Porous Lattice-based Transformer Encoder for Chinese NER

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Abstract
Incorporating lattices into character-level Chinese named entity recognition is an effective method to exploit explicit word information. Recent works extend recurrent and convolutional neural networks to model lattice inputs. However, due to the DAG structure or the variable-sized potential word set for lattice inputs, these models prevent the convenient use of batched computation, resulting in serious inefficient. In this paper, we propose a porous lattice-based transformer encoder for Chinese named entity recognition, which is capable to better exploit the GPU parallelism and batch the computation owing to the mask mechanism in transformer. We first investigate the lattice-aware self-attention coupled with relative position representations to explore effective word information in the lattice structure. Besides, to strengthen the local dependencies among neighboring tokens, we propose a novel porous structure during self-attentional computation processing, in which every two non-neighboring tokens are connected through a shared pivot node. Experimental results on four datasets show that our model performs up to 9.47 times faster than state-of-the-art models, while is roughly on a par with its performance. The source code of this paper can be obtained from https://github.com/xxx/xxx.

Introduction
Named Entity Recognition (NER) is one of the core tasks in natural language processing (NLP), which aims to automatically discover information entities and identify their corresponding categories from plain text. Many high-level NLP tasks, such as information retrieval (Berger and Lafferty 2007), relation extraction (Yu et al. 2019) and entity linking (Xue et al. 2019), need the NER tagger as one of their essential components. Different from English NER, many East Asian languages, including Chinese, are written without explicit word boundary. Such that Chinese named entities are much tricky to identify.

To overcome this limitation, recent state-of-the-art models make efforts to integrate latent word information into character-based models, they represent lexicon words from the sentence using a lattice structure model (Zhang and Yang 2018, Gu et al. 2019). As shown in the part highlighted by the dotted green lines of Figure 1, they construct a word-character lattice by matching a sentence with a vast external lexicon. Specifically, Zhang and Yang (2018) introduce lattice LSTM to integrate all potential words which match a lexicon into character sequence. While showing promising results, lattice LSTM demands multiple recurrent computation, one for character sequence and the others for latent words in sentence, which means this model is computationally expensive. Another strand of work is LR-CNN (Gu et al. 2019), which utilizes CNN with rethinking mechanism to encode character sequence and all potential word information based on different window sizes. Although achieving the recent state-of-the-art performance, LR-CNN also suffers from the running efficiency problem. This model is also computationally expensive due to the rethinking mechanism. Additionally, caused by directed acyclic graph (DAG) structure or the variable-sized potential word set for lattice inputs, neither lattice LSTM or LR-CNN can run in batch mode, which means these models are terribly inefficient.

Benefitting from the mask mechanism in self-attentional computation, transformer earns the power of proceeding in batches while handling lattice-structured inputs, thus becomes popular in many NLP tasks to learn the dependency

Figure 1: Illustration of the major difference in self-attentional computation between our proposed porous lattice-based transformer encoder and the standard lattice-based transformer encoder. Standard encoder make attentional computation for every token pairs (orange and blue), while our encoder only preserves local computation of neighboring tokens (orange) and models long range dependency via a pivot shared node (grey).
between lattice inputs. [Xiao et al. (2019)] and [Sperber et al. (2019)] explore lattice-based transformer and apply it to neural machine translation (NMT) and speech translation respectively. But it is challenging to directly apply these works to NER task for two issues. First, these lattice-based transformers are designed for encoder-decoder task, while NER is point-to-point; Second, these models fully take into account all the tokens in input sequences with a weighted averaging operation, which disperses the attentional distribution and overlooks the relation of neighbor tokens (Yang et al. 2018; Yang et al. 2019), while this distribution is crucial for NER task.

In this paper, we consider all these issues systematically and present a novel lattice-based transformer encoder with the porous mechanism to deal with these issues. Benefiting from the mask mechanism in transformer, our model earns the power of proceeding in batches and processing in parallel, which means our model is able to better exploit GPU parallelism compared with lattice LSTM and LR-CNN. We first adapt current lattice-based transformer to fit point-to-point task by removing its decoder architecture and reducing the number of the encoder layers. For the second issue, motivated by (Guo et al. 2019), we further introduce a novel porous mechanism into our lattice-based transformer encoder to enhance the local dependencies among neighboring tokens. The key insight is to sparse the self-attentional architecture by replacing the fully-connected topology with a pivot-shared structure. In this way, every two non-neighboring tokens are connected through a shared pivot node to weaken long-range dependencies, and for two neighboring tokens, we strengthen their dependency by connecting them directly. The major difference with the self-attention computation in the standard lattice-based transformer encoder ([Xiao et al. 2019]) is illustrated in Figure 1.

Specifically, our model consists of three layers. We first concatenate character sequence and all the potential words in sentence to get the lattice input embedding matrix. Then we feed it into the porous lattice-based transformer encoder layer. In this layer, we introduce several relationships among tokens to represent its relative position information. Besides, owing to our porous mechanism, one token in the lattice inputs just make direct attentional computation with its neighboring tokens, while for non-neighboring tokens, they are connected through a shared pivot node. With this strategy, our model can strengthen local dependencies and keep the ability to capture long distance dependencies. Finally, on top of lattice-based transformer encoder, we use a sequential BiGRU-CRF to decode labels for the whole sentence.

In summary, this paper makes the following contributions: (1) We propose a novel lattice-based transformer structure for Chinese NER, avoiding expensive computation of previous lattice-basedner models. (2) We propose a porous mechanism to strengthen local dependencies among neighboring tokens. (3) Experimental results on four datasets demonstrate that our model achieves comparable performance, and performs up to 9.47 times faster than state-of-the-art methods.

**Background**

In this section, we first briefly describe self-attention mechanism, then move on to current lattice-based transformer architecture that our model is built upon.

**Self-Attention**

Self-attention in general can be described using the terminology for queries, keys and values. Transformer (Vaswani et al. 2017) first employs $h$ attention heads to perform self-attention over an input sequence individually, then applies concatenation and linear transformation operations to each head, which is called multi-head attention. Given a vector sequence $X \in \mathbb{R}^{n \times d}$, we can use a query vector $q \in \mathbb{R}^{1 \times d}$ to perform soft selections of the relevant information:

$$\text{Att}(q, K, V) = \text{softmax}(\frac{qK^T}{\sqrt{d_k}})V$$  \hfill (1)

where $K = XW^K$, $V = XV^V$, and $W^K$, $V^V$ are learnable parameters of shape $[d \times d_k]$, $[d \times d_k]$ respectively. Then the multi-head attention can be defined as:

$$\text{MultiAtt}(q, X) = (z_1 \oplus z_2 \oplus ... \oplus z_h)W^O,$$  \hfill (2)

where $\oplus$ denotes the concatenation operation, and $W^K, W^V, W_i^K, W_i^V, W_i^O$ are learnable parameters.

**Lattice-Based Transformer**

The Lattice-based transformer follows the typical encoder-decoder architecture using stacked self-attention, point-wise fully connected layers, and the encoder-decoder attention layers. Each layer is in principle wrapped by a residual connection (He et al., 2016) and a postprocessing layer normalization (Ba et al., 2016). Different from standard version, lattice-based Transformer accepts lattice inputs and models the relation information between lattices ([Sperber et al. 2019] Xiao et al. 2019; Zhang et al. 2019). Formally, attentional computation in lattice-based Transformer can be represented as follows:

$$z_i = \text{Att}(XW^Q_i, XW^K_i, XV^K_i), i \in [1, h]$$  \hfill (4)

$$\text{Att}(Q, K, V) = \text{softmax}(\frac{QK^T + R}{\sqrt{d_k}})V$$  \hfill (5)

where $X$ denotes the lattice inputs and $R$ is the relation embedding sequence which indicates the relation between lattice input tokens, $W_i^Q, W_i^K, W_i^V$ are learnable parameters.

**Models**

Given a character sequence $c_{1:N} = \{c_1, c_2, ..., c_N\}$, we can define a potential word or a character unit starting from $c_i$ and ending by $c_j$ in our lattice-structured inputs as element $e_{ij}$. For example, in the top half of Figure 2, $e_{3,4}$ indicates the potential word named “Mayor” which contains $c_3$ named “City” and $c_4$ named “Long”. We place all these elements into an input token sequence $t_{1:M} = \{t_1, t_2, ..., t_M\}$ for transformer encoder. In our model, all the tokens are the actual input. The overall architecture is shown in Figure 2.
In addition, each word contains information about the position. In this work, we add the position embedding of the first character in one token to represent its position. For example, in Figure 1, the position of token “Nanjing” is defined as the index of its first character “South”.

**Word-Character Embedding Layer**

Consider a sentence that consists of \( n \) character \( S = \{c_1, \ldots, c_n\} \), where \( c_i \) is the \( i \)-th character, we first convert the characters to their char-level representations:

\[
x^c_i = E^c(c_i)
\]

where \( E^c \) denotes the character embedding matrix. Besides, character bigrams have shown useful for representing characters in word segmentation (Chen et al. 2015, Yang, Zhang, and Dong 2017), so that we also augment character embeddings with character bigrams embeddings. The final representation of character is defined as the concatenation of unigram-level and bigram-level embedding:

\[
x^c_i = [E^c(c_i); E^h(c_i, c_{i+1})]
\]

where \( E^h \) denotes the bigram character embedding matrix. In addition, each word \( e_{i:j} \) in lattices is represented as \( x^w_{i:j} \) by looking up a trainable word embedding table.

**Porous Latticed-based Transformer Encoder Layer**

As motivated in introduction, our primary goal is to adapt the standard transformer to the NER task with lattice inputs. To this end, we first introduce the position encoding strategy to incorporate such position relationships into attention layer, we integrate the relation embedding into self-attention weights. We directly modify Equation (5) and define the lattice-aware self-attentional encoder as follows:

\[
\alpha = \text{softmax}(QK^T + \text{einsum}(ijk, ij'k, Q, RK^K)) \quad (8)
\]

where \( RK^K \) and \( RV^K \) are two relation embedding tensors of shape \([n \times n \times d_k] \) and \([n \times n \times d_v] \) respectively, in which \((n, n)\) is the relational dimension. More concretely, \( RK^K[i, j] \) is obtained by first determining the relation between token \( t_i \) and \( t_j \) which refer to \( e_{pq} \) and \( e_{mn} \) respectively. Then we transform the relation into embedding by looking up a trainable relation embedding matrix \( A \in \mathbb{R}^{d_k \times d_k} \). Note that here we define nine types of embedding instead of eight relations in Table 1. The additional embedding is introduced to represent the interaction relation with a shared pivot node (described in the next section) and facilitate parallel computation. Figure 3 illustrates a detailed and vivid example.

Additionally, the new dot product term through \( \text{einsum} \) is available in Numpy, TensorFlow, and PyTorch.

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Figure 2: Left panel: The overall architecture of our proposed model. Right panel: Porous lattice-based Transformer encoder.
operation in Equation (8) and (9) is a tricky part, where e\_insum is an operation computing multilinear expressions (i.e., sums of products) using the Einstein summation convention. In our case, Q is a 2D array of shape \([n \times d_k]\) and \(\alpha\) is a 2D array of shape \([n \times n]\), in which \(n\) is the sentence length and \(d_k\) is the dimension of Q and K. \(\mathbf{R}^K\) and \(\mathbf{R}^V\) are two 3D arrays. We apply e\_insum to sum out the dimension of the hidden size, resulting in a new array of shape \([n \times n]\). More specifically, for the result of e\_insum(\(i\_\alpha, i\_k \rightarrow i\_j\), Q, \(\mathbf{R}^K\)), the element in i-th row and j-th column is \(\sum_\alpha Q_{i\_\alpha} R^K_{i\_k j}\).

### Porous Latticed-based Transformer Encoder

Considering standard self-attention mechanism encodes sequences by relating sequence items to one another through computation of pairwise similarity, it disperses the distribution of attention and overlooks the relation of neighboring elements, which is crucial for NER. To maintain the strength of capturing long distance dependencies and enhance the ability of capturing short-range dependencies, we sparsify the transformer architecture by replacing the fully-connected topology with a pivot-shaped structure referenced by (Guo et al. 2019). Specifically, given element set E and its embedding matrix \(\mathbf{X}\), where \(e_{ij} \in E\) and \(x_{ij} \in \mathbf{X}\) (if \(e_{ij}\) is a character then \(x_{ij} = x_{ij}^{c}\); else \(x_{ij} = x_{ij}^{p}\)), we define \(e_{ij}^{c}\) and its representation \(x_{ij}^{c}\), where \(e_{ij}^{c}\) indicates the element set whose relation with \(e_{ij}\) is \(r_k\), then we update the hidden state \(h_{i:j}\) of \(e_{ij}\) as follows:

\[
h_{i:j} = \text{MutiAtt}(x_{i:j}, c_{i:j}),
\]

where

\[
c_{i:j} = [x_{i:j}^1, x_{i:j}^2, x_{i:j}^3, x_{i:j}^4, x_{i:j}^5, x_{i:j}^6, x_{i:j}^7, s],
\]

\[
s = \frac{1}{n} \sum_{i:j} x_{i:j}
\]

As we can see, in our porous latticed-based transformer encoder, one element \(e_{ij}\) just make direct attentional computation with its neighboring elements and model the non-local compositions via the pivot shared node \(s\). As illustrated in Figure 3, \(e_{ij}\) doesn’t make direct self-attentional computation with the element set whose relation with \(e_{ij}\) is \(r_k\), thus we mask them. Under this lightweight porous structure, our transformer encoder has an approximate ability to strengthen local dependencies and keep the ability to capture long distance dependencies.

### BiGRU-CRF Decoding

After extracting the semantic information by the porous lattice-based transformer encoder layer, we feed them into a BiGRU-CRF model to make sequence tagging. Specially, taking \(h_1, h_2, ..., h_n\) as input, a bidirectional GRU is implemented to produce forward state \(\bar{h}_t\) and backward state \(\hat{h}_t\) for each time step:

\[
\bar{h}_t = \text{GRU}(\bar{h}_{t-1}, h_{1:t})
\]

\[
\hat{h}_t = \text{GRU}(\hat{h}_{t-1}, h_{t:n})
\]

These two separate hidden states capture both past (forward) and future (backward) information of the character sequence. Then, we concatenate \(\bar{h}_t\) and \(\hat{h}_t\) as the encoding output of the \(t\)-th character, donated as \(h_t = [\bar{h}_t; \hat{h}_t]\).

Finally, a standard CRF layer is used on top of \(h_1, h_2, ..., h_n\) to make sequence tagging. For a label sequence \(y = \{y_1, y_2, ..., y_n\}\), we define its probability to be:

\[
P(y|S) = \frac{\exp(\sum_i(W_{y_i} h_i + b_{y_i}^{\text{transition}}))}{\sum_y \exp(\sum_i(W_{y_i} h_i + b_{y_i}^{\text{transition}}))}
\]

Here \(y'\) denotes all possible tag sequences, \(W_{y_i}\) is a model parameter specific to \(y_i\), and \(b_{y_i}^{\text{transition}}\) is the transition score between \(y_{i-1}\) and \(y_i\). While decoding, we use the first-order Viterbi algorithm to find the label sequences that obtained the highest score.

### Training

Given a set of manually labeled training data \(\{(S_i, y_i)\}_{i=1}^N\), sentence-level log-likelihood loss with \(L_2\) regularization is used to train the model:

\[
L = \sum_{i=1}^N \log(P(y_i|S_i)) + \frac{\lambda}{2} ||\Theta||^2,
\]

where \(\lambda\) is the \(L_2\) regularization weight and \(\Theta\) represents the parameter set.
Table 2: Statistics of datasets.

| Dataset   | Type   | Train | Dev   | Test  |
|-----------|--------|-------|-------|-------|
| OntoNotes | Sentence | 15.7k | 4.3k  | 4.3k  |
|           | Char    | 491.9k| 200.5k| 208.1k|
| MSRA      | Sentence | 46.4k | -     | 4.4k  |
|           | Char    | 2169.9k| -      | 172.6k|
| Weibo     | Sentence | 1.4k  | 0.27k  | 0.27k  |
|           | Char    | 73.8k | 14.5k  | 14.8k  |
| Resume    | Sentence | 3.8k  | 0.46k  | 0.48k  |
|           | Char    | 124.1k| 13.9k  | 15.1k  |

Table 3: Main results on OntoNotes.

| Input                  | Models                  | P   | R   | F1  |
|------------------------|-------------------------|-----|-----|-----|
| Gold seg               | Che et al. (2013)       | 77.71| 72.51| 75.02|
|                        | Wang et al. (2013)      | 76.43| 72.32| 74.32|
|                        | Yang et al. (2016)      | 72.98| 80.15| 76.40|
| No seg                 | char baseline           | 68.79| 60.35| 71.70|
|                        | +bichar+softword        | 74.36| 70.12| 72.38|
|                        | Lattice LSTM (2018)     | 76.35| 71.56| 73.88|
|                        | LR-CNN (2019)           | 76.40| 72.60| 74.45|
|                        | Our model               | 76.78| 72.54| 74.60|
|                        | BERT-Tagger             | 78.01| 80.35| 79.16|
|                        | Our model[BERT]         | 79.62| 81.82| 80.60|

Experiments

Experimental Setup

Data We evaluate our proposed model on four datasets, including OntoNotes (Ralph et al. 2011), MSRA (Levow 2006), Weibo NER (Peng and Dredze 2015; He and Sun 2017b) and a Chinese Resume dataset (Zhang and Yang 2018). We use the same training, development, and test split as Zhang and Yang (2018). For these four datasets, both OntoNotes and MSRA are in simplified Chinese, while the Weibo and Resume NER are social media data.

Comparison Methods We compare our proposed model to several classic and state-of-the-art methods. In addition, to verify the effectiveness of the lattice inputs, we also evaluate another two character-level baseline models. All the evaluated methods are as follows:

- **Character baseline.** We implement this model by inputting the character sequence to a bi-directional LSTM (Hochreiter and Schmidhuber 1997), then the obtained character features are fed to a CRF layer for NER prediction.

- **Character-baseline+bichar+softword.** On the basis of Character baseline, similar to Zhang and Yang (2018), we concat three information as our input features: $x_m = [c_m \oplus b_m \oplus seg(c_m)]$, where $seg(c_m)$ is the segmentation representation and $b_m$ is the bigram features.

- **Lattice LSTM.** Lattice LSTM (Zhang and Yang 2018) exploit word information in character sequence through gated recurrent cells, which can avoid segmentation errors.

- **LR-CNN.** LR-CNN (Gui et al. 2019) is the latest state-of-the-art method on all the four datasets, which incorporates lexicons using a rethinking mechanism.

Hyper-parameter settings We use SGD to optimize all the trainable parameters. Learning rate is set to 0.045 initially and decay during training at a rate of 0.05. The character embedding size and word embedding size are set to 50. Dropout is applied to the embeddings and GRU layer with a rate of 0.5 and the transformer encoder layer with 0.3. For the biggest dataset MSRA and the smallest dataset Weibo, we set the dimensionality of GRU hidden states as 200 and 80 respectively. For the other datasets, this dimension is set to 100. The hidden size of the attention layer is set to 128. Following previous study (Zhang and Yang 2018), the character and word embeddings are pre-trained using word2vec (Mikolov et al. 2013) over the automatically segmented Chinese GigaWord and are finetuned during training.

Experimental Results

OntoNotes. The experimental results on OntoNotes are illustrated in Table 3. The “Input” column indicates that the input sentences have been segmented or not, where methods in Gold seg process word sequences with gold segmentation and No seg indicates that the input sentence is character sequence which has not been segmented.

With gold-standard segmentation, all of these word-level models (Che et al. 2013; Wang, Che, and Manning 2013; Yang et al. 2016) achieve great performance by using segmentation and external labeled data. But such information is not available in most datasets, such that we only use pre-trained character and word embeddings as our resource.

In No-segmentation settings, we present character baseline models and lattice-based models. With bichar and softword information, the F1-score over character baseline increases from 64.30% to 71.70%. To integrate potential word information into character sequence, Zhang and Yang (2018) propose the lattice LSTM model while Gui et al. (2019) apply CNN-based model with rethinking mechanism, which outperform character baseline models by 2.18% and 2.75% in F1-score respectively, indicating the importance of lexicon information in character sequence.

The last row shows the result of our proposed model. We achieve 2.00% improvement compared with character baseline, which proves the effectiveness of our proposed model to utilize lexicon information. Compared with the recent competitors, We outperform lattice-LSTM by 0.72% in F1 and give competitive results to the LR-CNN. At the same time, we make a great improvement in efficiency due to the power of proceeding in batches and processing in parallel of our model, which will be further discussed in the efficiency analysis section.

MSRA/Weibo/Resume Tables 4, 5, and 6 present the comparisons between the classic and state-of-the-art methods on the MSRA, Weibo, and Resume datasets. Especially, in Weibo benchmark, NE, NM and overall denote F1-scores for named entities, nominal entities (excluding named entities) and both, respectively. Existing statistical methods explore the rich statistical features (Zhou, Qu, and Zhang 2013) and character embedding features (Lu, Zhang, and Ji 2016). For neural based models, some existing models utilize multi-task learning (Peng and Dredze 2016; Cao et al. 2018) or semi-supervised learning (He and Sun 2017a).
Our proposed model can not only leverage global-level semantic information compared with DAG-structured inputs. Besides, our proposed model can use the lattice-based transformer encoder layer to learn information from latent words, which is capable of avoiding DAG-structured inputs. Additionally, our model also achieve comparable performance against the strong baseline LR-CNN in all of the datasets.

Table 4: Main results on MSRA.

| Models | NE | NM | Overall |
|--------|----|----|---------|
| Peng et al. (2016) | 55.28 | 62.97 | 58.99 |
| He et al. (2018) | 54.50 | 62.17 | 58.23 |
| Cao et al. (2018) | 54.34 | 57.35 | 58.70 |
| Zhu and Wang (2019) | 55.38 | 62.98 | 59.31 |
| char baseline | 46.11 | 55.29 | 52.77 |
| +bichar+softword | 50.55 | 60.11 | 56.75 |
| Lattice LSTM (2018) | 53.04 | 62.25 | 58.79 |
| LR-CNN (2019) | 57.14 | 66.67 | 59.92 |
| Our model | 53.55 | 64.90 | 59.76 |
| BERT-Tagger | 67.90 | – | – |
| Our model[BERT] | 69.23 | – | – |

Table 5: Main results on Weibo NER.

| Models | NE | NM | Overall |
|--------|----|----|---------|
| Zhou, Qu, and Zhang (2015) | 91.86 | 88.75 | 90.28 |
| Lu, Zhang, and Ji (2016) | 91.73 | 89.58 | 90.64 |
| Cao et al. (2018) | 55.38 | 62.98 | 59.31 |
| Zhu and Wang (2019) | 90.74 | 86.96 | 88.81 |
| char baseline | 92.97 | 90.80 | 91.87 |
| +bichar+softword | 93.57 | 92.79 | 93.18 |
| Lattice LSTM (2018) | 94.50 | 92.93 | 93.71 |
| LR-CNN (2019) | 94.25 | 92.30 | 93.26 |
| Our model | – | – | 93.69 |
| BERT-Tagger | – | – | 94.25 |
| Our model[BERT] | – | – | 94.25 |

Table 6: Main results on Resume NER.

| Models | NE | NM | Overall |
|--------|----|----|---------|
| Char baseline | 93.66 | 93.31 | 93.48 |
| +bichar+softword | 94.53 | 94.29 | 94.41 |
| Lattice LSTM (2018) | 94.81 | 94.11 | 94.46 |
| LR-CNN (2019) | 95.37 | 94.84 | 95.11 |
| Our model | 95.34 | 95.46 | 95.40 |
| BERT-Tagger | 96.12 | 95.45 | 95.78 |
| Our model[BERT] | 95.97 | 96.44 | 96.21 |

Our model[BERT] significantly outperform lattice LSTM, we consider that it is because lattice LSTM demands multiple recurrent computation, which results in failing to fully exploit GPU parallelism, and for LR-CNN, its rethinking mechanism is also computationally expensive. Alternatively, with lattice inputs, both lattice LSTM and LR-CNN have no ability in batch-training due to their DAG structure or variable-sized potential word sets, which means these two models are terribly inefficient. But our proposed model overcomes this limitation due to the mask mechanism in transformer. When the batch_size is set to 4, our model performs 9.47 times faster than lattice LSTM and nearly 4.25 times than LR-CNN on the OntoNotes dataset, which again confirms the excellent efficiency of our model.

To make further exploration, we design one more experiment on the OntoNotes dataset, as illustrated in Figure 4. We split this dataset into five parts according to the sentence length. The results in Figure 4 demonstrate that our proposed model performs always faster than the lattice LSTM and LR-CNN with different sentence lengths, especially for short sentences. In particular, when processing the sentences of which the length is equal to 20, our model is 9.64 times faster than lattice LSTM and 8.81 times faster than LR-CNN. For long sentences, the speed of LR-CNN was relatively stable, while the speed of our model and lattice LSTM decrease to a certain extent, but our model still has advantages over these two models. Overall, our model has enough strength in terms of efficiency.

Model Ablation study To demonstrate the effectiveness of each component, we conduct an ablation study on four datasets. From the results in Table 7, we can observe that:

- When replacing lattice-based self-attention with standard self-attentional computation for character sequence inputs without lexicon information, the results decrease 3.58, 0.99, 2.81 and 0.58 on four datasets respectively, which indicates that our lattice-based self-attention mechanism is effective for incorporating potential words information to character sequence.

- Removing porous mechanism and only applying standard lattice-based transformer encoder to Chinese NER hurt the result seriously. We suppose that with lattice inputs, each character make self-attentional computation with all the characters and potential words in the input sequence,
Table 7: Testing-time speedup of different models.

| Models          | OntoNotes | MSRA   | Weibo | Resume |
|-----------------|-----------|--------|-------|--------|
| Lattice LSTM (2018) | 73.88 1× | 93.18 1× | 58.79 1× | 94.46 1× |
| LR-CNN (2019)    | 74.45 2.23× | 93.71 1.57× | 59.92 2.41× | 95.11 1.44× |
| Our model (batch_size=1) | 74.60 4.30× | 93.26 3.03× | 59.76 4.65× | 95.40 3.35× |
| Our model (batch_size=4) | 74.60 9.47× | 93.26 6.81× | 59.76 7.45× | 95.40 7.78× |

Figure 4: Test speed against sentence lengths. Bat/s refers to the number of instances can be dealt with per second.

Table 8: An ablation study of our proposed model.

| Models          | OntoNotes | MSRA   | Weibo | Resume |
|-----------------|-----------|--------|-------|--------|
| Our model       | 74.60     | 93.26  | 59.76 | 94.40  |
| - Lattice       | 70.97     | 92.27  | 56.95 | 94.82  |
| - Porous        | 70.17     | 91.84  | 50.08 | 94.40  |
| - Lattice - Porous | 70.58 | 92.48  | 56.52 | 94.69  |

Related Work

In this section, we summarize the NER models based on neural networks and the lattice-based transformer which our work is in line with.

Huang, Xu, and Yu (2015) propose a BiLSTM-CRF model for NER and achieves good performance. Santos and Guimaraes (2015) is based on the CharWNN deep neural network to use word- and character-level representations, Ma and Hovy (2016) uses CNN to capture spelling characteristics and BiLSTM to model word information while Lample et al. (2016) uses a character LSTM and word LSTM for NER. But using these methods to model Chinese NER are difficult since they suffer from segmentation errors.

To avoid the segmentation errors, most NER models are character-based models. Peng and Dredze (2015) proposes a joint training objective for three types of neural embedding to better recognize entity boundary. Dong et al. (2016) investigates Chinese radical-level representations in BiLSTM-CRF architecture for character-based NER model. Lu, Zhang, and Ji (2016) presents a position-sensitive bigram model to learn multi-prototype Chinese character embeddings. He and Sun (2017) takes the positional character embedding into account. Although these methods have achieved excellent performance, they all ignore word information in character sequence.

Some researchers then devoted themselves to exploit rich word boundary information in character sequence. Cao et al. (2018) applies an adversarial transfer learning framework to integrate the task-shared word boundary information into Chinese NER. Wu et al. (2019) proposes a graph neural network with a multi digraph structure to incorporate multiple gazetteers into the NER system. Liu et al. (2019) explores four different strategies for Word-Character LSTM. Especially, recent state-of-the-art methods exploit lattice-structured models to integrate latent word information into character sequence. Specifically, Zhang and Yang (2018) uses the lattice LSTM to leverage explicit word information over character sequence labeling. Based on this method, Gui et al. (2019) proposes a CNN-based NER model that incorporates lexicons using a rethinking mechanism.

Lattice-based transformer has been exploited in NMT (Xiao et al. 2019), as well as speech translation task (Sperber et al. 2019; Zhang et al. 2019). Compared with existing work, our porous lattice-based transformer encoder is different in both motivation and structure. More specifically, we remove the decoder architecture and reduce the number of the encoder layers. Besides, we propose a novel porous mechanism to enhance the local dependencies among neighboring tokens. To our knowledge, we are the first to design a novel porous lattice-based transformer encoder for segmentation-free Chinese NER.

Conclusions

In this paper, we propose a novel porous lattice-based transformer encoder to handle lattice-structured inputs, which is capable to integrate potential words that match a lexicon into character sequence for Chinese NER. Benefiting from the mask mechanism in lattice transformer, our...
model earns the power of proceeding in batches and processing in parallel. At the same time, by using lattice-aware self-attentional computation and our proposed porous mechanism, our model can integrate lexicon information into character sequence and fully exploit this information by strengthen the local dependencies among neighboring tokens. Experimental results illustrate that our proposed model is up to 9.47 times faster than the state-of-the-art methods and also powerful in effectiveness.

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