Chinese Temporal Expression Extraction

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1. Domain Background

T-IR (Temporal Information Retrieval) is critical for many applications, such as deaing with queries like " Remind me to buy tickets at 9 o'clock tomorrow". [1] is a survey for T-IR problem, it divides T-IR into 2 steps：TimEx (Temporal Expression) Extraction and Normalization.TimEx extraction finds the words in a sentence that constitue a temporal expression, and normalization analyzes what is the specific time that the timex refer to. Both rule-based methods and machine learning methods are applied is solving TimEx extraction, but to the best of my knowledge, only rule-based methods ars used in TimEx normalization.

TempEval contests focused on temporal and event information retrieval, and TimEx extraction is a subproblem of them. TempEval-2 provided corpus for 6 languages including Chinese, but among the submitted systems, no one dealed with Chinese corpus. TempEval-3 provided English and Spanish corpus, and both the scale and quality is better than TempEval-2. In TempEval-3 T-IR subtask, the performance of rule-based methods and machine learning based methods are close[2]. SUTime[3] and HeidelTime[4] are rule based system, whose F-score are both about 90.3%. ClearTK-TIME[5] and ManTIME[6] are machine learning based system, the F-score of the former is 90.2%, the latter 88.1%.

[7] and [8] deals with Chinese corpus. [7] also based on HeidelTime system, developed rules for Chinese, and achieves 89.3% F-score. [8] achieves 84.7% F-score with CRF (conditional random field) method.

All the work mentioned above models TimEx extraction as a BOI (Inside–outside–beginning) tagging probem. In recent years, neural network and deep learning also get good performance in NLP tagging problem. [9] introduced an neural network methods for POS tagging. And it's supposed that this method can also apply to TimEx extraction.

This capstone project will focus on TimEx extraction for Chinese corpus.

2. Problem Statement

TimeML[10] is a markup language for temporal and event expressions for natural language. And the TIMEX3 specification of TimeML is used for temporal expression. It defines TimEx as a phrase composed of on or many time expression unit, and classify the expressions into four types：Data, Time, Duration and Set. For TimEx extraction, we only need to find which words in the sentence constitute a TimEx. In Chinese language, sentence are composed of words, so with BOI tagging model, we can tag the begin word of a TimEx as 'B', the other words in this TimEx as 'I', and all the words that are not in any TimEx as 'O'. An example:

> "今年/B 6月/I , /O 公司/O 发布/O 声明/O , /O 要/O 在/O 8月/B 推进/O 这项/O 计划/O ./O".

3. Datasets and Inputs

The TIMEX tagged Chinese corpus are very rare, TempEval-2 corpus and ACE2005 corpus are the only known corpus to my knowledge. And unfortunately, ACE2005 corpus can't be accessed for free, so in this project, I will only use TempEval-2 Corpus for training and evaluation. In this corpus, there 44 documents, 931 sentences,23180 words and 763 TimEx in the training set. And there are 8 documents, 195 sentences, 5313 words and 131 TimEx in the testing set.

Besides, some unsupervised learning methods such as word2vec can be trained with unannotated corpus. In this project, 1998 People Daily Corpus will be used.

4. Solution Statement

Many algorithms can be applied in sequece tagging probem, such as HMM and maximum entropy, et al. In this project, I will try 2 methods:

1. CRF based tagging
2. word embedding and neural network based tagging

5. Evaluation Metrics

I used the same metric as TempEval-2, evaluating the precison, recall and F-score of a system. First count the number of true positives (tp), true negatives (tn), false positives (fp) and false negatives (fn) on a token by token basis. E.g. if "明天 早上" is a TimEx, but only "明天" is recogized as TimEx, then there will be one true positive and one false negative.

The statistics calculation are:

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precision = tp / (tp + fp)
recall = tp / (tp + fn)
f1-measure = 2 * (precision * recall) / (precision + recall)
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6. Benchmark Model

First, a CRF-based tagger is implemented, which only use a small number of feature template. The precision, recall and F-score of this tagger is 82.5%, 92.8% and 74.3%.

> Feature template：
>
> 1. current word
> 2. last word or BOS (begin of sentence)
> 3. next word or EOS (end of sentence)
> 4. last character of the current word
> 5. first character of the current word

Besides, the performance of the system mentioned in the backgroup section is also shown in the table below.

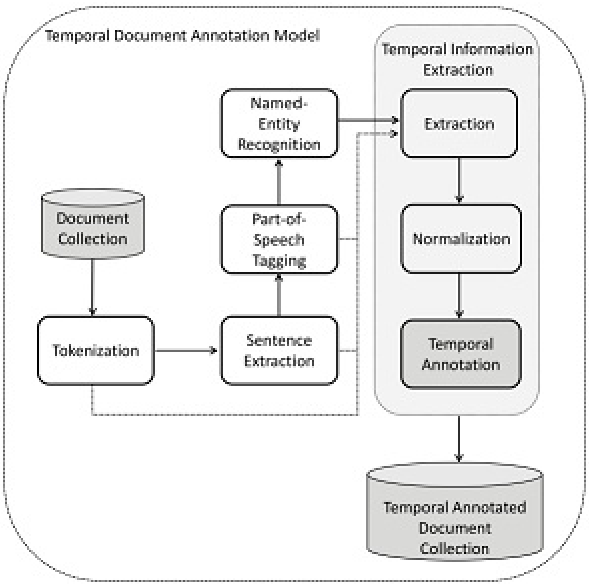
ID	System	Method	Language	F-score	Precision	Recall
1	SUTime	rule-based	English	90.32%	89.36%	91.30

2	HeidelTime	rule-based	English	90.30%	93.08%	87.67
3	ClearTK	machine learnin	English	90.23%	93.75%	86.96
4	ManTIME	machine learnin	English	89.66%	95.12%	84.78
5	HeidelTime	rule-based	Chinese	95.5%	83.8%	89.3%
6	POS-R[8]	machine learnin	Chinese	84.17%	85.16%	83.21%
7	Benchmard model	machine learnin	Chinese	82.5%	92.8%	74.3%

7. Project Design

7.1 CRF-based tagging

[1] provides a workflow for TimEx extraction, shown in the next figure, which consitutes of preprocessing and extraction.



The preprocessing step includes：

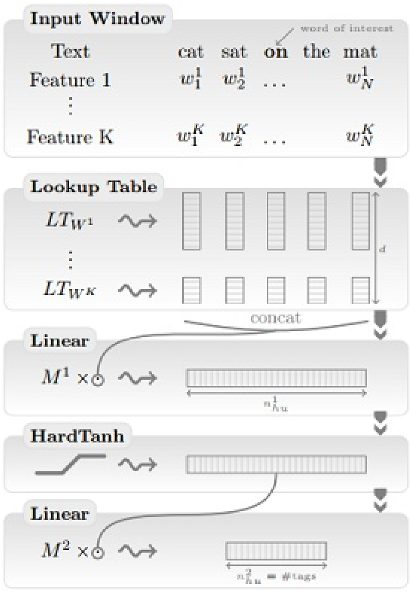
1. word segmentation
2. POS tagging
3. NER recoginition

As the corpus of TempEval-2 is already segmented, so step-1 is not needed. And to some extent, NER-Recoginition overlap with TimEx extraction, so step-3 is also ignored.

As for extraction, I will first prepare a number of syntactic, semantic of POS-based feature template manually, and then train the CRF model with the dataset.

7.2 Word embedding and neural network based tagging

Word embedding is a representation for words in natural language. And it is a real number array with low dimension (usually 50 or 100).[9] introduced a pos tagging methods based on word embedding and neural network. The structure of the network is shown in the figure below.



There are three layers in this network: linear layer, HardTanh layer and output layer. But before training, one must decide what is the input for this network. [9] first transforms each word into a word embedding with a pre-trained lookup table, then combied with the encoding of other features, such as pos tagging, forms a real number vector to be the input. Here, we can pretrain the word embedding with 1998-PeopleDaily corpus. Another point to note is, sentences are of variant length, how can deal with them with neural network? [9] introduced a windows-based method to solve this. This method assumes that the tag of a word is only related to its neighbors, so it defines a fix-length window, only the neighbors in this window will be used to predict the tag of the current word. So in this way, the dimension of the input will be fixed.

In this project, I will try to tag the TimEx in a similar way.

8. Appendix

The corpus to be used:

1. TempEval-2 Corpus
2. 1998 people daily

> If this webset is not accessible, please refer to http://www.cnblogs.com/eaglet/archive/2007/09/10/888377.html

The softwares that are expected to use in my capstone project:

1. Stanford POS Tagger
2. pycrfsuite
3. gensim
4. tensorflow

9. Reference

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