

Outer Dictionary Network: An Efficient Network to Join Knowledge for Named Entity Recognition

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Abstract

With the risen use of AI application, we need to extract some specific type of message from user's query, which is the main content of Named Entity Recognition (NER) task. In recent years, dictionary, one kind of outer knowledge, is proved to be useful, necessary, and applied more and more constantly in NER tasks. However, most of the current networks use it as word embedding vector, which will bring out such problems: a) out of vocabulary (OOV) problem; b) we need to retrain model when the list of words in dictionary is greatly changed. In this paper, we propose a new conception, called Outer Dictionary Network (ODN), which means to join the outer type knowledge of dictionary into Neural Networks (NN), without using the specific word or word embedding vector. In this way, the two mentioned problem will be solved. We then propose a new structure, called Tag Embedding LSTM (TE-LSTM) to implement the ODN. Experiment results shows that our model achieve a great improvement on several tasks within which gazetteer is heavily depended on, with comparison with current state-of-the-art methods. And the network will change its output along with the content variation of dictionary, without training again.

Introduction

Named Entity Recognition (NER) is a base task in Natural Language Processing (NLP) domain. Usually, we need to extract main information from users' sentences to help us understand their meanings, and then use the extracted information to do further process. For example, in weather domain, we may need to extract entities **date and position** to help us understand when and where the user is asked towards the weather; in music playing service, we may need to track entities **singer, song, style** to suit user's command; for many common use, we may need entities **person, location, organization** to understand a sentence.

To accomplish this task, many method has been explored. Convolution Neural Network (CNN) is first used in Image Classification (Krizhevsky, Sutskever and Geofrey 2012), and then also proved powerful in Text Classification (Kim 2014). Therefore, CNN is also useful in NER tasks, whether to capture character-level features (Chiu and

Nichols 2016; Ma and Hovy 2016; Peters et al. 2017), or to do word-level sequence labelling jobs (Santos, Xiang, and Zhou 2015; Strubell et al. 2017). To learn the correlation between words in sentence, Recurrent Neural Network (RNN) (Sutskever, Vinyals and Le 2014) and Long Short-Term Memory (LSTM) (Sak, Senior and Beaufays 2014) are proposed, and they achieve great success on machine translation and many other areas. They are then used in NER tasks and achieve significant improvement (Chiu and Nichols 2016; Ma and Hovy 2016; Peters et al. 2017). These structures can be combined together and used in different situations (Yang, Liang, and Zhang 2018).

Among these years, many works have made innovative attempts on contributing new NN structures. These models, like Transformer structure (Vaswani et al. 2017) and its derivative methods: OpenAI GPT (Radford et al. 2018), BERT (Devlin et al. 2018), XLNet (Yang et al. 2019), focus on base layer of NN structure, usually the embedding input layer, to get better sentence understanding. The output of these models can then be directly fed it or fine-tuned to do NLP tasks. Though will they make great improvement, it usually pays a long time to train these models. Through these works, we can conclude that, **The better and richer input knowledge there is, more efficient the model will be.**

Among NER tasks, there exists a little difference between different languages. In Chinese or other hieroglyphics language, a character is also a single word; and Chinese word is often referred to a character phrase which has length longer than one. In English or other letter-based language, character means a single letter, and word is a composition of letters; that is to say, English word is composed by characters, for which character level CNN can help improve NER tasks (Huang et al. 2015; Chiu and Nichols 2016; Ma and Hovy 2016; Peters et al. 2017; Yang, Liang, and Zhang 2018); but that can not be used in Chinese NER tasks, which is hieroglyphics, no letter is there in a word. What we call character embedding in Chinese NER tasks correspond to word embedding in English jobs; and the so-called word embedding in Chinese NER jobs is likened to word phrase embedding in English. For this reason, Chinese NER tasks is usually done by word baseline or character baseline structure, which

has the different meaning with English NER tasks. Among Word baseline structures, we may use word segmentor to split sentence into word tokens, and then use word embedding to turn these tokens into vectors (Peng and Dredez 2015; Peng and Dredez 2016); while character structures simply treat each sentence as a sequence of Chinese characters, and then using corresponding character embedding to do NLP tasks (Zhang and Yang 2018; Gui et al. 2019). Furthermore, it seems useful when using word embedding within character baseline structure, or the opposite, cause it can enrich the input knowledge.

On the higher layer, most of the state-of-the-art NER methods use Conditional Random Fields (CRF) (Lafferty, McCallum, and Pereira 2011) to decode the sequence labelling result and compute loss. CRF can work even without any NN cells. Hand-crafted features already achieve high performance (Finkel, Grenager, and Manning 2005; Okazaki 2007) on many jobs.

Though with these powerful networks, word background knowledge, usually dictionary (same meaning to lexicon and gazette), is still necessary to do NER jobs in some situations. For example, in music playing service, ‘You raise me up’ would be treated more likely as a chat intention rather than a song intention, unless the model is given that knowledge (see in Figure 1). Most of the state-of-the-art methods use word embedding to complete these tasks. But it then gives two problems:

- Out of vocabulary (OOV) problem. To our knowledge, word embedding will always lead to this problem. Furthermore, it is hard and burdensome to make embedding vector for every word in dictionary. As for entity **song** in music playing service, word embedding size will be too large; and sometimes will the length of song be too long to make word vector.
- Retraining problem. When the content of dictionary changes abundantly, the trained model would have poor performance doing the same job. Still use the entity **song** as an example, the dictionary would be changed monthly or even daily, which forces us to retrain the model synchronously.

Faced with these problems, we proposed a new conception, called Outer Dictionary Network (ODN), which means using the dictionary’s outer trait, without using its specific content. For example, we use the tag of word, like **song**, rather than a specific song name, to help model understand the outer knowledge. In this way, word embedding is no longer needed for Chinese NER task in ODN. Experiment results show that in dictionary depended-on task, ODN gives the best result among state-of-the-art methods. And when the content of dictionary changes, the model can synchronously update its result without retraining.

Contributions

In summary, we make these contributions:

- We proposed a new conception: Outer Dictionary Network (ODN), which is used to update the content of dictionary without retraining the model.

Chat: You/O raise/O me/O up/O

Song: You/B-SONG raise/I-SONG me/I-SONG up/E-SONG

Chat: 韩/O 红/O 的/O 家/O 乡/O

Song: 韩/O 红/O 的/O 家/B-SONG 乡/E-SONG

Figure 1: In certain NER situation, dictionary is necessary to do NER task. Given the certain knowledge, we tend to denote the corresponding words as a song rather than others.

- We proposed a new structure, Tag Embedding LSTM (TE-LSTM), to realize ODN. The networks use the word tag knowledge, rather than the word itself, to improve the performance of NER tasks.
- Experiment results have shown that, our model gives significant improvements on dictionary depended-on tasks among many state-of-the-art models.
- We release a new dataset on music service domain, which we use in our paper, for further scientific research.

Related Work

Success of BERT (Devlin et al. 2018) and XLNet (Yang et al. 2019) show that input embedding knowledge is important and useful for many upper NLP tasks. More useful knowledge is there in the input vector, more efficiently the model would work. To a great degree, embedding layer decides the performance. Many useful features have been explored in NER jobs, such as character level message, word level message, position message, handwriting message. Dictionary knowledge is one of them. Especially in some NER task, like music service, dictionary is heavily depended on to make better performance.

Most of the recent models use dictionary as word embedding input, or the word’s string format, to give the model related message. Lattice LSTM (Zhang and Yang 2018) use the dictionary message as additional input to character baseline LSTM, which can give the model more sentence information. Lexivon Rethinking CNN (Gui et al. 2019), incorporate the dictionary knowledge into correlated CNN layer, and then the conflict word tokens could be solved by rethinking. Stanford NER (Finkel, Grenager, and Manning 2005) use the dictionary knowledge as string format feature, matched them in sentences, in CRF model.

However, in some practical areas, the content of dictionary will change greatly and constantly. In this way, most of the recent model need to be retrained after every abundantly change. To solve this problem, we need to construct a model which can still be used after such change. We then come up with the idea of ODN, and use TE-LSTM to realize these model. As a result, no more word embedding is needed, and model needed only to be trained once. What we need is only the word tag knowledge to help the model better understand user’s intention.

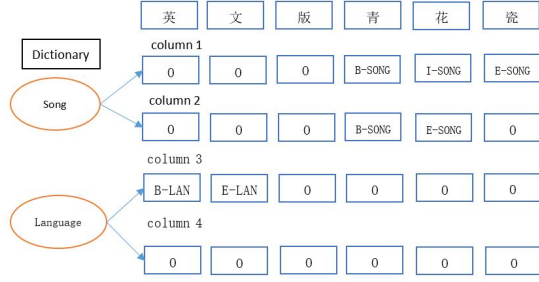


Figure 2: Illustration for tag embedding scheme. For dictionary ‘song’, there are two possible songs, the longer one is put in the first place (column 1). For dictionary ‘language’, only one possible result will be matched, however in this case, since we set the tag blank number to 2, we should add one more padding blank to fill the position, which is showed as column 4.

Outer Dictionary LSTM

In this chapter, we illustrate the specific method we use to realize the ODN. Our framework is based on Tensorflow (Abadi et al. 2015). We use the character baseline model for Chinese NER task, inspired by the results of Lattice LSTM (Zhang and Yang 2018) and Lexicon Rething CNN (Gui et al. 2019). In order to better understand the model, we make a appointment that: In Chinese or other hieroglyphics language, character means a single word; and word is a character phrase which has length longer than one. In English or other letter base language, character means a single letter, and a word is a composition of letters; then a phrase is composited of a set of words. For Chinese NER jobs, only character embedding will we use, and no more word embedding is needed, for we hold the following opinions towards these jobs:

- Common characters in hieroglyphics language, can be exhaustive, especially for Chinese, because there are no more than 100, 000 characters in simplified Chinese. Therefore, no OOV problem will there be when we use character embedding in Chinese NER task.
- Words in hieroglyphics language, will be uncountable, because there are still many new words or phrases are still created every day. Thus, OOV error can not be avoided in these case.

Thus, in Chinese NER jobs, we denote a sentence as a composition of many characters: $s = (c_1, c_2, \dots, c_n)$ as the base input to model.

Character-Base LSTM

We use character embedding lookup table to turn character id to vector:

$$a_i = e_c(c_i) \quad (1)$$

Usually a dropout layer is connected with the embedding output, which is proved useful in NER jobs (Ma and Hovy 2016). After that, bi-directional LSTM (Bi-LSTM),

the most common structure used in NER tasks, is applied to learn the character connection within the sentence. We use the hidden vector for LSTM output, that is, for input: $x = (a_1, a_2, \dots, a_n)$, we get output: $h = (h_1, h_2, \dots, h_n)$, where h_i is the concatenation of forward (\vec{h}_i) and backward (\overleftarrow{h}_i) LSTM hidden vector:

$$h_i = [\vec{h}_i; \overleftarrow{h}_i] \quad (2)$$

Tag Embedding Model

As case show in Figure ??, we need to use dictionary for certain NER tasks. However, the constant variation of dictionary may cause constant retrain problem. Therefore, we may not use the specific word in each dictionary, instead, only the outer information will be used, which is the main idea in ODN. Here, we implement our ODN through Tag Embedding (TE), which uses the tag embedding of the dictionary. Cause we use LSTM structure to utilize tag embedding info, we called our network TE-LSTM.

Specifically, we do this by two step:

- a) Match sentence with the word in dictionary using certain outer model method.
- b) Turn match result into embedding information, used as the input of LSTM.

Match Policy. In this part, we need to match all the word in given dictionary occurred in current sentence. We impletement this by using Aho-Corasick Automation Algorithm (Aho and Corasick 1975). In summary, we complete a KMP (Knuth, Morris, and Pratt 1977) + Trie Tree (Briandais 1959) algorithm to accomplish this task. In methemathical, given sentence $s = (c_1, c_2, \dots, c_n)$, and a dictionary d_i , which is composed of word set $D_i = \{w_1, w_2, \dots, w_V\}$. We denote the result of match policy as:

$$r_{d_i, j} = [(f_1, b_1), (f_2, b_2), \dots, (f_k, b_k)] \quad (3)$$

Here, f_i and b_i denote the front and back position of each match word. Let W_{f_i, b_i} represent the substring of sentence s with the rank $[f_i, b_i]$, then each (f_i, b_i) tuple forms a word in D_i . Parameter k means the total number of such word matched in d_i , which is uncertain. Cause there will be conflict intervals after AC algorithm is performed, we need to select the meaningful intervals, the footnote j thus means that there will be many valid interval arrays. To format the input, we make the following policy to select our valid interval arrays:

- We choose certain number of valid interval arrays, which is called **tag blank number**, denoted as w . If there is not enough candidate interval arrays, the padding interval arrays will be use, as showed in Figure 2.
- We choose the interval arrays which cover the most characters in sentence (words for English), and have no conflict intervals inside itself. And the more characters the interval array has, the prior it will be in embedding position.

Tag Embedding Scheme. After match policy is fulfilled, we need to turn that result into vector so that it can be understood by model. Cause the result of match policy is denoted

as position, we can simply use it to get a new sequence form from original sentence. With dictionary d_i and a matched word position rank range $[f_i, b_i]$, we then apply tag scheme for these sequence: turn the match word to correspond tag as shown in Figure 2, the unmatched part is turn to tag **O**.

Here, we choose **IOBES** scheme for it is proved better than IOB1 and IOB2 tag scheme in result by previous works (Chiu and Nichols 2016; Ma and Hovy 2016). Yet we need to emphasis that: the tag of dictionary here need not to be the same with the result tag species. As an illustration, to extract **name** entity, we can use dictionary **first name** and dictionary **last name** to match the sentence.

As related before, we choose **tag blank number**, w , of valid interval arrays and perform the tag scheme. We do the tag scheme in this way cause we think the position is important for model to understand, to fix the certain tag result in certain position and to fix the better result on the certain position. Of course, w could be variable for different dictionary, but that needs a bit more efforts and seems low performance increase.

With the tag embedding sequence produced, denoting each tag sequence as: $s_t = (t_1, t_2, \dots, t_n)$, we turn the result to vector using:

$$g_i = e_t(t_i) \quad (4)$$

where e_t is the tag embedding lookup table. We use random generated number to produce this lookup table. Then the char embedding output a_i and tag embedding output g_i is concatenated together:

$$x_i = (a_i; g_i) \quad (5)$$

The concat input is then fed into the Bi-LSTM layer.

Loss and Training

CRF layer is applied on the top, same with many previous works and proved to be useful (Collobert et al. 2011; Chiu and Nichols 2016; Ma and Hovy 2016; Yang, Liang, and Zhang 2018; Zhang and Yang 2018; Gui et al. 2019). Denote y_j as a possible label sequence for sentence s_i and Y as the total set of all possible y_j , then the probability of y_j is:

$$p(y_j|s_i) = softmax(\sum_i W_{c_i} * h_i + B_{c_i})_j \quad (6)$$

W_{c_i}, B_{c_i} is respectively the emission matrix and transformation matrix correlate to h_i , and j is the rank for y_j in all possible label sequence set Y . While training, we take the L_2 regularization for all parameters into account together with CRF loss. With batch number N and corresponding gold set (s_i, y_i) , the final loss can be computed as:

$$L = \sum_{i=1}^N \log(p(y_i|s_i)) + \frac{\lambda}{2} \|\theta\|^2 \quad (7)$$

λ is the L_2 hyper parameter, and θ stands for all the training parameters. At decoding step, we use the Viterbi algorithm (Viterbi 1967) to decode result, finding the label sequence with the highest score:

Table 1: Statistics of Sogou MusicNER dataset.

Count	Sentences	Tokens	Entities
Train	7,177	55,613	8,585
Dev	897	6,858	1,057
Test	897	6,775	1,047

Table 2: Hyperparameters

Layer	Hyper-parameters	Value
Char-layer	embeddding size	50
Tag-layer	embeddding size tag blank number	10 [1, 3]
LSTM	state size number of layers	200 1
Dropout	dropout rate	[0.0, 0.5]
	batch size	[1, 10]
	initial learning rate	[0.01, 0.03]
	decay rate	0.05
	momentum	0.9
	gradient clipping	5.0
	L2 λ	1e-8

$$y^* = \arg \max_{y_i \in Y} p(y_i|s_i) \quad (8)$$

Experiments

Settings

Here display the experiment settings within our work.

Dataset. For Chinese NER task, We explore **MSRA** (Levow, 2006), **Weibo NER** (Peng and Dredze, 2015) and **ResumeNER** (Zhang and Yang, 2018). On music domain, We use the music domain dataset obtained on China Conference on Knowledge Graph and Semantic Computing (CCKS) 2018 music dataset. Cause we could only get the training dataset, we split that file into three part with portion 8:1:1 as train set, dev set and test set. Call this dataset as **CCKS** dataset. Another music domain dataset is annotated by ourselves, and the tags defined is richer than CCKS. The statistics information of this dataset is listed in Table 1. We call it **Sogou MusicNER** dataset. For English NER task, we report the result on **CoNLL 2003** shared English NER dataset (Sang and Meulder, 2003).

Data Preprocessing. In our paper, all input file is turned to a certain jsonalized format, which we call standard NER format. For example, ‘**Peter/B-PER Blackburn/E-PER**’ is turned to jsonalized string as {‘**text**’: ‘**Peter Blackburn**’, ‘**slot**’: [0, 15, ‘**PER**’]}. The numbers stand for the start position and end position in the original sentence. We do it this way since we can get the original input sentence without splitting words, and turn it into all other tag scheme (mainly IOB1, IOB2, IOBES) easily. Furthermore, we can easily statistics the sentence number and entity numbers in this format. On training, we turn the standard NER format into

Table 3: Main Results on MSRA.

Model	Precision	Recall	F1
La-LSTM	93.57%	92.79%	93.18%
LR-CNN	94.50%	92.93%	93.71%
C-LSTM	92.49%	89.87%	91.16%
ST-NER	93.45%	89.80%	91.59%
TE-LSTM(*)	—	—	—

the tag scheme we appointed in hyperparameter file. In this way, take the CoNLL 2003 dataset as example, it will first be transformed into standard format, and turn to IOBES tag scheme when training. In truth, this transformation doesn't change the content of dataset at all, but make it easier to process different format of dataset, and allow us to get the original input sentence to match the dictionary.

Character Embedding. In order to compare with Lattice LSTM (Zhang and Yang 2018) and Lexicon Rethinking CNN (Gui et al. 2019), we use the word vector provided in their papers (these two paper use the same character embedding and word embedding). There are character embedding and word embedding, we use the latter one as character embedding for we treat English word as a character in Chinese case, not a set of single English characters.

Tag Embedding. Given tag embedding length l_t as hyper parameter, we use uniform random policy to generate the tag embedding lookup table.

Dictionary Knowledge. For Lattice LSTM and Lexicon Rethinking CNN, they use the same word embedding file to explore dictionary knowledge, which can not incorporate all types of dictionary directly. For Stanford NER (Finkel, Grenager, and Manning 2005) model and ODN, we use certain dictionaries correlate to the dataset. For the same dataset, the dictionary they used keep the same. We make up the dictionary according to the follow principles:

- For exhaustive tag, we list all the items of that tag, extracted from **Knowledge Graph**, as a dictionary. For example, entity **Country** and **Project**.
- For tag which is limited but updated constantly, we list the current item of that tag, collected from **Knowledge Graph**, as a dictionary. For example, entity **Singer** and **Song**.
- For tag that is unlimited but has common prefix or suffix, we list all the common prefix or suffix for it as a dictionary. For example, entity **Organization** usually has a common suffix, such as: inc., company, league.
- For tag which is unlimited and seems no rule inside, we don't use dictionary for it.
- We build the content of tag mainly through **Knowledge Graph** we build, some of the dictionary are enriched with the dataset.

Handcrafted Features. Handcrafted features is only used in Stanford NER model. Main features include previous word, next words, NGrams and so on.

Table 4: Main Results on Weibo NER.

Model	NE	NM	Overall
La-LSTM	53.04%	62.25%	58.79%
LR-CNN	57.14%	66.67%	59.92%
C-LSTM	51.03%	47.58%	49.25%
ST-NER	46.69%	57.32%	52.04%
TE-LSTM	48.78%	71.31%	60.10%

Table 5: Main Results on ResumeNER.

Model	Precision	Recall	F1
La-LSTM	94.81%	94.11%	94.46%
LR-CNN	95.37%	94.84%	95.11%
C-LSTM	94.31%	94.27%	94.29%
ST-NER	94.15%	93.74%	93.94%
TE-LSTM	95.31%	94.90%	95.11%

Compared Models

For compared purposed, we impletement these models below:

Lattice LSTM. The author of Lattice LSTM (Zhang and Yang 2018) has generously provided his code on website. We directly use his code and settings, and run on experiment dataset. We denote it as La-LSTM.

Lexicon Rethinking CNN. Same with Lattice LSTM, we use the code provided by the author (Gui et al. 2019) and run on our dataset. We denote it as LR-CNN.

Character LSTM. We basicly impletement the character-level LSTM as the first model, no any other properties (like bichar, softword, position etc.) used. We use the word embedding in Lattice LSTM as character embedding here for we need to match English word and treat it as a whole.

Stanford NER model. Stanford NER tool (Finkel, Grenager, and Manning 2005) is used in our work to do comparision, for it is convenient to add handcrafted features into model, and use dictionary (called gazette in its term) directly, which can be compared to our ODN intuitively. For short, denote it as ST-NER.

Tag Embedding LSTM. This is the model which we proposed in this paper. The character embedding is the same with C-LSTM, and the dictionary used is the same with ST-NER model for comparision. We denote it as TE-LSTM.

Hyper-parameters and Strategies

Shown in Table 2, we choose the hyper-parameters referring to BLSTM-CNNs-CRF structure (Ma and Hovy 2016). Other training strategies we used are list as follow:

- **Fine-tuning.** We apply fine-tuning on all the embedding vector, which is proved useful by previous works (Collobert et al. 2011; Peng and Dredze 2015; Ma and Hovy 2016).
- **Dropout.** We choose the dropout rate between 0.0 and

Table 6: Main Results on CCKS.

Model	Precision	Recall	F1
La-LSTM	87.34%	75.03%	80.72%
LR-CNN	88.17%	76.98%	82.2%
C-LSTM	75.66%	71.12%	73.32%
ST-NER	91.00%	76.15%	82.92%
TE-LSTM(*)	84.28%	84.51%	84.40%

Table 7: Main Results on Sogou MusicNER.

Model	Precision	Recall	F1
La-LSTM	86.24%	84.43%	85.33%
LR-CNN	85.99%	85.00%	85.49%
C-LSTM	84.11%	82.50%	83.30%
ST-NER	88.00%	85.48%	86.72%
TE-LSTM	93.09%	92.82%	92.96%

0.5, for different dataset, the best result will occur at different rate.

- **SGD policy.** We use stochastic gradient descent (SGD) policy to train model, with momentum set as 0.9.

Main Results

Compared to previous work, we report the best result of our experiment here.

MSRA Dataset. There is no dev set on this dataset. We split the training file and report results on the test set. Table 3 shows the experiment results. On this dataset, dictionary for **Chinese Last Name, Location, Organization Suffix** is used in both ST-NER and TE-LSTM.

Weibo NER Dataset. As comparison to previous works, shown in Table 4, we report the F1-score for named entities (NE), nominal entities (NM) and overall entities. The dictionaries we use here are the set of **GPE_NAM, ORG_NOM, PER_NOM, LOC_NOM** and **Chinese Last Name**.

ResumeNER Dataset. We use the same train, dev and test file as La-LSTM and LR-CNN. Dictionary for **Title Suffix, Organization Suffix, Project, China Peoples** is used here on ST-NER and TE-LSTM. Results on this dataset also prove the efficiency of ODN.

CCKS / Sogou MusicNER Dataset. Table 6 and 7 shows the result of music domain dataset. The mainly dictionary used here is **Singer** and **Song**. Results show that our model report the best result on both dataset for F1 score. With dictionary information given, we can see that ST-NER shows better performance than La-LSTM and LR-CNN. That, to some extent, cause by the lack of music domain word information in La-LSTM and LR-CNN. Compared to ST-NER, our model gives **1.48%** percent promotion of F1 score on **CCKS** dataset, and **6.24%** percent promotion of F1 score on **MusicNER** dataset. This result proves that TE-LSTM is useful to utilize the information of dictionary, though without specially making word embedding vector for each word in lexicon.

Table 8: Main Results on CoNLL 2003.

Model	Precision	Recall	F1
Ma and Hovy, 2016	91.35%	91.06%	91.21%
Yang et al, 2018	—	—	91.35%
Devlin et al., 2018	—	—	92.80%
C-LSTM	87.32%	85.25%	86.27%
ST-NER(*)	86.02%	84.63%	85.32%
TE-LSTM	96.63%	96.67%	96.65%

Before	After
播/o 放/o 三/o 加/o 四/o	播/o 放/o 三/B-SONG 加/I-SONG 四/E-SONG
播/o 放/o 一/o 杯/o	播/o 放/o 一/B-SONG 杯/E-SONG
开/o 心/o 就/o 好/o	开/B-SONG 心/I-SONG 就/I-SONG 好/E-SONG
忆/o 梦/o 琉/o 璃/o	忆/B-SONG 梦/I-SONG 琉/I-SONG 璃/E-SONG

Figure 3: After adding words into dictionary, the new entities can be recognized by the model.

CoNLL Dataset. On this dataset, we list some of the effective model results reported by previous works. And we use dictionary **English Last Name, Location, Organization, MISC** here. We make a suppose here that we can get all the real entities of location, organization and miscellaneous in English. With this prerequisite, we could see significant improvement on this dataset, shown in Table 8. Though the result is amazing, **we need to emphasis that, it is hard and burdensome to collect all the entities in these dictionaries in reality.** For simplicity, we use the set of entities extracted from the dataset here. So the result is a powerful proof to support ODN in dictionary message using, but usually impractical in fact.

Analysis

As a further summarization for experiment results, we can make the follow conclusion:

Out of vocabulary (OOV). We don't need to consider OOV problem for the networks in ODN, for we make the appointment that we only collect the dictionary which is exhaustive, among all time or a certain time range, and only the tag knowledge is used in ODN, not a specified word in that dictionary.

Conflict Solving. Though given dictionary knowledge, there exists many conflict items, labeled with different tag, to challenge the model. For example, **French Open**. The word **French** will be given both the **S-MISC** tag and **B-ORG** tag here, according to the message in the dictionary. As results shown in Table 8, TE-LSTM can solve the conflict cases very well by using all the message in dictionary together with the character embedding knowledge.

Helpful to Improve Recall. All the experiment results on different dataset get the highest recall score, proving that ODN is a powerful tool to get higher recall, mainly because we better utilize the message in dictionary.

Without Retraining. We show it here that TE-LSTM need not to retrain the model when dictionary is greatly changed. The cost of retraining a model is changed to be the cost of maintaining the dictionaries, which is more convenient and can be better understood and modified by human.

Before	After
播/O 放/O 青/B-SONG 云/I-SONG 志/E-SONG	播/O 放/O 青/O 云/O 志/O
播/O 放/O 海/B-SONG 贼/I-SONG 王/E-SONG	播/O 放/O 海/O 贼/O 王/O
天/B-SONG 气/I-SONG 真/I-SONG 好/E-SONG	天/O 气/O 真/O 好/O
王/B-SONG 者/I-SONG 荣/I-SONG 耀/E-SONG	王/O 者/O 荣/O 耀/O

Figure 4: After delete existing words in dictionary, the corresponding entities can be ignored by the model.

Before	After
播/O 放/O 西/B-SONG 游/I-SONG 记/E-SONG	播/O 放/O 西/B-SONG 游/I-SONG 记/E-SONG
播/O 放/O 红/B-SONG 楼/I-SONG 梦/E-SONG	播/O 放/O 红/B-SONG 楼/I-SONG 梦/E-SONG
播/O 放/O 王/B-SONG 者/I-SONG 荣/I-SONG 耀/E-SONG	播/O 放/O 王/O 者/O 荣/B-SONG 耀/E-SONG
播/O 放/O 速/B-SONG 度/I-SONG 与/I-SONG 激/I-SONG 情/E-SONG	播/O 放/O 速/O 度/O 与/O 激/B-SONG 情/E-SONG

Figure 5: After delete existing words in dictionary, some of the the result will not change.

Here, we use entity **Song**, in CCKS dataset, as example. Figure 3 shows the difference after adding corresponding words as song, the model can recognize this entities with the new given knowledge. Figure 4 shows the change after deleting redundant words in dictionary, the model will ignore these words. But there are also cases which will not change or partly change after deleting the words, shown in Figure 5, these cases exist because there exist certain sentence phrase to discriminate the word as a song, or part of the word is still in the dictionary.

Conclusion

We proposed a new model to better explored the information of dictionary without make embedding for each word, which helps us need not to retrain a model after the content of dictionary is greatly changed. And the result shows that our model reach higher performance on dictionary-depended task, which certificated that our model is a powerful structure to utilize the information of dictionary. And with ODN, the cost of training a new model is replaced by protecting the dictionaries, which is more understandable to human beings.

We have several dicrections to move ahead. For the structure itself, ODN can also be simply implemented using the Lattice LSTM structure, which also, is a powerful way to use lexicon message. Furthermore, the information of dictionary can be reached on website or knowledge graph, which can be more convinient and promising. On this way, the model need to understand and consult the needed information by itself. Our model is just the start of combining outer knowledge into neural network model.

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