱愛 (love) | 关心 (care) | 鬱心 (care) |
| 华为 (Huawei) | 韩生 (goods in stock) | 爱好 (hobby) | 愛好 (hobby) | 担心 (worry) | 擔心 (worry) |
| 微软 (Microsoft) | 贷款 (jelly) | 热爱 (love) | 熱愛 (love) | 关心 (care) | 鬱心 (care) |
| 鲜果 (fresh fruit) | 京东 (JD) | 爱玩 (Playful) | 愛玩 (Playful) | 爱情 (blame) | 愛懷 (blame) |
| 微软 (Microsoft) | 贷款 (seller) | 饮酒 (addict) | 喜爱 (adore) | 患心 (sad) | 懊(blame) |
| 谷歌 (Google) | 黄色 (butter) | 喜爱 (Playful) | 喜愛 (adore) | 患心 (sad) | 懊(blame) |
| 虚信 (Apple) | 贷后 (after-sales) | 喜爱 (adore) | 憶趣 (pleasure) | 患心 (sad) | 懊(blame) |

4.6. Transfer Capability

Since except for the criterion embedding, the left parts of the our model are shared between different criteria, we want to exploit whether a trained multi-criteria model can be transferred to a new criteria only by learning a new criterion embedding with few examples.

We leave-one-out strategy to evaluate the transfer capability of our Transformer-based multi-criteria model. We first train the model on seven datasets, then only learn the new criterion embedding with a few training instances from the left dataset. This scenario is also discussed in [13], we present their and our outcomes (averaged $F_1$ value) in Figure 4.

![Figure 4: Evaluation of the transfer capability. Switch-LSTMs and Transformer are trained on the given instances from scratch. Switch-LSTMs-T and Transformer-T are learned in transfer fashion.](image)

Firstly, for the different number of samples, our transferred model (Transformer-T) always largely outperforms the model learnt from scratch. We believe this indicates that learning a new criterion embedding is an effective way to transfer a trained
Transformer-based multi-criteria model to a new criterion. Secondly, the comparison between Switch-LSTMs and Transformer indicates that both of them have poor performances when just few samples are available. Thirdly, Transformer has superior transferability than Switch-LSTMs [13], since the average F1 values in the different number of target samples are all better than its Switch-LSTMs counterparts.

5. Related Work

Much prior work has focused on exploiting heterogeneous annotation data to improve various NLP tasks. Jiang et al. [25] proposed a stacking-based model which could train a model for one specific desired annotation criterion by utilizing knowledge from corpora with other heterogeneous annotations. Sun and Wan [26] proposed a structure-based stacking model to reduce the approximation error, which makes use of structured features such as sub-words. These models are unidirectional aid and also suffer from error propagation problem. Qiu et al. [22] used multi-tasks learning framework to improve the performance of POS tagging on two heterogeneous datasets. Li et al. [27] proposed a coupled sequence labeling model which could directly learn and infer two heterogeneous annotations. Chen et al. [28] adopted two neural models based on stacking framework and multi-view framework respectively, which boosts POS-tagging performance by utilizing corpora in heterogeneous annotations.

In our previous work [12, 13], we proposed a multi-criteria learning framework for CWS, which uses a shared layer to extract the common underlying features and a private layer for each criterion to extract criteria-specific features. He et al. [29] used a shared BiLSTM+CRF to deal with all the criteria by adding two artificial tokens at the beginning and end of an input sentence to specify the required target criteria. Huang et al. [30] proposed a domain adaptive segmenter to capture diverse criteria based on Bidirectional Encoder Representations from Transformers (BERT) [31].

Unlike the above models, we propose a fully-shared model for multi-criteria CWS based on Transformer. Given an input sentence, we just need a criterion indicator to specify the output criterion. Thus, we can use a single model to produce different segmented results for different criteria. It is also a first attempt to utilize the popular Transformer (learned from scratch) in CWS task.

6. Conclusion and Future Work

In this paper, we propose an effective framework for multi-criteria CWS by fully exploiting the underlying shared knowledge across multiple heterogeneous criteria. Experiments show that our proposed model is effective to extract the shared information and achieve significant improvements over the single-criterion methods.

In future work, we are planning to evaluate our model by incorporating other sequence labeling tasks, such as POS tagging and named entity recognition.

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References

[1] N. Xue, Chinese word segmentation as character tagging, Computational Linguistics and Chinese Language Processing 8 (2003) 29–48.

[2] X. Zheng, H. Chen, T. Xu, Deep learning for chinese word segmentation and pos tagging, in: Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing, 2013, pp. 647–657.

[3] W. Pei, T. Ge, B. Chang, Max-margin tensor neural network for Chinese word segmentation, in: Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), volume 1, 2014, pp. 293–303.

[4] X. Chen, X. Qiu, C. Zhu, X. Huang, Gated recursive neural network for Chinese word segmentation, in: Proceedings of Annual Meeting of the Association for Computational Linguistics., 2015.

[5] X. Chen, X. Qiu, C. Zhu, P. Liu, X. Huang, Long Short-Term Memory Neural Networks for Chinese Word Segmentation., in: EMNLP, 2015, pp. 1197–1206.

[6] D. Cai, H. Zhao, Neural word segmentation learning for Chinese, arXiv preprint arXiv:1606.04300 (2016).

[7] M. Zhang, Y. Zhang, G. Fu, Transition-based neural word segmentation, Proceedings of the 54nd ACL (2016).

[8] J. Ma, K. Ganchev, D. Weiss, State-of-the-art Chinese word segmentation with Bi-LSTMs, arXiv preprint arXiv:1808.06511 (2018).

[9] S. Yu, J. Lu, X. Zhu, H. Duan, S. Kang, H. Sun, H. Wang, Q. Zhao, W. Zhan, Processing norms of modern Chinese corpus, Technical Report, Technical report, 2001.

[10] X. Fei, The part-of-speech tagging guidelines for the penn chinese treebank (3.0), URL: http://www. cis. upenn. edu/~ chinese/segguide. 3rd. ch. pdf (2000).

[11] T. Emerson, The second international Chinese word segmentation bakeoff, in: Proceedings of the Fourth SIGHAN Workshop on Chinese Language Processing, Jeju Island, Korea, 2005, pp. 123–133.

[12] X. Chen, Z. Shi, X. Qiu, X. Huang, Adversarial multi-criteria learning for Chinese word segmentation, in: Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), volume 1, 2017, pp. 1193–1203.
[13] J. Gong, X. Chen, T. Gui, X. Qiu, Switch-lstms for multi-criteria chinese word segmentation, arXiv preprint arXiv:1812.08033 (2018).

[14] R. Caruana, Multitask learning, Machine learning 28 (1997) 41–75.

[15] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, Ł. Kaiser, I. Polosukhin, Attention is all you need, in: Advances in Neural Information Processing Systems, 2017, pp. 5998–6008.

[16] S. Hochreiter, J. Schmidhuber, Long short-term memory, Neural computation 9 (1997) 1735–1780.

[17] J. D. Lafferty, A. McCallum, F. C. N. Pereira, Conditional random fields: Probabilistic models for segmenting and labeling sequence data, in: Proceedings of the Eighteenth International Conference on Machine Learning, 2001.

[18] Y. Shao, C. Hardmeier, J. Tiedemann, J. Nivre, Character-based joint segmentation and pos tagging for chinese using bidirectional rnn-crf, arXiv preprint arXiv:1704.01314 (2017).

[19] M. Zhang, N. Yu, G. Fu, A simple and effective neural model for joint word segmentation and POS tagging, IEEE/ACM Transactions on Audio, Speech and Language Processing (TASLP) 26 (2018) 1528–1538.

[20] L. J. Ba, R. Kiros, G. E. Hinton, Layer normalization, CoRR abs/1607.06450 (2016).

[21] G. Jin, X. Chen, The fourth international chinese language processing bakeoff: Chinese word segmentation, named entity recognition and chinese pos tagging, in: Sixth SIGHAN Workshop on Chinese Language Processing, 2008, p. 69.

[22] X. Qiu, J. Zhao, X. Huang, Joint chinese word segmentation and POS tagging on heterogeneous annotated corpora with multiple task learning., in: EMNLP, 2013, pp. 658–668.

[23] W. Ling, C. Dyer, A. W. Black, I. Trancoso, Two/too simple adaptations of word2vec for syntax problems, in: Proceedings of the 2015 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, 2015, pp. 1299–1304.

[24] D. Kingma, J. Ba, Adam: A method for stochastic optimization, arXiv preprint arXiv:1412.6980 (2014).

[25] W. Jiang, L. Huang, Q. Liu, Automatic adaptation of annotation standards: Chinese word segmentation and POS tagging: a case study, in: Proceedings of the Joint Conference of the 47th Annual Meeting of the ACL and the 4th International Joint Conference on Natural Language Processing, 2009, pp. 522–530.
[26] W. Sun, X. Wan, Reducing approximation and estimation errors for chinese lexical processing with heterogeneous annotations, in: Proceedings of the 50th Annual Meeting of the Association for Computational Linguistics: Long Papers-Volume 1, Association for Computational Linguistics, 2012, pp. 232–241.

[27] Z. Li, J. Chao, M. Zhang, W. Chen, Coupled sequence labeling on heterogeneous annotations: POS tagging as a case study, in: Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing, 2015.

[28] H. Chen, Y. Zhang, Q. Liu, Neural network for heterogeneous annotations, Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing (2016).

[29] H. He, L. Wu, H. Yan, Z. Gao, Y. Feng, G. Townsend, Effective neural solution for multi-criteria word segmentation, in: Smart Intelligent Computing and Applications, Springer, 2019, pp. 133–142.

[30] W. Huang, X. Cheng, K. Chen, T. Wang, W. Chu, Toward fast and accurate neural chinese word segmentation with multi-criteria learning, arXiv preprint arXiv:1903.04190 (2019).

[31] J. Devlin, M. Chang, K. Lee, K. Toutanova, BERT: pre-training of deep bidirectional transformers for language understanding, CoRR abs/1810.04805 (2018).