# **Back Attention Knowledge Transfer** for Low-resource Named Entity Recognition

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#### **Abstract**

In recent years, great success has been achieved in the field of natural language processing (NLP), thanks in part to the considerable amount of annotated resources. For named entity recognition (NER), most languages do not have such an abundance of labeled data as English, so the performances of those languages are relatively lower. To improve the performance, we propose a general approach called Back Attention Network (BAN). BAN uses a translation system to translate other language sentences into English and then applies a new mechanism named back attention knowledge transfer to obtain task-specific information from pre-trained high-resource languages NER model. This strategy can transfer high-layer features of well-trained model and enrich the semantic representations of the original language. Experiments on three different language datasets indicate that the proposed approach outperforms other state-of-the-art methods.

## Introduction

Named entity recognition (NER) is a sequence tagging task that extracts the continuous tokens into specified classes, such as person names, organizations and locations. The state-of-the-art NER approaches usually employ long shortterm memory recurrent neural networks (LSTM RNNs) and a subsequent conditional random field (CRF) to predict the sequence labels (Huang, Xu, and Yu 2015). Performances of neural NER models are compromised if the training data are not sufficient (Zhang et al. 2016). This problem is severe for many languages due to the lack of labeled datasets, e.g., German and Spanish. The reason is that manual labeling of data is costly, and many institutions or researchers with limited resources can not afford large, high-quality datasets. In comparison, NER on English is well developed, and there exist abundant labeled data for training purpose. Therefore, in this work, we regard English as a high-resource language, while other languages, even Chinese, as low-resource languages (Feng et al. 2018).

In recent years, however, a vast amount of translated parallel texts have been generated in our increasingly connected multilingual world. Compared with obtaining labeled data,

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acquiring bilingual parallel data is more cheaper and easier. Parallel corpora have been mainly leveraged to train neural machine translation systems (Gehring et al. 2017). Nevertheless, the possibility of utilizing parallel corpora to improve systems outside of neural machine translation has been increasingly considered recently. For example, Che et al. (2013) predict entities labels by NER models designed for labeled parallel datasets, and use aligned word pairs between both languages to constrain the two models to agree with each other by making joint prediction.

There are two intractable problems when leveraging English NER system for other languages. First, the sentences with the same meaning in different languages may have different lengths, and the orders of words usually do not correspond. As shown in Figure 1, given a sentence "The chairman of the Federal Reserve is Jerome Powell", the alignment between English and Chinese is disordered. As can be seen from this example, it is difficult to find a general rule to align sentences between different languages. Second, the tags in different languages may be different. Even if all word pairs can be found in both languages, we can not use the tags in another language directly, because the lengths of different entities between both languages can lead to different annotations. Therefore, there is no simple and effective way to exchange information between different languages. Previous work such as (Feng et al. 2018) makes use of the each translated single word embedding and the features of the property of the translated word to enrich the monolingual word embedding. However, the semantic information of entire sentences have not been explored. To the best of our knowledge, there is no approach that employs the whole translation information and transfers the high-layers features of another language pre-trained NER model to improve the performance of the monolingual NER system.

To address the above problems, this paper introduces an extension of the BiLSTM-CRF model (Lample et al. 2016), which fully makes use of model knowledge transferred from a pre-trained English NER system. Firstly, the translation model translates the source language sentences into English. According to (Vaswani et al. 2017), the performances of attention-based machine translation systems are close to the human level. In contemporary translation models, attention

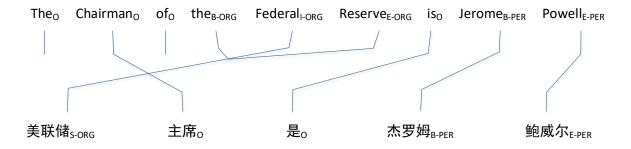


Figure 1: Example of NER labels between two word-aligned bilingual parallel sentences. (BIOES format)

mechanism plays a supporting role in producing the target elements. It makes the decoder concentrate on a local region to get relevant information for generating the next word, which can make the translation results more accurate. And there is another useful property in this mechanism, i.e., the global attention weights could represent the alignment information (Bahdanau, Cho, and Bengio 2015). In other words, it implies the correspondence of words between the source language and the target language. Secondly, after translating the low-resource language into English, the pre-trained English NER model is utilized to predict the translated sentences, and the output states of BiLSTM are recorded in this model. The output states contain the semantic and taskspecific information of the translated sentences. Thirdly, using global attention weights generated by the translation model as a transformation matrix, we manage to transfer the model knowledge (i.e., the output states of BiLSTM in pre-trained NER model) of high-resource languages (i.e., English) to other low-resource languages (i.e., Chinese and Spanish). The proposed method achieves the above by learning the transferred model knowledge as follows: T = AR, where A represents global attention weights produced by source-English neural machine translation model, R is original representations generated by pre-trained English NER model, and T is the transferred model knowledge for lowresource language. The proposed model has the following benefits:

- BAN provides a simple but effective way to improve the performance of NER models in low-resource languages using the pre-trained NER model in high-resource languages (i.e., English). This method can take full advantage of the high layer features of a well-trained NER model into another language.
- The transferred model knowledge contains complete syntactic, semantic and task-specific information obtained by the pre-trained English NER model.
- The transferred model knowledge is naturally aligned by global attention without additional processing. The length of the transferred information is equal to the length of source sentence, and the model knowledge of each word

contains all information about the target sentence.

Experiments show that BAN obtains new state-of-the-art results on CoNLL-2003 German dataset (Sang and De Meulder 2003), CoNLL 2002 Spanish dataset (Tjong Kim Sang 2002), OntoNotes 4 dataset (Weischedel et al. 2011) and Weibo NER dataset (Peng and Dredze 2015).

## Model

In this section, we introduce the proposed BAN model in four parts. BAN model is based on the mainstream NER model (Lample et al. 2016), using BiLSTM-CRF as the main network structure. Given a sentence  $\mathbf{x}=(x_1,\cdots,x_m)$  and corresponding labels  $\mathbf{y}=(y_1,\cdots,y_m)$ , where  $x_i$  denotes the ith token and  $y_i$  denotes the ith label. The NER task is to estimate the probability  $P(\mathbf{y}|\mathbf{x})$ . Figure 2 shows the main architecture of BAN model.

#### **Attention-based Translation Module**

Following (Gehring et al. 2017), we use the convolutional sequence to sequence model in our neural machine translation (NMT) module. It divides translation process into two steps. First, in the encoder step, given an input sentence  $\mathbf{s} = (s_1, \cdots, s_m)$  of length m,  $\mathbf{e}^s(s_i)$  represents each word  $s_i$  as word embedding  $\mathbf{w}_i^s$ :

$$\mathbf{w}_i^s = \mathbf{e}^s(s_i),\tag{1}$$

where  $\mathbf{e}^s$  signifies the word embedding lookup table. After that, the absolute position information of input elements  $(\mathbf{p}_1,\cdots,\mathbf{p}_m)$  is combined with the embedding. Both vectors are concatenated to get input sentence representations  $(\mathbf{w}_1^s+\mathbf{p}_1,\cdots,\mathbf{w}_m^s+\mathbf{p}_m)$ . Similarly, the output elements  $(\mathbf{g}_1,\cdots,\mathbf{g}_n)$  generated from decoder network have the same structure. A convolutional neural network (CNN) is used to get the hidden state of the sentence representation from left to right. Second, in the decoder step, attention mechanism is used in each CNN layer. In order to acquire the attention value, we combine the current decoder state  $\mathbf{h}_i^l$  with the embedding of previous decoder output value  $\mathbf{g}_i$ :

$$\mathbf{d_i^l} = \mathbf{W}_d^l \mathbf{h}_i^l + \mathbf{b}_d^l + \mathbf{g}_i. \tag{2}$$

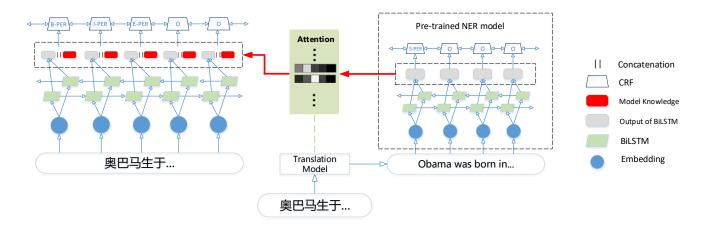


Figure 2: Overview of back attention network, The source sentences are translated into English and BAN records the attention weights. Then the sentences are put into English NER model. After acquiring the outputs of BiLSTM in the English model, BAN uses back attention mechanism to obtain transfer knowledge to aid in the generation of results.

For the lth layer, the attention  $a_{ij}^l$  of the ith source element and the jth state is computed as a dot-product between the decoder state summary  $\mathbf{d}_{i}^{l}$  and each output  $\mathbf{z}_{i}$  of the last encoder layer:

$$a_{ij}^{l} = \frac{\exp(\mathbf{d}_{j}^{l} \cdot \mathbf{z}_{i})}{\sum_{t=1}^{m} \exp(\mathbf{d}_{j}^{l} \cdot \mathbf{z}_{t})}.$$
 (3)

And then, following the normal decoder implementation, it gets target sentence  $\mathbf{t} = (t_1, \dots, t_n)$  by beam search strategies (Freitag and Al-Onaizan 2017).

# **Pre-trained English NER Module**

We use the model proposed in (Akbik, Bergmann, and Vollgraf 2019), which is one of the state-of-the-art English NER system. This model utilizes a bidirectional LSTM as a character-level language model to take context information for word embedding generation. The hidden states of the character language model are used to create contextualized word embeddings to represent the input words.

In the forward direction of character language model, the system uses the next hidden state of the last character of the word as the word vector, which contains the contextual information from the beginning of the sentence. The backward direction model works in the same way but in reversed direction. Formally, we define the forward and backward character embedding of each word  $w_i$  as  $\mathbf{h}_1^{fi}, \cdots, \mathbf{h}_l^{fi}$  and  $\mathbf{h}_1^{bi}, \cdots, \mathbf{h}_l^{bi}$ , where l indicates the length of the word.  $\mathbf{h}_{l+1}^{fi}$ and  $\mathbf{h}_{l-1}^{bi}$  represent the next hidden state of the last character of the word at forward direction and the last hidden state of the first character of the word at backward direction, respectively. Then, the character language model generates the contextual embedding:

$$\mathbf{e}_i^{CharLM} = [\mathbf{h}_{l+1}^{fi}; \mathbf{h}_{l-1}^{bi}]. \tag{4}$$

 $\mathbf{e}_{i}^{CharLM} = [\mathbf{h}_{l+1}^{fi}; \mathbf{h}_{1-1}^{bi}]. \tag{4}$  The final word embedding  $\mathbf{e}_{i}$  is concatenated by the embedding  $\mathbf{e}_{i}^{CharLM}$  and GLOVE embedding  $\mathbf{e}_{i}^{GLOVE}$  (Pennington, Socher, and Manning 2014). A standard BiLSTM-CRF NER model (Huang, Xu, and Yu 2015) takes  $\mathbf{E} =$ 

 $(\mathbf{e}_1, \cdots, \mathbf{e}_n)$  to address the NER task. The English NER model is trained on CoNLL-2003 English dataset (Sang and De Meulder 2003) and we fix the parameters to predict translated sentences.

## **Back Attention Knowledge Transfer**

The sentences in low-resource languages are used as input to the model. Given an input sentence  $\mathbf{s} = (s_1, \dots, s_m)$ in low-resource language, the translation module translates s into English and the output is  $\mathbf{t} = (t_1, \dots, t_n)$ . Simultaneously, the average of attention layers' weights for all L decoder layers are recorded:

$$\mathbf{A} = \frac{\mathbf{A}^1 + \dots + \mathbf{A}^L}{L}.$$
 (5)

To explore the performance of different attention layers for transformation matrices, the weights of the first attention layer and the last attention layer are also saved.

After that, using the pre-trained English NER model to predict the translated sentence t, we obtain the BiLSTM output states:

$$\mathbf{r}_i^t = [\mathbf{r}_i^{tf}; \mathbf{r}_i^{tb}],\tag{6}$$

where  $\mathbf{r}_i^{tf}$  and  $\mathbf{r}_i^{tb}$  denote the ith forward and backward direction outputs, respectively.  $\mathbf{r}_i^t$  contains the semantic and task-specific information of the translated sentence. And the jth row of the attention weights matrix,  $A_i =$  $(\mathbf{A}_{j1},\cdots,\mathbf{A}_{jm})$ , represents the correlation between source word j with all words in target sentence t. Thereafter, the transferred model knowledge  $\mathbf{t}_i^e$  of source word is acquired by using the attention weights reversely:

$$\mathbf{t}_i^e = \mathbf{A}_i \mathbf{R}^t, \tag{7}$$

where  $\mathbf{R}^t = (\mathbf{r}_1^t, \cdots, \mathbf{r}_n^t)$  represents the whole outputs of BiLSTM in pre-trained English model, and  $\mathbf{A} \in \mathbb{R}^{m \times n}$ ,  $\mathbf{A}_j \in \mathbb{R}^{1 \times n}$ ,  $\mathbf{R}^t \in \mathbb{R}^{n \times d}$ .  $\mathbf{t}_i^e$  denotes the transferred model knowledge of ith word in low-resource language and  $\mathbf{t}_i^e$  has the same dimensions with  $\mathbf{r}_{i}^{t}$ .

# **Named Entity Recognition Architecture**

The low-resource language named entity recognition architecture is based on (Lample et al. 2016). The word embeddings of low-resource language are passed into a BiLSTM-CRF sequence labeling network. Denoting  $e^s$  represents the embeddings of each word  $s_i$ :

$$\boldsymbol{w}_i = \mathbf{e}^s(s_i). \tag{8}$$

The embeddings  $W=(\mathbf{w}_1,\cdots,\mathbf{w}_m)$  are used as inputs to the BiLSTM. In each direction, the representations of each input words are modeled with a single hidden state. Given an initial value, every time step, the model consumes an input word and changes its hidden state recurrently. Take the forward LSTM for example. Denoting the initial state as  $\overrightarrow{r}^0$ , the recurrent state transition step for calculating  $\overrightarrow{r}^1,\cdots,\overrightarrow{r}^{m+1}$  is defined as follows (Graves and Schmidhuber 2005):

$$\hat{\boldsymbol{i}}_{t} = \sigma(\boldsymbol{W}_{i}\boldsymbol{w}_{t} + \boldsymbol{U}_{i}\overrightarrow{\boldsymbol{r}}_{t-1} + \boldsymbol{b}_{i}) 
\hat{\boldsymbol{f}}_{t} = \sigma(\boldsymbol{W}_{f}\boldsymbol{w}_{t} + \boldsymbol{U}_{f}\overrightarrow{\boldsymbol{r}}_{t-1} + \boldsymbol{b}_{f}) 
\boldsymbol{o}_{t} = \sigma(\boldsymbol{W}_{o}\boldsymbol{w}_{t} + \boldsymbol{U}_{o}\overrightarrow{\boldsymbol{r}}_{t-1} + \boldsymbol{b}_{o}) 
\boldsymbol{u}_{t} = \tanh(\boldsymbol{W}_{u}\boldsymbol{w}_{t} + \boldsymbol{U}_{u}\overrightarrow{\boldsymbol{r}}_{t-1} + \boldsymbol{b}_{u}) 
\boldsymbol{i}_{t}, \boldsymbol{f}_{t} = \operatorname{softmax}(\hat{\boldsymbol{i}}_{t}, \hat{\boldsymbol{f}}_{t}) 
\boldsymbol{c}_{t} = \boldsymbol{c}_{t-1} \odot \boldsymbol{f}_{t} + \boldsymbol{u}^{t} \odot \boldsymbol{i}_{t} 
\overrightarrow{\boldsymbol{r}}_{t} = \boldsymbol{o}_{t} \odot \tanh(\boldsymbol{c}_{t}),$$
(9)

where  $w_t$  denotes the word representation;  $i_t$ ,  $o_t$ ,  $f_t$  and  $u_t$  represent the values of an input gate, a output gate, a forget gate and an actual input at time step t, respectively, which controls the information flow for a recurrent cell  $c_t$  and the state vector  $r_t$ ;  $W_x$ ,  $U_x$  and  $b_x$  ( $x \in i, o, f, u$ ) are model parameters.  $\sigma$  is the sigmoid function.

The backward LSTM follows the same process as described in Eq. (9) but in an opposite direction. Then concatenating the value of  $\overrightarrow{r}_t$  and  $\overleftarrow{r}_t$ , we obtain  $\mathbf{r}_t^s$ :

$$\mathbf{r}_t^s = [\overrightarrow{r}_t; \overleftarrow{r}_t]. \tag{10}$$

Before passing the forward and backward output states  $\mathbf{r}_i^s$  into CRF, a new representation is obtained by concatenation of  $\mathbf{r}_i^s$  and  $\mathbf{t}_i^e$ :

$$\mathbf{r}_i = [\mathbf{r}_i^s; \mathbf{t}_i^e],\tag{11}$$

where  $\mathbf{t}_i^e$  represents the hidden states transferred from pretrained English NER model and  $\mathbf{r}_i$  is the input to CRF.

CRF employs  $(\mathbf{r}_1, \cdots, \mathbf{r}_m)$  to give the final sequence probability on the possible sequence label  $\mathbf{y}$ :

$$\hat{P}(\mathbf{y}_{0:m}|\mathbf{R}) \propto \prod_{i=1}^{m} \psi_i(y_{i-1}, y_i, \mathbf{r}_i), \tag{12}$$

where:

$$\psi_i(y_{i-1}, y_i, \mathbf{r}_i) = \exp(\mathbf{W}_{y_{i-1}, y_i} \mathbf{r}_i + \mathbf{b}_{y_{i-1}, y_i}).$$
 (13)

## **Experiments Settings**

We perform experiments on four public datasets to evaluate the effectiveness of our back attention mechanism on NER task. All experiments are conducted using a GeForce GTX 1080Ti with 11G memory.

Language	Dataset	Train	Dev	Test
German	CoNLL-2003	12705	3068	3160
Spanish	CoNLL-2002	8323	1915	1517
Chinese	Weibo	1350	270	270
Chinese	OntoNotes 4.0	15509	4405	4462

Table 1: The statistics of sentences in experiment datasets.

#### **Datasets**

Four datasets are used in this work, including CoNLL 2003 German (Sang and De Meulder 2003), CoNLL 2002 Spanish (Tjong Kim Sang 2002), OntoNotes 4 (Weischedel et al. 2011) and Weibo NER (Peng and Dredze 2015). The last two are Chinese datasets. We follow (Che et al. 2013) to select a part of OntoNotes 4 as a NER dataset. All the annotations are mapped to the BIOES format. Those datasets are chosen from different domains. The CoNLL 2003 German, CoNLL 2002 Spanish and OntoNotes 4 datasets are in the news domain and the WeiBo dataset is drawn from the social media website (i.e.,Sina Weibo¹). Table 1 shows the detailed statistics of the datasets used in this experiments.

# **Experimental Setup**

We implement the base BiLSTM-CRF model using PyTorch framework and follow the configurations of (Huang, Xu, and Yu 2015) for comparative evaluation. FASTTEXT embeddings² are used for generating basic word embeddings. The pre-trained static word embeddings, such as FASTTEXT, lose a lot of syntactic and task-specific information of the sentences. Only using static embeddings can not achieve the start-of-the-art performance. Therefore, we utilize pre-trained contextual word embeddings (Devlin et al. 2019). The translation component is implemented by Fairseq³, an efficient convolutional sequence to sequence nurual translation model. And the models are trained on United Nation Parallel Corpus. Pre-trained English NER module employs the default NER model of Flair⁴, one of the state-of-the-art English sequence labeling framework.

#### **Parameters**

We train the NER model using vanilla stochastic gradient descent with no momentum for 150 epochs, with an initial learning rate of 0.1 and a learning rate annealing method in which the train loss does not fall in 3 consecutive epochs. The hidden size of BiLSTM model is set to 256 and the number of BiLSTM layers is set to 1. With different datasets, we choose the learning rate  $\in \{0.025, 0.05, 0.1\}$  and minibatch size  $\in \{8, 16, 32\}$  to get the best performance. All parameters are chosen by performance on the validation set. Dropout is applied to word embeddings with a rate of 0.1 and to BiLSTM with a rate of 0.05, which follows the recommendations of (Reimers and Gurevych 2017). The hidden state size of pre-trained English NER model is also 256.

https://www.weibo.com/

<sup>&</sup>lt;sup>2</sup>https://github.com/facebookresearch/fastText

<sup>&</sup>lt;sup>3</sup>https://github.com/pytorch/fairseq

<sup>&</sup>lt;sup>4</sup>https://github.com/zalandoresearch/flair

Approach	German	Spanish
(Gillick et al. 2016)	-	82.95
(Lample et al. 2016)	78.76	85.75
(Akbik, Blythe, and Vollgraf 2018)	88.32	-
BiLSTM+CRF	81.41	82.49
+BAN <sup>first</sup>	82.23	82.73
+BAN <sup>last</sup>	82.45	84.23
+BAN <sup>ave</sup>	84.32	84.78
CharLM+BiLSTM+CRF	88.21	87.33
+BAN <sup>first</sup>	88.20	87.43
+BAN <sup>last</sup>	88.41	88.16
+BAN <sup>ave</sup>	88.29	88.09

Table 2: Evaluation on German and Spanish NER

The transformed hidden state has the same size but has different length with the hidden state of pre-trained English NER model. The first attention layer's weights, last attention layer's weights and the average value of all attention layers' weights are recorded as transformation matrices, respectively. All experiments are repeated 5 times with different random seeds, and report average performance on test set as final performance.

# **Experiments on Indo-European languages**

In this section, we choose two of the Indo-European languages, German and Spanish, to evaluate the performance of the proposed approach. Both low-resource languages, i.e, German and Spanish, and English belong to the same language family, which is the largest language family in the world. All labels are modified from BIO format to BIOES format following (Akbik, Blythe, and Vollgraf 2018). BAN<sup>first</sup>, BAN<sup>last</sup> and BAN<sup>ave</sup> represent that the proposed model uses the first attention layer, the last attention layer and the average of all attention layers to transfer well-trained English NER model knowledge.

## **Result on German and Spanish NER**

Experimental results of German and Spanish are shown in table 2. Evaluation metric is F1-score. As shown in the table, the performances of BiLSTM+CRF and CharLM+BiLSTM+CRF can be further improved by integrating with BAN. After adding BAN to baseline model (i.e., BiLSTM+CRF), the performance of using first attention matrix, BAN<sup>first</sup>, is almost equivalent to the model using last layer attention matrix and the BANave has the best performance. This means that although higher level attention captures deeper semantic dependencies (Chaudhari et al. 2019), its performance is not good as averaging all attention matrices. In addition, we can also note that the poorest performances of BAN are usually better than that of the base models. This indicates that the proposed BAN method is quite robust and the information transferred from English NER model is truly beneficial for original task. The baseline model achieves a F1-score of 81.41% and 82.49%, respectively. Adding back attention information, the F1-score is increased to 84.32% and 84.78%. Existing state-of-the-art systems utilize language

input	Approach	P(%)	R(%)	F1(%)
	(Yang, Salakhutdinov, and Cohen 2016)	65.59	71.84	68.57
	(Yang, Salakhutdinov, and Cohen 2016)	72.98	80.15	76.40
	(Che et al. 2013)	77.71	72.51	75.02
	(Wang, Che, and Manning 2013)	76.43	72.32	74.32
No Seg	(Zhang and Yang 2018)	76.35	71.56	73.88
	Char+BiLSTM+CRF	69.51	53.17	60.25
	+BAN <sup>first</sup>	74.54	61.09	67.15
	+BAN <sup>last</sup>	75.74	68.59	71.99
	+BAN <sup>ave</sup>	75.92	69.85	72.76
	+BERT+BAN <sup>first</sup>	78.12	78.36	78.24
	+BERT+BAN <sup>last</sup>	80.42	82.02	81.21
	+BERT+BAN <sup>ave</sup>	79.58	81.05	80.31

Table 3: Evaluation on OntoNotes 4.0

model to produce contextual embedding, which are orthogonal to our work. Therefore, using the character-level language models to generate word embedding, the performance of *CharLM+BiLSTM+CRF* is close to the state-of-the-art. After adding BAN, the performances of each model are improved. The *CharLM+BiLSTM+CRF+BAN*<sup>last</sup> obtains the SOAT F1-score of 88.41% and 88.16%.

# **Experiments on Sino-Tibetan languages**

In the previous section, the effectiveness of our method for NER is confirmed when a language is in the same language family with English. In this section, to explore the generalization of proposed approach on other language families, we focus on the second largest language family, i.e., Sino-Tibetan languages. This language family is distinct from Indo-European language family, and Chinese is the representative of Sino-Tibetan languages. In Chinese, sentences consist of characters, and there are no spaces between words. If model uses words as the smallest unit and corpus do not have the word segmentation, sentences need to be split into words, which would bring some inevitable error. Therefore, only the character-level embeddings are adopted in our model. And all tags are converted to character level. BAN<sup>first</sup>, BAN<sup>last</sup> and BAN<sup>ave</sup> have the same meanings as in previous section.

## **Result on OntoNotes 4.0**

Table 3 shows the results on Chinese OntoNotes 4.0. Evaluation metric is precision, recall and F1-score. For NotoNotes dataset, gold-standard segmentation is available. Gold Seg and No Seg indicate whether or not to use the word segmentation information. Existing stateof-the-art results are achieved by (Yang, Salakhutdinov, and Cohen 2016), with gold-standard segmentation, discrete features and semi-supervised data. Using the baseline model (i.e., Char+BiLSTM+CRF), the performance on Chinese OntoNotes 4.0 without segmentation is relatively lower. The F1-score of Char+BiLSTM+CRF is 60.25%. Adding BANfirst, BANflast and BANave to the baseline model leads to an increase from 60.25% to 67.15%, 71.99% and 72.76%, respectively. In order to further improve the performance, we use the BERT model (Devlin et al. 2019) to produce character embedding. Our best model Char+BiLSTM+CRF+BERT+BAN<sup>last</sup> yields 81.21% F1-score with no segmentation, which outperforms the previous best approach with no segmentation. Even compared with the state-of-the-art method of using gold segmentation information, our model also has a 4.81% improvement.

#### **Result on Weibo**

Results on the Weibo dataset are shown in Table 4, where NE, NM and Overall denote named entities, nominal entities and both, respectively. The previous best model (Peng and Dredze 2016) explores cross-domain data for semi-supervised learning. Since the dataset is too small, the baseline model (i.e., *Char+BiLSTM+CRF*) gives 32.35%, 35.31% and 32.18% F1-score on named entities, nominal entities and both without external data and manual features. Using the transferred model knowledge captured by BAN, the model achieves significant improvements. Observations on the performances of different BANs are consistent with that on OntoNotes. The BAN<sup>ave</sup> achieves the best performance, which yields 11.33% improvements on average.

Moreover, we also explore the effectiveness of BAN with a contextual embedding, which has rich syntactic information. Utilizing BERT model to produce character embedding, the model *BERT+BiLSTM+CRF* achieves 69.53% F1-score on both NE and NM. It can be seen that BAN still gets consistent improvements on this model. With back attention knowledge, the F1-score of *BERT+BiLSTM+CRF* increases from 69.53% to 71.98%. We also observe that BAN achieves the highest improvements on named entities. This demonstrates that the entities identified in pre-trained English model can be correctly recognized in Chinese model via back attention knowledge transfer.

# Task-Specific Information from Back Attention Network

Previous work (Liu et al. 2019) indicates that the representations from higher-level layers of NLP models are more task-specific. Although the proposed model does the same task among different languages, the target domains of different datasets are slightly different. To demonstrate that back attention knowledge generated by BAN could capture valuable task-specific information between different languages, we compare the performances of baseline model with three different word embeddings on the NER task. The random embedding is a random generation of vectors for each character and the same characters have the same embedding. This embedding does not contain any syntactic or semantic information. The FastText embedding (Bojanowski et al. 2017) uses the morphology of words and character n-grams to represent words, which is an efficient morphological representation. For BAN embedding, we use the transferred representation as word embeddings. BAN embedding  $^{first}$ , BAN embedding  $^{last}$  and BAN embedding ave use the first attention layer's value, last attention layer's value and the average value of all attention layers, respectively. In this experiment, all embeddings have the same dimension.

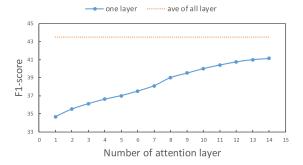


Figure 3: The result of Weibo NER with FastText embedding and knowledge transferred from different layers

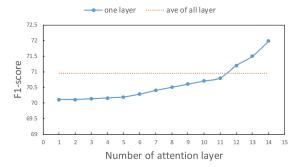


Figure 4: The result of Weibo NER with BERT embedding and knowledge transferred from different layers

Experimental results are shown in Table 5. The FastText embedding and all BAN embeddings significantly outperform the random embedding. And BAN representation is competitive with the FastText embeding. These results indicate that our embedding captures useful information. Furthermore, BAN has a terrific advantage that the data required is much less than other pre-trained embeddings like FastText. The data used in our method is at least two orders of magnitude smaller than FastText. Moreover, BAN embedding last and BAN embedding ave achieve better performances than FastText, in terms of recall and F1-score. This experiment illustrates that back attention knowledge transferred from BAN has inherent semantic information and could transfer task-specific information.

## Impact of attention level

As shown in the above experiments, using different word embeddings to obtain optimal performance requires different transfer information. We would like to better understand why the performances with different embeddings are inconsistent and which attention layer is more effective for back attention knowledge transfer. A hypothesis is that the higher level attention layer of neural machine translation model can capture deeper syntactic and semantic information. We record the weights of fourteen attention layers in our neural machine translation model in the process of translating Weibo dataset into English. From this formula-

Annroach	NE		NM		Overall				
Approach	P(%)	<b>R</b> (%)	F1(%)	P(%)	R(%)	F1(%)	P(%)	R(%)	F1(%)
(Peng and Dredze 2016)	66.67	47.22	55.28	74.48	54.55	62.97	-	-	58.99
(He and Sun 2017)	61.68	48.82	54.50	74.13	53.54	62.17	-	-	58.23
(Zhang and Yang 2018)	-	-	53.04	-	-	62.25	-	-	58.79
Char+BiLSTM+CRF	60.55	22.07	32.35	58.70	21.91	31.91	59.55	22.05	32.18
+BAN <sup>first</sup>	61.15	23.67	34.13	58.62	25.12	35.17	60.73	24.25	34.66
+BAN <sup>last</sup>	60.72	31.57	41.54	58.81	30.62	40.27	61.21	30.96	41.12
+BAN <sup>ave</sup>	61.18	34.51	44.13	58.50	33.86	42.89	61.57	33.64	43.51
BERT+BiLSTM+CRF	72.97	67.71	70.24	76.96	61.73	68.51	74.52	65.17	69.53
+BAN <sup>first</sup>	72.99	68.85	70.86	77.19	62.66	69.17	74.30	66.37	70.11
$+BAN^{last}$	73.50	71.45	72.46	77.01	64.99	70.49	74.17	69.91	71.98
+BAN <sup>ave</sup>	73.44	69.87	71.61	77.28	63.76	69.87	74.20	67.97	70.95

Table 4: Evaluation on Weibo NER

			F1(%)
Random Embedding + BiLSTM+CRF			
		22.05	
$\overline{{\sf BAN Embedding}^{first}} + \overline{{\sf BiLSTM+CRF}}$	50.01	23.66	32.12
		26.09	
BAN Embedding <sup>ave</sup> +BiLSTM+CRF	59.18	26.12	36.24

Table 5: Comparison of different embeddings on Weibo

tion T = AR, the different transferred model knowledge (T) can be obtained by back attention knowledge transfer mechanism by using different layers weights. Figures 3 and 4 show the F1-score of using FastText and BERT embeddings with the same back attention knowledge transferred from different attention layers. The dotted line denotes using average value of all attention layers as transformation matrix. As can be seen from the figures, the performances increase with using deeper attention layers. We believe that the static embeddings, which only obtain shallow semantic information, could acquire more extra semantic and taskspecific information from BAN than contextual embeddings. Since the translation and pre-trained English model have inevitable errors, there exists some noise information in the transfer knowledge. Averaging the attention values could reduce the variance and combine the shallow and deep semantic information. That is why the performance of the model using static embedding can be improved. However, the average attention value could not reduce the bias and contextual embedding have the same semantic information with the shallow layers. Therefore, the best performance does not appear when applying contextual embedding and the average weights. Instead, employing the last layer's weight obtains the best performance.

# **Analysis**

The proposed approach transfers the hidden states of pretrained models in high-resource languages to low-resource languages to improve the performance of monolingual NER model. The training time with or without BAN is almost the same , because the translation module and the English NER module are pre-trained.

On larger datasets, BAN achieves small improvements. The potential reason is that some of transfer knowledge obtained from BAN is duplicated with the information learned by the monolingual models. On smaller datasets, e.g., Weibo dataset, significant improvements have been achieved after adding transferred model knowledge to the base model. The potential reason is that these datasets are too small to be fully trained, and the testing datasets may have many characters not existing in the training datasets. Moreover, there may also exist some unrecognized characters or symbols in the testing datasets. Therefore, some tags labeled incorrectly by monolingual models could be labeled correctly with the model knowledge which contains semantic and task-specific information obtained by BAN. On the other hand, our method is orthogonal to other sequence labeling techniques(Zhang and Yang 2018) and can be used to further improve the performance.

#### Conclusion

In this paper, we seek to improve the performance of NER on low-resource languages by leveraging the well-trained English NER system. This is achieved by using a back attention network, which is a simple yet effective approach that can transfer the high-layer features in a pre-trained model from one language to another. Empirical experiments demonstrate that, for smaller datasets, the proposed approach can lead to significant improvements on the performance. This property is of great practical importance for low-resource languages. In addition, we have also studied the influence of different transfer matrices, which use different attention layers' value in the neural machine translation model. For future work, we would like to extend our method on other NLP tasks, e.g., relation extraction and coreference resolution.

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