Back Attention Knowledge Transfer for Low-Resource Named Entity Recognition

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In recent years, great success has been achieved in the field of natural language processing (NLP), especially in English thanks in part to the considerable amount of labeled resources. For named entity recognition (NER), however, most languages (low-resource) do not have such an abundance of labeled data as English (high-resource), so performances of those languages are relatively lower. To improve the performance of low-resource NER, Back Attention Network (BAN) is proposed in this paper. BAN exploits a translation module to translate low-resource languages into English and applies a novel mechanism, named back attention knowledge transfer, to obtain aligned high-resource semantic features from a pre-trained high-resource NER model. In this way, BAN leverages high-level features of a well-trained model to enrich semantic representations of low-resource languages. Experiments on four low-resource NER datasets show that the proposed approach outperforms other state-of-the-art methods, which indicates the effectiveness of BAN.

CCS Concepts:
- Computing methodologies → Information extraction.

Additional Key Words and Phrases: Named Entity Recognition, Back Attention Network, Transfer Learning

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1 INTRODUCTION

Named entity recognition (NER) is usually regarded as a sequence tagging task that extracts continuous tokens into specified classes, such as persons, organizations, and locations. The state-of-the-art NER approaches usually employ long short-term memory recurrent neural networks (LSTM) and a subsequent conditional random field (CRF) to tag tokens of a sequence [22]. As a result, these approaches require large-scale data to train due to the deployment of deep neural networks.

As English is widely used and studied in the world, there is a wealth of available labeled data in NER for training large models [37, 46]. Consequently, NER on English is well developed. Languages other than English, unfortunately, are not still fully studied due to the lack of labeled data. The insufficiency of labeled data is partly due to the fact that manually labeling data is expensive and time-consuming and many institutions or researchers with limited resources are hard to...
afford large amounts of high-quality data. Performances of neural NER models on these low-resource languages are compromised since the training data are insufficient [49]. Generally, English is regarded as the high-resource language, while other languages, even Chinese, are treated as low-resource languages [15].

Recently, many cross-lingual learning methods are applied to address the low-resource NER task. Previous work is mostly based on heuristic approaches that transfer low-level (i.e. word level) information between two languages [45]. For example, Che et al. [8] predict entity labels on labeled parallel datasets of two languages. Words in the two languages are aligned to form word pairs. Then, two NER models trained on the two languages are constrained to be consistent in the form of joint prediction when predicting word pairs. These approaches require labeled parallel corpora, which are more expensive than monolingual labeled corpora [8]. Without labeling additional data, some approaches utilized translation models to establish an alignment between the low-resource and high-resource languages. For example, Feng et al. [15] enrich the embedding of a source word with the embedding of its translated word in another language. The core idea is to exploit the alignment between words in two languages.

However, it is difficult to align words precisely in two languages. Generally, a sentence in one language has a different length from the one that shares the same meaning in another language. For example, as shown in Figure 1, the sentence “The chairman of the Federal Reserve is Jerome Powell” in English consists of 9 words, while its version in Chinese is “美联储主席是杰罗姆鲍威尔”, which has 12 words. Additionally, through this example, one can see that the orders of words in the two languages are often different. Therefore, it is hard to find a general rule to align words in the two languages.

Besides, the tags in the two languages are difficult to align. In Figure 1, the Federal Reserve is composed of three English words, which are tagged as B-ORG, I-ORG, and E-ORG, respectively, while in Chinese, the Federal Reserve is represented by one Chinese word “美联储”, which is tagged as S-ORG. Even if words in the two languages can be aligned, the tags in one language cannot be directly projected to the other language.

In a word, misalignment between words and misalignment between tags in two languages impede the application of transfer learning that is based on translation models from high-resource NER to low-resource NER.

To address the above issue, this paper proposes Back Attention Network (BAN) to enhance the usability of transfer learning on NER. Unlike previous work that enriches the embedding of a source word with the embedding (low-level) of its translated word in the high-resource language, BAN transfers high-level features (i.e. the outputs of BiLSTM) of the high-resource language to a low-resource language through the encoder-decoder attention weights generated
by attention-based translation models [17]. The core idea is that the global attention weights in the encoder-decoder
attention layers can represent the alignment information [3]. Namely, it implies the alignment of words between the
source language and the target language. Therefore, the information extracted by the target language pre-trained NER
model could be transferred into the source language by using the attention weights reversely.

Compared with shared representation approaches [4], the proposed approach has the advantage of leveraging
semantic and task-specific features extracted by a well-trained NER model without finding universal features on
different languages. In addition, the high-resource semantic features are naturally aligned by the encoder-decoder
attention weights without additional processing. Note that BAN does not acquire any hand-craft features and labeled
parallel corpora, which are expensive for the low-resource scenario.

The contributions of this paper are summarized as follows:

• A novel approach, BAN, is proposed to transfer high-level semantic features from the high-resource language
to low-resource languages by attention weights obtained from translation models. BAN exploits the attention
weights to address misalignment between words and misalignment between tags in two languages.
• Extensive experiments on four datasets from two language families empirically show that BAN can improve
performances of multiple baselines, which indicates the effectiveness of BAN.

The rest of the paper is organized as follows. Section 2 discusses related work. The proposed approach is presented
in Section 3. In Section 4, the experimental results of the NER task in three different languages (i.e., German, Spanish,
and Chinese) are presented. Section 5 further analyses the effectiveness of the proposed approach BAN and the effect of
different attention layers on BAN. Section 6 concludes the paper and discusses the future work.

2 RELATED WORK
2.1 Named Entity Recognition

NER is the task of recognizing mentions from text and classifying them into predefined semantic types, such as
person, organization, location. Existing approaches usually treat NER as a sequence labeling problem. Various sequence
labeling models, such as hidden markov models (HMM) [16], conditional random fields (CRF) [25], have achieved
decent performance before deep learning is widely used. With the widespread use of deep learning, many neural
based methods have been proposed, such as Long Short-Term Memory networks (LSTM) [20], LSTM-CRF [26, 28, 35]
where CRF is utilized on the top of LSTM. Convolutional neural networks (CNN) have also been used on the NER task.
Collobert et al. [9] exploited a CNN-CRF structure for NER. Ma et al. [30] proposed a neural network architecture,
called LSTM-CNN-CRF, combing LSTM and CNN. Strubell et al. [38] applied Iterated Dilated Convolutional Neural
Networks (ID-CNNs) to NER. Furthermore, sentences are treated as sequences of characters by neural networks. This
way has two distinct advantages. Firstly, it is helpful for solving the Out-Of-Vocabulary (OOV) problem. Secondly, it
can capture additional morphological and orthographic information. Therefore, Dos et al. [12] applied a character-level
CNN to boost a CNN-CRF model. Recently, Zhang and Yang [50] proposed a lattice-structured LSTM model, which
leveraged word and character information at the same time. They showed that lattice-structured LSTM could make a
great improvement on NER. In this paper, the architecture of the proposed approach is based on the most widely used
LSTM-CRF, and cross-lingual knowledge is utilized to improve the performance of low-resource NER.

1To be consistent with translation models, the original (low-resource) sentences are regarded as the source sentences and the translated (high-resource)
sentences as the target sentences.
2.2 Cross-lingual Learning

Cross-lingual learning approaches are proposed to address low-resource NER. At present, there are two main types of approaches: one is annotation projection based on parallel corpora and the other is the shared representation based on transfer learning.

2.2.1 Annotation Projection. Annotation projection relies on parallel corpora and the alignment of words. The tags of tokens in the high-resource language sentence are projected to their aligned tokens in low-resource languages. Under the cross-lingual setting, many approaches are proposed in various NLP tasks, such as POS tagging, parsing, and NER. In the POS tagging task, many representative approaches made great improvements [10, 39]. In the parsing task, Hwa et al. [23] proposed a direct projection algorithm for syntactic dependency annotation, and Tiedemann [41] utilized cross-lingually harmonized annotation schemes. On the NER task, NER tags are projected within language pairs by annotation projection [13, 48, 52]. However, annotation projection is heavily dependent on the alignment of source and target languages, whose quality is dependent on the size of the parallel data. The assumption implied in this kind of approaches is that the alignment of source and target languages is correct. Unfortunately, misalignment between words and misalignment between tags in languages are inevitable, since sentence length is difficult to guarantee consistency between languages. This issue impedes the application of annotation projection.

2.2.2 Shared Representation. Shared representation relies on universal features that are transferred from a high-resource language to a low-resource language. Therefore once a model is trained in the high-resource language using delexicalized features that do not depend on the forms of the words, it can be directly applied to a low-resource language. Tackstrom et al. [40] enhanced the model by building cross-lingual word clusters. The word clusters were induced by large parallel corpora and used to generate universal features. Bharadwaj et al. [4] bridged the high-resource language and low-resource languages through phonemic transcription. Ni et al. [31] proposed to project distributed representations of words (word embeddings) into a common space as language independent features. Chaudhary et al. [7] adapted continuous word representations using linguistically motivated sub-word units: phonemes, morphemes, and graphemes. Other approaches that help build common feature representations include building a bilingual dictionary [14, 51], utilizing Wikipedia data [24, 43]. Different from obtaining features only in high-resource language, multitask learning is jointly trained across different languages by sharing parameters. For example, Lin et al. [27] used shared character and word embeddings which were trained in a multi-task setting to improve the performance of each dataset. The main advantage of shared representation is that it requires minimal dependency on parallel resources. However, this approach is, currently, strongly limited by the fact that it requires a generic feature representation across languages.

3 BACK ATTENTION NETWORK

In this section, the proposed approach BAN is introduced in four parts, i.e., attention-based translation module, pre-trained NER module, back attention knowledge transfer, and knowledge augmented NER module. Figure 2 illustrates the architecture of BAN.

3.1 Attention-based Translation Module

Following [17], we use the convolutional sequence to sequence model in the neural machine translation (NMT) module. It divides the translation process into two steps. Firstly, in the encoder step, given an input sentence \( s = (s_1, \ldots, s_m) \) of
Fig. 2. The architecture of BAN. The low-resource sentences are translated into English and BAN records the attention weights. Then the sentences in the high-resource language are fed into a pre-trained model. After acquiring the outputs of BiLSTM in the model, BAN uses the back attention knowledge transfer mechanism to obtain the aligned high-resource features which are combined with the low-resource features to enrich representations of low-resource words in the low-resource NER model.

length \( m \), \( e^s(s_i) \) maps each word \( s_i \) to a word embedding \( w^s_i \):

\[
w^s_i = e^s(s_i), \tag{1}
\]

where \( e^s \) denotes the word embedding lookup table. After that, the absolute position information of input elements \( [p_1, \ldots, p_m] \) is combined with the embedding. Both vectors are added to get input sentence representations \( [w^s_i + p_1, \ldots, w^s_m + p_m] \). Similarly, the embeddings \( [g_1, \ldots, g_n] \) of target words in the decoder network are generated in the same way. A convolutional neural network (CNN) is used to extract features of a sentence from left to right. Secondly, in the decoder step, attention mechanism is used in each CNN layer. In order to acquire the attention value, the current decoder state \( h^l_i \) is combined with the embedding of the previous decoder output value \( g_i \):

\[
d^l_i = W^l_d h^l_i + b^l_d + g_i, \tag{2}
\]

where \( W^l_d \) and \( b^l_d \) are learned parameters.

For the \( l \)th encoder-decoder attention layer, the weight \( a^l_{ij} \) is computed as a dot-product between the decoder state summary \( d^l_j \) and the \( i \)th output (denoted by \( z_i \)) of the encoder block:

\[
a^l_{ij} = \frac{\exp(d^l_j \cdot z_i)}{\sum_{t=1}^m \exp(d^l_t \cdot z_i)}. \tag{3}
\]

And then, following the normal decoder implementation, it gets target sentence \( t = (t_1, \ldots, t_n) \) by beam search strategies.

### 3.2 Pre-trained NER Module

We use the model proposed in [1], which is one of the state-of-the-art English NER approaches. This model utilizes a BiLSTM network as a character-level language model (CharLM) to take contextual information. 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 the character-level language model, the last character of a word is regarded as the word vector, which contains the contextual information from the beginning of the sentence. The backward direction model functions in the same way but in the reversed direction. Formally, we define the forward and backward character embeddings of each word $s_i$ as $\overrightarrow{h}_1, \cdots, \overrightarrow{h}_l$ and $\overleftarrow{h}_1, \cdots, \overleftarrow{h}_l$, where $l$ indicates the length of the word. Then, the contextual embedding of the word $s_i$ is represented as follows:

$$e_{i}^{CharLM} = [\overrightarrow{h}_i; \overleftarrow{h}_1],$$

(4)

where $\overrightarrow{h}_i$ and $\overleftarrow{h}_1$ denote the hidden state of the last character of the word in the forward direction and the hidden state of the last character of the word in the backward direction, respectively. The concatenation operation is denoted by $[;]$.

The final embedding (denoted by $e_i$) of the word $s_i$ is formed by concatenating the character-level language model embedding $e_i^{CharLM}$ and its GloVe embedding $e_i^{GloVe}$ [34]. Namely, $e_i = [e_i^{CharLM}; e_i^{GloVe}]$. A standard BiLSTM-CRF model takes the embedding $E = \{e_1, \cdots, e_n\}$ to address the NER task. The English NER model is trained on the CoNLL-2003 English dataset [37] and the parameters are fixed to predict translated sentences.

3.3 Back Attention Knowledge Transfer

Given an input sentence $s = (s_1, \cdots, s_m)$ in a low-resource language, the translation module translates $s$ into English and the output is $t = (t_1, \cdots, t_n)$. At the moment, the weights of the encoder-decoder attention layers can be recorded as the bridge of transfer learning.

In the high-resource language, the BiLSTM output state for the word $t_j$ in the pre-trained English NER model is:

$$r_j^t = [r_j^f; r_j^b] \in \mathbb{R}^{2d},$$

(5)

where $r_j^f$ and $r_j^b$ denote the $j$th forward and backward direction outputs, respectively, and $d$ is the dimension of the hidden state of the forward (backward) LSTM. $r_j^f$ contains the semantic and task-specific features of the translated sentence. It, however, is unsuitable to be used directly in the low-resource language, since the alignment is obscure between the high-resource language and the low-resource languages.

The encoder-decoder attention weights imply the alignment of words between the source sentence and the target sentence. The weights of an attention layer could be a transformation matrix as the bridge of transfer from the high-resource language to a low-resource language. Note that the number of rows of the attention weight matrix is equal to the length of the source sentence and the number of columns of the attention weight matrix is equal to the length of the target sentence. And the $i$th row of the attention weight matrix, $a_i = [a_{i1}, \cdots, a_{in}]$, indicates the correlation between the source word $s_i$ with each word in the target sentence\(^2\). Thereafter, the aligned high-resource semantic feature (denoted by $t_i^a$) of the $i$th word $s_i$ in the source sentence is acquired by the weighted sum of the outputs of BiLSTM in the pre-trained English model:

$$t_i^a = \sum_{j=0}^{m} a_{ij} r_j^t = a_i R^t,$$

(6)

where $R^t = [r_1^t, \cdots, r_n^t]^T \in \mathbb{R}^{n \times 2d}$ represents the whole outputs of BiLSTM in the pre-trained English model, and $a_i \in \mathbb{R}^{1 \times n}, t_i^a \in \mathbb{R}^{2d}$. Note that $t_i^a$ has the same dimension as $r_i^f$.

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\(^2\)The subscript $l$ in Eq. 3 that denotes the attention is obtained from the $l$th layer is omitted for brevity.
As for the whole source sentence, the aligned high-resource semantic features (denoted by $T^a$) can be obtained by the production of the attention weight matrix and the outputs of BiLSTM in the pre-trained English model:

$$ T^a = AR^t, $$

where $T^a = [t_1^a, \ldots, t_m^a]^T \in \mathbb{R}^{m \times 2d}$ and $A = [a_1^T, \ldots, a_m^T]^T \in \mathbb{R}^{m \times n}$.

### 3.4 Knowledge Augmented BiLSTM-CRF Module

The low-resource knowledge augmented NER module is based on the BiLSTM-CRF model, which has the same structure as the pre-trained English NER model introduced in Subsection 3.2. The original features are obtained by BiLSTM from the low-resource language and then combined with the high-resource semantic features to form final representations that are fed into the last CRF layer. In the following, the proposed approach, BAN, is depicted in detail.

Firstly, each word in the low-resource language is mapped into a word embedding:

$$ w_i = e^s(s_i). $$

Thus, a sentence $s = (s_1, \ldots, s_m)$ in a low-resource language is mapped into $W = [w_1, \ldots, w_m]$.

Secondly, BiLSTM takes the sentence as input to obtain the contextual representation of each word. In each direction, the representation of each input word is modeled with a single hidden state. Given an initial value, every time step, LSTM consumes an input word and obtains its hidden state recurrently. Take the forward LSTM for an example, the recurrent state for the $k$th word $r^>_k$ is obtained as follows [19]:

$$
\begin{align*}
    i_k &= \sigma(W_i w_k + U_i r^<_{k-1} + b_i) \\
    f_k &= \sigma(W_f w_k + U_f r^<_{k-1} + b_f) \\
    o_k &= \sigma(W_o w_k + U_o r^<_{k-1} + b_o) \\
    u_k &= \tanh(W_u w_k + U_u r^<_{k-1} + b_u) \\
    c_k &= c_{k-1} \odot f_k + u_k \odot i_k \\
    r^>_k &= o_k \odot \tanh(c_k),
\end{align*}
$$

where $i_k$, $o_k$, $f_k$, and $u_k$ denote the values of an input gate, an output gate, a forget gate, and an actual input at time step $k$, respectively. These gates control the information flow for a recurrent cell $c_k$ and the state vector $r^>_k$. $W_x$, $U_x$ 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) yet in an opposite direction. The output of the backward LSTM for the word $s_j$ is denoted by $r^<_j$.

Thirdly, the original low-resource representation (denoted by $r_j^>$) for the word $s_j$ is obtained by concatenating $r^>_i$ and $r^<_i$:

$$ r_j^> = [r^>_i; r^<_i] \in \mathbb{R}^{2d}. $$

Finally, the original low-language representation ($r_j^>$) and the high-resource semantic representation ($t_j^a$ in Eq. 6) are concatenated to form the final representation (denoted by $r_j$) for the word $s_j$:

$$ r_j = [r_j^; t_j^a] \in \mathbb{R}^{4d}. $$
Table 1. The statistics of datasets

| Language | Dataset         | Train | Dev  | Test  |
|----------|-----------------|-------|------|-------|
| German   | CoNLL-2003      | 12,705| 3,068| 3,160 |
| Spanish  | CoNLL-2002      | 8,323 | 1,915| 1,517 |
| Chinese  | OntoNotes 4.0   | 15,509| 4,405| 4,462 |
| Chinese  | Weibo           | 1,350 | 270  | 270   |

Then, a standard CRF layer is utilized on the top of the final representation $R = [r_1, \cdots, r_m]^T \in \mathbb{R}^{m \times d}$. The state score is obtained by a linear layer with the softmax function:

$$P = \text{softmax}(WR + 1b^T),$$

where $W \in \mathbb{R}^{4d \times c}$, $b \in \mathbb{R}^c$ are learning parameters, $1 \in \mathbb{R}^c$ is a vector with all 1s and $c$ is the number of the tags.

For a sequence of prediction $y = (y_1, \cdots, y_m)$, its score is defined by:

$$\text{score}(s, y) = \sum_{i=1}^{m} T_{y_i, y_{i+1}} + \sum_{i=1}^{m} P_{i,j},$$

where $T$ is the matrix of transition scores, $T_{y_i, y_{i+1}}$ denotes the score of a transition from tag $y_i$ to tag $y_{i+1}$, and $P_{i,j}$ denotes the status score that the $i$th word is tagged $y_i$.

4 EXPERIMENTS

4.1 Experiments Settings

Datasets. Experiments on four standard datasets are carried out to evaluate the proposed algorithm on the NER task. These standard datasets include CoNLL 2003 German [37], CoNLL 2002 Spanish [42], OntoNotes 4 [46], and Weibo NER [32], where the last two are Chinese datasets. The datasets from different language families are involved to prove the extensive effectiveness of the proposed method. We follow [8] to select a part of OntoNotes 4 as a NER dataset. Table 1 shows the detailed statistics of these datasets. All the annotations are mapped to the BIOES format. These datasets are chosen from different domains. The CoNLL 2003 German, CoNLL 2002 Spanish, and OntoNotes 4 datasets are in the news domain while the Weibo dataset is drawn from the social media website.\(^3\)

Experimental Setup. We implement the base BiLSTM-CRF model using the PyTorch framework and follow the configurations in [22] for comparative evaluation. FastText embeddings\(^4\) are used for serving as basic word embeddings. The pre-trained static word embeddings, such as FastText, lose a lot of syntactic information of the sentences. Therefore, the pre-trained contextual word embeddings [11] are also utilized. The translation module is implemented by Fairseq\(^5\). And the translation modules are trained on German-English, Spanish-English, and Chinese-English corpora in United Nation Parallel Corpus, respectively. The pre-trained English NER module employs the default NER model of Flair\(^6\).

We train the proposed model using stochastic gradient descent with no momentum for 150 epochs\(^7\), with an initial learning rate of 0.1 and a learning rate annealing method in which the training loss does not fall in 3 consecutive epochs.

The hidden size of BiLSTM is set to 256 and the layer of BiLSTM is set to 1. With different datasets, we choose the

\(^1\)https://www.weibo.com/

\(^2\)https://github.com/facebookresearch/fastText

\(^3\)https://github.com/pytorch/fairseq

\(^4\)https://github.com/zalandoresearch/flair

\(^5\)These models are trained on two Nvidia GTX 1080Ti graphic cards.

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Table 2. Results on German and Spanish NER datasets

| Approaches          | German | Spanish |
|---------------------|--------|---------|
| Gillick et al. (2016) [18] | -      | 82.95   |
| Lample et al. (2016) [26] | 78.76  | 85.75   |
| Akbik et al. (2018) [2]  | 88.32  | -       |
| BiLSTM+CRF           | 81.41  | 82.49   |
| +BAN_{first}         | 82.23  | 82.73   |
| +BAN_{last}          | 82.45  | 84.23   |
| CharLM+BiLSTM+CRF   | 88.21  | 87.33   |
| +BAN_{first}         | 88.20  | 87.43   |
| +BAN_{last}          | 88.41  | 88.16   |

Learning rate from \(\{0.025, 0.05, 0.1\}\) and mini-batch size from \(\{8, 16, 32\}\). 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 in [36]. The hidden state size of the pre-trained English NER model is also 256. The aligned high-resource semantic feature has the same size as the hidden state of the pre-trained English NER model. The weights of the first attention layer and the weights of the last attention layer are recorded as transformation matrices. All experiments are repeated 5 times with different random seeds, and we report average performance on the test set as the final performance.

4.2 Experiments on Indo-European languages

In this subsection, 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, belong to the same language family as English, which is the largest language family in the world. All labels are modified from BIO format to BIOES format following [2]. Since the translation model has multiple encoder-decoder attention layers, two representative layers (the first layer and the last layer) are chosen in the proposed approach and the impact of different layers on BAN is explored in Subsection 5.2. BAN_{first} and BAN_{last} denotes that the proposed model exploits the first and the last encoder-decoder attention weights to transfer the high-resource semantic features, respectively.

Experimental results of German and Spanish are shown in Table 2. The evaluation metric is F1-score. BiLSTM+CRF denotes the BiLSTM-CRF model with FastText embedding, which is treated as a baseline model. The baseline model achieves a F1-score of 81.41\% and 82.49\% on German and Spanish, respectively. The F1-scores of the model equipped with BAN_{first} (BAN_{last}) are increased to 82.23\% (82.65\%) and 82.73\% (84.23\%) on German and Spanish, respectively, which indicates the effectiveness of the proposed BAN.

Existing state-of-the-art approaches utilize language models to produce contextual embedding, which are orthogonal to our work. CharLM+BiLSTM+CRF denotes the BiLSTM-CRF model with the character-level language model to generate contextual word embedding, which is regarded as another baseline model. It achieves a F1-score of 88.21\% and 87.33\% on German and Spanish, respectively. The performances of CharLM+BiLSTM+CRF overtake consistently BiLSTM+CRF, indicating the effectiveness of the character-level language model. CharLM+BiLSTM+CRF+BAN_{first} achieves comparative F1-scores, i.e. 88.20\% and 87.43\%, and CharLM+BiLSTM+CRF+BAN_{last} obtains better F-scores, i.e. 88.41\% and 88.16\%. This indicates once again the effectiveness of the proposed BAN.
Table 3. Evaluation on OntoNotes 4.0. Gold Seg and No Seg denote whether or not to use the word segmentation, respectively.

| Input | Approaches                  | P(%) | R(%) | F1(%) |
|-------|-----------------------------|------|------|-------|
| Gold Seg | Yang et al. (2016) [47]    | 65.59| 71.84| 68.57 |
|       | Yang et al. (2016) [47]    | 72.98| 80.15| 76.40 |
|       | Che et al. (2013) [8]      | 77.71| 72.51| 75.02 |
|       | Wang et al. (2013) [44]    | 76.43| 72.32| 74.32 |
| No Seg | Zhang and Yang (2018) [50] | 76.35| 71.56| 73.88 |
|        | +BAN<sub>first</sub>        | 74.54| 61.09| 67.15 |
|        | +BAN<sub>last</sub>         | 75.74| 68.59| 71.99 |
|        | +BERT+BAN<sub>first</sub>   | 78.12| 78.36| 78.24 |
|        | +BERT+BAN<sub>last</sub>    | **80.42** | **82.02** | **81.21** |

Based on BiLSTM+CRF and CharLM+BiLSTM+CRF, BAN can further improve their performances on seven out of eight cases except for CharLM+BiLSTM+CRF+BAN<sub>first</sub> on German, since the high-resource semantic features are transferred by BAN no matter the weights from the first or the last attention layer. Meanwhile, BAN with the last attention transfer performs higher than with the first attention transfer. This may be due to the fact that a higher layer of attention can capture more semantic dependency [6].

4.3 Experiments on Sino-Tibetan languages

In the previous subsection, the effectiveness of the proposed approach is confirmed on German and Spanish that belong to the same language family with English. In this subsection, to explore the generalization of the proposed approach on other language families, we focus on the second largest language family, i.e., the Sino-Tibetan language family. This language family is distinct from the Indo-European language family, and Chinese is the most widely used Sino-Tibetan language. Unlike English, sentences in Chinese consist of characters, and no space split these characters. Model based on words needs to first split sentences into words if there is no word explicitly segmented in sentences, which would bring some inevitable errors. Therefore, only the character-level embedding based approaches are considered in this subsection when no word is explicitly segmented in sentences.

**OntoNotes 4.0.** Table 3 presents the results on Chinese OntoNotes 4.0. Evaluation metrics are precision, recall, and F1-score. For the OntoNotes dataset, gold-standard segmentation is available. Existing state-of-the-art results are achieved by [47], 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%. Equipping BAN<sub>first</sub> (BAN<sub>last</sub>) to the baseline model leads to an increase from 60.25% to 67.15% (71.99%). The effectiveness of the proposed BAN is once again confirmed on a distinct language family. Similarly, Char+BiLSTM+CRF+BAN<sub>last</sub> outperforms Char+BiLSTM+CRF+BAN<sub>first</sub>, which confirms the assumption that a higher layer of attention can capture more semantic dependency [6]. In order to further improve the performance, we use the BERT model [11] to produce character embedding. Our best model Char+BiLSTM+CRF+BERT+BAN<sub>last</sub> yields 81.21% F1-score with no segmentation, which outperforms previous state-of-the-art approaches with no segmentation.

**Weibo.** Results on the Weibo dataset are shown in Table 4, where NE, NM, and Overall denote named entities, nominal entities, and both of them, respectively. Evaluation metrics are precision, recall, and F1-score. The previous model [33] explores cross-domain data for semi-supervised learning. As the dataset is too small, the baseline model...
Table 4. Results on Weibo NER. NE, NM, and Overall denote named entities, nominal entities, and both of them, respectively.

| Approaches            | NE | NM | Overall |
|-----------------------|----|----|---------|
|                       | P(%) | R(%) | F1(%) | P(%) | R(%) | F1(%) | P(%) | R(%) | F1(%) |
| Peng and Dredze [33]  | 66.67 | 47.22 | 55.28 | 74.48 | 54.55 | 62.97 | -    | -    | 58.99 |
| He and Sun [21]       | 61.68 | 48.82 | 54.50 | 74.13 | 53.54 | 62.17 | -    | -    | 58.23 |
| Zhang and Yang [50]   | -    | -    | 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<sub>first</sub>  | 61.15 | 23.67 | 34.13 | 58.62 | 25.12 | 35.17 | 60.73 | 24.25 | 34.66 |
| +BAN<sub>last</sub>   | 60.72 | 31.57 | 41.54 | 58.81 | 30.62 | 40.27 | 61.21 | 30.96 | 41.12 |
| Char+BiLSTM+CRF+BAN<sub>first</sub> | 72.97 | 67.71 | 70.24 | 76.96 | 61.73 | 68.51 | 74.52 | 65.17 | 69.53 |
| Char+BiLSTM+CRF+BAN<sub>last</sub> | 73.50 | 71.45 | 72.46 | 77.01 | 64.99 | 70.49 | 74.17 | 69.91 | 71.98 |

(i.e., Char+BiLSTM+CRF) gives 32.35%, 31.91%, and 32.18% F1-score on NE, NM, and Overall without external data and manual features. Using the aligned high-resource semantic features captured by BAN, Char+BiLSTM+CRF+BAN<sub>last</sub> achieves significant improvements on NE (41.51%), NM (40.27%), and Overall (41.12%). Observations on the performances of different BANs (BAN<sub>first</sub> and BAN<sub>last</sub>) are consistent with those on OntoNotes. Char+BiLSTM+CRF+BAN<sub>last</sub> yields 8.94% improvements on average, in terms of F1-score, compared to Char+BiLSTM+CRF.

Moreover, we also explore the effectiveness of BAN with a contextual embedding (i.e. BERT), which has rich syntactic information. Utilizing BERT to produce character embedding, the model BERT+BiLSTM+CRF, which serves as a baseline model, achieves 70.24%, 68.51%, and 69.14% F1-scores on NE, NM, and Overall, respectively. The F1-scores of BERT+BiLSTM+CRF+BAN<sub>last</sub> are 72.16%, 70.09%, and 71.28% on NE, NM, and Overall, respectively. It can be seen that the performance still gets consistent improvements with the aligned high-resource semantic features obtained by BAN. This indicates the effectiveness of BAN.

5 DETAILED ANALYSIS

5.1 BAN Embedding

To assess the aligned high-resource semantic features obtained by BAN, we regard the aligned high-resource semantic features as special embeddings, named BAN embedding. The performances of BiLSTM-CRF on a NER task are compared among three different embeddings: random embedding, FastText embedding, and the proposed BAN embedding. The random embedding is to randomly generate a vector for each character and the same character has the same embedding. The random embedding does not contain any syntactic or semantic information. FastText embedding uses the morphology and n-grams of words to represent words, which is an efficient morphological representation. As to BAN embedding, like the previous part, the aligned high-resource semantic features obtained by BAN with the weights of the first and the last attention layers are denoted as BAN<sub>first</sub> embedding and BAN<sub>last</sub> embedding, respectively.

Experimental results are shown in Table 5. FastText embedding and both BAN (BAN<sub>first</sub> and BAN<sub>last</sub>) embeddings significantly outperform the random embedding. BAN<sub>first</sub> Embedding (32.12%) is comparable with FastText embedding (32.18%). BAN<sub>last</sub> embedding obtains 35.84% F1-score, which is 3.66% higher than FastText embedding. These results indicate that BAN embedding can effectively transfer high-resource language information by aligned high-resource semantic features. Furthermore, BAN embeddings, especially BAN<sub>last</sub>, achieve better recall than FastText embedding.
Table 5. Comparison of BiLSTM-CRF with different embeddings on the Weibo dataset

| Embedding | P(%) | R(%) | F1(%) |
|-----------|------|------|-------|
| Random    | 36.12| 10.55| 16.33 |
| FastText  | 59.55| 22.05| 32.18 |
| BAN<sub>first</sub> | 50.01| 23.66| 32.12 |
| BAN<sub>last</sub> | 57.22| 26.09| 35.84 |

Fig. 3. The performances of BiLSTM-CRF on Weibo with high-resource semantic features transferred from different layers. The dotted line denotes the performances of BAN with FastText embedding. The solid line denotes the performances of BAN with BERT embedding.

which may be due to the fact that BAN embeddings capture the task-specific information contained in the pre-trained high-resource NER model and thus help BiLSTM+CRF find more named entities in the low-resource language. Meanwhile, it is consistent with previous work [29] that indicates the representations from higher-level layers of NLP models are more task-specific. These experimental results illustrate that the aligned high-resource semantic features obtained by BAN contain inherent semantic information and could transfer task-specific information from the pre-trained high-resource NER model to the low-resource one.

5.2 Impact of Different Attention Layers

As can be seen from the above experiments, different performances are obtained when exploiting different aligned high-resource semantic features. In this subsection, the aligned high-resource semantic features transferred by different attention weights are studied to better understand and utilize BAN. A hypothesis is that a higher layer of attention weights in the neural machine translation model can capture deeper syntactic and semantic information. The weights of fifteen attention layers in the neural machine translation model are recorded in the process of translating the Weibo dataset into English.

Figure 3 presents the performances of BiLSTM-CRF using different aligned high-resource semantic features transferred by various encoder-decoder attention layers. The dotted line denotes the performances of BAN with FastText embedding. The solid line denotes the performances of BAN with BERT embedding.

As the layer of attention used in BAN increases, the performances show an upward trend. When the first to fourth attention layers is utilized to transfer the high-resource semantic features, the performances have small improvements.
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One potential reason is that the attention weights in rather shallower layers capture shallower syntactic and semantic information which may hardly transfer extracted features correctly. When the weights of the eighth or higher attention layers, the performances are good and plateauing. The optimal performance is achieved by using the tenth or the eleventh attention layer. This indicates that there is no need to rely too much on the depth of attention layers used on BAN.

6 CONCLUSION AND FUTURE WORK

In this paper, we seek to improve the performance of NER on low-resource languages by leveraging well-trained high-resource English NER models. This can be achieved by the proposed approach, back attention network (BAN), which can transfer aligned semantic features in a pre-trained model from the high-resource language to low-resource languages. Extensive experiments empirically indicate that, the proposed approach can improve significantly baseline models to achieve better performances, especially for small datasets. This is of great practical importance for low-resource language datasets. For future work, we would like to extend the proposed method to other NLP tasks, e.g., relation extraction and coreference resolution.

REFERENCES

[1] Alan Akbik, Tanja Bergmann, and Roland Vollgraf. 2019. Pooled contextualized embeddings for named entity recognition. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies. 724–728.
[2] Alan Akbik, Duncan Blythe, and Roland Vollgraf. 2018. Contextual string embeddings for sequence labeling. In Proceedings of the 27th International Conference on Computational Linguistics. 1638–1649.
[3] Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. 2015. Neural Machine Translation by Jointly Learning to Align and Translate. In Proceedings of the 3rd International Conference on Learning Representations.
[4] Akash Bharadwaj, David Mortensen, Chris Dyer, and Jaime Carbonell. 2016. Phonologically aware neural model for named entity recognition in low resource transfer settings. In Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing. 1462–1472.
[5] Piotr Bojanowski, Edouard Grave, Armand Joulin, and Tomas Mikolov. 2017. Enriching Word Vectors with Subword Information. Transactions of the Association for Computational Linguistics 5 (2017).
[6] Sneha Chaudhari, Gungor Polatkan, Rohan Ramanath, and Varun Mithal. 2019. An attentive survey of attention models. arXiv preprint arXiv:1904.02874 (2019).
[7] Matti Chaulhary, Chunting Zhou, Lori Levin, Graham Neubig, David R Mortensen, and Jaime Carbonell. 2018. Adapting Word Embeddings to New Languages with Morphological and Phonological Subword Representations. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing. 3285–3295.
[8] Wanxiang Che, Mengjia Wang, Christopher D Manning, and Ting Liu. 2013. Named entity recognition with bilingual constraints. In Proceedings of the 2013 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies. 52–62.
[9] Ronan Collobert, Jason Weston, Léon Bottou, Michael Karlen, Koray Kavukcuoglu, and Pavel Kuksa. 2011. Natural language processing (almost) from scratch. Journal of machine learning research 12, Aug (2011), 2493–2537.
[10] Dipanjan Das and Slav Petrov. 2011. Unsupervised part-of-speech tagging with bilingual graph-based projections. In Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies. Association for Computational Linguistics, 600–609.
[11] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT. Pre-training of Deep Bidirectional Transformers for Language Understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies. 4171–4186.
[12] Cicero dos Santos, Victor Guimaraes, RJ Niterói, and Rio de Janeiro. 2015. Boosting Named Entity Recognition with Neural Character Embeddings. In Proceedings of NEWS 2015 The Fifth Named Entities Workshop. 25.
[13] Maud Ehrmann, Marco Turchi, and Ralf Steinberger. 2011. Building a multilingual named entity-annotated corpus using annotation projection. In Proceedings of the International Conference Recent Advances in Natural Language Processing 2011. 118–124.
[14] Meng Fang and Trevor Cohn. 2017. Model Transfer for Tagging Low-resource Languages using a Bilingual Dictionary. In Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics. 587–593.
[15] Xiaocheng Feng, Xiaohong Feng, Bing Qin, Zhangyin Feng, and Ting Liu. 2018. Improving Low Resource Named Entity Recognition using Cross-lingual Knowledge Transfer. In Proceedings of the 27th International Joint Conferences on Artificial Intelligence. 4071–4077.

Manuscript submitted to ACM
[16] Radu Florian, Abe Ittycheriah, Hongyan Jing, and Tong Zhang. 2003. Named entity recognition through classifier combination. In Proceedings of the 2003 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies. 168–171.

[17] Jonas Gehring, Michael Auli, David Grangier, Denis Yarats, and Yann N Dauphin. 2017. Convolutional sequence to sequence learning. In Proceedings of the 34th International Conference on Machine Learning. 1243–1252.

[18] Dan Gillick, Cliff Brunk, Oriol Vinyals, and Amarnag Subramanya. 2016. Multilingual Language Processing From Bytes. In Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies. 1296–1306.

[19] Alex Graves and Jurgen Schmidhuber. 2005. Framewise phoneme classification with bidirectional LSTM and other neural network architectures. Neural Networks 18 (2005), 602–610.

[20] James Hammerton. 2003. Named entity recognition with long short-term memory. In Proceedings of the seventh conference on Natural language learning at HLT-NAACL 2003. Association for Computational Linguistics, 172–175.

[21] Hangfeng He and Xu Sun. 2017. A unified model for cross-domain and semi-supervised named entity recognition in chinese social media. In 31st AAAI Conference on Artificial Intelligence.

[22] Zhiheng Huang, Wei Xu, and Kai Yu. 2015. Bidirectional LSTM-CRF models for sequence tagging. arXiv preprint arXiv:1508.01991 (2015).

[23] Rebecca Iwa, Philip Resnik, Amy Weinberg, Clara Cabezas, and Okan Kolak. 2005. Bootstrapping parsers via syntactic projection across parallel texts. Natural language engineering 11, 3 (2005), 311–325.

[24] Sungchul Kim, Kristina Toutanova, and Hwanjo Yu. 2012. Multilingual named entity recognition using parallel data and metadata from wikipedia. In Proceedings of the 50th Annual Meeting of the Association for Computational Linguistics. Association for Computational Linguistics, 694–702.

[25] John Lafferty, Andrew McCallum, and Fernando CN Pereira. 2001. Conditional random fields: Probabilistic models for segmenting and labeling sequence data. In Proceedings of the 18th International Conference on Machine Learning. 282–289.

[26] Guillaume Lample, Miguel Ballesteros, Sandeep Subramanian, Kazuwa Kawakami, and Chris Dyer. 2016. Neural Architectures for Named Entity Recognition. In Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies. 260–270.

[27] Ying Lin, Shengqgi Yang, Veselin Stoyanov, and Heng Ji. 2018. A multi-lingual multi-task architecture for low-resource sequence labeling. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics. 799–809.

[28] Liyuan Liu, Jingbo Shang, Xiang Ben, Frank Fangzheng Xu, Huan Gui, Jian Peng, and Jiawei Han. 2018. Empower sequence labeling with task-aware neural language model. In 32nd AAAI Conference on Artificial Intelligence.

[29] Nelson F Liu, Matt Gardner, Yonatan Belinkov, Matthew E Peters, and Noah A Smith. 2019. Linguistic Knowledge and Transferability of Contextual Representations. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies. 1073–1094.

[30] Xuezhe Ma and Eduard Hovy. 2016. End-to-end Sequence Labeling via Bi-directional LSTM-CNNs-CRF. In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers). Association for Computational Linguistics, Berlin, Germany, 1064–1074. https://doi.org/10.18653/v1/P16-1101

[31] Jian Ni, Georganina Dinu, and Radu Florian. 2017. Weakly Supervised Cross-Lingual Named Entity Recognition via Effective Annotation and Representation Projection. In Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics. 1470–1480.

[32] Nanyun Peng and Mark Dredze. 2015. Named entity recognition for chinese social media with jointly trained embeddings. In Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing. 548–554.

[33] Nanyun Peng and Mark Dredze. 2016. Improving Named Entity Recognition for Chinese Social Media with Word Segmentation Representation Learning. In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics. 149–153.

[34] Jeffrey Pennington, Richard Socher, and Christopher Manning. 2014. Glove: Global vectors for word representation. In Proceedings of the 2014 conference on empirical methods in natural language processing. 1532–1543.

[35] Matthew Peters, Walter Ammar, Chandra Bhagavatula, and Russell Power. 2017. Semi-supervised sequence tagging with bidirectional language models. In Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics. 1756–1765.

[36] Nils Reimers and Iryna Gurevych. 2017. Reporting Score Distributions Makes a Difference: Performance Study of LSTM-networks for Sequence Tagging. In Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing. 338–348.

[37] Erik F Tjong Kim Sang and Fien De Meulder. 2003. Introduction to the CoNLL-2003 Shared Task: Language-Independent Named Entity Recognition. In Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers). Association for Computational Linguistics, Berlin, Germany, 1064–1074.

[38] Emma Strubell, Patrick Verga, David Belanger, and Andrew McCallum. 2017. Fast and Accurate Entity Recognition with Iterated Dilated Convolutions. In Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing. 2670–2680.

[39] Oscar Täckström, Dipanjan Das, Slav Petrov, Ryan McDonald, and Joakim Nivre. 2013. Token and type constraints for cross-lingual part-of-speech tagging. Transactions of the Association for Computational Linguistics 1 (2013), 1–12.

[40] Oscar Täckström, Ryan McDonald, and Jakob Uszkoreit. 2012. Cross-lingual word clusters for direct transfer of linguistic structure. In Proceedings of the 2012 conference of the North American chapter of the association for computational linguistics: Human language technologies. Association for Computational Linguistics, 477–487.

[41] Jörg Tiedemann. 2014. Rediscovering annotation projection for cross-lingual parser induction. In Proceedings of COLING 2014, the 25th International Conference on Computational Linguistics: Technical Papers. 1854–1864.

Manuscript submitted to ACM
[42] Erik F. Tjong Kim Sang. 2002. Introduction to the CoNLL-2002 Shared Task: Language-Independent Named Entity Recognition. In Proceedings of the 6th Conference on Natural Language Learning. 155–158.

[43] Chen-Tse Tsai, Stephen Mayhew, and Dan Roth. 2016. Cross-lingual named entity recognition via wikification. In Proceedings of The 20th SIGNLL Conference on Computational Natural Language Learning. 219–228.

[44] Mengqiu Wang, Wanxiang Che, and Christopher D Manning. 2013. Effective bilingual constraints for semi-supervised learning of named entity recognizers. In Proceedings of the 27th AAAI Conference on Artificial Intelligence.

[45] Mengqiu Wang and Christopher D Manning. 2014. Cross-lingual projected expectation regularization for weakly supervised learning. Transactions of the Association for Computational Linguistics 2 (2014), 55–66.

[46] Ralph Weisschedel, Sameer Pradhan, Lance Ramshaw, et al. 2011. OntoNotes Release 4.0. (2011).

[47] Jie Yang, Zhiyang Teng, Meishan Zhang, and Yue Zhang. 2016. Combining discrete and neural features for sequence labeling. In International Conference on Intelligent Text Processing and Computational Linguistics. 140–154.

[48] David Yazowsky, Grace Ngai, and Richard Wicentowski. 2001. Inducing multilingual text analysis tools via robust projection across aligned corpora. In Proceedings of the first international conference on Human language technology research. Association for Computational Linguistics, 1–8.

[49] Boliang Zhang, Xiaoman Pan, Tianhu Wang, Ashish Vaswani, Heng Ji, Kevin Knight, and Daniel Marcu. 2016. Name tagging for low-resource incident languages based on expectation-driven learning. In Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies. 249–259.

[50] Yue Zhang and Jie Yang. 2018. Chinese NER Using Lattice LSTM. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics. 1554–1564.

[51] Ayah Zirikly and Masato Hagiwara. 2015. Cross-lingual transfer of named entity recognizers without parallel corpora. In Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing. 390–396.

[52] Imed Zitouni and Radu Florian. 2008. Mention detection crossing the language barrier. In Proceedings of the Conference on Empirical Methods in Natural Language Processing. Association for Computational Linguistics, 600–609.