Chinese Named Entity Recognition using Conditional Random Fields

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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.

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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.

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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).

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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

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Tagging Scheme

- We need to convert the labels to fit the sequence labeling task.

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Tagging Scheme

- We need to convert the labels to fit the sequence labeling task.
- 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

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Tagging Scheme

- We need to convert the labels to fit the sequence labeling task.

- 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)

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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.

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Lexical Features

- Lexical features are the most basic features that everyone
  would exploit.

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Lexical Features

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- But extravagant utilization of lexical features would result in severe sparsity problem.

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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.

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Lexical Features

- Lexical features are the most basic features that everyone would exploit.
- 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.

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POS Tags

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

- Named Entities are very likely to possess a specific subset of POS tags (NR, for example).

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POS Tags

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

- 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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Prefixes & Suffixes

In Chinese, much helpful knowledge can be revealed by examining the prefix and suffix of a word.

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Prefixes & Suffixes

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- e.g. Patterns like Zhang XX, Li XX suggests a high probability of persons.

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Prefixes & Suffixes

In Chinese, much helpful knowledge can be revealed by examining
the prefix and suffix of a word.

- e.g. Patterns like Zhang XX, Li XX suggests a high
  probability of persons.
- e.g. Patterns like XX Shi, XX Xian suggests a high probability
  of locations.

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Prefixes & Suffixes

In Chinese, much helpful knowledge can be revealed by examining the prefix and suffix of a word.

- e.g. Patterns like Zhang XX, Li XX suggests a high probability of persons.
- 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.

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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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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)

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*.

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Word Clustering

- Word clustering is another approach that deals with the sparsity.

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Word Clustering

- Word clustering is another approach that deals with the sparsity.
- 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

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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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Therefore, we are trying to incorporate the **mkcls** clustering by Franz Josef Och (Och, 1999).

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Therefore, we are trying to incorporate the **mkcls** clustering by Franz Josef Och (Och, 1999).
Experiments on Word Clustering are still on-going.

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Experiments

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Experiment Settings

- We use Stanford Segmenter(Tseng et al., 2005) for word
  segmentation

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- We use Stanford Segmenter(Tseng et al., 2005) for word segmentation
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- We use Stanford Segmenter(Tseng et al., 2005) for word segmentation
- We use Stanford POS Tagger(Toutanova and Manning, 2000) for POS tagging.
- We use CRF++ as implementation of CRF.

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Experiment Settings

- We use Stanford Segmenter(Tseng et al., 2005) for word segmentation
- We use Stanford POS Tagger(Toutanova and Manning, 2000) for POS tagging.
- 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.

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Sample Training Data

Figure: Sample Training Data

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Results

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

Table below shows the **Overall** 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	87.61	89.40
+Gazetteer	**88.52**	**90.05**

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Results on PERSON

Table below shows the F1 score of **PERSON** recognition.

Setting	F1(Term-level)	F1(Character-level)
Lexical	42.51	41.94
+POS	71.30	79.52
+Pre/Suffix	79.95	86.44
+Surname List	85.01	88.06
+Gazetteer	85.67	88.69

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Results on LOCATION

Table below shows the F1 score of **LOCATION** recognition.

Setting	F1(Term-level)	F1(Character-level)
Lexical	79.32	76.79
+POS	84.52	83.61
+Pre/Suffix	89.59	89.74
+Surname List	90.21	90.62
+Gazetteer	91.23	91.33

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Results on ORGANIZATION

Table below shows the F1 score of **ORGANIZATION** recognition.

Setting	F1(Term-level)	F1(Character-level)
Lexical	65.90	73.19
+POS	78.74	82.28
+Pre/Suffix	86.85	89.94
+Surname List	85.66	89.22
+Gazetteer	86.57	89.78

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Analysis & Insights

1. LOCATION is a relatively easier task under our word-based system

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Analysis & Insights

1. LOCATION is a relatively easier task under our word-based system
2. PERSON has the lowest accuracy.

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Analysis & Insights

1. LOCATION is a relatively easier task under our word-based system
2. PERSON has the lowest accuracy.
   - A character based system is more suitable for Chinese person name recognition.

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Analysis & Insights

1. LOCATION is a relatively easier task under our word-based system
2. PERSON has the lowest accuracy.
   - A character based system is more suitable for Chinese person name recognition.
   - Pre/Suffix and surname list incurred significant improvement in PERSON task.

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Analysis & Insights

1. LOCATION is a relatively easier task under our word-based system
2. PERSON has the lowest accuracy.
   - A character based system is more suitable for Chinese person name recognition.
   - Pre/Suffix and surname list incurred significant improvement in PERSON task.
3. ORGANIZATION has a much better char-level F1 than term-level F1.

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1. LOCATION is a relatively easier task under our word-based system
2. PERSON has the lowest accuracy.
   - A character based system is more suitable for Chinese person name recognition.
   - Pre/Suffix and surname list incurred significant improvement in PERSON task.
3. ORGANIZATION has a much better char-level F1 than term-level F1.
   - It is difficult to precisely judge the boundary of a ORG.

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1. LOCATION is a relatively easier task under our word-based system

2. PERSON has the lowest accuracy.
   - A character based system is more suitable for Chinese person name recognition.
   - Pre/Suffix and surname list incurred significant improvement in PERSON task.

3. ORGANIZATION has a much better char-level F1 than term-level F1.
   - It is difficult to precisely judge the boundary of a ORG.

4. Gazetteers can bring noticeable improvement on every task despite its mediocre quality.

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The End

Thank you!

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