An Encoding Strategy Based Word-Character LSTM for Chinese NER

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Abstract
A recently proposed lattice model has demonstrated that words in character sequence can provide rich word boundary information for character-based Chinese NER model. In this model, word information is integrated into a shortcut path between the start and the end characters of the word. However, the existence of shortcut path may cause the model to degenerate into a partial word-based model, which will suffer from word segmentation errors. Furthermore, the lattice model can not be trained in batches due to its DAG structure. In this paper, we propose a novel word-character LSTM(WC-LSTM) model to add word information into the start or the end character of the word, alleviating the influence of word segmentation errors while obtaining the word boundary information. Four different strategies are explored in our model to encode word information into a fixed-sized representation for efficient batch training. Experiments on benchmark datasets show that our proposed model outperforms other state-of-the-arts models.

1 Introduction
Name Entity Recognition (NER) is a basic task of many NLP systems including Information Retrieval (Virga and Khudanpur, 2003), Relationship Extraction (Miwa and Bansal, 2016), Question Answering (Mollá et al., 2006). The main task of NER is to identify named entities such as person, location, organization, etc. in given text. Various methods have been proposed to tackle this problem, including Hidden Markov Models(HMMs) (Saito and Nagata, 2003), Maximum Entropy Models(ME) (Chieu and Ng, 2003), Support Vector Machines(SVM) (Ekbal and Bandyopadhyay, 2010) and Conditional Random Fields(CRF) (Feng et al., 2006). With the development of deep learning, neural networks (Huang et al., 2015; Lample et al., 2016; Habibi et al., 2017) have been introduced to NER task. To avoid the segmentation errors, most of neural Chinese NER models are character-based.

Although character-based method has achieved good performance, it does not exploit word information in character sequence. Entity boundaries usually coincide with some word boundaries, which suggests that words in character sequence can provide rich boundary information for character-based model. To integrate words information into character-based model, Zhang and Yang (2018) propose a lattice-structured LSTM...
model to encode a sequence of input characters as well as all potential words that match a lexicon. Their model is an extension of character-based LSTM-CRF model and uses extra "shortcut paths” to link the memory cell between the start and the end characters of a word for utilizing word information. And the gated recurrent unit is used to control the contribution of shortcut paths and path between adjacent characters. However, as the study of (Yang et al., 2018) shown, the gate mechanism fails to choose the right path sometimes. As shown in Figure 1, wrong choices may cause lattice model to degenerate into a partial word-based model, which suffers from word segmentation errors. In addition, due to the variable length of words, the length of the whole path is not fixed. Besides, each character is bounded with a variable-sized candidate word sets, which means the amount of incoming and outcoming paths is not fixed either. In this case, lattice LSTM model is deprived of the power of batch training, and hence it is highly inefficient.

To address the above problems, we propose a novel word-character LSTM(WC-LSTM) to integrate word information into character-based model. To prevent our model from degenerating into a partial word-based model, we assign word information to a single character and ensure that there are no shortcut paths between characters. Specifically, word information is assigned to its end character and start character in forward WC-LSTM and backward WC-LSTM respectively. We introduce four strategies to extract fixed-sized useful information from different words, which ensures that our proposed model can perform batch training without losing word information.

We demonstrate the effectiveness of our architecture on four widely used datasets. Experimental results show that our proposed model outperforms other state-of-the-art models on the four datasets.

Our contributions of this paper can be concluded as follows:

- We propose a novel word-character LSTM(WC-LSTM) to incorporate word information into character-based model.
- We explore four different strategies to encode word information into a fixed-sized vector, which enables our proposed model to be trained in batches and adapted to various application scenarios.
- Our proposed model outperforms other models and achieves new state-of-the-art over four Chinese NER datasets. We release the source code for further research1.

2 Related Work

Neural Networks have been shown to achieve impressive results on Name Entity Recognition task (Gregoric et al., 2018; Lin and Lu, 2018). Based on the level of granularity, most of the models can be divided into three categories: word-based models, character-based models, and hybrid models.

Word-Based Models. Collobert and Weston (2008) propose one of the first word-based models for NER, with feature constructed from orthographic features, dictionaries and lexicons (Yadav and Bethard, 2018). Collobert et al. (2011) replace the hand-crafted features with word embeddings. Huang et al. (2015) propose a BiLSTM-CRF model for NER and achieves good performance. Ma and Hovy (2016) and Chiu and Nichols (2016) use CNN to capture spelling characteristics and Lample et al. (2016) use LSTM instead. When applied to Chinese NER, the above models all suffer from segmentation errors, since Chinese word segmentation is compulsory for those models.

Character-Based Models. Peng and Dredze (2015) propose to add segmentation features for better recognition of entity boundary. Dong et al. (2016) integrate radical-level features into character-based model. To eliminate the ambiguity of character, Sun and He (2017) take the position of character into account. Although the above models have achieved good results, they all ignore word information in character sequence.

Hybrid Models. Some efforts have been made to integrate word boundary information into character-based models. Motivated by the success of multi-task learning for Natural Language Processing (Liu et al., 2016, 2017; Zhang et al., 2018), Peng and Dredze (2016) first proposed to jointly train Chinese NER with Chinese word segmentation(CWS) task. Cao et al. (2018) apply adversarial transfer learning framework to integrate the task-shared word boundary information into Chinese NER task. Another way to obtain word boundary information is proposed by (Zhang and Yang, 2018), using a lattice LSTM to integrate word information into character-based model, which is similar to what is proposed in

1https://github.com/liuwei1206/CCW-NER
this paper. The main differences are as follows. Firstly, they exploit word information by a DAG-structured LSTM, while we use a chain-structured LSTM. Secondly, instead of integrating to the hidden state of LSTM, our model add word information into the input vector. Finally, our model can be trained in batches and is more efficient.

3 Method

The architecture of our proposed model is shown in Figure 2. Same as the widely used neural Chinese NER model, we use LSTM-CRF as our main network structure. The differences between our model and a standard LSTM-CRF model are mainly on the embedding layer and LSTM and can be summarized as follows. First, we represent a Chinese sentence as a sequence of character-words pairs to integrate word information into each character. Second, to enable our model to train in batches and to meet different application requirements, we introduce four encoding strategies to extract fixed-sized but different information from words. Finally, a chain-structured word-character LSTM is used to extract features from both character and word for better predicting.

Next, we will explain the main ideas for each component, including word-character embedding layer, word encoding strategy, and word-character LSTM.

Formally, we denote a Chinese sentence as $s = \{c_1, c_2, \ldots, c_n\}$, where $c_i$ denotes the $i_{th}$ character. We use $c_{b,e}$ to denote a character subsequence in $s$, which begins with $b_{th}$ character and ends with $e_{th}$ character. Take the sentence in Figure 2 for example, $c_{1,2}$ is ”涨(Rise)”. We use $\overline{w_{s_i}}$ to denote words assigned to $i_{th}$ character in forward WC-LSTM, which are a set of character subsequences $c_{b,i}$, where $b < i$ and $c_{b,i}$ matches a word in lexicon $D$. The lexicon $D$ is the same as the one used in (Zhang and Yang, 2018), which is built by using automatically segmented large raw text. Similarly, we use $\overline{w_{s_i}}$ to denote the words for $i_{th}$ character in backward WC-LSTM, which are a set of character subsequences $c_{i,e}$, where $e > i$ and $c_{i,e}$ matches a word in lexicon $D$. Finally, the sentence $s$ is represented as $\overrightarrow{rs} = \{(c_1, \overrightarrow{w_{s_1}}), (c_2, \overrightarrow{w_{s_2}}), \ldots, (c_n, \overrightarrow{w_{s_n}})\}$ in our model, and its reverse representation is $\overleftarrow{rs} = \{(c_n, \overleftarrow{w_{s_n}}), (c_{n-1}, \overleftarrow{w_{s_{n-1}}}), \ldots, (c_1, \overleftarrow{w_{s_1}})\}$.

3.1 Word-Character Embedding Layer

In our model, Each position $i$ in $\overrightarrow{rs}$ consists of two parts: $i_{th}$ character $c_i$ and the assigned words $\overrightarrow{w_{s_i}}$. The origin number of words in $\overrightarrow{w_{s_i}}$ is $s_i^1$ and words are sorted by their length. We ensure each $\overrightarrow{w_{s_i}}$ has the same number $s_i^2$ in the whole batch by padding. We embed each character $c_i$ in dis-

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$\overrightarrow{rs}$ The number depends on the maximum $s_i^2$ in the whole batch, and it can not be less than 1.
tributional space as $x_i^c$:

$$x_i^c = e^c(c_i)$$

(1)

where $e^c$ denotes a pre-trained character embedding lookup table. Similarly, for each $w_{si}^l$, the $l_{th}$ word $w_{li}^m$ in $w_{si}^l$ is represented using

$$x_{li}^m = e^w(w_{li}^m)$$

(2)

where $e^w$ denotes a pre-trained word embedding lookup table. As a result, the distributional representation of words $w_{si}^l$ is $\{x_{i1}^m, \ldots, x_{ils_i}^m\}$.

3.2 Words Encoding Strategy

Although the number of assigned words $s_i^p$ for each character $c_i$ is same in one batch, the number varies from batch to batch. As a result, the size of input to the model is not fixed, which is not conducive to batch training. To acquire fixed-sized input, we introduce four different encoding strategies in this section. And we use $x_i^{w1b}$ to denote the final representation of word information for position $i$ in following sections.

**Shortest Word First:** For each word set $w_{si}^l = \{w_{i1}^l, \ldots, w_{ils_i}^l\}$, we simply select word whose length is the shortest, i.e. $w_{i1}^l$. Then

$$\bar{x}_{i}^b = x_{i1}^m$$

(3)

**Longest Word First:** Contrary to the shortest word first, we select word whose length is the longest, i.e. $w_{ils_i}^l$. Note that $s_i^l$ may be 0, in this case, we set it to 1. Then

$$\bar{x}_{i}^b = x_{ils_i}^m$$

(4)

**Average:** While the first two strategies can only use the information of partial words, we introduce an average strategy to utilize all word information. As its name indicates, the average strategy computes the centroid of the embeddings of all elements except paddings in word set, i.e. $\{w_{i1}^l, \ldots, w_{ils_i}^l\}$. If $s_i^l = 0$, we simply average all the padding value in the word set. Then

$$\bar{x}_{i}^b = \left\{ \begin{array}{ll} \frac{1}{s_i^l} \sum_{l=1}^{s_i^l} x_{il}^m, & \text{if } s_i^l > 0 \\ \frac{1}{s_i^l} \sum_{l=1}^{s_i^l} x_{il}^m, & \text{if } s_i^l = 0 \end{array} \right.$$  

(5)

**Self-Attention:** Inspired by self-attention mechanism applied to sentence embedding (Lin et al., 2017), we exploit self-attention to better capture useful information from assigned words. For simplicity, we denote all the $x_{i1}^m$ as $W$, which has the size $s_i^p$ by $d_w^u$, where $d_w^u$ denotes the dimensionality of word embedding $e^w$.

$$W_i = (x_{i1}^m, \ldots, x_{ils_i}^m)$$

(6)

We use self-attention mechanism to obtain a linear combination of $s_i^p$ word embeddings in $W_i$. The attention mechanism takes $W_i$ as input, and generates a weight vector $a_i$.

$$a_i = \text{softmax}(w_2 \text{tanh}(W_1 W_i^T))$$

(7)

$W_1$ is a weight matrix with the size of $d_a$ by $d_w^u$ and $w_2$ is a $d_a$ dimensional vector, where $d_a$ is a hyperparameter. Both of them are trainable parameters.

If $s_i^l > 0$, we use the mask to exclude the padding values; otherwise we reserve them. Finally, we use $a_i$ to get the weighted sum of all words.

$$x_{i}^{w1b} = \left\{ \begin{array}{ll} \sum_{l=1}^{s_i^l} a_{il} x_{il}^m, & \text{if } s_i^l > 0 \\ \sum_{l=1}^{s_i^l} a_{il} x_{il}^m, & \text{if } s_i^l = 0 \end{array} \right.$$  

(8)

where $a_{il}$ denotes the $l_{th}$ value in $a_i$.

3.3 Word-Character LSTM (WC-LSTM)

Inspired by the way character bigram is integrated into sequence labeling model (Chen et al., 2015; Yang et al., 2017), we concatenate each $x_i^c$ with $x_i^{w1b}$ to utilize word information. And this is quite different from the way used in (Zhang and Yang, 2018), since they use extra shortcut paths to integrate word information into the hidden layer of LSTM. By concatenating, there is no shortcut path in our model and information can only flow between adjacent characters, which ensures that our model will not degenerate into a partial word-based model. Then the WC-LSTM functions are:

$$
\begin{bmatrix}
  c_i \\
  o_i \\
  i_i \\
  f_i
\end{bmatrix}
= \begin{bmatrix}
  \text{tanh} \\
  \sigma \\
  \sigma \\
  \sigma
\end{bmatrix}
\begin{bmatrix}
  W_p \begin{bmatrix} x_i & x_{i-1} \end{bmatrix} + b_p \\
  x_i \\
  x_i^c \oplus x_i^{w1b} \\
  c_i \\
  c_i \circ i_i + c_{i-1} \circ f_i \\
  h_i
\end{bmatrix}
$$

(9)

$$
\begin{bmatrix}
  x_i \\
  h_i
\end{bmatrix}
= \begin{bmatrix}
  x_i = x_i^c \oplus x_i^{w1b} \\
  c_i = c_i \circ i_i + c_{i-1} \circ f_i \\
  h_i = o_i \circ \text{tanh}(c_i)
\end{bmatrix}
$$

(10)

where $o_i$, $i_i$ and $f_i$ denote output gate, input gate and forget gate respectively. $W_p$ and $b_p$ are parameters of affine transformation; $\sigma$ denotes the
The bidirectional WC-LSTM is applied in our model to leverage both information from the past and the future. To get the future information, we use a second WC-LSTM that reads the reverse representation of \( \tilde{r}s \), i.e., \( \tilde{r}s = \{(c_n, \tilde{w}s_{n}), (c_{n-1}, \tilde{w}s_{n-1}), \ldots, (c_1, \tilde{w}s_1)\} \). And the following operations to get each backward WC-LSTM hidden vector \( \tilde{h}_i \) is the same as the one in the forward WC-LSTM. Finally, the update of each bidirectional WC-LSTM unit can be written as follows:

\[
\begin{align*}
\tilde{x}_i &= x_i^f \oplus x_i^b \\
\tilde{c}_i &= x_i^f \oplus x_i^b \\
\tilde{h}_i &= \text{WC} - \text{LSTM}(\tilde{h}_{i-1}, \tilde{x}_i) & (11) \\
\tilde{h}_n &= \text{WC} - \text{LSTM}(\tilde{h}_{n+1}, \tilde{x}_i) \\
\tilde{h}_i &= \tilde{h}_i^f \oplus \tilde{h}_i^b
\end{align*}
\]

where \( \tilde{h}_1^f \) and \( \tilde{h}_1^b \) are hidden states at position \( i \) of forward and backward WC-LSTM respectively, and \( \oplus \) denotes concatenation operation.

### 3.4 Decoding and Training

Considering the dependencies between successive labels, we use a CRF layer to make sequence tagging. We define matrix \( \mathbf{O} \) to be scores calculated based on the output \( \mathbf{H} = \{h_1, h_2, \ldots, h_n\} \):

\[
\mathbf{O} = \mathbf{W}_o \mathbf{H} + \mathbf{b}_o & (12)
\]

For a label sequence \( y = \{y_1, y_2, \ldots, y_n\} \), we define its probability to be:

\[
p(y|s) = \frac{\exp \left( \sum_i \left( O_{i,y_i} + T_{y_{i-1},y_i} \right) \right)}{\sum_{\hat{y}} \exp \left( \sum_i \left( O_{i,\hat{y}_i} + T_{\hat{y}_{i-1},\hat{y}_i} \right) \right)} & (13)
\]

Where \( \mathbf{W}_o \) and \( \mathbf{b}_o \) are parameters to calculate \( \mathbf{O} \); \( \mathbf{T} \) is a transition score matrix and \( \hat{y} \) denotes all possible tag sequences.

While decoding, we use the Viterbi algorithm to find the label sequences that obtained the highest score:

\[
y^* = \underset{y \in \hat{y}}{\arg \max} \sum_i \left( O_{i,y_i} + T_{y_{i-1},y_i} \right) & (14)
\]

Given \( N \) manually labeled data \( \{(s_j, y_j)\}_{j=1}^N \), we minimize the sentence-level negative log-likelihood loss to train the model:

\[
L = - \sum_j \log(p(y_j|s_j)) & (15)
\]

### 4 Experiments

#### 4.1 Experimental Settings

**Dataset.** We evaluate our model on four datasets, including OntoNotes4 (Weischedel et al., 2011), MSRA (Levow, 2006), Weibo NER (Peng and Dredze, 2015) and a Chinese resume dataset (Zhang and Yang, 2018). Both OntoNotes4 and MSRA datasets are news in simplified Chinese. Weibo NER dataset is social media data, which is drawn from the Sina Weibo. Chinese resume dataset consists of resumes of senior executives, which is annotated by (Zhang and Yang, 2018). For OntoNotes, we use the same training, development and test splits as (Che et al., 2013). For other datasets which have already been split, and we don’t change them. We summarize the datasets in Table 1.

**Implementation Details.** We utilize the character and word embeddings used in (Zhang and Yang, 2018), both of which are pre-trained on Chinese Giga-Word using word2vec model. Following (Zhang and Yang, 2018), we use the word embedding dictionary as Lexicon \( \mathbf{D} \) in our model. For characters and words that do not appear in the pretrained embeddings, we initialize them with a uniform distribution\(^3\). When training the model, character embeddings and word embeddings are updated along with other parameters.

For hyper-parameter configurations, we mostly refer to the settings in (Zhang and Yang, 2018). We set both character embedding size and word embedding size to 50. The dimensionality of each unidirectional multi-input LSTM hidden states is 100 for Weibo NER and Chinese Resume, and 200 for OntoNote4 and MSRA. For self-attention strategy, we set the \( d_a \) to 50. To avoid overfitting, we apply dropout to both embeddings and LSTM with a rate of 0.5. We use SGD to optimize all the trainable parameters. Learning rate is set to 0.015 initially and decays during training at a rate

\[^3\text{The range is } \left[-\sqrt{\frac{3}{dim}}, +\sqrt{\frac{3}{dim}}\right], \text{ where dim denotes the size of embedding.}\]
of 0.05.

For evaluation, we use the Precision(P), Recall(R) and F1 score as metrics in our experiments.

### 4.2 Experimental Results

**OntoNotes.** Table 2 shows the experimental results on OntoNote 4 dataset. The "Input" column shows the representation of input sentence, where "Gold seg" means a sequence of words with gold-standard segmentation, and "No seg" means a sequence of character without any segmentation.

The first block in Table 2 are the results of word-based models (Wang et al., 2013; Che et al., 2013; Yang et al., 2016). By using gold-standard segmentation and external labeled data, all of them achieve good performance. But the only resource used in our model are pretrained character and word embeddings.

The first two rows in the second block show the performance of the lattice model and character-based model. The character baseline denotes the original character-based BiLSTM-CRF model. Zhang and Yang (2018) propose a lattice LSTM to exploit word information in character sequence, giving the F1 score of 73.88%. Compared with the character baseline, lattice model gains 8.92% improvement in F1 score, which shows the importance of word information in character sequence.

In the last four rows, we list the results of our proposed model. The results show that all of our models outperform other character-based models, and the one with self-attention strategy achieves the best result. Without gold-standard segmentation and external labeled data, our model gives competitive results to the word-based models on this dataset. Compared with the character baseline, our model with self-attention obtains 9.48% improvement in F1 score, which proves the effectiveness of our way to integrating word information. Compared with lattice model, all of our models achieve better results, which shows that our approach to integrating word information is more reasonable than lattice model.

**MSRA.** Table 3 shows the results on MSRA dataset. Zhang et al. (2006) and Zhou et al. (2013) use the statistical model with rich hand-crafted features. Dong et al. (2016) exploit radical features in Chinese character. Cao et al. (2018) joint train Chinese NER task with Chinese word segmentation, in which adversarial learning and self-attention mechanism are applied for better performance. We can observe that our proposed models outperform the above models and the one with average strategy achieves new state-of-the-art performance.

**Weibo.** Table 4 shows the results on Weibo dataset. The "NE", "NM" and "Overall" columns denote F1-score for named entities, nominal entities(excluding named entities) and both respectively. We can see that WC-LSTM model with longest word first strategy achieves new state-of-the-art performance. Multi-task learning (Peng and Dredze, 2015, 2016; Cao et al., 2018) and semi-supervised learning (Sun and He, 2017; He and Sun, 2017) are the most common methods.

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Table 2: Results on OntoNotes

| Input      | Models                                      | P   | R   | F1  |
|------------|---------------------------------------------|-----|-----|-----|
| Gold seg   | Wang et al. (2013)                          | 76.43 | 72.32 | 74.32 |
|            | Che et al. (2013)                           | 77.71 | 72.51 | 75.02 |
|            | Yang et al. (2016)                          | 65.59 | 71.84 | 68.57 |
|            | Lattice (Zhang and Yang, 2018)              | 76.35 | 71.56 | 73.88 |
|            | Character baseline                          | 70.08 | 60.53 | 64.95 |
|            | WC-LSTM + shortest                          | 76.39 | 72.39 | 74.34 |
|            | WC-LSTM + longest                           | 75.62 | 72.76 | 74.16 |
|            | WC-LSTM + average                           | 76.04 | 72.03 | 73.98 |
|            | WC-LSTM + self-attention                    | 76.09 | 72.85 | 74.43 |

Table 3: Results on MSRA

| Models                                      | NE   | NM   | Overall |
|---------------------------------------------|------|------|---------|
| Peng and Dredze (2015)                      | 51.96 | 61.05 | 56.05   |
| Peng and Dredze (2016)                      | 55.28 | 62.97 | 58.99   |
| Sun and He (2017)                           | 54.50 | 62.17 | 58.23   |
| He and Sun (2017)                           | 50.60 | 59.32 | 54.82   |
| Cao et al. (2018)                           | 54.34 | 57.35 | 58.70   |
| Lattice (Zhang and Yang, 2018)              | 53.04 | 62.25 | 58.79   |
| Character baseline                          | 47.98 | 57.94 | 52.88   |
| WC-LSTM + shortest                          | 52.99 | 65.75 | 59.20   |
| WC-LSTM + longest                           | 52.55 | 67.41 | 59.84   |
| WC-LSTM + average                           | 53.19 | 64.17 | 58.67   |
| WC-LSTM + self-attention                    | 49.86 | 65.31 | 57.51   |

Table 4: Results on Weibo NER

| Models                                      | NE   | NM   | Overall |
|---------------------------------------------|------|------|---------|
| Peng and Dredze (2015)                      | 51.96 | 61.05 | 56.05   |
| Peng and Dredze (2016)                      | 55.28 | 62.97 | 58.99   |
| Sun and He (2017)                           | 54.50 | 62.17 | 58.23   |
| He and Sun (2017)                           | 50.60 | 59.32 | 54.82   |
| Cao et al. (2018)                           | 54.34 | 57.35 | 58.70   |
| Lattice (Zhang and Yang, 2018)              | 53.04 | 62.25 | 58.79   |
| Character baseline                          | 47.98 | 57.94 | 52.88   |
| WC-LSTM + shortest                          | 52.99 | 65.75 | 59.20   |
| WC-LSTM + longest                           | 52.55 | 67.41 | 59.84   |
| WC-LSTM + average                           | 53.19 | 64.17 | 58.67   |
| WC-LSTM + self-attention                    | 49.86 | 65.31 | 57.51   |

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4The results of (Peng and Dredze, 2015, 2016) are taken from (Peng and Dredze, 2017)
Table 5: Results on Chinese Resume

| Models                          | P       | R       | F1      |
|--------------------------------|---------|---------|---------|
| Lattice (Zhang and Yang, 2018) | 94.81   | 94.11   | 94.46   |
| Character baseline             | 93.26   | 93.44   | 93.35   |
| WC-LSTM + shortest             | 94.97   | 94.91   | **94.94**|
| WC-LSTM + longest              | **95.27** | **95.15** | **95.21** |
| WC-LSTM + average              | 95.09   | 94.97   | **95.03** |
| WC-LSTM + self-attention       | 95.14   | 94.79   | **94.96** |

Table 6: Time per epoch of models

| Time(s)/epoch                  |
|--------------------------------|
| Character baseline (batch size=1) | 880     |
| Character baseline (batch size=8) | 253     |
| Lattice                         | 2245    |
| WC-LSTM (batch size=1)          | 980     |
| WC-LSTM (batch size=8)          | 350     |

Resume. Table 5 shows the results on Chinese Resume dataset. Consistent with the previous results, our models outperform lattice model (Zhang and Yang, 2018). The above experimental results strongly verify that our method to utilize word information is more effective than the lattice model.

Our proposed model has achieved state-of-the-art results on various domains such as news, social media, and Chinese resume.

4.3 Efficiency

To further explore the efficiency of our model, we conduct some comparative experiments on training time and convergence speed. The lattice model proposed in (Zhang and Yang, 2018) is our principal comparison object, since it also utilizes the word information in character sequence. Our model is an extension of the character-based model, so we also report the results on character-based model as character baseline. We only conduct our experiments on OnteNotes dataset due to space limitation. And we choose the model with the self-attention strategy for the comparative experiments, as it outperforms other strategies on OntoNotes dataset.

The training time of each epoch for all models is shown in Table 6. The lattice model needs the most training time for each epoch, since it can only be trained with batch size=1 due to its complex DAG structure. Compared with it, our model with batch size=1 only need half of the training time. Which shows that our model is more efficient. With batch size=8, our model is nearly 6 times faster than the lattice model, which further demonstrates the efficiency of our model. Compared with the character baseline, our model only adds a small amount of training time but greatly improves the performance. All the experiments are conducted on a single GPU with NVIDIA Tesla K40m.

Figure 3 shows the learning curve of the models in Table 6. As we can see from the figure, whether with batch size=1 or 8, our model can converge within the same epochs as lattice model does. “1” and “8” denotes batch size. Lattice model can only be trained with batch size=1 due to its DAG structure.

Figure 3: Convergence curve of models. Our model can converge within the same epochs as lattice model does. “1” and “8” denotes batch size. Lattice model can only be trained with batch size=1 due to its DAG structure.

4.4 Detailed Analysis

Case Study. Word information is very useful for Chinese NER task, since it can provide rich word boundary information. To verify that our model can better utilize the boundary information, we analyze an example from OntoNotes dataset. As shown in Table 7, the character-based model cannot detect the existence of the entity “Northeast Asia” without word information. The lattice model incorrectly recognizes "Northeast Asia"
Table 7: An example of that our models can mitigate the influence of wrong boundary information while utilizing word information. "Latent words" denotes all words in character sequences; "Character" denotes the character-based model; "Lattice" denotes lattice model and the last four rows are our models with different encoding strategies.

Strategies Analysis. In this part, we analyze the difference between strategies. The application scenarios of shortest word first and longest word first can be explained by Nested Name Entity Recognition (Ju et al., 2018; Sohrab and Miwa, 2018). Short word first is good at identifying inner nested entities due to the short word information, while longest word first tends to identify flat entities with the help of long word information. Taking "长江三角洲(Yangtze River Delta)" as an example, shortest word first recognizes "长江(Yangtze)" and "三角洲(Delta)" as entities, but longest word first tend to think that they are part of the entity "长江三角洲(Yangtze River Delta)". Both results are reasonable, but the right result depends on specific needs.

The average and self-attention strategies are the combination of all words information and can use more information. Intuitively, they should outperform the shortest word first and the longest word first. But results on Weibo NER(Table 4) and Resume(Table 5) show the opposite effect. We conjecture that this is caused by the small amount of training data since more word information but small dataset will lead to overfitting. The average strategy is a special case of the self-attention strategy where all weights are the same, so we would like to see the latter outperforms the former when training data is sufficient. Surprisingly, the average strategy achieves higher F1 score than the self-attention strategy in MSRA dataset(Table 3). We carefully analyze the experimental results and find that there are a large number of informal texts in the MSRA test set. Specifically, the MSRA test set contains some very long sentences, in which there are a series of Chinese person name without delimiter. As shown in Table 8, when applied to such informal text, the self-attention strategy fails to determine the entity boundary sometimes while the average strategy correctly recognizes the entities. And we conjecture that, with more trainable parameters, the self-attention strategy can better fit the formal text in the training set but cannot adapt well to the informal data in the test set, so it performs worse than the average strategy.

Finally, the application scenarios of different strategies can be summarized as followings. If the training data is sufficient, we recommend using self-attention for formal texts and average strategy for informal texts. If there is only a very small amount of annotated data, we recommend using the shortest words first for inner nested entities and longest word first strategy for flat entities.

Lexicon and Embeddings. To further analyze the contribution from word lexicon and pretrained word embeddings, we conduct some comparative experiments by using the same word lexicon with and without pretrained embeddings. We choose the strategy that achieving the best performance for each dataset. We estimate the contribution of the lexicon by replacing pretrained word embeddings with randomly initialized embeddings. As shown in Table 9, both lexicon

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5Same initialization strategy as in "Implement Details".
Table 9: Comparison F1 scores between our proposed model with and without pretrained word embeddings. Where “init” and “pretrain” denote without and with pretrained embeddings respectively. “+” denotes the boost value to baseline.

and pretrained word embeddings are useful to our model. However, different from the result in lattice model (Yang et al., 2018), pretrained word embeddings contribute more than lexicon to our model. Taking the result on Ontonote for example, the contribution of pretrained embeddings can be estimated as \((9.48\% - 2.86\%) = 6.62\%\), which is higher than the contribution of lexicon 2.86%. The results show that our model relies more on pretrained embeddings instead of the lexicon, which explains the excellent performance of our model in different domains.

5 Conclusion and Future Work

In this paper, we propose a novel method to utilize word information in character sequence for Chinese NER. Four encoding strategies are introduced to extract fixed-sized but different information for batch training. By using WC-LSTM to extract features from the character vector and word vector, our model can effectively exploit word boundary information and mitigate the influence of word segmentation errors. Experiments on datasets in different domains show that our model is more efficient and faster than the lattice model and also outperforms other state-of-the-art models.

In the future, we plan to further improve and perfect the proposed method, such as exploring some strategies to handle OOV words. Also, the proposed methods can be further extended to other Chinese NLP tasks, such as CWS, Text Classification, and Sentiment Analysis.

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