Chinese Named Entity Recognition using Conditional Random Fields

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Section 1

Introduction

Subsection 1

Named Entity Recognition

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- NER is a task aimed at extracting named entities from raw text and classifying into their corresponding categories, such as persons, locations, organizations, etc.

Named Entity Recognition

- NER is a task aimed at extracting named entities from raw text and classifying into their corresponding categories, such as persons, locations, organizations, etc.
- In this task, we are required to identify three entity categories: PER, LOC, ORG given a Chinese text.

NER as a Sequence Labeling Task

Sequence Labeling has been the state-of-the-art approach to a number of NLP tasks:

- Word Segmentation(Tseng et al., 2005).
- POS Tagging(Toutanova and Manning, 2000).
- Chunking(Shallow Parsing)(Sha and Pereira, 2003).
- Named Entity Recognition(McCallum and Li, 2003).

Subsection 2

Sequence Labeling

Sequence Labeling

Hidden Markov Model (HMM)

- Generative Model
- Cannot incorporate long distance features

Maximum Entropy Markov Model (MEMM)

- Discriminative Model
- Can incorporate long distance features
- Optimize conditional probability

Conditional Random Field (CRF) — *Our Choice*

- Discriminative Model
- Can incorporate long distance features
- Optimize joint probability (Has looser assumption of independency)
- High cost, long training time

Section 2

Proposed Approach

Subsection 1

Preprocessing

Tagging Scheme

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- We adopt the classic IOB tagging method with totally 7 tags: B-PER, I-PER, B-LOC, I-LOC, B-ORG, I-ORG and Others
- Gain produced by more complex tagging methodologies like IOBES remains elusive.(Collobert et al., 2011)

Word Segmentation & POS Tagging

Word Segmentation

We adopt a word-based approach rather than character-based one under the rationale:

- In Chinese, words can better encode semantics atomics than characters.
- By word segmentation, additional useful features such as POS tags can be introduced.

POS Tagging

- Named Entities are more likely to have particular POS tags (e.g. Proper Nouns).
- POS Tagging can ameliorate the problem of data sparsity.

Subsection 2

Features

Lexical Features

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- But extravagant utilization of lexical features would result in severe sparsity problem.
- Hence we incorporate some but limited lexical features of unigram, bigram and trigram features.
- We also set a relatively large cutoff value to avoid the bias induced by lexical features of extremely low frequency.

POS Tags

As we said before, POS tags can benefit the NER task.

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- Named Entities are very likely to possess a specific subset of POS tags (NR, for example).
- POS tags does not suffer from the data sparsity as the lexical features.

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- e.g. Patterns like XX Shi, XX Xian suggests a high probability of locations.
- e.g. Patterns like XX Ju, XX Chu suggests a high probability of organizations.

Gazetteers

(Ratinov and Roth, 2009) argued that numerous works have reported that gazetteers would substantially help the performance of a NER system.(Cohen and Sarawagi, 2004; Kazama and Torisawa, 2007; Florian et al., 2003)

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We collected a dozen of gazetteers from various sources (Experiments are still on-going, not final choice)

- A list of 300 most common Chinese Surnames
- Classified gazetteers from *Sogou Cell Lexicon*.

Word Clustering

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- Socher and Chris Manning from Stanford pointed out in their tutorial at ACL 2012(Socher et al., 2012) that Word Clustering can improve the accuracy of NER, as shown in Figure 6.

	POS WSJ (acc.)	NER CoNLL (F1)
Supervised NN	96.37	81.47
NN with Brown clusters	96.92	87.15

Word Clustering (Cont.)

Weiwei Sun from PKU reported similar gain by using word clustering on POS tagging (Sun and Uszkoreit, 2012) in her talk at MSRA last week.

Features	Brown	MKCLS
Supervised	94.48%	
+ #100	94.82%	94.93%
+ #500	94.92%	94.99%
+ #1000	94.90%	95.00%

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Experiments on Word Clustering are still on-going.

Section 3

Experiments

Experiment Settings

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- We use CRF++ as implementation of CRF.
- Data Selection:

  Training Set First 950/1000 documents in the training data.

  Dev Set Last 50/1000 documents in the training data.

Preliminary Results

We are still keep polishing our models and conducting further experiments, hence the results presented here are not our final version.

Table below shows the F1 score on Dev Set.

Setting	**F1(Term-level)**	**F1(Character-level)**
Lexical	66.91	67.51
+POS	79.02	81.95
+Pre/Suffix	85.99	**88.89**
+Surname List	**86.53**	88.70
+Gazetteer	Not Ready	Not Ready
+mkcls	Not Ready	Not Ready

The End

Thank you!

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