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Abstract. Named entity recognition is a fundamental task in natural language processing and has been widely studied. The construction of a recognizer requires training data that contains annotated named entities. However, it is expensive to construct such training data for low-resource domains. In this paper, we propose a recognizer that uses not only training data but also a domain specific dictionary that is available and easy to use. Our recognizer first uses character-based distributed representations to classify words into categories in the dictionary. The recognizer then uses the output of the classification as an additional feature. We conducted experiments to recognize named entities in recipe text and report the results to demonstrate the performance of our method.

Keywords: Named entity recognition · recipe text · neural network

1 Introduction

Named entity recognition (NER) is one of the fundamental tasks in natural language processing (NLP) [20]. The task is typically formulated as a sequence labeling problem, for example, estimating the most likely tag sequence $Y = (y_1, y_2, \ldots, y_N)$ for a given word sequence $X = (x_1, x_2, \ldots, x_N)$. We can train a recognizer using annotated data that consists of (X, Y).

However, the construction of such annotated data is labor-intensive and time-consuming. Although the beginning, inside, and outside (BIO) format is often used in NER, it is challenging to annotate sentences with tags, particularly for people who are not familiar with NLP. Furthermore, there are low-resource domains that do not have a sufficient amount of data. We focus on the recipe domain as an example of such a domain.

Even in such domains, we can find a variety of dictionaries available. For example, Nanba et al. [13], constructed a cooking ontology, Harashima et al. [3] constructed a dictionary for ingredients, and Yamagami et al. [21]

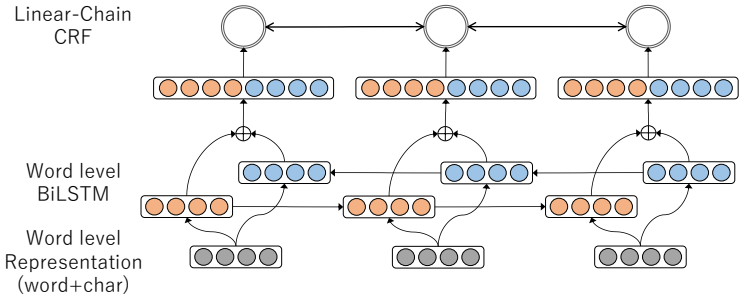

Fig. 1. LSTM-CRF based neural network.

built a knowledge base for basic cuisine. These resources can be utilized for NER.

In this paper, we propose a method to integrate a domain-specific dictionary into a neural NER using a character-based word classifier. We demonstrate the effectiveness of the proposed method using experimental results on the Cooking Ontology dataset [13] as a dictionary. We report our experimental results on the recipe domain NE corpus [12].

2 Related Work

In recent years, NER methods that use long short-term memory (LTSM) [4] and conditional random fields (CRF) [7] have been extensively studied [8, 9, 19, 15, 10]. This type of neural network is based on Huang et al. [5]. Note that they used Bidirectional LSTM (Bi-LSTM), which concatenate two types of LSTM; one is forward LSTM, and another is backward LSTM. In these studies, the researchers assumed that training data with sequence label annotation was provided in advance.

In our experiments, we use recipe text as a low-resource domain to evaluate our proposed method. Although Mori et al. [12] constructed an r-NE corpus, it consists of only 266 Japanese recipes. To overcome this problem, Sasada et al. [18] proposed an NE recognizer that is trainable from partially annotated data. However, as seen in Section 5.4, the method does not perform better than recent neural network-based methods.

Preparing training data for NER is time-consuming and difficult. In addition to the strategy that uses partial annotation, there have been attempts to make use of available resources. Peters et al. [15, 16] acquired informative features using language modeling. However, these approaches require a large amount of unlabeled text for training, which makes it difficult in a low-resource scenario. To avoid this difficulty, making use of a task that does not require a large amount of data could be useful.

Whereas it is time-consuming to prepare training data for NER, it is relatively easy to construct a domain-specific dictionary [1, 13, 21]. Some researchers have used a dictionary as an additional feature [19, 10]. Pham et al. [10] incorporated dictionary matching information as additional dimensions of a feature vector of a token. In their method, the representations are zero vectors for words that are not in the dictionary. Our proposed method overcomes this limitation by extracting character-based features from a classifier trained on a dictionary.

3 Baseline Method

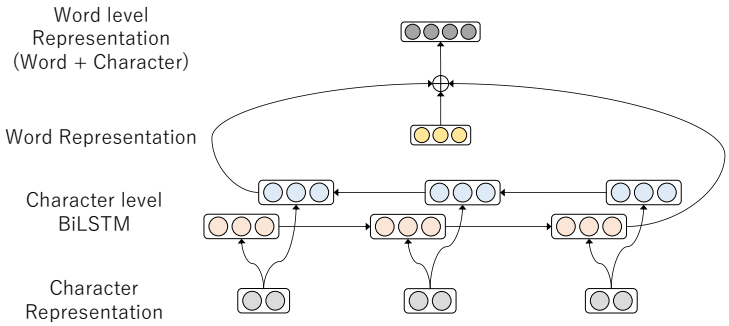

Fig. 2. Word-level feature extractor proposed by Lample et al. [8]

As described in Section 2, the popular methods use Bi-LSTM (bidirectional-LSTM) and CRF, which is so called LSTM-CRF. Lample et al. [8] takes account of not only word-level but also character-level information to extract features. We show an illustration of the word-level feature extractor proposed by Lample et al. in Fig. 2. Let $X = (x_1, x_2, \ldots, x_N)$ be an input

word sequence and $C_t = (c_{t,1}, c_{t,2}, \ldots, c_{t,M})$ be the character sequence of the t'th word. A word distributed representation corresponding to x_t is defined by $\mathbf{v}_{x_t}$, and a character distributed representation corresponding to $C_{t,k}$ is defined by $\mathbf{v}_{C_{t,k}}$. Let $V_{C_t} = (\mathbf{v}_{C_{t,1}}, \mathbf{v}_{C_{t,2}}, \ldots, \mathbf{v}_{C_{t,M}})$. Then their model can be represented as

$$\mathbf{w}_t{}^{(char)} = \text{Bi-LSTM}^{(char)}(V_{C_t}), \tag{1}$$

$$\mathbf{x}_t = [\mathbf{w}_t; \mathbf{w}_t{}^{(char)}]. \tag{2}$$

Then, let $V_X = (\mathbf{x_1}, \mathbf{x_2}, \ldots, \mathbf{x_N})$,

$$\mathbf{h}_t = \text{Bi-LSTM}(V_X)_t, \tag{3}$$

where $\mathbf{w_t}$ indicates the word representation corresponding to x_t.

After extracting the feature vector $\mathbf{h}_t$ of the sequence, they applied CRF to predict the tag sequence considering their tag transitions. Let $\mathbf{y} = (y_1, y_2, \ldots, y_N)$ be a tag sequence. Using $\mathbf{H} = (\mathbf{h}_1, \mathbf{h}_2, \ldots, \mathbf{h}_N)$, we can calculate the probability of the tag sequence using

$$P(\mathbf{y} \mid \mathbf{H}; \mathbf{W}, b) = \frac{\prod_{i=1}^{n} \psi_i(y_{i-1}, y_i, \mathbf{H})}{\sum_{\mathbf{y}' \in \mathcal{Y}(\mathbf{H})} \prod_{i=1}^{n} \psi_i(y'_{i-1}, y'_i, \mathbf{H})}, \tag{4}$$

where $\psi_i(y_{i-1}, y_i, \mathbf{H}) = \exp(\mathbf{W}_{y_i}^T \mathbf{h}_i + b_{y_{i-1}, y_i})$. $\mathbf{W}_{y_i}$ is the weight vector and b_{y_{i-1}, y_i} is the bias term. What we want is the optimal tag sequence $\hat{\mathbf{y}}$, which is defined by

$$\hat{\mathbf{y}} = \underset{\mathbf{y}' \in \mathcal{Y}(\mathbf{H})}{\text{argmax}}\, P(\mathbf{y}' \mid \mathbf{H}; \mathbf{W}, b_{y_{i-1}, y_i}). \tag{5}$$

We can obtain the optimal tag sequence $\hat{\mathbf{y}}$ by maximizing P using the Viterbi algorithm.

4 Proposed Method

In this paper, we propose a recognizer that uses not only training data but also a domain-specific dictionary. As described in Section 1, it is expensive to construct training data for a recognizer. We thus make use of a domain-specific dictionary that contains pairs that consist of a word and category.

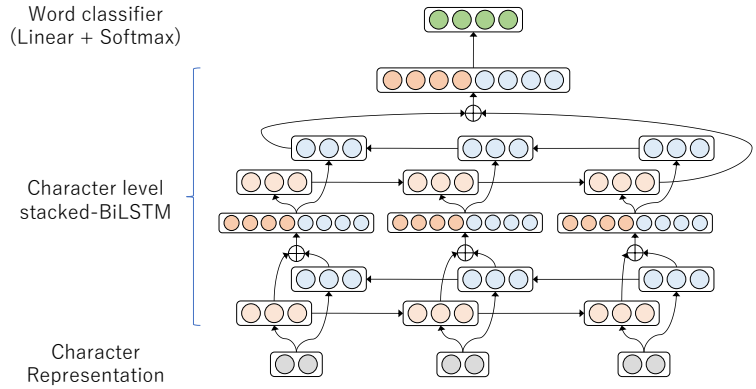

Fig. 3. Overview of the character-based word classifier. We use a 3 stacked Bi-LSTM.

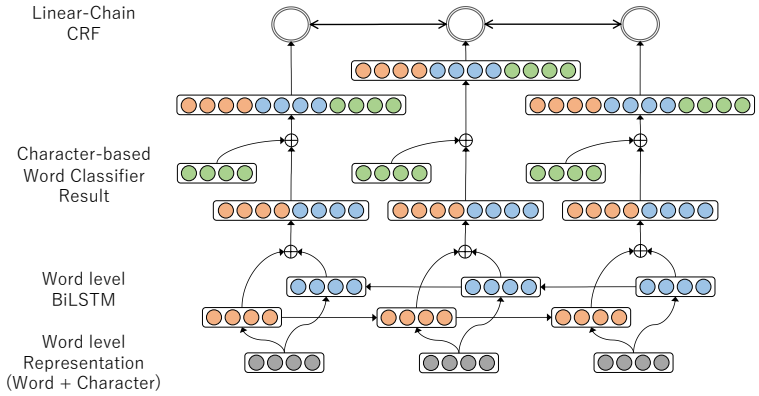

Fig. 4. Overview of the proposed method. We concatenate the classifier output to a feature vector from the Bi-LSTM.

Fig. 4 shows the architecture of our proposed recognizer. Our recognizer can be considered as an extension of Lample et al. [8]. We incorporate the character-based word classifier which calculates $\mathbf{a}_t$ as follows:

$$\mathbf{h}^{(classifier)}{}_t = \text{Stacked Bi-LSTM}(C_t) \tag{6}$$

$$\mathbf{a}'_t = \mathbf{W}\mathbf{h}^{(classifier)}{}_t + \mathbf{b} \tag{7}$$

$$\mathbf{a}_t = \text{Softmax}(\mathbf{a}'_t), \tag{8}$$

This classifier is a neural network that consists of a embedding layer, a stacked Bi-LSTM layer, and a fully connected layer. Stacked Bi-LSTM is one kind of neural network which applies Bi-LSTM k times where $k > 1$.

Table 1. The statistics of corpora using our experiments. Note that the **r-NE corpus is annotated for NEs with the BIO format**. We show character-level information only for r-NE because it is used to train a recognizer.

Attribute	Cookpad	Wikipedia	r-NE
Doc	1,715,589	1,114,896	436
Sent	12,659,170	18,375,840	3,317
Token	216,248,517	600,890,895	60,542
Type	221,161	2,306,396	3,390
Char token	–	–	91,560
Char type	–	–	1,130

Table 2. r-NEs and their frequencies.

NE	Description	# of Examples
F	Food	6,282
T	Tool	1,956
D	Duration	409
Q	Quantity	404
Ac	Action by the chef	6,963
Af	Action by foods	1,251
Sf	State of foods	1,758
St	State of tools	216

Classifier takes the character sequence of words as input and predicts categories of it defined in a dictionary. After passing the word classifier, our method concatenates the hidden state calculated in Section 3 and the output of Classifier defined by $\mathbf{h}'_t = \mathbf{h}_t \oplus \mathbf{a}_t$. Finally, as in Section 3, our method transforms $\mathbf{h}'$ by $\mathbf{z}_t = \mathbf{W}\mathbf{h}'_t + \mathbf{b}'$, and the CRF predicts the most likely tag sequence.

Although our method is simple, it has two advantages: First, our method is based on character-level distributed representations, which avoid the mismatching problem between words in the training data and words in the dictionary. Second, the method can use a dictionary with arbitrary categories that are not necessarily equal to the NE categories in the sequence labels. Consequently, our method can be applied in all scenarios in which there is a small amount of training data that contains NEs and there is a domain dictionary constructed arbitrarily.

Table 3. Word categories, frequencies, and results on classification.

Category	# of Examples	Prec.	Recall	Fscore
Ingredient-seafood (example: salmon)	452	0.60	0.62	0.61
Ingredient-meat (example: pork)	350	0.88	0.83	0.85
Ingredient-vegetable (example: lettuce)	935	0.75	0.79	0.77
Ingredient-other (example: bread)	725	0.75	0.71	0.73
Condiment (example: salt)	907	0.81	0.84	0.83
Kitchen tool (example: knife)	633	0.79	0.74	0.76
Movement (example: cut)	928	0.94	0.99	0.96
Other	896	0.70	0.66	0.68

5 Experiments

5.1 Datasets

We used the following four datasets:

r-NE [12] : used to train and test methods. We used 2,558 sentences for training, 372 for validation, and 387 for testing.

Cooking Ontology [13] : used to train the word classifier. We use 3,825 words for training, 1,000 for validation, and 1,000 for testing.

Cookpad [2] : used to train word embeddings. Cookpad corpus contains 1.7M recipe texts.

Wikipedia : used to train word embeddings. There were various types of topics in this corpus. We downloaded the raw data of this corpus from the Wikipedia dump[3]. Wikipedia corpus contains 1.1M articles.

As in Table. 2 and Table. 3, the categories in the cooking ontology were different from the tags in the r-NE corpus. However, as described in Section 4, our method flexibly incorporated such information into its network.

5.2 Methods

We compared the following methods in our experiments:

Sasada et al. [18] is a pointwise tagger. They use Logistic Regression as the tagger.

[3] `https://dumps.wikimedia.org/jawiki/`

Table 4. Results on NER (averaged over five times except for Sasada et al. [18] because KyTea [14], the text analysis toolkit used in their experiments, does not have the option to specify a random seed).

Method	Decoder	Embedding	Prec.	Recall	Fscore
Sasada et al. [18]	–	–	82.34	80.18	81.20
Sasada et al. [18]	DP	–	82.94	82.82	82.80
Lample et al. [8]	CRF	Uniform	82.59 (± 0.94)	88.19 (± 0.25)	85.24 (± 0.46)
Lample et al. [8]	CRF	Cookpad	84.54 (± 1.22)	88.47 (± 0.69)	86.40 (± 0.89)
Lample et al. [8]	CRF	Wikipedia	85.31 (± 0.67)	88.22 (± 0.65)	86.68 (± 0.47)
Dictionary	CRF	Uniform	82.36 (± 1.25)	88.28 (± 0.25)	85.18 (± 0.71)
Dictionary	CRF	Cookpad	83.91 (± 1.21)	88.60 (± 0.41)	86.16 (± 0.72)
Dictionary	CRF	Wikipedia	85.44 (± 1.04)	87.67 (± 0.25)	86.50 (± 0.56)
Proposed	CRF	Uniform	82.81 (± 0.88)	88.40 (± 0.41)	85.46 (± 0.58)
Proposed	CRF	Cookpad	85.08 (± 1.30)	88.46 (± 0.18)	86.68 (± 0.71)
Proposed	CRF	**Wikipedia**	**85.63 (± 0.52)**	**88.87 (± 0.37)**	**87.18 (± 0.34)**

Sasada et al. [18]+DP is an extension of LR, which optimizes LR's prediction using dynamic programming. This method achieved state-of-the-art performance for the r-NE task.

Lample et al. [8] is an LSTM-CRF tagger described in Section 2.

Dictionary is an LSTM-CRF based naive baseline that uses a dictionary. A dictionary feature is added to Lample's feature in the form of a one-hot vector.

Proposed is the proposed method that uses the character-level word classifier described in Section 4.

5.3 Pre-trained Word Embeddings

In NLP, a popular approach is to make use of pre-trained word embeddings to initialize parameters in neural networks. In this paper, three strategies are used to initialize word vectors:

Uniform initializes word vectors by sampling from the uniform distribution over $[\frac{-3}{\mathrm{dim}}, \frac{3}{\mathrm{dim}}]$.

Wikipedia initializes word vectors using those trained on the Wikipedia corpus. Word vectors not in pre-trained word vectors are initialized by **Uniform**.

Table 5. Results on named entity recognition (for each NE, averaged over five times).

NE	Precision	Recall	Fscore
Ac	91.77 (± 1.02)	95.23 (± 0.42)	93.46 (± 0.33)
Af	78.87 (± 3.68)	78.12 (± 1.19)	78.46 (± 2.22)
D	96.63 (± 1.71)	93.88 (± 2.88)	95.23 (± 2.16)
F	85.84 (± 0.94)	89.01 (± 0.65)	87.39 (± 0.59)
Q	58.70 (± 3.81)	70.00 (± 3.19)	63.69 (± 1.82)
Sf	75.12 (± 4.40)	78.17 (± 1.95)	76.52 (± 2.04)
St	66.03 (± 5.64)	52.63 (± 4.70)	58.46 (± 4.52)
T	82.53 (± 2.30)	89.09 (± 1.26)	85.66 (± 1.21)

Cookpad initializes word vectors using those trained on the Cookpad corpus. Word vectors not in pre-trained word vectors are initialized by **Uniform**.

We use train word embeddings with skip-gram with negative sampling (SGNS) [11]. As the hyperparameter of SGNS, we set 100 as the dimension of the word vector, 5 for the size of the context window, and 5 for the size of negative examples, and use default parameters defined in Gensim [17] for other parameters.

In our proposed network, we set 50 dimensions for character-level distributed representations and 2×50 for character-level Bi-LSTM as a word classifier. The word feature extracted by the word classifier is concatenated with the word-level representation and fed into the word-level Bi-LSTM to obtain the entire word features. To train neural networks, we use the Adam optimizer [6] with mini-batch size 10 and clip gradient with threshold 5.0.

5.4 Experimental Results and Discussion

Table. 3 shows the performance of our word classifier. Our classifier successfully classified words with a certain degree of accuracy. We show the results of comparing each recognizer in Table. 4 In our experiments, **(i) pre-trained word vectors played an essential role in improving the performance of NER** and **(ii) our classifier enhanced the performance of the Lample's method**. Interestingly, we obtained the best result when pre-trained word vectors were trained on the Wikipedia corpus, which is not a domain-specific corpus. This suggests that our method to have successfully combined universal knowledge from pre-trained word vectors and domain-specific knowledge from the classifier trained on a domain-specific dictionary.

We show the label-wise results of prediction in Table. 5. In this result, we can see that the proposed model successfully predicted tags of Ac, D, F, and T. However, prediction performances for Af, Q, Sf, and St were limited because there is no entry for these categories in our dictionary.

Fig. 5. Prediction results for an example

Example	Yoji	de	to	me	te	
Translation	Cocktail stick	DAT	clip			
Ground Truth	B-T	O	B-Ac	O	O	
Baseline	B-Sf	O	B-Ac	O	O	
Proposed method	**B-T**	O	B-Ac	O	O	

Fig. 6. Prediction results for another example

Example	Denshi renji	(	500	W	)	de	
Translation	Microwave	(	500	W	)	DAT	
Ground Truth	B-T	I-T	O	B-St	I-St	O	O
Baseline	B-T	I-T	O	B-T	I-T	O	O
Peoposed method	B-T	I-T	O	**B-St**	**I-St**	O	O

Fig. 5 and Fig. 6 show prediction results for the baseline and our methods. Note that the abbreviation DAT means dative. In the first example, the word classifier taught the model that **cocktail stick** was a kitchen tool, which made the proposed method successfully recognize it as a tool. In the second example, the word classifier taught the model that **500W** is not a kitchen tool. Then, the proposed method avoided the baseline's failure and estimate the correct NE tag sequence.

6 Conclusion

We proposed a recognizer that is trainable from not only annotated NEs but also a list of examples for some categories related to NE tags. The proposed method uses the output of a character-based word classifier. Thanks to this character-based modeling, the proposed method considers sub-word information to extract dictionary features for words not in the dictionary.

Our experiment demonstrates that our method achieves state-of-the-art performance on the r-NE task. This implies that the proposed method successfully extracts an informative feature to improve the performance of NER.

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