

Named Entity Recognition on Queries

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Abstract

Query is a form of text which is widely used now. Named entity recognition on query is a hard task. In this paper, we built a word plus char level neural network for named entity recognition on queries to capture the information of both words and characters of queries and compared it with the baseline word level Bi-LSTM-CRF model. The result showed that word plus char NN model does not have an advantage for short queries corpus compared word level model, which contradicts to the performance enhancement on formal text. The reason is that informal syntax and shortness of queries destructed the sequential pattern in text. The characters brought up more chaos to the word sequence, negating the performance of NN model.

1. Introduction

Named entity recognition is a classical task in Natural language processing. It is a subtask of information extraction that seeks to locate and classify the named entity mentioned in text. Traditionally, named entity recognition have predefined categories, such as location, person, product and time, etc. Recently, named entity recognition has been a heated topic both in academia and industry.

In Collins dictionary, a query is a question, especially one that you ask an organization, publication, or expert. The most common use of queries is the search query. When we asked a question, it is a query parsed by the search engine. In the industry, many AI assistants like Siri and Alexa are becoming important product offered by IT firms. A main work of these AI assistant is to deal with queries generated in daily conversations with customers. This requires deep understanding to the queries for machine. Therefore, the understanding of queries has become crucial to the development of AI assistant system (Liu et al 2013). Fortunately, the development of NLP opens a door to the automation processing on queries.

As a classic task of NLP, named entity recognition laid the foundation of information extraction, leading to more efficient language processing application, such as web search. For instance, for traditional search, if the search engine returns millions of documents to each search

query, it will be a very inefficient search. However, with the help of named entity recognition, search engine can pre classify the documents by entities and tags, then return those are most relative with the parsing result of search queries.

Even though most search queries contain named entity (Guo et al, 2009) and theoretically named entity can help speeding up the search process, there are many features for queries that leads problem to practical implementation on named entity recognition on queries. There are mainly two features included, first, queries are short. Compared with other corpus like novel or speech, queries are usually short. They are questions asked under some circumstance instead of long and organized corpus. Another feature of queries is that they are messy or informal. Since queries are just short questions asked by people, they are less organized. An similar case to query is tweet. There are many misspelling, incorrect capitalization and wrong punctuation in tweets. Similarly, queries also are informal texts. When people propose queries to the search engine or personal assistant, it is common that people will not spend much time editing or polishing those queries.

The features of query make applying named entity recognition on it different to on traditional corpus. In this paper, we applied the word and character level named entity recognition on queries and compare its result to the baseline model. The second section is literature review, the third section is design of experiments and algorithms, the fourth section includes results and analysis and the final section is conclusion.

2. Literature Review

Named entity recognition has been a long discussed NLP task for many years. The term “named entity” dates back the 1990s on Sixth Message Understanding Conference (Grishman and Sundheim, 1996).

Researchers had tried many approaches to do experiment on named entity recognition on corpus. The first class of approach is supervised learning. Bikel et al. (1998) firstly applied Hidden Markov Model to for named entity recognition. They proposed a rule to recognize the data for named entity. Zhou and Su (2002) also utilized Hidden Markov Model on named entity recognition and they gave a bigger number of named entities and reached a high model performance. On the bass of Hidden Markov Model, Malouf (2002) used Maximum Entropy to do named entity recognition and compared the results of it with that of Hidden Markov Model. Sekine (1998) experimented on decision trees for named entity recognition on Japanese.

McCallum and Li (2003) utilized conditional random field (CRF) for named entity recognition. Actually, CRF becomes a standard model for the named entity recognition for recent research.

Another approach for named entity recognition is unsupervised learning. Clustering is the main method in the unsupervised learning class. The advantage of clustering on named entity is that we don't need a huge amount of data to train the model.

Inverse document frequency is a frequently used index for infer topics of the document. Zhang and Elhadad (2013) used it combined with syntactical features for Named entity recognition. They applied it on two types of data and it turned out that both corpus have good prediction accuracy. Etzioni et al. (2005) used an unsupervised information oriented approach (mutual information) for named entities classification. They defined a space of features which corresponds to each entity.

The researches above-mentioned all relate to traditional corpus. However, the performance for traditional named entity recognition is not convincing on queries (Strauss, 2016). This is because the majority of named entity recognition approach is training on formal text, particularly, most on newswire text. Even though those approach have a good effect on traditional corpus, it is not guaranteed that they will have comparable performance on informal data, such as queries or tweets.

Neural network approach is now widely used for named entity recognition. Besides the word level NN model or char level NN model, a newly proposed model in named entity recognition is the word plus char model (Ma and Hovy, 2016). This model tried to capture the sequential information of both word and character level. It turned out that this combined NN model have a better performance on formal text (Chiu and Nichols, 2015). However, applying this model for named entity recognition on short queries is rare. In this paper, we investigated the performance (training complexity and F score) of this model on short queries and compared it to the baseline word level NN model and infer the insight of application of different models on named entity recognition on queries.

3. Design of Experiments and Algorithms

3.1 Data

In this paper, we used the MIT restaurant corpus¹ for dataset. MIT restaurant corpus is collected by MIT Computer Science and Artificial Intelligence Lab, spoken language system

¹ Source: <https://groups.csail.mit.edu/sls/downloads/restaurant/restauranttrain.bio>

(SLS). SLS group collected a bunch of data in which MIT restaurant corpus is included. This dataset is semantically tagged training and test corpus with BIO format for Named entities label. They are spoken queries and the whole training dataset is 742K.

3.2 Algorithm

The algorithm we proposed to solve the named entity recognition on queries task is word + char level neural networks architecture. The algorithm includes two main parts:

1) Bi-directional Long short-term memory

Bi-directional Long short-term (Bi-LSTM) is an advanced architecture for Recurrent neural network framework. The best part of Bi-LSTM is that it not only captures the sequential information of queries while avoid gradient explosion as LSTM model, but also uses forward and backward information for tokens in the text. For our model, we applied Bi-LSTM on two layers. The first layer is on the character level. We applied the Bi-LSTM to get the vector representation of characters of queries. Secondly, we used the Bi-LSTM on the combined word representation. On this layer, Bi-LSTM is to capture the whole vector representation of words.

2) Conditional Random Field

Conditional Random Field (CRF) is a typical model for named entity recognition. CRF is part of sequential models. The chain structure of CRF predicts the label of sequence of texts. CRF is a graphical model which depicts a conditional distribution of observed and output variables. Now CRF is popular in many NLP tasks, such as POS tag, named entity recognition and parsing. We applied the the CRF layer on the top of the second LSTM layer and try to predict the final named entity labels.

The whole architecture is shown in Figure 1.

3.3 Implementation

We firstly used pandas for data ETL. We loaded the data and converted into data frame. Fortunately, the dataset is already tokenized by SLS group, which means we save the step of tokenization in NLP. Then we built a function to extract the token and corresponding named entity labels in the data and organized them by sentence.

The next step is to vectorize those tokens and labels. We built a dictionary to count the frequencies of tokens and labels, transferring them to numbers and convert them to numpy arrays for use. Since we also used the characters as another features, we preprocess the text and extract the characters, transferred it into vector and used numpy array to represent it. The steps for vectorize character are similar to that of vectorize word.

Finally, we used Keras and Keras_contrib to build the main structure for deep learning model. The Keras is used to build Bi-LSTM layer and the other layers like input, output embedding and dropout layer. The Keras_contrib is only used to construct the conditional random field layer. We construct this layer only before the output.

Finally, we used scikit learn for train test split and check the metrics data of the model. We use precision, recall and F1 score as metrics.

For comparison, we also built the word level neural network (BiLSTM+CRF) as baseline. As a typical neural network model for named entity recognition, word level NN model has been proved to have good performance on most kinds of text. Here we use this model as a baseline and compare its performance with the word plus character model.

4. Results and Analysis

The train loss is shown as in figure 2. We can find out that the training epochs is long for our model. Exactly, we set the epoch of training epochs to 1000. As shown in the the figure, the train loss decreases drastically before 200 epochs, and it slowly decreases, after 800 epochs, the curve is basically stabilized.

The reason that we need a longer than average epoch is that we have longer batch size and more complex neural network than vanilla Bi-LSTM-CRF model. Exactly, we construct two LSTM layer in the model. In addition, by deep learning theory, longer epochs are required to achieve same accuracy when batch size is larger.

Now let us investigate the the metric table about the model (as shown in Table 1). First of all, the average f score is only 0.29 for all labels. In addition, the average precision is 0.31 and average recall is 0.31. This may seems very disappointing at first glance. However, it turns out that named entity recognition on informal text falls far behind the formal text. For example, the baseline (Bi-LSTM-CRF) model on tweets has only 0.30 f score (Strauss, 2016). Therefore, even 0.29 F1 score is not a good result, but it is still acceptable.

Second, when we dive into the the metrics on different categories, there are some more interesting facts. The amenity and location have the highest metrics score among 8 categories listed. This shows that our model has a better prediction power on amenity and location in queries than other named entities. On the other hand, named entities like hours, ratings and price only have small metrics score, which means the model does not behave well on these named entities. Another interesting fact is that the recall for named entity cuisine is as high as 0.57, while

other named entities are far behind this score on recall. This means cuisine has a higher percentage of relevant results which is correctly classified than others.

We now compared the result of word plus character NN model to the word level model from Figure 3 and Table 2. We have several findings as follows: 1) the training time for word plus character model is longer than the baseline model. The reason is that as a fancier model, word plus char model has more layers and more vectors, which leads to more parameters to be trained. Two layer of Bi-LSTM makes the model time costly. 2) the F score for word plus char model is also smaller than the baseline word level NN model (29% to 52%). This result contradicts to the performance on formal data like newswire or books. The main reason is that the sequential information for characters in short queries is more chaotic than that of formal text, which makes the word plus character NN model fails to predict accurately. The informal syntax of characters actually negates the sequential pattern of word captured by LSTM model, instead of enhancing them like on formal text.

5. Conclusion

We built a word-char level NN model and applied the model on named entity recognition on short queries. From the experiment result, we have conclusions as follows:

First, the performance of word plus char NN model on named entity recognition on queries is acceptable, even though they are not high. By check precision, recall and F1 score, we found out basically all the metrics are about 0.31. These results are still smaller than that on formal text. The reasons are as follows: 1) the queries are short. This feature leads to the bad performance on LSTM layer. Since we use LSTM layer to try to capture the sequential information in sentences, the shortness of queries obstructs this consistency in text and may fail our attempt. 2) the queries violate formal syntactical rules. As people who propose queries often gave syntactically wrong sentences, the sequential relation of named entities may not obey the formal syntactical rules. This may destruct our CRF layer performance and further model performance.

Second, according to running time of word plus char NN model, it is slower than the common Bi-LSTM-CRF model on word level. There are several potential reasons. Firstly, we build a model including two LSTM layer and CRF layer. This means that we have more parameters to train compared with common NN models. The training on parameters is costly. Another reason that our model is slow is that we concatenate the representation of character vector and representation of word vector as input to the second layer Bi-LSTM. This concatenation built a longer vector than plain word vectors, which takes more time to train. In

general, even though word plus char NN model have a better performance than baseline word level model on formal data, our result shows that word level model still outperforms the word plus char level NN model.

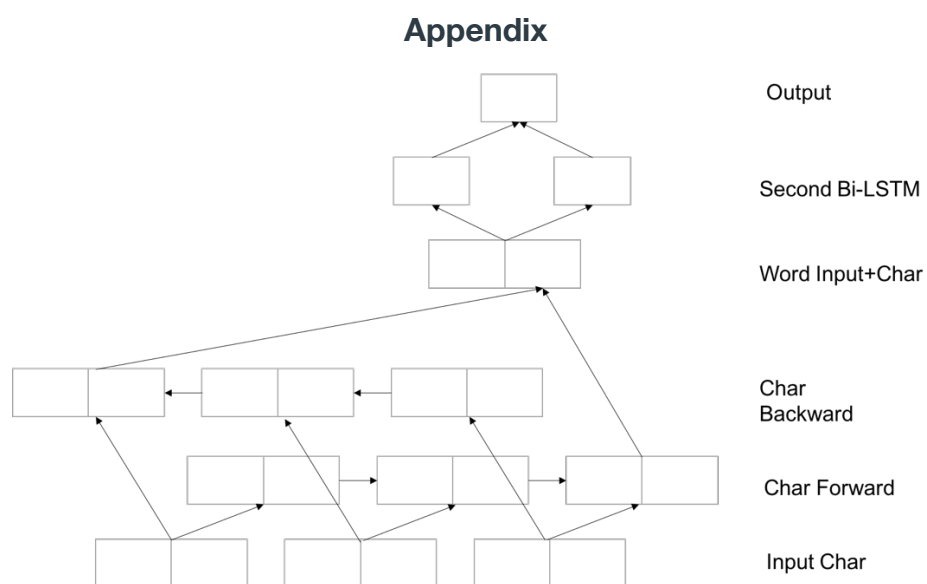


Figure 1 The word + char NN model architecture

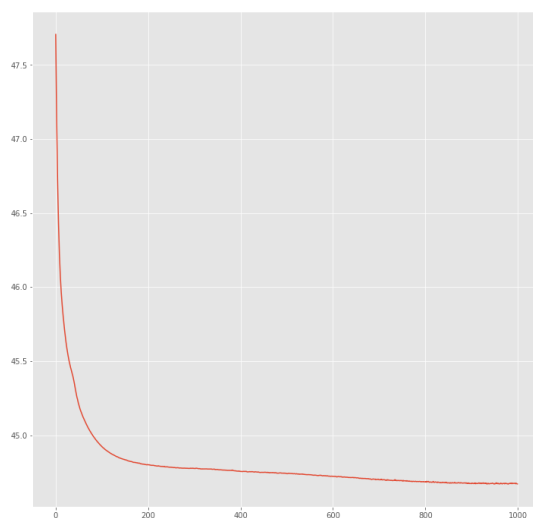


Figure 2 Train loss for word + char level NN model

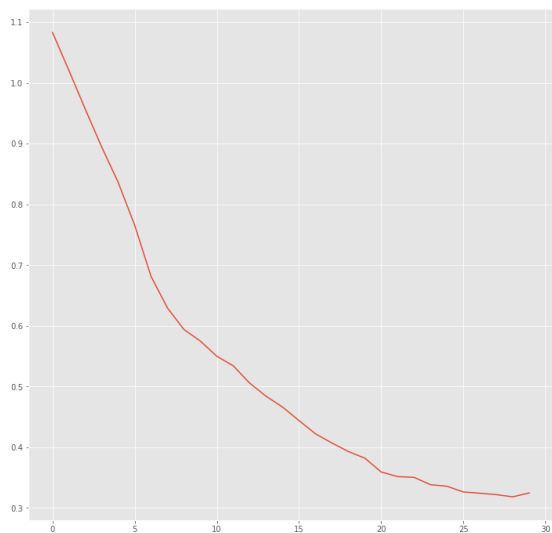


Figure 3 Train loss for word level NN model

Table 1 Metrics for word + char level NN model

	Precision	recall	F score	Support
Amenity	0.31	0.39	0.35	167
Rating	0.29	0.16	0.21	49
Location	0.31	0.31	0.31	236
Restaurant_Name	0.25	0.19	0.22	124
Hours	0.15	0.05	0.08	55
Price	0.20	0.23	0.22	43
Cuisine	0.36	0.57	0.45	164
Dish	0.50	0.13	0.21	93
Avg/total	0.31	0.31	0.29	931

Table 2 Metrics for word level NN model

	Precision	recall	F score	Support
Amenity	0.46	0.49	0.47	167
Rating	0.46	0.43	0.44	49
Location	0.70	0.69	0.69	236
Restaurant_Name	0.40	0.35	0.37	124
Hours	0.42	0.43	0.43	55
Price	0.53	0.37	0.44	43
Cuisine	0.50	0.64	0.56	164
Dish	0.50	0.30	0.38	93
Avg/total	0.52	0.52	0.52	931

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