NFLAT: Non-Flat-Lattice Transformer for Chinese Named Entity Recognition

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Abstract—Recently, Flat-LAttice Transformer (FLAT) has achieved great success in Chinese Named Entity Recognition (NER). FLAT performs lexical enhancement by constructing flat lattices, which mitigates the difficulties posed by blurred word boundaries and the lack of word semantics. In FLAT, the positions of starting and ending characters are used to connect a matching word. However, this method is likely to match more words when dealing with long texts, resulting in long input sequences. Therefore, it significantly increases the memory and computational costs of the self-attention module. To deal with this issue, we advocate a novel lexical enhancement method, InterFormer, that effectively reduces the amount of computational and memory costs by constructing non-flat lattices. Furthermore, with InterFormer as the backbone, we implement NFLAT for Chinese NER. NFLAT decouples lexicon fusion and context feature encoding. Compared with FLAT, it reduces unnecessary attention calculations in “word-character” and “word-word”. This reduces the memory usage by about 50% and can use more extensive lexicons or higher batches for network training. The experimental results obtained on several well-known benchmarks demonstrate the superiority of the proposed method over the state-of-the-art hybrid (character-word) models. The source code of the proposed method is publicly available at https://github.com/CoderMusou/NFLAT4CNER.

Index Terms—Chinese NER, Lattice, Inter-attention, InterFormer, Transformer.

I. INTRODUCTION

AMED Entity Recognition (NER) is usually handled as a sequence tagging task, which plays an essential role in Natural Language Processing (NLP). NER often extracts valuable information from unstructured text, which can be used for many other high-level tasks, such as information retrieval [1], knowledge graph [2], question answering [3], public opinion analysis [4], biomedicine [5], recommendation system [6] and many others.

Compared with English [7]–[12], Chinese NER is more challenging. First, Chinese word boundaries are blurred, and there is no separator, such as space, to clarify word boundaries. If a character-level model (Fig. 1a) is used for Chinese NER, it will have the problem of missing word semantics and boundary information. On the other hand, if we use word-level models (Fig. 1b), wrong word segmentation will also degrade the performance. In addition, there are more complex properties in Chinese, such as complex combinations, entity nesting, indefinite length [13], and network neologisms. Moreover, Chinese does not have case-sensitive and root-affix properties and lacks the expression of much semantic information. Therefore, in recent years, the mainstream Chinese NER methods have focused on the use of external data, such as lexicon information [14], glyph information [15], [16], syntactic information [17], and semantic information [18], for performance boosting.

Flat-LAttice Transformer (FLAT) [19] is a very popular lexical enhancement method that effectively extracts entity boundaries and rich word semantics. However, FLAT increases the computational and memory costs significantly. Also, it is very difficult to use large-scale lexicons in FLAT. To mitigate these issues, we propose a novel and efficient lexical enhancement method, NFLAT, that uses a non-flat-lattice architecture. The main contributions include:

- We propose a new InterFormer network with a non-flat-lattice architecture, which jointly models character and
word sequences at different lengths.
- With InterFormer as the backbone, we further develop a non-flat lexical enhancement method, namely NFLAT, for Chinese NER.
- To achieve further performance boosting, we use an extra tag to help the model automatically suppress noisy information and discover correct words.
- We evaluate NFLAT on several well-known benchmarks with different lexicons and the results demonstrate the superiority of our method over the state-of-the-art approaches.

II. RELATED WORK

a) Deep Learning in Chinese NER: Wu et al. [20] firstly applied deep networks to extract critical clinical information from Chinese documents with NER. Peng and Dredze [21] proposed a multi-task learning model based on LSTM-CRF, which improves the performance of NER by jointly training it with the word segmentation task. Inspired by the character-level features in English NER, Lample et al. [7] and Dong et al. [19] designed a BiLSTM-CRF model that introduces features containing both characters and radicals. He and Sun [22, 23] tried to improve the NER performance in Chinese social media using cross-domain, semi-supervised data and rich embedding features based on BiLSTM-MMNN. After that, Zhang and Yang [13] proposed a character-word hybrid model, Lattice-LSTM, for Chinese NER. This method augments the character-level model with lexicon information, avoiding potential segmentation errors in word-level models and missing boundaries in character-level models. It demonstrates the merits of using lexicon information in Chinese NER.

b) Lexical Enhancement Methods: Besides Lattice-LSTM, existing lexical enhancement methods also use many other network architectures, such as CNN in LR-CNN [24], graph networks in LGN [25], CGN [26] and the Neural Multi-digraph Model (NMDM) [27]. More recently, the popular Transformer model has also been used for lexical enhancement, such as PLTE [28] and FLAT [19]. Note that some methods, e.g., WC-LSTM [29] and SoftLexicon [30], fuse lexicon information at the embedding layer.

FLAT is the most relevant study to the proposed method. FLAT significantly improves the performance of Chinese NER by introducing lexicon information via a flat lattice with two positional encodings. However, this method increases the input sequence length by more than 40% on average, resulting in several practical issues. First, using longer sequences significantly increases the memory and computational costs in self-attention. Second, FLAT is unable to use a larger or more comprehensive lexicon. Last, it unnecessarily computes attention scores for “word-character” and “word-word”. To address these issues, we propose a novel lexical enhancement method with a more flexible structure and superior performance over the above methods.

III. BACKGROUND

FLAT achieves relatively high performance from scratch and further performance boosting when used with BERT. Since the underlying structure of FLAT is based on Transformer [31], FLAT can extract robust features with high efficiency. The self-attention mechanism is the key of Transformer, which establishes a connection between each pair of tokens of the input. Transformer is different from RNN [32], LSTM [33], GRU [34] and other recurrent neural networks, in which the input at each moment needs to depend on the output of the previous moment. Additionally, Transformer captures long-range dependencies of deep feature maps, resulting in better performance than CNNs and RNNs.

As shown in Fig. 2a, FLAT models characters and words by introducing two positional encodings and constructing a set of flat lattices as the input of the model. It solves the problems of blurred word boundaries and the lack of word semantics. However, this method may match more words when dealing with long texts, resulting in long input sequences and more computational cost. So FLAT struggles when dealing with sentences with lengths greater than 200. More importantly, we argue that the computation between “word-character” and “word-word” in self-attention is not necessary (Fig. 2b).

Another Transformer-based Chinese NER method is the character-based TENER [35]. When using Transformer for Chinese NER, TENER proposed two optimizations: 1) The attention score is calculated using relative position encoding with orientation and distance awareness. 2) The attention score results can be calculated smoothly without scaling factors. We implement NFLAT using InterFormer with the help of TENER. NFLAT decouples lexicon fusion and context feature
encoding, which has more advantages than FLAT in both accuracy and efficiency.

IV. MODEL ARCHITECTURE

For Chinese NER, NFLAT has three main stages. The first stage applies InterFormer to fuse the words’ boundary and semantic information. Then the second stage uses Transformer to encode the context with lexicon information. Last, we use a Conditional Random Field (CRF) [36] as the decoder to predict sequence labels. The overall architecture of NFLAT is shown in Fig. 3.

A. InterFormer

The proposed InterFormer method contains a multi-head inter-attention and a feed-forward neural network, as demonstrated in Fig. 3. InterFormer aims to construct a non-flat-lattice and jointly model two sequences of characters and words with different lengths. It enables the sequence of characters to fuse word boundaries and semantic information.

1) Inter-Attention Module: The Chinese character sequence, C = {c1, c2, ..., cn}, and word sequence, W = {w1, w2, ..., wn}, can be obtained by lexicon matching. The input Q, K, V are obtained by the linear transformation of characters and words feature embedding:

\[ [Q, K, V] = [X^C W_q, X^W W_k, X^W W_v], \]  \tag{1}

where the token embeddings of character and word sequences, \( X^C = \{x_{c1}, x_{c2}, ..., x_{cn}\} \) and \( X^W = \{x_{w1}, x_{w2}, ..., x_{wn}\} \), are obtained by a word embedding lookup table. And each W is a learnable parameter. In this paper, we use inter-attention to fuse lexicon information:

\[ \text{InterAtt}(A, V) = \text{softmax}(\text{mask}(A)) \cdot V. \]  \tag{2}

\[ A_{ij} = (Q_i + u)^\top K_j + (Q_i + v)^\top R_{ij}, \]  \tag{3}

where \( 1 \leq i \leq n, 1 \leq j \leq m \). The \( u, v \) are learnable parameters. Eq. (3) is from Dai et al. [37]. mask() is the inter-attention score mask of characters and words, which is 2-dimensional for a single batch and 3-dimensional for a multi-batch. It is used to fill empty positions in the sequence with the value of \( 10^{-15} \), so that the attention weights of these positions are close to 0 when \( \text{softmax}(\cdot) \) normalization. \( R_{ij} \) is calculated in a similar way to FLAT, using two relative positions:

\[ R_{ij} = \text{ReLU}(W_r (p_{ij} - h^w_j \oplus p_{ij} - t^w_j)), \]  \tag{4}

where \( W_r \) is a learnable parameter, \( h \) and \( t \) are the position numbers of the first and last characters of the word in the input text, and the superscripts \( c \) and \( w \) represent characters and words, respectively. \( h^c_i - h^w_j \) represents the head position offset of the \( i \)-th character and the \( j \)-th word, \( t^c_i - t^w_j \) represents the tail position offset of the \( i \)-th character and the \( j \)-th word, that is, the relative position. The position encoding \( p \) generation method is proposed by Vaswani et al. [31]:

\[ p_{(2k)}^{(2k)} = \sin \left( \frac{\text{span}}{10000^{2k/d_{\text{model}}}} \right), \]  \tag{5}

\[ p_{(2k+1)}^{(2k+1)} = \cos \left( \frac{\text{span}}{10000^{2k/d_{\text{model}}}} \right), \]  \tag{6}

where span represents \( h^c_i - h^w_j \) and \( t^c_i - t^w_j \), \( k \) is the k-th dimension, and \( d_{\text{model}} \) is the hidden size.

2) Multi-Head Inter-Attention: In our preliminary experiments, we found that multi-head inter-attention can more effectively fuse lexicon information, and the information of different heads has complementary effects. The multi-head inter-attention is calculated as follows:

\[ \text{Head}^{(s)} = \text{InterAtt} \left( X^{C,(s)}, X^{W,(s)} \right), \]  \tag{7}

\[ \text{MultiHead} \left( X^C, X^W \right) = \left[ \text{Head}^{(1)}, ..., \text{Head}^{(l)} \right], \]  \tag{8}
where \( l \) is the number of inter-attention heads, Head\(^{(s)}\) \( l \) is the output result of the \( s \)-th inter-attention head on the character and word vector subspaces. \( X_{C}^{s}(\cdot) \) and \( X_{W}^{s}(\cdot) \) are the vector representations of characters and words in their subspaces.

3) Feed-Forward Neural Network Module: This paper refers to the design of the Transformer encoder. It implements the feed-forward neural network sub-module of the inter-attention encoder, using two fully connected layers:

\[
FFN_1(x) = \max(0, xW_1 + b_1)W_2 + b_2. \tag{9}
\]

In addition, we also use residual connection and layer normalization [38] in the above two sub-modules to speed up the convergence of network training and prevent the gradient vanishing problem:

\[
output = \text{LayerNorm}(X + \text{SubModule}(X)) \tag{10}
\]

where \( X \) are the outputs of the above two sub-modules.

B. Transformer Encoder

After InterFormer, the character features are fused with the lexicon information. Then, we use the Transformer encoder to encode the contextual information. This part is inspired by Yan et al. [35], in which the unscaled self-attention is found more suitable for NER. In addition, the relative position encoding with orientation and distance awareness is adopted. After this, we use the linear layer to project output into the label space and use CRF for decoding.

V. EXPERIMENTS

We evaluate the proposed NFLAT method using the F1 score (F1), precision (P), and recall (R) metrics, with a comparison of several character-word hybrid models. At the same time, this section visually analyzes the inter-attention weights to verify the effectiveness of the proposed non-flat-lattice method. Last, we also examine the complexity of NFLAT and the flexibility of InterFormer and compare the effects of other lexicons and the use of pre-trained models.

A. Experimental Settings

| Datasets     | Items    | Train | Dev  | Test  |
|--------------|----------|-------|------|-------|
| Weibo        | Sentences| 1.35k | 0.27k| 0.27k |
|              | Entities | 1.89k | 0.39k| 0.42k |
| Resume       | Sentences| 3.8k  | 0.46k| 0.48k |
|              | Entities | 1.34k | 0.16k| 0.16k |
| MSRA         | Sentences| 46.4k | -    | 4.4k  |
|              | Entities | 74.8k | -    | 6.2k  |
| OntoNotes 4.0| Sentences| 15.7k | 4.3k | 4.3k  |
|              | Entities | 13.4k | 6.95k| 7.7k  |

a) Data: This section evaluates the performance of NFLAT on four mainstream Chinese NER benchmarking datasets, including three publicly available datasets, i.e., Weibo [22], Resume [14], and MSRA [40], and one licensed dataset, i.e., Ontonotes 4.0 [41]. Table I shows the statistical information of these datasets. Our models are all trained with a RTX 2080 Ti card.

b) Word Embedding: The lighter structure of NFLAT allows us to evaluate its performance on lexicons of different sizes. We conducted experiments on three lexicons, YJ [42], LEX [43], and TX [44]. Their statistics can be viewed in the appendix.

c) Hyper-parameter Settings: This paper uses only one layer of InterFormer encoder and one layer of Transformer encoder to handle Chinese NER. More details can be found in the appendix.

B. Experimental Results

To compare the experimental results more reasonably, we use YJ, the most widely used in lexical enhancement methods, as the external lexicon. We compare our NFLAT method with almost all the lexical enhancement models, including Lattice-LSTM [14], WC-LSTM [29], LR-CNN [24], LGN [25], PLTE [28], SoftLexicon [30], and FLAT [19]. The experimental results are shown in Table II. Note that we use TENER [35] and FLAT as the baseline models. We can see that NFLAT significantly improves the performance of TENER. The overall F1 score on Weibo is increased by 3.77%. The F1 score obtained on Resume is increased by 0.58%. The F1 score on Ontonotes 4.0 is increased by 4.78%, and the recall is 79.37%. For the MSRA dataset, the propose method increases the F1 score by 1.81%, and achieves the best performance in terms of precision (P) and recall (R). NFLAT outperforms all the other methods, including FLAT, on all the datasets. Without using other data augmentation methods and pre-trained language models, NFLAT achieves state-of-the-art performance on the Weibo, Ontonotes 4.0, and MSRA datasets.

C. Analysis of Inter-Attention

a) Features: The proposed inter-attention module can be understood as an interactive attention mechanism. Self-attention expects all tokens in a sequence to be connected pairwise. Inter-attention is different from self-attention, which expects to establish the connections between tokens belonging to two sequences of indeterminate length. Similar attention mechanisms tend to appear in reading comprehension tasks [45]. Unlike the existing attention mechanism, we draw on FLAT to design the relative position encoding to enable it to discover the potential relationship between the tokens in two sequences. The original intention of this paper is to establish a connection between character sequences and word sequences so that the character sequence can fuse the boundary and semantic information of words.
TABLE II
A COMPARISON WITH OTHER LEXICAL ENHANCEMENT METHODS. YJ LEXICON IS USED HERE.

| Models    | Weibo | Resume | Ontonotes 4.0 | MSRA   |
|-----------|-------|--------|---------------|--------|
|           | NE    | NM     | Overall       | P      | R    | F1   | P      | R    | F1   | P    | R    | F1   |
| Lattice-LSTM | 53.04 | 62.25  | 58.79         | 94.81  | 94.11| 95.41| 76.35  | 71.56| 73.88| 93.57| 92.79| 93.18|
| WC-LSTM   | 53.19 | 67.41  | 59.84         | 95.27  | 95.15| 95.21| 76.09  | 72.85| 74.43| 94.58| 92.91| 93.74|
| LR-CNN    | 57.14 | 66.67  | 59.92         | 95.37  | 95.46| 95.37| 76.13  | 73.68| 74.89| 94.19| 92.73| 93.46|
| LGN       | 55.34 | 64.98  | 60.21         | 95.28  | 95.46| 95.37| 76.13  | 73.68| 74.89| 94.19| 92.73| 93.46|
| PLTE      | 53.55 | 64.90  | 59.76         | 95.34  | 95.46| 95.40| 76.78  | 72.54| 74.60| 94.25| 92.30| 93.26|
| SofiLexicon | 59.08 | 62.22  | 61.42         | 95.71  | 95.77| 95.74| 77.13  | 75.22| 76.16| 94.73| 93.40| 94.06|
| TENER     |       | -      | 58.17         | -      | -    | 95.00| -      | -    | 72.43| -    | -    | 92.74|
| FLAT      |       | -      | 60.32         | -      | -    | 95.45| -      | -    | 76.45| -    | -    | 94.12|
| N FLAT    | 59.10 | 63.76  | 61.94         | 95.63  | 95.52| 95.58| 75.17  | 79.37| 77.21| 94.92| 94.19| 94.55|

**Fig. 4.** Visualization of the proposed inter-attention module.

b) **Auto-discovery:** As shown in Fig. 4, we visualize the attention weights obtained by the inter-attention module. The heatmap will be a massive square if the FLAT method is used. It can be seen that the inter-attention module can effectively learn the correlation between characters and words. It is worth noting that the word “washing machine” in this sentence is given a higher weight than those of the characters “washing” and “clothing” than “clothing”. The same is true for “today”, “night” and “dinner”; “micro wave” and “microwave”; “ing” and “in”; “not think” and “think”. Therefore, inter-attention can automatically discover valid words and increase their weights while reducing the weights of invalid words.

c) **Auto-suppression:** It can also be seen from Fig. 4 that the proposed method adds the <non_word> tag. This tag establishes the connections between punctuation marks, single characters, or characters that do not match the lexicon. According to the visualization result, the attention weights of punctuation marks such as “，” “．” “” “” “” “” “” are concentrated on the <non_word> tag. Besides, the stop words such as “的” “是” “你” are more concerned with the <non_word> tag. There are also characters not matched to the lexicon, which are also assigned to the weights of the <non_word> tag, such as “甩 swing”, “干 dry”, “— one”, “脸 face”. So inter-attention can automatically suppress irrelevant characters and reduce noise information.

d) **Interpretability:** We further examine the focus of other attention heads for multi-head interactive attention. Some of them pay more attention to the first character, and some have closer attention to the last character. This provides favorable evidence for interpreting the proposed method. The inter-attention module can be confirmed to learn the boundary relationship between Chinese characters and words very well. Moreover, it incorporates lexicon information to improve the performance of Chinese NER.

This paper does not purposely design ablation experiments for the inter-attention module. Since the superstructure of N FLAT is TENER, it can be directly compared with the experimental results of the baseline TENER method. From Table II, we can see that N FLAT outperforms TENER, which is since the input of the self-attention encoder has fused lexicon information through the inter-attention encoder. This verifies the effectiveness of the non-flat-lattice architecture.
TABLE III
Performance Evaluation on Other Lexicons or Pretrained Models. The result marked with † is what we get by running the open source code. The results marked with * are from Li et al. [19]. And With Pre. indicates whether to use a pre-trained model. (%)

| Models       | Lexicon | With Pre. | Weibo | Resume | Ontonotes | MSRA |
|--------------|---------|-----------|-------|--------|-----------|------|
| CGN          | LS      | ✗         | 63.09 | 94.12* | 74.79     | 93.47|
| FLAT         | LS      | ✗         | 63.42 | 94.93  | 75.70     | 94.35|
| NFLAT        | LS      | ✗         | 64.38 | 95.20  | 75.86     | 94.73|

| Lattice-LSTM | TX(v0.1.0)| ✗         | 60.79 | 94.98† | 75.79†    | 94.20†|
| NFLAT        | TX(v0.1.0)| ✗         | 66.40 | 95.62  | 76.80     | 94.76 |

| BERT + CRF   | -       | ✓         | 68.20*| 95.53* | 80.14*    | 94.95*|
| BERT + NFLAT | TX(v0.1.0)| ✓         | 71.04 | 96.86  | 82.78     | 96.40 |

constructed by the inter-attention mechanism for performance boosting.

D. Complexity Analysis

a) Time Complexity: Let us only consider the attention module. NFLAT includes the inter-attention of characters and words($O(nmd)$), and the self-attention($O(n^2d)$) of context, so the total complexity is ($O((n + m)nmd)$). The lattice attention complexity of FLAT is ($O((n + m)^2d)$). As the length $n$ of the Chinese character sequence increases, the size $m$ of the matched word sequence must also increase, making the computational complexity difficult to estimate. Fig. 5a compares NFLAT and FLAT in the inference speed on one RTX 3090 card. We choose 1,000 sentences for each length, set the batch size to 1 and calculate the overall time (s/1k) used for processing all the 1k sentences. We can see that FLAT and NFLAT perform similarly when the sentence length is lower than 400. After that, NFLAT becomes faster than FLAT as the sentence length increases. When the sentence length exceeds 700, FLAT can not run on the GPU card due to its high memory usage.

b) Space Complexity: We also compare FLAT and NFLAT in terms of memory usage when processing sentences with different lengths in Fig. 5b. In FLAT, the self-attention computation requires multiplying two $(n + m) \times d$ matrices, so the space complexity is $O((n + m)^2)$. The space complexity of self-attention and inter-attention in NFLAT is $O(n^2)$ and $O(nm)$, respectively. The larger $n$ is, the larger $m$ is. So the memory usage of NFLAT is almost half of that of FLAT. As shown in the figure, FLAT occupies more and more memory as the sentence length increases until it stops working on the RTX 3090 card. On the other hand, NFLAT has a more stable memory occupancy rate. It still works after the sentence length exceeds 1000 and can improve the utilization of the device during the training stage.

c) Model Size: With different hyper-parameter settings, the parameter size of NFLAT is between 0.43M and 1.27M.

E. Flexibility of InterFormer

InterFormer can be extracted from NFLAT as a separate module. Compared with FLAT, it is more flexible because it does not rely on Transformer. It can be connected to LSTM, Bi-LSTM, CNN, Transformer, and even pre-trained models according to different tasks at the fusion layer. InterFormer can also refer to the design of LEBERT [46] and add it to the middle layer of a pre-trained model. In addition, because it can establish a relationship between two sequences of different
TABLE IV
ABLATION EXPERIMENTAL RESULTS. WE REMOVE THE RELATIVE POSITION ENCODING IN EQ. \text{(3)} AND THE EXTRA TAGS MENTIONED IN SECTION 5.COC WHICH ARE NOTED BY '-RPE' AND '-TAG', RESPECTIVELY. (%)

| Models   | Weibo | Resume | Ontonotes | MSRA |
|----------|-------|--------|-----------|------|
| TENER    | 58.17 | 95.00  | 72.43     | 92.74|
| FLAT     | 60.32 | 95.45  | 76.45     | 94.12|
| NFLAT    | 61.94 | 95.58  | 77.21     | 94.55|
| - RPE    | 58.24 | 95.18  | 73.58     | 93.03|
| - TAG    | 59.51 | 95.46  | 76.41     | 93.66|

lengths, we can directly use a layer of InterFormer to model “characters” and “characters + words”. Although this method is not as efficient as NFLAT, it still has a decent performance.

F. How Inter-Attention Performs

The key to the success and effectiveness of NFLAT lies in the inter-attention module of InterFormer. Note that inter-attention could be easily misunderstood as cross-attention because they are computed similarly. However, inter-attention additionally uses the relative position encoding information to associate character-word pairs.

To verify the effectiveness of inter-attention, we perform two ablation experiments. First, we remove the relative position encoding, which makes inter-attention more similar to cross-attention. We denote this method as ‘-RPE’. Second, we remove the <non_word> tag to evaluate the performance of using this extra tag, which is denoted as ‘-TAG’. The results of the ablation experiments are reported in Table IV.

Based on the ablation experimental results, we can see that the performance of NFLAT degrades when removing the relative position encoding. The ‘-RPE’ method, which is more similar to cross-attention, loses word boundary information. It simply fuses the semantic information of words, so the performance is only marginally improved as compared with TENER. But it still performs significantly worse than FLAT. We also test the performance of NFLAT by retaining the relative position encoding but removing the auxiliary tags, denoted as ‘-TAG’. Again, the performance of the ‘-TAG’ method is degraded. This is because inter-attention introduces additional noisy information when some characters may not have matching words. The self-attention module of FLAT forces these characters to pay more attention to themselves. NFLAT resolves this issue by using auxiliary tags thus inter-attention pays more attention to these tags.

G. Compatibility with Other Lexicons and Pre-trained Models

Since NFLAT uses the lighter InterFormer as a module for fusing lexicon information, it is possible to use a larger and richer lexicon. We additionally evaluate the performance of NFLAT on two larger lexicons, LS and TX, and compare other models using them. The experimental results are reported in Table III. As the size of the lexicon increases, the performance of NFLAT improves. So a larger and richer lexicon is beneficial for NFLAT. NFLAT outperforms FLAT and CGN when we use LS as the lexicon. NFLAT performs better than Lattice-LSTM when they use the TX lexicon. NFLAT has the best performance when a larger scale lexicon, TX, is used.

Furthermore, NFLAT can easily integrate the pre-trained model into the embedding layer. In this paper, we use BERT-wwm released by [47]. It can be seen from Table III that NFLAT further improves the performance of the pre-trained model ‘BERT+CRF’.

VI. Conclusion

We presented a novel non-flat-lattice InterFormer module, as well as the NFLAT architecture, for Chinese NER with lexical enhancement. NFLAT decouples FLAT and divides Chinese NER into two stages: lexicon fusion and context encoding, which have apparent performance advantages and efficiency. InterFormer can flexibly associate two indefinite-length sequences and achieve significant performance boosting for Chinese NER. InterFormer breaks the stereotype of the self-attention mechanism. We believe that it has certain universality and can be extended to any task that requires joint modeling of two information sequences. It is instrumental in multi-modal tasks, such as text and image sequences or speech and text sequences.

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TABLE V
STATISTICS OF THE LEXICONS. THE Single, Two, AND Three REPRESENT THE NUMBER OF CHARACTERS IN THE WORD, RESPECTIVELY. THE Other MEANS THE NUMBER OF WORDS WITH MORE CHARACTERS. THE Dimension IS THE DIMENSION OF THE WORD EMBEDDING.

| Lexicons | Total   | Single  | Two   | Three  | Other  | Dimension |
|----------|---------|---------|-------|--------|--------|-----------|
| YJ       | 704.4k  | 5.7k    | 291.5k| 278.1k | 129.1k | 50d       |
| LS       | 1292.6k | 18.5k   | 347.7k| 415.6k | 511.3k | 300d      |
| TX (v0.1.0) | 8824.3k | 22.7k   | 2031.2k| 2034.6k| 4735.8k| 200d      |

TABLE VI
MATCH STATISTICS ON EACH LEXICON FOR DIFFERENT DATASETS. WE HAVE DONE A SEGMENTATION PROCESS FOR MSRA AND ONTONOTES 4.0.

| Datasets | Char Length Avg. | Matching Word Length | Lex. YJ | Lex. LS | Lex. TX |
|----------|------------------|----------------------|---------|---------|---------|
| Weibo    | 175              | Avg. 22              | 22      | 27      | 43      |
| Resume   | 178              | Avg. 25              | 25      | 24      | 40      |
| Ontonotes 4.0 | 273             | Avg. 19              | 19      | 19      | 31      |
| MSRA     | 281              | Avg. 25              | 25      | 143     | 166     |

APPENDIX

A. Statistics of Lexicons

Table VII shows the statistics of the external lexicons used in this paper, mainly including their total words, single-character words, two-character words, three-character words, and words with more characters. Also, we list the dimensions of the word vectors in each lexicon.

We list the maximum and average character lengths for each dataset sample in Table VI. It also shows the lengths of words matched on each lexicon for the four datasets. It can be found that as the size of the lexicon increases, the length of matching words also becomes longer. So it makes FLAT challenging to deal with large-scale lexicons, and NFLAT can make up for this shortcoming and bring better performance.

B. Hyper-parameters Selection

We manually selected parameters on the two large-scale datasets, including Ontonotes 4.0 and MSRA. We used the SMAC [48] algorithm to search for the best hyper-parameters for the two small datasets, Weibo and Resume. The range of parameters is listed in Table VII.

C. Case Study

Tables VIII - IX show several case studies comparing the results of FLAT and NFLAT on the Ontonotes 4.0 test data.

The results in Table VIII show that NFLAT significantly improves recall due to its incorporation of lexicon information. Nevertheless, it also brought a slight decrease in precision. It can be seen from Table VIII that there are some problems with missing gold labels in the Ontonotes 4.0 test data. In sentence 1, “九龙街 Kowloon Street” is not annotated, but both FLAT and NFLAT can correctly identify it. In sentence 2, “梁 Liang” is missing the gold label, and both FLAT and NFLAT recognize this entity, while NFLAT’s results are more accurate than FLAT. In sentence 3, neither the gold label nor FLAT annotates “萨国 Republic of El Salvador”, only the NFLAT prediction is correct. Accordingly, if the test data is correctly annotated, we believe that NFLAT will get a higher F1 with its excellent recall.

The advantages of NFLAT over FLAT can be analyzed from the case studies in Table IX. In sentence 1, FLAT truncates the 13-character long entity into a GPE entity and an ORG entity, while NFLAT does not. It shows that FLAT is not as good as NFLAT in identifying the boundaries of long entities. In sentences 2 and 3, FLAT increases the boundary range of the entity. Nevertheless, the NFLAT gives the correct answer due to the effect of the “¡non_word” tag in the NFLAT can automatically disable noise words. In sentence 4, “津巴布韦 Zimbabwe” (GPE) and “斯 · 埃万 Si Aiwan” (PER) were not predicted by FLAT, while NFLAT effectively predicted them. The above suggests that NFLAT’s ability to incorporate lexicon information is better than FLAT in some aspects.

D. Learning Curves

We evaluate the performance of NFLAT on each dataset with different seeds. The results are shown in Fig. 6. It can be seen that its results on Resume, Ontonotes 4.0, and MSRA become more stable with increasing training iterations. However, the performance fluctuates significantly during the training process on Weibo. Weibo data is relatively small from the field of social media, and the text is colloquial. There are network words, noise information, and differences in the data, so the fluctuation is relatively large. This phenomenon also appears in other models, such as FLAT.

E. Societal Impacts

The weights of word embeddings and pre-trained models used in this article are all from assets released by others. It
### TABLE VII
**Range of Hyper-parameters.**

| Hyper-parameter | Caption                                      | Range                     |
|-----------------|----------------------------------------------|---------------------------|
| warmup          | The warm-up ratio.                           | [0.05, 0.1, 0.2, 0.3, 0.4]|
| batch_size      | The batch size.                              | [8, 10, 16]               |
| char_embed_dropout| The dropout rate of the character embedding. | [0.3, 0.4, 0.5]           |
| word_embed_dropout| The dropout rate of the word embedding.    | [0.001, 0.002, 0.003]     |
| lr              | The learning rate.                           | [0.001, 0.002, 0.003]     |
| multi-head      | The number of multi-head and the dimensions of each head. | [8-16, 8-20, 8-32, 12-16, 12-20] |
| fc_dropout1     | The dropout rate of the linear layer in Transformer and InterFormer. | [0, 0.2, 0.4]             |
| fc_dropout2     | The dropout rate of the linear layer in NFLAT. | [0, 0.2, 0.4]             |
| attn_dropout    | The dropout rate of the weight for self-attention and inter-attention. | [0, 0.1, 0.2]             |
| is_less_head    | Whether the number of self-attention heads is half of that of the inter-attention heads. | [True, False]             |

is difficult to guarantee that this information is free from bias regarding gender, race, abuse, violence, physical ability, etc. It is mainly related to the corpus used for training. We do not avoid these biases, but they generally do not occur in our experimental datasets.

In addition to this, the datasets we use are collected from the web or news. Some data may contain sensitive content involving privacy, politics, and offensiveness. We have avoided presenting this kind of data in our case studies.

**F. Limitations**

The NER method used in this paper is limited to Chinese. We did not evaluate NFLAT performance in other languages. Although we think this method might not work for English, it might work for Japanese, Thai, etc., similar to Chinese. A feature of these languages is that there is no clear word boundary between words, just like the use of spaces to separate words in English sentences. Besides, the performance of our method is limited by the quality, size, richness, and domain of the lexicon. These factors will affect the performance of NER to varying degrees, as Section V-G describes the results obtained with different richness or sizes.
TABLE VIII
THE LACK OF ANNOTATIONS ON THE TEST DATASET ON ONTONOTES 4.0.

| Sentence #1 (Truncated) | ... Construction of Kowloon Street started again ... |
|-------------------------|-----------------------------------------------------|
| Characters              | 又 开 始 了 九 龙 街 的 建 设 |
| Gold Labels             | O O O O B-LOC M-LOC E-LOC O O O |
| FLAT                    | O O O O B-LOC M-LOC E-LOC O O O |
| NFLAT                   | O O O O B-LOC M-LOC E-LOC O O O |

| Sentence #2 (Truncated) | ... Village Chief Liang frowned deeply ... |
|-------------------------|------------------------------------------|
| Characters              | 梁 乡 长 眉 头 深 锁 |
| Gold Labels             | B-PER M-PER E-PER O O O O |
| FLAT                    | B-PER M-PER E-PER O O O O |
| NFLAT                   | B-PER M-PER E-PER O O O O |

| Sentence #3 (Truncated) | ... More than 1,200 people from the Republic of El Salvador ... |
|-------------------------|---------------------------------------------------------------|
| Characters              | 一 千 两 百 多 位 萨 国 民 众 |
| Gold Labels             | O O O O O O O O O O |
| FLAT                    | O O O O O O O O O O |
| NFLAT                   | O O O O O O B-GPE E-GPE O O |

Fig. 6. Learning curves on four datasets. The lexicon used is YJ. There is no dev set in the MSRA dataset. And the result with averages and standard deviations across 3 seeds. (a) Learning curve on Weibo. (b) Learning curve on Resume. (c) Learning curve on Ontonotes 4.0. (d) Learning curve on MSRA.
| Sentence #1 (Truncated)                                                                 | ... 美国必纯士国际实业有限公司 ... |
|----------------------------------------------------------------------------------------|-----------------------------------|
|                                                                                       | ... *American Betwons International Industrial Co., Ltd.* ... |
| Characters                                                                             | 美 国 必 纯 士 国 际 实 业 有 限 公 司 |
| Gold Labels                                                                            | B-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG E-ORG |
| FLAT                                                                                   | B-GPE E-GPE O O O B-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG E-ORG |
| NFLAT                                                                                   | B-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG E-ORG |

| Sentence #2 (Truncated)                                                                | ... 中部秀姑峦山区的红桧林 ... |
|----------------------------------------------------------------------------------------| ... *The red cypress forest in the Xiugulian Mountains in central* ... |
| Characters                                                                             | 中 部 秀 姑 倬 壮 区 的 红 桧 林 |
| Gold Labels                                                                            | O O B-LOC M-LOC M-LOC M-LOC E-LOC O O O O ... |
| FLAT                                                                                   | O O B-LOC M-LOC M-LOC E-LOC O O O O ... |
| NFLAT                                                                                   | O O B-LOC M-LOC M-LOC E-LOC O O O O ... |

| Sentence #3 (Truncated)                                                                | ... 龙山国中训导主任陈采卿 ... |
|----------------------------------------------------------------------------------------| ... *Caiqing Chen, the director of Longshan junior high school* ... |
| Characters                                                                             | 龙 山 国 中 训 导 主 任 陈 采 卿 |
| Gold Labels                                                                            | B-ORG M-ORG M-ORG E-ORG O O O B-PER M-PER E-PER ... |
| FLAT                                                                                   | B-ORG M-ORG M-ORG M-ORG M-ORG E-ORG O O B-PER M-PER E-PER ... |
| NFLAT                                                                                   | B-ORG M-ORG M-ORG E-ORG O O B-PER M-PER E-PER ... |

| Sentence #4 (Truncated)                                                                | ... 津巴布韦选手斯·埃万 ... |
|----------------------------------------------------------------------------------------| ... *The competitor from Zimbabwe, Si Aiwan* ... |
| Characters                                                                             | 津 巴 布 韦 选 手 斯· 埃 万 |
| Gold Labels                                                                            | B-GPE M-GPE M-GPE E-GPE O O B-PER M-PER M-PER E-PER ... |
| FLAT                                                                                   | O O O O O O M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-ORG M-OG