Sentences Embedding for Slot Filling via Convolutional Neural Networks

Jinjian Zhang, Siliang Tang*, and Fei Wu
College of Computer Science and Technology,
Zhejiang University
Hangzhou, Zhejiang, China
{jinjianzhang, siliang, wufei}@zju.edu.cn

Abstract

This report describes the DCD slot filling system for the TAC Cold Start evaluations 2016 Task. The DCD_SF 2016 slot filling system mainly uses neural networks methods to obtain the slot filler. For Named Entity Recognize and coreference, we apply Stanford Core NLP system. For generating training data, we use the distant supervision, which is a very popular way among the slot-filling task. For relation classification, our system uses convolution neural network, which achieve exciting accuracy in sentences classification.

1 Introduction

In this paper, we describe the DCD_SF system for TAC KBP 2016 Cold Start Slot Filling (SF) task, which is organized by NIST. This year is our second time to participate this competition.
We used a combination of distant supervision (Mintz et al., 2009) and Convolutional Neural Networks (Kim Y, 2014) structured prediction.
This paper is organized as follows: First, an overview of our team's slot filling system (Section 2). Second, the technical details of our distant supervision method. Finally, the performance of the system in the shared task is presented.

2 System Overview

Our slot filling system is a combination of distant supervision and Convolutional Neural Networks. Slot filling task aims to obtain the information about entities like person, organization or geometry political entities from unstructured text data like news or web forums. There are many challenges in the task like alias of entity, information retrieval, coreference resolution, query expansion, training data generation, relation classification and slot filler inference.
Our slot filling system tries to alleviate and address these problems. In order to get the slot filler about a person, organization or geo-political entity, the following steps need to be performed:

1. Preprocessing the documents
2. Expansion of query
3. Retrieval of documents
4. Retrieval of sentences
5. Mapping relations
6. Relation classification
7. Searching provenances

3 Extraction of candidates

In our slot filling system, we need to extract the candidates, which contain the slot filler information first.

3.1 Preprocessing Documents

All the source documents used by our system have been tokenized. We use Stanford Core NLP (Manning C D et al., 2014) to do this job.

3.2 Expanding Queries

The relation classification model needs many candidates. We need expand queries to address this problem. We add alias for every entity. The aliases were extracted by Freebase dataset (www.freebase.com).

* corresponding author

3.3 Searching Candidates

Our system searching the candidates by whoosh, an open source, fast and pure python search engine library. Whoosh has following advantages (Matt Chaput, et al.):

- Whoosh is fast, but uses only pure Python, so it will run anywhere Python runs, without requiring a compiler.
- Whoosh's ranking function can be easily customized.
- Whoosh creates very small indexes compared to many other search libraries.
- All indexed text in Whoosh must be Unicode.
- Whoosh lets you store arbitrary Python objects with indexed documents.

4 Features

The representation of candidates mainly based on embedding features and syntactic features. This representation mainly comes from Zeng's way (Zeng., 2015).

4.1 Word Embedding

Word embeddings are distributed representations of words that map each word in a text to a 'k'-dimensional real-valued vector. They have recently been shown to capture both semantic and syntactic information about words very well, setting performance records in several word similarity tasks. Using word embeddings that have been trained a priori has become common practice for. enhancing many other NLP tasks.

A common method of training a neural network is to randomly initialize all parameters and then optimize them using an optimization algorithm. Recent research (Erhan et al., 2010) has shown that neural networks can converge to better local minima when they are initialized with word embeddings. Word embeddings are typically learned in an entirely unsupervised manner by exploiting the co-occurrence structure of words in unlabeled text. Researchers have proposed several methods of training word embeddings. In this paper, we use the Skip-gram model to train word embeddings.

4.2 Syntactic Features

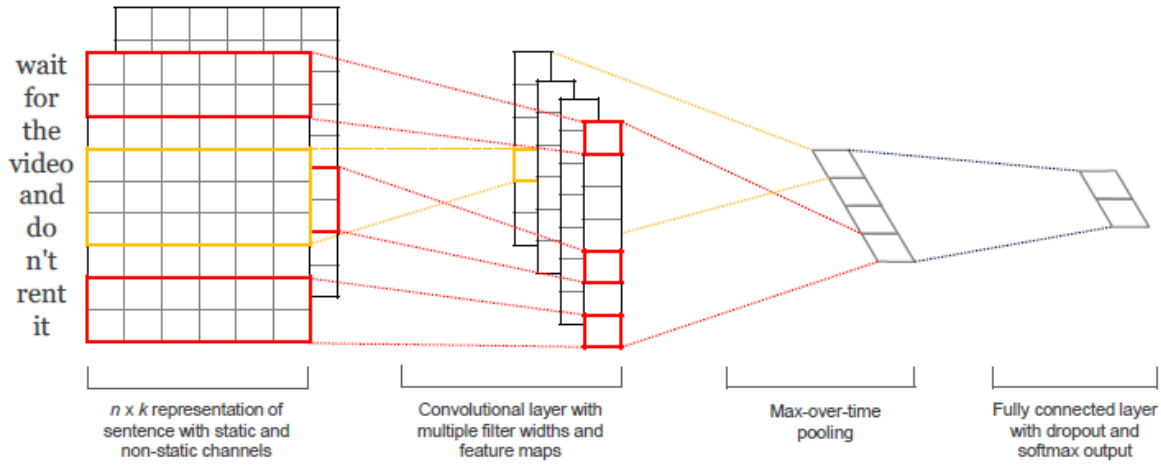
A dependency parse consists of a set of words and chunks (e.g. 'Edwin Hubble', 'Missouri', 'born'), linked by directional dependencies. For each sentence, we extract a dependency path between each pair of entities. A dependency path consists of a series of dependencies, directions and words/ chunks representing a traversal of the parse. Part-of-speech tags are not included in the dependency path. They consist of the conjunction of:

- A dependency path between the two entities
- For each entity, one 'window' node that is not part of the dependency path

As for the implementation, we use the Stanford Core NLP system (Manning C D et al., 2014).

5 Relation Classification

Given the candidates of slot filler and sentences contain the entity and slot filler information, our systems applied our Convolutional Neural Networks model to label the candidates and get the relation. This work is similar with Kim's way (Kim Y et al., 2014).



The model architecture, shown in figure 1, is a slight variant of the CNN architecture of Collobert et al. (2011). In relation extraction, an input sentence that is marked as containing the target entities corresponds only to a relation type; it does not predict labels for each word. Thus, it might be necessary to utilize all local features and perform this prediction globally. When using a neural network, the convolution approach is a natural means of merging all these features.

6 Slot Filling results

6.1 Additional Data

As training data, we use the data from LDC. Additionally, we use the Freebase dataset (www.freebase.com) to get the aliases of entity and slot filler.

6.2 Submissions

We have submitted two submissions for the TAC KBP Cold Start slot-filling track.

- DCD_SF1 Features of this submit are embedding and syntactic features.
- DCD_SF2 Features of this submit are embedding and position features.

Experimental results of these systems are shown in Table 1.

	Precision	Recall	F1
DCD_SF1	0.0792	0.0651	0.0659
DCD_SF2	0.0875	0.0733	0.0747

Table 1. Results

7 Conclusion

In this paper, we presented an overview of the DCD_SF system for the KBP 2016 English Cold Start Slot Filling (SF) task. The system uses a combination of distant supervision and Convolutional Neural Networks. In the future work, we would like to use soother me neural networks ways like RNN and LSTM.

Acknowledgments

This work was supported in part by the China Knowledge Centre for Engineering Sciences and Technology (CKCEST), the NSFC (No. 61402401), and the Zhejiang Provincial NSFC (No. LQ14F010004).

We would like to acknowledge Hongliang Dai for his help in developing this system and writing.

References

Kim Y. Convolutional Neural Networks for Sentence Classification[J]. Eprint Arxiv, 2014.

Surdeanu M, Tibshirani J, Nallapati R, et al. Multi-instance multi-label learning for relation extraction[C]//Proceedings of the 2012 Joint Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning. Association for Computational Linguistics, 2012: 455-465.

Riedel S, Yao L, McCallum A. Modeling relations and their mentions without labeled text[C]//Joint European Conference on Machine Learning and Knowledge Discovery in Databases. Springer Berlin Heidelberg, 2010: 148-163.

www.freebase.com

Mintz M, Bills S, Snow R, et al. Distant supervision for relation extraction without labeled data[C]//Proceedings of the Joint Conference of the 47th Annual Meeting of the ACL and the 4th International Joint Conference on Natural Language Processing of the AFNLP: Volume 2-Volume 2. Association for Computational Linguistics, 2009: 1003-1011.

Manning C D, Surdeanu M, Bauer J, et al. The Stanford CoreNLP Natural Language Processing Toolkit[C]//ACL (System Demonstrations). 2014: 55-60.

Angeli G, Tibshirani J, Wu J, et al. Combining Distant and Partial Supervision for Relation Extraction[C]//EMNLP. 2014: 1556-1567.

Matt Chaput, et al. http://bitbucket.org/mchaput/whoosh

Min B, Grishman R. Challenges in the Knowledge Base Population Slot Filling Task[C]//LREC. 2012: 1137-1142.

Angeli G, Gupta S, Jose M, et al. Stanford's 2014 slot filling systems[J]. TAC KBP, 2014, 695.

Hoffmann R, Zhang C, Ling X, et al. Knowledge-based weak supervision for information extraction of overlapping relations[C]//Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies-Volume 1. Association for Computational Linguistics, 2011: 541-550.

Zeng D, Liu K, Chen Y, et al. Distant Supervision for Relation Extraction via Piecewise Convolutional

Neural Networks[C]// Conference on Empirical Methods in Natural Language Processing. 2015.