Abstract

This paper describes a novel character tagging approach to Chinese word segmentation and named entity recognition (NER) for our participation in Bakeoff-4. It integrates unsupervised segmentation and conditional random fields (CRFs) learning successfully, using similar character tags and feature templates for both word segmentation and NER. It ranks at the top in all closed tests of word segmentation and gives promising results for all closed and open NER tasks in the Bakeoff. Tag set selection and unsupervised segmentation play a critical role in this success.

1 Introduction

A number of recent studies show that character sequence labeling is a simple but effective formulation of Chinese word segmentation and named entity recognition for machine learning (Xue, 2003; Low et al., 2005; Zhao et al., 2006a; Chen et al., 2006). Character tagging becomes a prevailing technique for this kind of labeling task for Chinese language processing, following the current trend of applying machine learning as a core technology in the field of natural language processing. In particular, when a full-fledged general-purpose sequence learning model such as CRFs is involved, the only work to do for a given application is to identify an ideal set of features and hyperparameters for the purpose of achieving the best learning model that we can with available training data. Our work in this aspect provides a solid foundation for applying an unsupervised segmentation criterion to enrich the supervised CRFs learning for further performance enhancement on both word segmentation and NER.

This paper is intended to present the research for our participation in Bakeoff-4, with a highlight on our strategy to select character tags and feature templates for CRFs learning. Particularly worth mentioning is the simplicity of our system in contrast to its success. The rest of the paper is organized as follows. The next section presents the technical details of the system and Section 3 its evaluation results. Section 4 looks into a few issues concerning character tag set, unsupervised segmentation, and available name entities (NEs) as features for open NER test. Section 5 concludes the paper.

2 System Description

Following our previous work (Zhao et al., 2006a; Zhao et al., 2006b; Zhao and Kit, 2007), we continue to apply the order-1 linear chain CRFs (Lafferty et al., 2001) as our learning model for Bakeoff-4. Specifically, we use its implementation CRF++ by Taku Kudo freely available for research purpose. We opt for a similar set of character tags and feature templates for both word segmentation and NER.

In addition, two key techniques that we have explored in our previous work are applied. One is to introduce more tags in the hope of utilizing more precise contextual information to achieve more pre-
Table 1: An example of NE tagging for a character sequence

| Characters | /x4f /x57 /x57 /xec/x14/x71/x96/xaf/xfc/xd1 |
|------------|---------------------------------------------|
| Tags       | B-ORG B₂-ORG B₃-ORG E-ORG O S-LOC O O O O |

Table 2: Illustration of character tagging

| Word length | Tag sequence for a word |
|-------------|-------------------------|
| 1           | S                       |
| 2           | B E                     |
| 3           | B B₂ E                  |
| 4           | B B₂ B₃ E               |
| 5           | B B₂ B₃ M E             |
| ≥ 6         | B B₂ B₃ M ... M E       |

In addition to these n-gram features, unsupervised segmentation outputs are also used as features, for the purpose of providing more word boundary information via global statistics derived from all unlabeled texts of the training and test corpora. The basic idea is to inform a supervised learner of which substrings are recognized as word candidates by a given unsupervised segmentation criterion and how likely they are to be true words in terms of that criterion (Zhao and Kit, 2007; Kit and Zhao, 2007).

We adopt the accessor variety (AV) (Feng et al., 2004a; Feng et al., 2004b) as our unsupervised segmentation criterion. It formulates an idea similar to linguist Harris’ (1955; 1970) for segmenting utterances of an unfamiliar language into morphemes to facilitate word extraction from Chinese raw texts. It is found more effective than other criteria in supporting CRFs learning of character tagging for word segmentation (Zhao and Kit, 2007). The AV value of a substring $s$ is defined as

$$AV(s) = \min\{L_{av}(s), R_{av}(s)\},$$

where the left and right AV values $L_{av}(s)$ and $R_{av}(s)$ are defined, respectively, as the numbers of its distinct predecessor and successor characters.

In our work, AV values for word candidates are derived from an unlabeled corpus by substring counting, which can be efficiently carried out with the aid of the suffix array representation (Manber and Myers, 1993; Kit and Wilks, 1998). Heuristic rules are applied in Feng et al.’s work to remove insignificant substrings. We do not use any such rule.

Multiple feature templates are used to represent word candidates of various lengths identified by the AV criterion. For the sake of efficiency, all candidates longer than five characters are given up. To accommodate the word likelihood information, we need to extend the feature representation in (Zhao and Kit, 2007), where only the candidate substrings are used as features for word segmentation. Formally put, our new feature function for a word can-
Table 3: Training corpora for assistant learners

| Track  | CityU NER | MSRA NER |
|-------|-----------|----------|
| Ass. Seg. | CityU (Bakeoff-1 to 4) | MSRA (Bakeoff-2) |
| ANER-1 | CityU (Bakeoff-3) | CityU (Bakeoff-3) |
| ANER-2 | MSRA (Bakeoff-3) | CityU (Bakeoff-4) |

Table 4: NE lists from Chinese Wikipedia

| Category               | Number |
|------------------------|--------|
| Place name suffix      | 85     |
| Chinese place name     | 6,367  |
| Foreign place name     | 1,626  |
| Chinese family name    | 573    |
| Most common Chinese family name | 109 |
| Foreign name           | 2,591  |
| Chinese university     | 515    |

The first group includes three segmentation feature templates. One is character type feature template $T(C_{-1})T(C_0)T(C_1)$, where $T(C)$ is the type of character $C$. For this, five character types are defined, namely, number, foreign letter, punctuation, date and time, and others. The second group comes from the outputs of two assistant NE recognizers (ANERs), both trained with a corresponding 6-tag set and the same six n-gram feature templates. They share a similar feature representation as the assistant segmenter. Table 3 lists the training corpora for the assistant CRFs segmenter and the ANERs for various open NER tests.

The third group consists of feature templates generated from seven NE lists acquired from Chinese Wikipedia. The categories and numbers of these NE items are summarized in Table 4.

### 2.3 Features for Open NER

Three extra groups of feature template are used for the open NER beyond those for the closed.

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### 3 Evaluation Results

The performance of both word segmentation and NER is measured in terms of the F-measure $F = 2RP/(R + P)$, where $R$ and $P$ are the recall and precision of segmentation or NER.

We tested the techniques described above with the previous Bakeoffs’ data (Sproat and Emerson, 2003; Emerson, 2005; Levow, 2006). The evaluation results for the closed tests of word segmentation are reported in Table 5 and those for the NER on two corpora of Bakeoff-3 are in the upper part of Table 7. ‘+’/–AV’ indicates whether AV features are applied.

For Bakeoff-4, we participated in all five closed tracks of word segmentation, namely, CityU, CKIP, CTB, NCC, and SXU, and in all closed and open NER tracks of CityU and MSRA. The evaluation
results of word segmentation and NER for our system are presented in Tables 6 and 7, respectively.

For the purpose of comparison, the word segmentation performance of our system on Bakeoff-4 data using the 2- and 4-tag sets and the best corresponding n-gram feature templates as in (Tsai et al., 2006; Xue, 2003). The experimental results are given in Table 8, showing that the 6-tag set costs nearly twice as much time as the 4-tag set and about three times as the 2-tag set. Fortunately, its memory cost with the six n-gram feature templates remains very close to that of the 2- and 4-tag sets with the n-gram feature template sets from (Tsai et al., 2006; Xue, 2003).

4 Discussion

4.1 Tag Set and Computational Cost

Using more labels in CRFs learning is expected to bring in performance enhancement. Inevitably, however, it also leads to a huge rise of computational cost for model training. We conducted a series of experiments to study the computational cost of CRFs training with different tag sets using Bakeoff-3 data. This comparison reconfirms the conclusion in (Zhao et al., 2006b) about tag set selection for character tagging for word segmentation that the 6-tag set is more effective than others, each with its own best corresponding feature template set.

For our official submission to Bakeoff-4, we also used an ANER trained on the MSRA NER training corpus of Bakeoff-3. This makes our official evaluation results extremely high but trivial, for a part of this corpus is used as the MSRA NER test corpus for Bakeoff-4. Presented here are the results without using this ANER.

Open1 is the result of Open1 using no NE list feature.

CityU data sets in any other situation than the Bakeoff.

The templates for the 2-tag set, adopted from (Tsai et al., 2006), include C_{−2}, C_{−1}, Co, C1, C_{−3}C_{−1}, C_{−2}Co, C_{−2}C_{−1}, C_{−1}Co, C_{−1}C1 and C0C1. Those for the 4-tag set, adopted from (Xue, 2003) and (Low et al., 2005), include C_{−2}, C_{−1}, C0, C1, C2, C_{−2}C_{−1}, C_{−1}Co, C_{−1}C1, C0C1 and C1C2.
Table 9: Comparison of computational cost

| Tags | Templates | AS | CityU | CTB | MSRA |
|------|-----------|----|-------|-----|------|
|      |           | 2  |       |     |      |
|      |           | 4  |       |     |      |
|      |           | 6  |       |     |      |

Training time (Minutes)

| Tag | Tsai | Xue | Zhao |
|-----|------|-----|------|
| 2   | 112  | 206 | 402  |
| 4   | 52   | 79  | 146  |
| 6   | 16   | 28  | 47   |

Feature numbers ($\times 10^6$)

| Tag | Tsai | Xue | Zhao |
|-----|------|-----|------|
| 2   | 13.2 | 16.1| 15.6 |
| 4   | 7.3  | 9.0 | 8.8  |
| 6   | 3.1  | 3.9 | 3.8  |

Memory cost (Giga bytes)

| Tag | Tsai | Xue | Zhao |
|-----|------|-----|------|
| 2   | 5.4  | 6.6 | 6.4  |
| 4   | 2.4  | 2.8 | 2.7  |
| 6   | 0.9  | 1.1 | 1.0  |

| Tag | Tsai | Xue | Zhao |
|-----|------|-----|------|
| 2   | 1.8  | 2.2 | 2.1  |

4.2 Unsupervised Segmentation Features

Our evaluation results show that the unsupervised segmentation features bring in performance improvement on both word segmentation and NER for all tracks except CTB segmentation, as highlighted in Table 6. We are unable explain this yet, and can only attribute it to some unique text characteristics of the CTB segmented corpus. An unsupervised segmentation criterion provides a kind of global information over the whole text of a corpus (Zhao and Kit, 2007). Its effectiveness is certainly sensitive to text characteristics.

Quite a number of other unsupervised segmentation criteria are available for word discovery in unlabeled texts, e.g., boundary entropy (Tung and Lee, 1994; Chang and Su, 1997; Huang and Powers, 2003; Jin and Tanaka-Ishii, 2006) and description-length-gain (DLG) (Kit and Wilks, 1999). We found that among them AV could help the CRFs model to achieve a better performance than others, although the overall unsupervised segmentation by DLG was slightly better than that by AV. Combining any two of these criteria did not give any further performance improvement. This is why we have opted for AV for Bakeoff-4.

4.3 NE List Features for Open NER

We realize that the NE lists available to us are far from sufficient for coping with all NEs in Bakeoff-4. It is reasonable that using richer external NE lists gives a better NER performance in many cases (Zhang et al., 2006). Surprisingly, however, the NE list features used in our NER do not lead to any significant performance improvement, according to the evaluation results in Table 7. This is certainly another issue for our further inspection.

5 Conclusion

Without doubt our achievements in Bakeoff-4 owes not only to the careful selection of character tag set and feature templates for exerting the strength of CRFs learning but also to the effectiveness of our unsupervised segmentation approach. It is for the sake of simplicity that similar sets of character tags and feature templates are applied to two distinctive labeling tasks, word segmentation and NER. Relying on little preprocessing and postprocessing, our system simply follows the plain training and test routines of machine learning practice with the CRFs model and achieves the best or nearly the best results for all tracks of Bakeoff-4 in which we participated. Simple is beautiful, as Albert Einstein said, “Everything should be made as simple as possible, but not one bit simpler.” Our evaluation results also provide evidence that simple can be powerful too.

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