

# Enhancement of Feature Engineering for Conditional Random Field Learning in Chinese Word Segmentation Using Unlabeled Data

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## Abstract

This work proposes a unified view of several features based on frequent strings extracted from unlabeled data that improve the conditional random fields (CRF) model for Chinese word segmentation (CWS). These features include character-based  $n$ -gram (CNG), accessor variety based string (AVS) and its variation of left-right co-existed feature (LRAVS), term-contributed frequency (TCF), and term-contributed boundary (TCB) with a specific manner of boundary overlapping. For the experiments, the baseline is the *6-tag*, a state-of-the-art labeling scheme of CRF-based CWS, and the data set is acquired from the 2005 CWS Bakeoff of Special Interest Group on Chinese Language Processing (SIGHAN) of the Association for Computational Linguistics (ACL) and SIGHAN CWS Bakeoff 2010. The experimental results show that all of these features improve the performance of the baseline system in terms of *recall*, *precision*, and their harmonic average as  $F_1$  *measure score*, on both accuracy ( $F$ ) and out-of-vocabulary recognition ( $F_{OOV}$ ). In particular, this work presents compound features involving LRAVS/AVS and TCF/TCB that are competitive with other types of features for CRF-based CWS in terms of  $F$  and  $F_{OOV}$ , respectively.

**Keywords:** Conditional Random Fields, Word Segmentation, Accessor Variety, Term-contributed Frequency, Term-contributed Boundary.

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## 1. Introduction

### Background

Many intelligent text processing tasks, such as information retrieval, text-to-speech, and machine translation assume the ready availability of a tokenization into words, which is relatively straightforward in languages with word delimiters (*e.g.*, space) but is a little difficult for Asian languages, such as Chinese and Japanese.

Chinese word segmentation (CWS) has been an active area of research in computational linguistics for two decades. SIGHAN, the Special Interest Group for Chinese Language Processing of the Association for Computational Linguistics, has conducted five word segmentation bakeoffs (Emerson, 2005; Jin & Chen, 2007; Levow, 2006; Sproat & Emerson, 2003; Zhao & Liu, 2010). After years of intensive research, CWS has achieved high accuracy, but the issue of out-of-vocabulary (OOV) word recognition remains.

### The State of the Art of CWS

Traditional approaches for CWS adopt a dictionary and rules to segment unlabeled texts, such as the work of Ma and Chen (2003). In recent years, there has been a potent trend of using statistical machine learning models, especially the conditional random fields (CRF) (Lafferty *et al.*, 2001), which displays moderate performance for the sequential labeling problem and achieves competitive results with character-position based methods (Zhao *et al.*, 2010).

### Unsupervised Feature Selection for CWS

In this work, unsupervised feature selection for CWS is based on frequent strings that are extracted automatically from unlabeled corpora. For convenience, these features are referred to as *unsupervised features* in the rest of this paper. Unsupervised features are suitable for closed training evaluation where external resources or extra information is not allowed, especially for cross-domain tasks, such as SIGHAN CWS bakeoff 2010 (Zhao & Liu, 2010). Without proper knowledge, the closed training evaluation of word segmentation can be difficult with OOV words, where frequent strings collected from the test data may help. For incorporating unsupervised features into character-position based CRF for CWS, Zhao and Kit (2007) tried strings based on *accessor variety* (AV), which was developed by Feng *et al.* (2004), and based on *co-occurrence strings* (COS). Jiang *et al.* (2010) applied a feature similar to COS, called *term-contributed boundary* (TCB).

According to Zhao and Kit (2007), AV-based string (AVS) is one of the most effective unsupervised features for CWS by character-position based CRF. One motivation here is to seek deeper understanding of AVS's success. This work suspects that, since AVS is designed to keep overlapping substrings via the outer structure of a string while COS/TCB is usually selected via the inner structure of a string with its longest-first (*i.e.*, non-overlapping) nature before integration into CRF, combining overlapping and outer information with

non-overlapping and inner information may enhance CRF-based CWS. Hence, a series of experiments is conducted to examine this hypothesis.

The remainder of the article is organized as follows. Section 2 briefly introduces CRF. Common unsupervised features based on the concept of frequent strings are explained in Section 3. Section 4 discusses related works. Section 5 describes the design of the labeling scheme and feature templates, along with a framework that is able to encode those overlapping features in a unified way. Details about the experiment are reported in Section 6. Finally, the conclusion is presented in Section 7.

## 2. Conditional Random Fields

Conditional random fields (CRF) are undirected graphical models trained to maximize a conditional probability of random variables  $X$  and  $Y$ , and the concept is well established for the sequential labeling problem (Lafferty *et al.*, 2001). Given an input sequence (or observation sequence)  $X = x_1 \dots x_T$  and a label sequence  $Y = y_1 \dots y_T$ , a conditional probability of linear-chain CRF with parameters  $\Lambda = \lambda_1 \dots \lambda_n$  can be defined as:

$$P_{\lambda}(Y | X) = \frac{1}{Z_X} \exp \left( \sum_{t=1}^T \sum_k \lambda_k f_k(y_{t-1}, y_t, X, t) \right) \quad (1)$$

where  $Z_X$  is the normalization constant that makes probability of all label sequences sum to one;  $f_k(y_{t-1}, y_t, X, t)$  is a feature function which is often binary valued, but can be real valued; and  $\lambda_k$  is a learned weight associated with feature  $f_k$ .

The feature functions can measure any aspect of state transition  $y_{t-1} \rightarrow y_t$ , and the entire observation sequence  $X$  is centered at the current position  $t$ .

Given the model defined in (1), the most probable labeling sequence for an input sequence  $X$  is as follows:

$$y^* = \underset{Y}{\operatorname{argmax}} P_{\Lambda}(Y | X) \quad (2)$$

Equation (2) can be efficiently calculated by dynamic programming using the Viterbi algorithm. More details about the concepts of CRF and learning parameters could be found in Wallach (2004). For sequential labeling tasks, like CWS, a linear-chain CRF is currently one of the most popular choices.

### 3. Unified View via Frequent String

#### 3.1 Character-based $N$ -gram

The word boundary and the word frequency are the standard notions of frequency in corpus-based natural language processing. Word-based  $n$ -gram is an intuitive and effective solution of language modeling. For languages without explicit word boundaries, such as Chinese, character-based  $n$ -gram (CNG) is usually insufficient. For example, consider some sample texts in Chinese:

- “自然科學的重要性” (the importance of natural science), and
- “自然科學的研究是唯一的途徑” (natural science research is the only way),

where many character-based  $n$ -grams can be extracted, but some of them are out of context, such as “然科” (so; discipline) and “學的” (study; of), even when they are relatively frequent. For the purpose of interpreting overlapping behavior of frequent strings, however, character-based  $n$ -grams could still be useful for baseline analysis and implementation.

#### 3.2 Reduced $N$ -gram

The lack of correct information about the actual boundary and frequency of a multi-character/word expression’s occurrence has been researched in different languages. The distortion of phrase boundaries and frequencies was first observed in the Vodis Corpus, where the word-based bigram “RAIL ENQUIRIES” and word-based trigram “BRITISH RAIL ENQUIRIES” were estimated and reported by O’Boyle (1993) and Ha *et al.* (2005). Both of them occur 73 times, which is a large number for such a small corpus. “ENQUIRIES” follows “RAIL” with a very high probability when “BRITISH” precedes it. When “RAIL” is preceded by words other than “BRITISH,” however, “ENQUIRIES” does not occur, but words like “TICKET” or “JOURNEY” may. Thus, the bigram “RAIL ENQUIRIES” gives a misleading probability that “RAIL” is followed by “ENQUIRIES” irrespective of what precedes it.

A common solution to this problem is that, if some  $n$ -grams consist of others, then the frequencies of the shorter ones have to be discounted with the frequencies of the longer ones. For Chinese, Lin & Yu (2011) reported a similar problem and its corresponding solution in the sense of *reduced  $n$ -gram* of Chinese characters. By excluding  $n$ -grams with their numbers of appearance that fully depend on other superstrings, “然科” and “學的” from the sample texts in the previous sub-section are no longer candidates of the string. Zhao and Kit (2007) described the same concept briefly as *co-occurrence string* (COS). Sung *et al.* (2008) invented a specific data structure for suffix array algorithm to calculate exact boundaries of phrase-alike string and their frequencies called *term-contributed boundaries* (TCB) and *term-contributed frequencies* (TCF), respectively, to analogize similarities and differences

with the term frequencies. Since this work uses the program of TCB and TCF (namely YASA, yet another suffix array) for experiments, the family of *reduced n-gram* will be referred as TCB hereafter for convenience.

### 3.3 Uncertainty of Succeeding Character

Feng *et al.* (2004) proposed *accessor variety* (AV) to measure the likelihood a substring is a Chinese word. Another measurement, called *boundary entropy* or *branching entropy* (BE), exists in some works (Chang & Su, 1997; Cohen *et al.*, 2007; Huang & Powers, 2003; Tanaka-Ishii, 2005; Tung & Lee, 1994). The basic idea behind those measurements is closely related to one particular perspective of *n-gram* and information theory, *cross-entropy* or *perplexity*. According to Zhao and Kit (2007), AV and BE both assume that the border of a potential Chinese word is located where the uncertainty of successive character increases. They believe that AV and BE are the discrete and continuous version, respectively, of a fundamental work of Harris (1970), and they decided to adopt AVS as an unsupervised feature for CRF-based CWS. This work follows their choice in hope of producing a comparable study. AV of a string  $s$  is defined as:

$$AV(s) = \min \{L_{av}(s), R_{av}(s)\} \tag{3}$$

In (3),  $L_{av}(s)$  and  $R_{av}(s)$  are defined as the number of distinct preceding and succeeding characters, respectively, except, when the adjacent character is absent because of a sentence boundary, the pseudo-character of sentence beginning or sentence ending will be accumulated. Feng *et al.* (2004) also developed more heuristic rules to remove strings that contain known words or adhesive characters. For the strict meaning of unsupervised feature and for the sake of simplicity, these additional rules are dropped in this study.

Since a recent work of Sun and Xu (2011) used both  $L_{av}(s)$  and  $R_{av}(s)$  as features of CRF, this work will apply a similar approach, which is denoted as LRAVS, to make a thorough comparison.

## 4. Other Related Works

### 4.1 Frequent String Extraction Algorithm

Besides previous works of TCB and TCF extraction (Sung *et al.*, 2008), Chinese frequent strings (Lin & Yu, 2001), and *reduced n-gram* (Ha *et al.*, 2005), which have already been mentioned, the article about a linear algorithm for *frequency of substring with reduction* (Lü & Zhang, 2005) also falls into this category. Most of these projects focused on the computational complexity of algorithms. Broader algorithms for frequent string extraction are suffix array (Manber & Myers, 1993) and PAT-tree (Chien, 1997).

## 4.2 Unsupervised Word Segmentation Method

Zhao and Kit have explored several unsupervised strategies with their unified goodness measurement of logarithm ranking (Zhao & Kit, 2007), including *frequency of substring with reduction* (Lü & Zhang, 2005), *description length gain* (Kit & Wilks, 1999), *accessor variety* (Feng et al., 2004), and *boundary/branching entropy* (Chang & Su, 1997; Cohen et al., 2007; Huang & Powers, 2003; Tanaka-Ishii, 2005; Tung & Lee, 1994). Unlike the technique described in this paper for incorporating unsupervised features into supervised CRF learning, those methods usually filter out word-alike candidates using their own scoring mechanism directly as unsupervised word segmentation.

## 4.3 Overlapping Ambiguity Resolution

Subword based tagging of Zhang et al. (2006) utilizes confidence measurement. Other overlapping ambiguity resolution approaches are Naïve Bayesian classifiers (Li et al., 2003), mutual information, difference of *t*-test (Sun et al., 1997), and sorted table look-up (Qiao et al., 2008). These works concentrate on overlapping of words according to some (supervised) standard, rather than overlapping of substrings from unsupervised selection.

## 5. CRF Labeling Scheme

### 5.1 Character Position Based Labels

In this study, the CRF label set for CWS prediction adopts the *6-tag* approach of Zhao et al. (2010), which achieves very competitive performance and is one of the most fine-grained character position based labeling schemes. According to Zhao et al. (2010), since less than 1% of Chinese words are longer than five characters in most corpora from SIGHAN CWS bakeoffs 2003, 2005, 2006, and 2008, the coverage of a *6-tag* approach should be sufficient. This configuration of CRF without additional unsupervised features is also the control group of the experiment. Table 1 provides a sample of labeled training data.

**Table 1. Sample of the 6-tag labels.**

Character	Label
反	<i>B</i>
而	<i>E</i>
會	<i>S</i>
欲	<i>B</i>
速	<i>C</i>
則	<i>D</i>
不	<i>I</i>
達	<i>E</i>

For the sample text “反而 (contrarily) / 會 (make) / 欲速則不達 (more haste, less speed)” (on the contrary, haste makes waste), the tag *B* stands for the beginning character of a word, while *C* and *D* represent the second character and the third character of a word, respectively. The ending character of a word is tagged as *E*. Once a word consists of more than four characters, the tag for all of the middle characters between *D* and *E* is *I*. Finally, the tag *S* is reserved specifically for single-character words.

## 5.2 Feature Templates

Feature instances are generated from templates based on the work of Ratnaparkhi (1996). Table 2 explains their abilities.  $C_{-1}$ ,  $C_0$ , and  $C_1$  stand for the input tokens individually bound to the prediction label at the current position. For example, in Table 1, if the current position is at the label *I*, features generated by  $C_{-1}$ ,  $C_0$ , and  $C_1$  are “則,” “不,” and “達,” respectively. Meanwhile, for window size 2,  $C_{-1}C_0$ ,  $C_0C_1$ , and  $C_{-1}C_1$  expands features of the label *I* to “則不,” “不達,” and “則達,” respectively. One may argue that the feature template should expand to five tokens to cover the whole range of the 6-tag approach; however, according to Zhao *et al.* (2010), the context window size in three tokens is effective to catch parameters of the 6-tag approach for most strings that do not exceed five characters. Our pilot test for this case also showed that context window size in two tokens would be sufficient without a significant decrease in performance (Jiang *et al.*, 2010).

Unsupervised features that will be introduced in the next subsection are generated by the same template, except the binding target moves column by column, as listed in tables of the next subsection.

**Table 2. Feature template**

Feature	Function
$C_{-1}, C_0, C_1$	Previous, current, or next token
$C_{-1}C_0$	Previous and current tokens
$C_0C_1$	Current and next tokens
$C_{-1}C_1$	Previous and next tokens

## 5.3 Unified Feature Representation of CNG/AVS/TCF/TCB

To our knowledge, TCF, which is designed to fulfill a symmetrical comparison between the properties of inner pattern (CNG, TCF, or COS/TCB) vs. outer pattern (AVS) and between overlapping string (CNG, AVS, or TCF) vs. maximally matched string (COS/TCB), has not been evaluated in any previous work. In short, while the original version of COS/TCB selects the maximally matched string (*i.e.*, *non-overlapping* string) as the feature (Feng *et al.*, 2004; Jiang *et al.*, 2010; Zhao & Kit, 2007), TCF collects features of *reduced n-gram* from

every character position with additional rank of likelihood converted from *term-contributed frequency*, as its name implies. To compare different types of overlapping strings as unsupervised features systematically, this work extends the previous work of Zhao and Kit (2007) into a unified representation of features. The representation accommodates both character position of a string and the string’s likelihood ranked in the logarithm. Formally, the ranking function for a string  $s$  with a score  $x$  counted by CNG, AVS, or TCF is defined as:

$$f(s) = r, \text{ if } 2^r \leq x < 2^{r+1} \quad (4)$$

The logarithm ranking mechanism in (4) is inspired by Zipf’s law with the intention to alleviate the potential data sparseness problem of infrequent strings. The rank  $r$  and the corresponding character positions of a string then are concatenated as feature tokens. To give the reader a clearer picture about what feature tokens look like, a sample representation, which is denoted in regex as “[0-9]+[B|C|D|I|E|S]” for rank and character position, of CNG, AVS, or TCF is demonstrated and explained by Figure 1 and Table 3.

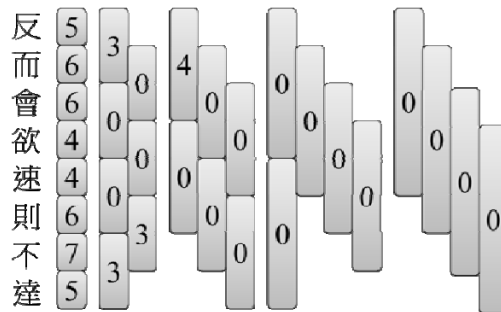


Figure 1. Example of overlapping strings with ranks.

Table 3. Sample of the unified feature representation for overlapping strings.

Input	Unsupervised Feature					Label
	1 char	2 char	3 char	4 char	5 char	
反	5S	3B	4B	0B	0B	B
而	6S	3E	4C	0C	0C	E
會	6S	0E	4E	0D	0D	S
欲	4S	0E	0E	0E	0I	B
速	4S	0E	0E	0E	0E	C
則	6S	3B	0E	0E	0E	D
不	7S	3E	0E	0E	0E	I
達	5S	3E	0E	0E	0E	E



For example, judging by strings with two characters, one of the strings “反而” gets rank  $r = 3$ ; therefore, the column of two-character feature tokens has “反” denoted as  $3B$  and “而” denoted as  $3E$ . If another two-character string “而會” competes with “反而” at the position of “而” with a lower rank  $r = 0$ , then  $3E$  is selected for feature representation of the token at a certain position.

Note that, when the string “則不” conflicts with the string “不達” at the position of “不” with the same rank  $r = 3$ , the corresponding character position with rank of the leftmost string, which is  $3E$  in this case, is applied arbitrarily.

Although those are indeed common situations of overlapping strings, this work simply implements the above rules by Zhao and Kit (2007) for the sake of compatibility. In fact, pilot tests have been done with a more complicated representation, like  $3E-OB$  for “而” and  $3E-3B$  for “不,” to keep the overlapping information within each column, but the test result shows no significant differences in terms of accuracy and OOV recognition. Since the statistics of the pilot tests could be redundant, they are omitted in this paper.

To make an informative comparison, this work also applies the original version of *non-overlapping* COS/TCB features that is without ranks and is selected by the forward maximum matching algorithm (Feng *et al.*, 2004; Jiang *et al.*, 2010; Zhao & Kit, 2007). Table 4 illustrates a sample representation of features in this case. Notably, there are several features encoded as  $-1$  individually to represent that the desired string is unseen. For the *non-overlapping* siblings of the *reduced n-grams* family, such as COS/TCB, either the string is always occupied by other superstrings or it simply does not appear more than once.

**Table 4. Sample of the unified feature representation for Non-overlapping COS/TCB strings.**

Input	Original COS/TCB Feature	Label
反	$B$	$B$
而	$C$	$E$
會	$E$	$S$
欲	$-1$	$B$
速	$-1$	$C$
則	$-1$	$D$
不	$-1$	$I$
達	$-1$	$E$

The length of a string is limited to five characters for the sake of efficiency and consistency with the *6-tag* approach.

## 6. Experiments

CRF++ 0.54 (<http://crfpp.sourceforge.net/>) employs L-BFGS optimization and the tunable hyper-parameter (CRF++ training function argument “-c”), *i.e.*, the Gaussian prior, set to 100 throughout the whole experiment.

### 6.1 Data Set

The corpora used for the experiment are from the SIGHAN CWS bakeoff 2005 (Emerson, 2005) and SIGHAN CWS bakeoff 2010 (Zhao & Liu, 2010). SIGHAN 2005 comes with four different standards, including Academia Sinica (AS), City University of Hong Kong (CityU), Microsoft Research (MSR), and Peking University (PKU). SIGHAN 2010 provides a Traditional Chinese corpus and a Simplified Chinese corpus. Each corpus has training/test sets of four domains, including literature, computers, medicine, and finance, that are denoted as domains A, B, C, and D, respectively. For comparison, statistics on most corpora of SIGHAN 2003, 2006, and 2008 that have been obtained are listed in the appendix.

### 6.2 Unsupervised Feature Selection

Unsupervised features are collected according to pairs of corresponding training/test corpora. CNG and AVS are arranged with the help from SRILM (Stolcke, 2002). TCB strings and their ranks converted from TCF are calculated by YASA (Sung *et al.*, 2008). To distinguish the ranked and overlapping features of TCB/TCF from those of the original version of non-overlapping COS/TCB-based features, the former are denoted as TCF to indicate the score source of frequency for ranking, and the abbreviation of the later remains as TCB.

### 6.3 Evaluation Metrics

The evaluation metrics of CWS task are adopted from SIGHAN bakeoffs, including test *precision* ( $P$ ), test *recall* ( $R$ ), and their harmonic average  $F_1$  *measure score* ( $F$ ), as (5), (6), and (7), respectively. For performance of OOV, formulae that are similar to P/R/F are employed. To estimate the differences of performance between configurations of CWS experiments, this work uses the confidence level, which has been applied since SIGHAN CWS bakeoff 2003 (Sproat & Emerson, 2003). The confidence level assumes that the *recall* (or *precision*)  $X$  of *accuracy* (or *OOV recognition*) represents the probability that a word (or OOV word) will be identified from  $N$  words in total and that a binomial distribution is appropriate for the experiment. Confidence levels of  $P$ ,  $R$ ,  $P_{OOV}$ , and  $R_{OOV}$  appear in Tables 5-10 under the columns  $C_P$ ,  $C_R$ ,  $C_{P_{OOV}}$ , and  $C_{R_{OOV}}$ , respectively, and they are calculated at the 95% confidence interval with the formula  $\pm 2 \sqrt{([X(1-X)] / N)}$ . Two configurations of CWS experiments then are considered to be statistically different at a 95% confidence level if **one of** their  $C_P$ ,  $C_R$ ,

$C_{Poov}$ , or  $C_{Roov}$  is different.

$$P = \frac{\text{the number of words that are correctly segmented}}{\text{the number of words that are segmented}} \times 100\% \quad (5)$$

$$R = \frac{\text{the number of words that are correctly segmented}}{\text{the number of words in the gold standard}} \times 100\% \quad (6)$$

$$F = \frac{2 \times P \times R}{P + R} \quad (7)$$

## 6.4 Experimental Results

The most significant type of error is unintentionally segmented alphanumeric sequences, such as English words or factoids in Arabic numerals. Rather than developing another set of feature templates for non-Chinese characters that may violate the rules of closed training evaluation, post-processing, which is mentioned in the official report of SIGHAN CWS bakeoff 2005 (Emerson, 2005), has been applied to remove spaces between non-Chinese characters in the gold standard data of the AS corpus manually, since there are no urgent expectations of correct segmentation on non-Chinese text. In SIGHAN 2005 and 2006, however, some participants used character types, such as digits, date/time specific Chinese characters, English letters, punctuation, and others (Chinese characters) as extra features, which triggered a debate of closed training criteria (Zhao *et al.*, 2010). Consequently, SIGHAN 2010 decided to allow four types of characters, distinguished as Chinese characters, English letters, digits, and punctuation. This work provides preliminary tests on non-Chinese patterns extracted from SIGHAN 2010 unlabeled training corpora A and B, extra features of character types (in character based trigram,  $T_{-1}T_0T_1$ , where  $T$  can be E, D, P, or C for alphabets, digits, punctuations, or Chinese characters, respectively), and their combinations to verify the performance impact of these special treatments, as shown in Table 5 –Table 8. On the one hand, the statistics indicate that the character types perform well and stably on most of the corpora. On the other hand, the features, such as AVS and TCF, may still need help from non-Chinese patterns of unlabeled training corpora A and B. As a matter of fact, our other preliminary test suggests that SIGHAN 2010 test corpora contain a lot of OOV and inconsistent segments from non-Chinese text (for example, inconsistency of usage on full-width or half-width non-Chinese characters, some English words and factoids being segmented but some of them not, *etc.*), which only can be memorized from the non-Chinese patterns. Consequently, the experimental results of SIGHAN 2010 corpora involve non-Chinese treatment based on the combination of the extra character type features and the non-Chinese patterns, but the experimental results of SIGHAN 2005 corpora do not.

**Table 5. Non-Chinese treatment on SIGHAN'10 simplified Chinese corpora.**

Domain	Feature	$P$	$C_P$	$R$	$C_R$	$F$
A	Original 6-tag	92.16 ±0.002869		91.63 ±0.002956		91.89
	+(Non-Chinese Pattern)	92.32 ±0.002842		91.27 ±0.003013		91.79
	+(Character Type)	92.70 ±0.002777		<b>92.33</b> ±0.002840		92.51
	+(Non-Chinese Pattern, Character Type)	<b>92.71</b> ±0.002775		<b>92.33</b> ±0.002841		<b>92.52</b>
B	Original 6-tag	77.44 ±0.004558		86.72 ±0.003701		81.82
	+(Non-Chinese Pattern)	89.85 ±0.003294		83.62 ±0.004036		86.62
	+(Character Type)	91.68 ±0.003013		<b>93.58</b> ±0.002673		<b>92.62</b>
	+(Non-Chinese Pattern, Character Type)	<b>92.93</b> ±0.002795		91.19 ±0.003091		92.05
C	Original 6-tag	89.61 ±0.003466		90.64 ±0.003309		90.12
	+(Non-Chinese Pattern)	90.87 ±0.003272		89.77 ±0.003443		90.32
	+(Character Type)	91.11 ±0.003233		<b>92.02</b> ±0.003078		<b>91.56</b>
	+(Non-Chinese Pattern, Character Type)	<b>91.54</b> ±0.003161		91.29 ±0.003203		91.42
D	Original 6-tag	89.82 ±0.003367		91.24 ±0.003148		90.52
	+(Non-Chinese Pattern)	93.48 ±0.002749		91.06 ±0.003176		92.25
	+(Character Type)	92.35 ±0.002960		<b>93.99</b> ±0.002646		93.16
	+(Non-Chinese Pattern, Character Type)	<b>93.97</b> ±0.002650		93.61 ±0.002723		<b>93.79</b>

**Table 6. Non-Chinese treatment OOV on SIGHAN'10 simplified Chinese corpora.**

Domain	Feature	$R_{OOV}$	$C_{R_{OOV}}$	$P_{OOV}$	$C_{P_{OOV}}$	$F_{OOV}$
A	Original 6-tag	55.52 ±0.019647		52.00 ±0.019752		53.71
	+(Non-Chinese Pattern)	53.71 ±0.019714		52.34 ±0.019746		53.01
	+(Character Type)	<b>62.42</b> ±0.019149		58.86 ±0.019455		<b>60.59</b>
	+(Non-Chinese Pattern, Character Type)	61.77 ±0.019212		<b>59.24</b> ±0.019427		60.48
B	Original 6-tag	36.06 ±0.014105		20.49 ±0.011855		26.13
	+(Non-Chinese Pattern)	41.38 ±0.014467		52.17 ±0.014673		46.16
	+(Character Type)	<b>76.27</b> ±0.012496		71.40 ±0.013274		<b>73.76</b>
	+(Non-Chinese Pattern, Character Type)	67.49 ±0.013759		<b>76.28</b> ±0.012495		71.62
C	Original 6-tag	59.69 ±0.016736		49.40 ±0.017059		54.06
	+(Non-Chinese Pattern)	58.80 ±0.016793		54.76 ±0.016982		56.71
	+(Character Type)	<b>68.14</b> ±0.015898		59.69 ±0.016736		<b>63.64</b>
	+(Non-Chinese Pattern, Character Type)	66.03 ±0.016159		<b>60.54</b> ±0.016677		63.17
D	Original 6-tag	48.79 ±0.018869		35.90 ±0.018109		41.36
	+(Non-Chinese Pattern)	53.98 ±0.018815		55.56 ±0.018757		54.76
	+(Character Type)	<b>68.81</b> ±0.017487		57.73 ±0.018648		62.79
	+(Non-Chinese Pattern, Character Type)	68.64 ±0.017514		<b>66.30</b> ±0.017844		<b>67.45</b>

**Table 7. Non-Chinese treatment on SIGHAN'10 traditional Chinese corpora.**

Domain	Feature	$P$	$C_P$	$R$	$C_R$	$F$
A	Original 6-tag	90.63	$\pm 0.003065$	88.72	$\pm 0.003326$	89.66
	+(Non-Chinese Pattern)	90.73	$\pm 0.003049$	88.58	$\pm 0.003344$	89.64
	+(Character Type)	<b>92.95</b>	$\pm 0.002691$	92.16	$\pm 0.002826$	92.55
	+(Non-Chinese Pattern, Character Type)	92.94	$\pm 0.002693$	<b>92.20</b>	$\pm 0.002819$	<b>92.57</b>
B	Original 6-tag	94.52	$\pm 0.002248$	93.28	$\pm 0.002474$	93.90
	+(Non-Chinese Pattern)	94.12	$\pm 0.002325$	91.32	$\pm 0.002781$	92.70
	+(Character Type)	<b>96.15</b>	$\pm 0.001902$	<b>95.53</b>	$\pm 0.002042$	<b>95.84</b>
	+(Non-Chinese Pattern, Character Type)	95.63	$\pm 0.002019$	94.22	$\pm 0.002307$	94.92
C	Original 6-tag	92.95	$\pm 0.002479$	91.42	$\pm 0.002712$	92.18
	+(Non-Chinese Pattern)	92.69	$\pm 0.002521$	90.77	$\pm 0.002803$	91.72
	+(Character Type)	<b>94.72</b>	$\pm 0.002167$	<b>93.95</b>	$\pm 0.002308$	<b>94.33</b>
	+(Non-Chinese Pattern, Character Type)	94.62	$\pm 0.002186$	93.77	$\pm 0.002341$	94.19
D	Original 6-tag	94.06	$\pm 0.002199$	93.39	$\pm 0.002312$	93.72
	+(Non-Chinese Pattern)	93.85	$\pm 0.002236$	92.73	$\pm 0.002416$	93.28
	+(Character Type)	<b>95.50</b>	$\pm 0.001928$	<b>95.51</b>	$\pm 0.001926$	<b>95.51</b>
	+(Non-Chinese Pattern, Character Type)	95.48	$\pm 0.001933$	95.34	$\pm 0.001961$	95.41

**Table 8. Non-Chinese treatment OOV on SIGHAN'10 traditional Chinese corpora.**

Domain	Feature	$R_{OOV}$	$C_{Roov}$	$P_{OOV}$	$C_{Poov}$	$F_{OOV}$
A	Original 6-tag	72.50	$\pm 0.015297$	57.20	$\pm 0.016951$	63.95
	+(Non-Chinese Pattern)	71.62	$\pm 0.015446$	57.04	$\pm 0.016959$	63.50
	+(Character Type)	75.45	$\pm 0.014745$	67.72	$\pm 0.016017$	71.38
	+(Non-Chinese Pattern, Character Type)	<b>75.60</b>	$\pm 0.014715$	<b>68.44</b>	$\pm 0.015923$	<b>71.84</b>
B	Original 6-tag	76.46	$\pm 0.014455$	71.38	$\pm 0.015399$	73.83
	+(Non-Chinese Pattern)	68.49	$\pm 0.015828$	65.20	$\pm 0.016229$	66.80
	+(Character Type)	<b>80.44</b>	$\pm 0.013514$	<b>81.81</b>	$\pm 0.013143$	<b>81.12</b>
	+(Non-Chinese Pattern, Character Type)	74.07	$\pm 0.014931$	76.40	$\pm 0.014466$	75.22
C	Original 6-tag	73.48	$\pm 0.015336$	58.33	$\pm 0.017128$	65.03
	+(Non-Chinese Pattern)	69.69	$\pm 0.015968$	56.31	$\pm 0.017232$	62.29
	+(Character Type)	<b>76.91</b>	$\pm 0.014641$	<b>68.87</b>	$\pm 0.016087$	<b>72.67</b>
	+(Non-Chinese Pattern, Character Type)	75.97	$\pm 0.014843$	68.18	$\pm 0.016181$	71.87
D	Original 6-tag	78.54	$\pm 0.013963$	66.01	$\pm 0.016110$	71.73
	+(Non-Chinese Pattern)	75.53	$\pm 0.014622$	63.69	$\pm 0.016355$	69.11
	+(Character Type)	<b>81.58</b>	$\pm 0.013184$	<b>76.99</b>	$\pm 0.014315$	<b>79.22</b>
	+(Non-Chinese Pattern, Character Type)	80.64	$\pm 0.013438$	76.22	$\pm 0.014481$	78.37

This empirical decision implies that CWS benchmarking corpus should be prepared more carefully to avoid unpredictable side effects from non-Chinese text. Note that the treatment does not use unlabeled training corpora A and B separately. Further discussions are mainly based on this treatment, hopefully without loss of generality and of interest for comparative studies. Numbers in bold face and italic style indicate the best and the second best results of a certain evaluation metric, respectively, except for the topline and the best record from each year of SIGHAN bakeoffs. Configurations with the same values of confidence level on  $P$  or  $R$  are underlined, but only records that have the same confidence level on **both**  $P$  and  $R$  should be considered as statistically insignificant, and this phenomenon did not occur in our experiment results.

Unlike the previous work, which showed a relatively clearer trend of feature selection (Jiang *et al.*, 2011), CWS performance may vary between different CWS standards and domains in this study. Considering either the best or second best records in terms of  $F$ , feature combinations consisting of LRAVS or AVS usually outperform, except on MSR of SIGHAN 2005 corpora. Nevertheless, in terms of  $F_{OOV}$ , feature combinations consisting of TCF or TCB consistently increase in performance on every corpus. Similar situations also can be recognized from the experiments on some of the SIGHAN 2003, 2006, and 2008 corpora; please refer to the appendix for details. This complicated phenomenon indicates that, since CWS studies usually struggle with incremental and small improvements, different CWS standards and/or domains can make comparative research difficult and cause experimental results of related works to be incompatible. For equipping supervised CWS with unsupervised feature selection from unlabeled data, the experimental results of this work suggests that using LRAVS+TCF with more careful non-Chinese text treatments and CRF parameter tuning (*e.g.*, more cross-validations to find a specific hyper-parameter of Gaussian prior) would be a very good choice. Nevertheless, it is still worth noting that the best performance of this work in terms of  $F$  is found on the best official records on traditional Chinese domain B (Computer) of SIGHAN 2010 corpora and all of the SIGHAN 2005 corpora except the PKU corpus. This is especially true when this work does not apply any special treatment of character type and non-Chinese text that many other related works do on SIGHAN 2005 corpora. Note that “Our Baseline/Topline” in the following tables indicates where official baseline/topline suffered from official release script for maximum matching malfunctions on data in UTF-8 encoding and/or some uncertain incompatibilities between obtained corpora and official ones that caused inconsistent statistics during experiment reproductions.

**Table 9. Performance comparison of accuracy on SIGHAN 2005 AS corpus.**

Configuration	$P$	$C_P$	$R$	$C_R$	$F$
6-tag	94.50	±0.001308	95.74	±0.001159	95.12
CNG	95.12	±0.001236	95.53	±0.001186	95.32
AVS	95.14	±0.001234	95.86	±0.001143	95.50
TCB	94.48	±0.001311	95.73	±0.001160	95.10
TCF	94.86	±0.001267	95.92	±0.001135	95.39
AVS+TCB	95.21	±0.001226	95.96	±0.001130	95.58
AVS+TCF	<b>95.27</b>	±0.001218	<b>96.02</b>	±0.001121	<b>95.65</b>
LRAVS	94.88	±0.001265	95.91	±0.001136	95.39
LRAVS+TCB	95.03	±0.001247	<b>96.02</b>	±0.001122	95.52
LRAVS+TCF	95.00	±0.001251	96.01	±0.001124	95.50
<hr style="border-top: 1px dashed black;"/>					
2005 Best	95.10	±0.001230	95.20	±0.001220	95.20
2005 Baseline	85.70	±0.002000	90.90	±0.001643	88.20
Our Baseline	86.40	±0.001967	91.15	±0.001629	88.71
2005 Topline	98.50	±0.000694	97.90	±0.000819	98.20
Our Topline	98.64	±0.000665	97.97	±0.000809	98.30

**Table 10. Performance comparison of OOV on SIGHAN 2005 AS corpus.**

Configuration	$R_{Oov}$	$C_{R_{Oov}}$	$P_{Oov}$	$C_{P_{Oov}}$	$F_{Oov}$
6-tag	66.09	±0.012356	61.85	±0.012678	63.90
CNG	67.39	±0.012235	66.81	±0.01229	67.10
AVS	68.93	±0.012078	70.73	±0.011875	69.82
TCB	66.16	±0.012349	64.02	±0.012668	64.02
TCF	<b>70.27</b>	±0.011929	63.89	±0.012536	66.93
AVS+TCB	69.31	±0.012037	<b>71.49</b>	±0.011783	<b>70.38</b>
AVS+TCF	69.59	±0.012006	70.94	±0.011850	70.26
LRAVS	66.31	±0.012336	67.07	±0.012266	66.69
LRAVS+TCB	67.33	±0.012241	67.91	±0.012184	67.62
LRAVS+TCF	69.82	±0.011981	66.15	±0.012350	67.94
<hr style="border-top: 1px dashed black;"/>					
2005 Best	69.60	±0.012005	N/A	N/A	N/A
2005 Baseline	0.40	±0.001647	N/A	N/A	N/A
Our Baseline	1.41	±0.003080	3.08	±0.004512	1.94
2005 Topline	99.60	±0.001647	N/A	N/A	N/A
Our Topline	99.59	±0.001677	95.48	±0.005420	97.49

**Table 11. Performance comparison of accuracy on SIGHAN 2005 CityU corpus.**

Configuration	$P$	$C_P$	$R$	$C_R$	$F$
6-tag	94.82	$\pm 0.002207$	94.64	$\pm 0.002245$	94.73
CNG	<b>95.55</b>	$\pm 0.002055$	94.39	$\pm 0.002292$	94.97
AVS	95.27	$\pm 0.002115$	94.93	$\pm 0.002185$	95.10
TCB	95.21	$\pm 0.002129$	94.93	$\pm 0.002186$	95.07
TCF	95.30	$\pm 0.002107$	94.96	$\pm 0.002180$	95.13
AVS+TCB	95.34	$\pm 0.002100$	95.13	$\pm 0.002145$	95.23
AVS+TCF	95.39	$\pm 0.002088$	95.15	$\pm 0.002140$	95.27
LRAVS	95.35	$\pm 0.002099$	95.08	$\pm 0.002155$	95.21
LRAVS+TCB	95.45	$\pm 0.002077$	<b>95.21</b>	$\pm 0.002127$	<b>95.33</b>
LRAVS+TCF	95.41	$\pm 0.002085$	95.20	$\pm 0.002130$	95.30
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2005 Best	94.60	$\pm 0.002230$	94.10	$\pm 0.002330$	94.30
2005 Baseline	79.00	$\pm 0.004026$	88.20	$\pm 0.003189$	83.30
Our Baseline	83.84	$\pm 0.003667$	90.81	$\pm 0.002877$	87.19
2005 Topline	99.10	$\pm 0.000934$	98.80	$\pm 0.001076$	98.20
Our Topline	99.24	$\pm 0.000867$	98.90	$\pm 0.001040$	99.07

**Table 12. Performance comparison of OOV on SIGHAN 2005 CityU corpus.**

Configuration	$R_{Oov}$	$C_{R_{Oov}}$	$P_{Oov}$	$C_{P_{Oov}}$	$F_{Oov}$
6-tag	69.15	$\pm 0.016141$	65.54	$\pm 0.016609$	67.30
CNG	69.68	$\pm 0.016063$	69.41	$\pm 0.016104$	69.55
AVS	70.48	$\pm 0.015942$	71.90	$\pm 0.015709$	71.18
TCB	71.83	$\pm 0.015721$	70.12	$\pm 0.016236$	70.12
TCF	<b>72.39</b>	$\pm 0.015624$	68.76	$\pm 0.016198$	70.53
AVS+TCB	71.14	$\pm 0.015836$	72.70	$\pm 0.01557$	71.91
AVS+TCF	70.97	$\pm 0.015863$	72.77	$\pm 0.015556$	71.86
LRAVS	69.78	$\pm 0.016048$	72.09	$\pm 0.015676$	70.92
LRAVS+TCB	70.57	$\pm 0.015926$	73.06	$\pm 0.015505$	71.80
LRAVS+TCF	71.17	$\pm 0.015831$	<b>73.22</b>	$\pm 0.015475$	<b>72.18</b>
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2005 Best	69.80	$\pm 0.016046$	N/A	N/A	N/A
2005 Baseline	0.00	$\pm 0.000000$	N/A	N/A	N/A
Our Baseline	16.22	$\pm 0.012882$	33.91	$\pm 0.016544$	21.94
2005 Topline	99.70	$\pm 0.001911$	N/A	N/A	N/A
Our Topline	99.74	$\pm 0.001794$	98.82	$\pm 0.003771$	99.28



**Table 13. Performance comparison of accuracy on SIGHAN 2005 MSR corpus.**

Configuration	$P$	$C_P$	$R$	$C_R$	$F$
6-tag	97.29	$\pm 0.000998$	97.03	$\pm 0.001042$	97.16
CNG	97.02	$\pm 0.001045$	96.87	$\pm 0.001069$	96.95
AVS	97.24	$\pm 0.001007$	96.91	<u><math>\pm 0.001063</math></u>	97.07
TCB	<b>97.32</b>	$\pm 0.000993$	<b>97.09</b>	$\pm 0.001033$	<b>97.20</b>
TCF	97.02	$\pm 0.001044$	96.70	$\pm 0.001097$	96.86
AVS+TCB	97.16	$\pm 0.001020$	96.91	<u><math>\pm 0.001063</math></u>	97.04
AVS+TCF	97.25	$\pm 0.001005$	97.00	$\pm 0.001049$	97.12
LRAVS	97.20	$\pm 0.001014$	97.01	$\pm 0.001046$	97.10
LRAVS+TCB	97.21	$\pm 0.001012$	97.05	$\pm 0.001040$	97.13
LRAVS+TCF	97.29	$\pm 0.000997$	96.43	$\pm 0.001139$	96.86
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2005 Best	96.60	$\pm 0.001110$	96.20	$\pm 0.001170$	96.40
2005 Baseline	91.20	$\pm 0.001733$	95.50	$\pm 0.001268$	93.30
Our Baseline	91.74	$\pm 0.001691$	95.69	$\pm 0.001247$	93.67
2005 Topline	99.20	$\pm 0.000545$	99.10	$\pm 0.000578$	99.10
Our Topline	99.31	$\pm 0.000510$	99.10	$\pm 0.000580$	99.20

**Table 14. Performance comparison of OOV on SIGHAN 2005 MSR corpus.**

Configuration	$R_{Oov}$	$C_{R_{Oov}}$	$P_{Oov}$	$C_{P_{Oov}}$	$F_{Oov}$
6-tag	72.22	$\pm 0.015108$	60.52	$\pm 0.016487$	65.85
CNG	71.37	$\pm 0.015247$	62.08	$\pm 0.016365$	66.40
AVS	69.88	$\pm 0.015474$	61.96	$\pm 0.016375$	65.68
TCB	72.96	$\pm 0.014982$	<b>66.73</b>	$\pm 0.016414$	66.73
TCF	<b>73.81</b>	<u><math>\pm 0.014830</math></u>	58.68	$\pm 0.016608$	65.38
AVS+TCB	70.41	$\pm 0.015395$	62.11	$\pm 0.016362$	66.00
AVS+TCF	71.12	$\pm 0.015286$	62.54	$\pm 0.016325$	66.56
LRAVS	70.91	$\pm 0.015319$	63.02	$\pm 0.016283$	66.73
LRAVS+TCB	71.05	$\pm 0.015297$	63.49	$\pm 0.016239$	<b>67.06</b>
LRAVS+TCF	<b>73.81</b>	<u><math>\pm 0.014830</math></u>	59.28	$\pm 0.016571$	65.75
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2005 Best	71.70	$\pm 0.015194$	N/A	N/A	N/A
2005 Baseline	0.00	$\pm 0.000000$	N/A	N/A	N/A
Our Baseline	2.47	$\pm 0.005240$	16.71	$\pm 0.012582$	4.31
2005 Topline	99.80	$\pm 0.001507$	N/A	N/A	N/A
Our Topline	99.79	$\pm 0.001552$	99.37	$\pm 0.002676$	99.58

**Table 15. Performance comparison of accuracy on SIGHAN 2005 PKU corpus.**

Configuration	$P$	$C_P$	$R$	$C_R$	$F$
6-tag	93.73	$\pm 0.001512$	92.70	$\pm 0.001623$	93.21
CNG	<b>94.36</b>	$\pm 0.001438$	<b>93.57</b>	$\pm 0.001530$	<b>93.96</b>
AVS	94.21	$\pm 0.001457$	93.24	$\pm 0.001566$	93.72
TCB	93.97	$\pm 0.001485$	92.76	$\pm 0.001616$	93.36
TCF	93.94	$\pm 0.001488$	92.81	$\pm 0.001611$	93.37
AVS+TCB	94.33	<u><math>\pm 0.001443</math></u>	93.31	$\pm 0.001559$	93.81
AVS+TCF	94.25	$\pm 0.001451$	93.44	<u><math>\pm 0.001544</math></u>	93.85
LRAVS	<i>94.34</i>	$\pm 0.001441$	<i>93.48</i>	$\pm 0.001540$	<i>93.91</i>
LRAVS+TCB	94.32	<u><math>\pm 0.001443</math></u>	93.44	<u><math>\pm 0.001544</math></u>	93.88
LRAVS+TCF	93.91	$\pm 0.001492$	92.20	$\pm 0.001672$	93.05
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2005 Best	94.60	$\pm 0.001400$	95.30	$\pm 0.001310$	95.00
2005 Baseline	83.60	$\pm 0.002292$	90.40	$\pm 0.001824$	86.90
Our Baseline	84.29	$\pm 0.002269$	90.68	$\pm 0.001813$	87.37
2005 Topline	98.80	$\pm 0.000674$	98.50	$\pm 0.000752$	98.70
Our Topline	98.96	$\pm 0.000634$	98.62	$\pm 0.000726$	98.79

**Table 16. Performance comparison of OOV on SIGHAN 2005 PKU corpus.**

Configuration	$R_{Oov}$	$C_{Rov}$	$P_{Oov}$	$C_{Pov}$	$F_{Oov}$
6-tag	57.48	$\pm 0.012083$	48.04	$\pm 0.012211$	52.33
CNG	<b>65.58</b>	$\pm 0.011612$	<b>57.87</b>	$\pm 0.012068$	<b>61.48</b>
AVS	62.69	$\pm 0.011821$	55.60	$\pm 0.012144$	58.93
TCB	60.07	$\pm 0.011970$	54.87	<u><math>\pm 0.012220</math></u>	54.87
TCF	60.39	$\pm 0.011954$	50.41	<u><math>\pm 0.012220</math></u>	54.95
AVS+TCB	64.02	$\pm 0.011730$	56.97	$\pm 0.012101$	60.29
AVS+TCF	63.80	$\pm 0.011746$	56.06	$\pm 0.012130$	59.68
LRAVS	65.02	$\pm 0.011656$	57.31	$\pm 0.012089$	60.92
LRAVS+TCB	65.42	$\pm 0.011625$	57.60	$\pm 0.012079$	61.26
LRAVS+TCF	60.42	$\pm 0.011952$	48.92	$\pm 0.012218$	54.07
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2005 Best	63.60	$\pm 0.011760$	N/A	N/A	N/A
2005 Baseline	5.90	$\pm 0.005759$	N/A	N/A	N/A
Our Baseline	6.86	$\pm 0.006178$	6.10	$\pm 0.005850$	6.46
2005 Topline	99.40	$\pm 0.001888$	N/A	N/A	N/A
Our Topline	99.37	$\pm 0.001938$	97.72	$\pm 0.003645$	98.54

**Table 17. Non-Chinese treatment performance comparison of accuracy on SIGHAN 2010 simplified Chinese domain A (Literature) corpus.**

Configuration	$P$	$C_P$	$R$	$C_R$	$F$
6-tag	92.83	$\pm 0.002754$	92.37	$\pm 0.002833$	92.60
CNG	93.69	$\pm 0.002595$	91.94	$\pm 0.002906$	92.81
AVS	93.47	$\pm 0.002638$	92.89	$\pm 0.002744$	93.18
TCB	93.12	$\pm 0.002702$	92.56	$\pm 0.002801$	92.84
TCF	93.18	$\pm 0.002690$	92.52	$\pm 0.002808$	92.85
AVS+TCB	93.68	$\pm 0.002596$	92.99	$\pm 0.002726$	93.33
AVS+TCF	93.67	$\pm 0.002600$	93.10	$\pm 0.002705$	93.38
LRAVS	93.55	$\pm 0.002623$	93.08	$\pm 0.002709$	93.31
LRAVS+TCB	93.56	$\pm 0.002620$	93.11	$\pm 0.002703$	93.33
LRAVS+TCF	<b>93.72</b>	$\pm 0.002589$	<b>93.28</b>	$\pm 0.002673$	<b>93.50</b>
2010 Best	94.60	$\pm 0.002390$	94.50	$\pm 0.002410$	94.60
2010 Baseline	86.20	$\pm 0.003648$	91.70	$\pm 0.002919$	88.90
Our Baseline	86.24	$\pm 0.003676$	91.67	$\pm 0.002949$	88.88
2010 Topline	99.00	$\pm 0.001053$	98.60	$\pm 0.001243$	98.80
Our Topline	99.02	$\pm 0.001052$	98.57	$\pm 0.001268$	98.79

**Table 18. Non-Chinese treatment performance comparison of OOV on SIGHAN 2010 simplified Chinese domain A (Literature) corpus.**

Configuration	$R_{OOV}$	$C_{R_{OOV}}$	$P_{OOV}$	$C_{P_{OOV}}$	$F_{OOV}$
6-tag	62.62	$\pm 0.019128$	59.98	$\pm 0.01937$	61.27
CNG	<b>65.36</b>	$\pm 0.018812$	62.81	$\pm 0.019109$	64.06
AVS	64.80	$\pm 0.018882$	66.63	$\pm 0.018643$	65.70
TCB	64.48	$\pm 0.018921$	63.35	$\pm 0.019164$	63.35
TCF	65.00	$\pm 0.018858$	62.36	$\pm 0.019155$	63.65
AVS+TCB	65.04	$\pm 0.018853$	67.43	$\pm 0.018528$	66.22
AVS+TCF	64.96	$\pm 0.018863$	67.60	$\pm 0.018502$	66.26
LRAVS	63.67	$\pm 0.019015$	66.71	$\pm 0.018632$	65.15
LRAVS+TCB	64.35	$\pm 0.018936$	67.09	$\pm 0.018578$	65.69
LRAVS+TCF	64.92	$\pm 0.018868$	<b>68.48</b>	$\pm 0.018368$	<b>66.65</b>
2010 Best	81.60	$\pm 0.015320$	N/A	N/A	N/A
2010 Baseline	15.60	$\pm 0.014346$	N/A	N/A	N/A
Our Baseline	15.69	$\pm 0.014378$	30.61	$\pm 0.01822$	20.74
2010 Topline	99.60	$\pm 0.002495$	N/A	N/A	N/A
Our Topline	99.60	$\pm 0.002505$	96.48	$\pm 0.007282$	98.02

**Table 19. Non-Chinese treatment performance comparison of accuracy on SIGHAN 2010 simplified Chinese domain B (Computer) corpus.**

Configuration	$P$	$C_P$	$R$	$C_R$	$F$
6-tag	90.95	$\pm 0.003129$	92.46	$\pm 0.002880$	91.70
CNG	91.45	$\pm 0.003050$	92.36	$\pm 0.002898$	91.90
AVS	91.25	$\pm 0.003081$	92.72	$\pm 0.002833$	91.98
TCB	91.21	$\pm 0.003087$	92.53	$\pm 0.002867$	91.87
TCF	90.86	$\pm 0.003143$	92.62	$\pm 0.002852$	91.73
AVS+TCB	91.60	$\pm 0.003026$	92.67	$\pm 0.002842$	92.13
AVS+TCF	90.81	$\pm 0.003151$	92.16	$\pm 0.002932$	91.48
LRAVS	91.71	$\pm 0.003007$	92.61	$\pm 0.002854$	92.16
LRAVS+TCB	<b>91.97</b>	$\pm 0.002963$	<b>92.76</b>	$\pm 0.002826$	<b>92.37</b>
LRAVS+TCF	91.28	$\pm 0.003077$	92.60	$\pm 0.002856$	91.93
2010 Best	95.00	$\pm 0.002320$	95.30	$\pm 0.002250$	95.10
2010 Baseline	63.20	$\pm 0.005132$	85.60	$\pm 0.003736$	72.70
Our Baseline	63.26	$\pm 0.005258$	85.68	$\pm 0.003820$	72.78
2010 Topline	99.30	$\pm 0.000887$	99.10	$\pm 0.001005$	99.20
Our Topline	99.25	$\pm 0.000940$	99.06	$\pm 0.001052$	99.16

**Table 20. Non-Chinese treatment performance comparison of OOV on SIGHAN 2010 simplified Chinese domain B (Computer) corpus.**

Configuration	$R_{OOV}$	$C_{R_{OOV}}$	$P_{OOV}$	$C_{P_{OOV}}$	$F_{OOV}$
6-tag	70.62	$\pm 0.013380$	67.66	$\pm 0.013740$	69.11
CNG	70.38	$\pm 0.013412$	65.17	$\pm 0.013994$	67.67
AVS	69.85	$\pm 0.013479$	66.16	$\pm 0.013898$	67.96
TCB	71.23	$\pm 0.013297$	<b>69.66</b>	$\pm 0.013684$	69.66
TCF	<b>72.01</b>	$\pm 0.013187$	66.02	$\pm 0.013913$	68.89
AVS+TCB	70.25	$\pm 0.013429$	67.22	$\pm 0.013788$	68.70
AVS+TCF	69.63	$\pm 0.013507$	63.73	$\pm 0.014123$	66.55
LRAVS	71.25	$\pm 0.013294$	68.25	$\pm 0.013673$	69.72
LRAVS+TCB	71.81	$\pm 0.013216$	69.47	$\pm 0.013528$	<b>70.62</b>
LRAVS+TCF	70.92	$\pm 0.013340$	66.13	$\pm 0.013902$	68.44
2010 Best	82.70	$\pm 0.011111$	N/A	N/A	N/A
2010 Baseline	16.30	$\pm 0.010850$	N/A	N/A	N/A
Our Baseline	16.65	$\pm 0.010944$	6.39	$\pm 0.007185$	9.24
2010 Topline	99.00	$\pm 0.002923$	N/A	N/A	N/A
Our Topline	99.00	$\pm 0.002930$	98.08	$\pm 0.004028$	98.54

**Table 21. Non-Chinese treatment performance comparison of accuracy on SIGHAN 2010 simplified Chinese domain C (Medicine) corpus.**

Configuration	$P$	$C_P$	$R$	$C_R$	$F$
6-tag	91.27	$\pm 0.003207$	91.96	$\pm 0.003089$	91.61
CNG	92.84	$\pm 0.002928$	92.07	$\pm 0.003069$	92.46
AVS	92.40	$\pm 0.003011$	92.89	$\pm 0.002919$	92.64
TCB	91.55	$\pm 0.003159$	92.19	$\pm 0.003048$	91.87
TCF	91.62	$\pm 0.003147$	92.21	$\pm 0.003045$	91.91
AVS+TCB	92.73	$\pm 0.002949$	92.90	$\pm 0.002917$	92.82
AVS+TCF	92.82	$\pm 0.002933$	93.07	$\pm 0.002885$	92.94
LRAVS	93.12	$\pm 0.002876$	93.22	$\pm 0.002856$	93.17
LRAVS+TCB	<b>93.12</b>	$\pm 0.002875$	<b>93.33</b>	$\pm 0.002834$	<b>93.23</b>
LRAVS+TCF	93.07	$\pm 0.002884$	93.20	$\pm 0.002859$	93.14
2010 Best	93.60	$\pm 0.002760$	94.20	$\pm 0.002630$	93.90
2010 Baseline	77.40	$\pm 0.004714$	88.60	$\pm 0.003582$	82.60
Our Baseline	77.46	$\pm 0.004746$	88.64	$\pm 0.003604$	82.68
2010 Topline	99.10	$\pm 0.001064$	98.90	$\pm 0.001176$	99.00
Our Topline	99.18	$\pm 0.001025$	98.97	$\pm 0.001146$	99.08

**Table 22. Non-Chinese treatment performance comparison of OOV on SIGHAN 2010 simplified Chinese domain C (Medicine) corpus.**

Configuration	$R_{OOV}$	$C_{R_{OOV}}$	$P_{OOV}$	$C_{P_{OOV}}$	$F_{OOV}$
6-tag	66.70	$\pm 0.016081$	61.15	$\pm 0.016630$	63.80
CNG	70.90	$\pm 0.015498$	70.46	$\pm 0.015567$	70.68
AVS	71.02	$\pm 0.015479$	69.61	$\pm 0.015692$	70.31
TCB	66.41	$\pm 0.016115$	60.67	$\pm 0.016667$	63.41
TCF	66.44	$\pm 0.016112$	60.65	$\pm 0.016668$	63.41
AVS+TCB	70.10	$\pm 0.015621$	69.00	$\pm 0.015780$	69.54
AVS+TCF	69.66	$\pm 0.015685$	69.11	$\pm 0.015765$	69.38
LRAVS	<b>71.62</b>	$\pm 0.015382$	<b>70.91</b>	$\pm 0.015497$	<b>71.26</b>
LRAVS+TCB	71.45	$\pm 0.015410$	70.39	$\pm 0.015576$	70.92
LRAVS+TCF	71.56	$\pm 0.015392$	70.53	$\pm 0.015556$	71.04
2010 Best	75.00	$\pm 0.014774$	N/A	N/A	N/A
2010 Baseline	12.30	$\pm 0.011206$	N/A	N/A	N/A
Our Baseline	12.33	$\pm 0.011218$	15.34	$\pm 0.012294$	13.67
2010 Topline	98.00	$\pm 0.004777$	N/A	N/A	N/A
Our Topline	98.21	$\pm 0.004519$	97.21	$\pm 0.005623$	97.71

**Table 23. Non-Chinese treatment performance comparison of accuracy on SIGHAN 2010 simplified Chinese domain D (Finance) corpus.**

Configuration	$P$	$C_P$	$R$	$C_R$	$F$
6-tag	93.01	$\pm 0.002838$	93.74	$\pm 0.002697$	93.38
CNG	94.40	$\pm 0.002561$	93.66	$\pm 0.002714$	94.02
AVS	93.54	$\pm 0.002736$	94.30	$\pm 0.002581$	93.92
TCB	93.35	$\pm 0.002774$	94.14	$\pm 0.002614$	93.74
TCF	93.10	$\pm 0.002822$	93.88	$\pm 0.002669$	93.49
AVS+TCB	<b>94.56</b>	$\pm 0.002526$	<b>94.49</b>	$\pm 0.002540$	<b>94.53</b>
AVS+TCF	94.05	$\pm 0.002633$	94.10	$\pm 0.002624$	94.08
LRAVS	94.30	$\pm 0.002582$	94.13	$\pm 0.002616$	94.21
LRAVS+TCB	94.36	$\pm 0.002568$	94.16	$\pm 0.002611$	94.26
LRAVS+TCF	94.36	$\pm 0.002569$	94.19	$\pm 0.002604$	94.28
2010 Best	96.00	$\pm 0.002160$	95.90	$\pm 0.002180$	95.90
2010 Baseline	80.30	$\pm 0.004377$	91.40	$\pm 0.003085$	85.50
Our Baseline	80.26	$\pm 0.004431$	91.41	$\pm 0.003119$	85.48
2010 Topline	99.50	$\pm 0.000776$	99.40	$\pm 0.000850$	99.40
Our Topline	99.56	$\pm 0.000734$	99.47	$\pm 0.000810$	99.52

**Table 24. Non-Chinese treatment performance comparison of OOV on SIGHAN 2010 simplified Chinese domain D (Finance) corpus.**

Configuration	$R_{OOV}$	$C_{R_{OOV}}$	$P_{OOV}$	$C_{P_{OOV}}$	$F_{OOV}$
6-tag	67.60	$\pm 0.017666$	61.28	$\pm 0.018388$	64.28
CNG	73.53	$\pm 0.016655$	67.77	$\pm 0.017642$	70.53
AVS	71.10	$\pm 0.017111$	64.17	$\pm 0.018101$	67.46
TCB	70.58	$\pm 0.017201$	66.44	$\pm 0.018250$	66.44
TCF	70.13	$\pm 0.017277$	61.19	$\pm 0.018396$	65.35
AVS+TCB	<b>73.80</b>	$\pm 0.016598$	<b>70.79</b>	$\pm 0.017166$	<b>72.26</b>
AVS+TCF	70.76	$\pm 0.017172$	67.73	$\pm 0.017648$	69.21
LRAVS	71.66	$\pm 0.017012$	68.54	$\pm 0.017528$	70.07
LRAVS+TCB	72.63	$\pm 0.016831$	69.82	$\pm 0.017328$	71.20
LRAVS+TCF	72.38	$\pm 0.016878$	69.40	$\pm 0.017396$	70.86
2010 Best	82.70	$\pm 0.014279$	N/A	N/A	N/A
2010 Baseline	23.30	$\pm 0.015958$	N/A	N/A	N/A
Our Baseline	23.32	$\pm 0.015963$	14.15	$\pm 0.013157$	17.61
2010 Topline	99.50	$\pm 0.002663$	N/A	N/A	N/A
Our Topline	99.72	$\pm 0.001985$	99.34	$\pm 0.003047$	99.53

**Table 25. Non-Chinese treatment performance comparison of accuracy on SIGHAN 2010 traditional Chinese domain A (Literature) corpus.**

Configuration	$P$	$C_P$	$R$	$C_R$	$F$
6-tag	93.06	$\pm 0.002672$	92.31	$\pm 0.002802$	92.68
CNG	93.66	$\pm 0.002562$	91.16	$\pm 0.002985$	92.39
AVS	93.61	<u><math>\pm 0.002572</math></u>	92.78	$\pm 0.002721$	93.19
TCB	93.21	$\pm 0.002646$	92.33	$\pm 0.002798$	92.77
TCF	93.33	$\pm 0.002623$	92.58	$\pm 0.002756$	92.95
AVS+TCB	93.61	<u><math>\pm 0.002572</math></u>	92.85	$\pm 0.002709$	93.23
AVS+TCF	93.68	$\pm 0.002559$	92.98	$\pm 0.002685$	93.33
LRAVS	93.77	$\pm 0.002542$	93.04	$\pm 0.002676$	93.40
LRAVS+TCB	<b>93.77</b>	$\pm 0.002541$	<b>93.06</b>	$\pm 0.002673$	<b>93.41</b>
LRAVS+TCF	93.65	$\pm 0.002564$	92.92	$\pm 0.002697$	93.28
2010 Best	94.20	$\pm 0.002450$	94.20	$\pm 0.002450$	94.20
2010 Baseline	78.80	$\pm 0.004286$	86.30	$\pm 0.003606$	82.40
Our Baseline	78.83	$\pm 0.004295$	86.39	$\pm 0.003605$	82.44
2010 Topline	98.80	$\pm 0.001142$	98.10	$\pm 0.001432$	98.50
Our Topline	98.83	$\pm 0.001130$	98.11	$\pm 0.001430$	98.47

**Table 26. Non-Chinese treatment performance comparison of OOV on SIGHAN 2010 traditional Chinese domain A (Literature) corpus.**

Configuration	$R_{OOV}$	$C_{R_{OOV}}$	$P_{OOV}$	$C_{P_{OOV}}$	$F_{OOV}$
6-tag	75.89	$\pm 0.014654$	68.68	$\pm 0.015889$	72.11
CNG	74.12	$\pm 0.015004$	69.46	$\pm 0.015780$	71.71
AVS	75.10	$\pm 0.014816$	73.34	$\pm 0.015148$	74.21
TCB	<b>77.19</b>	$\pm 0.014376$	69.27	$\pm 0.015807$	73.01
TCF	77.10	$\pm 0.014395$	69.82	$\pm 0.015727$	73.28
AVS+TCB	75.54	$\pm 0.014727$	73.46	$\pm 0.015127$	74.48
AVS+TCF	75.60	$\pm 0.014715$	73.92	$\pm 0.015042$	74.75
LRAVS	75.42	$\pm 0.014751$	74.93	$\pm 0.014848$	75.18
LRAVS+TCB	75.66	$\pm 0.014703$	<b>75.12</b>	$\pm 0.014810$	<b>75.39</b>
LRAVS+TCF	75.27	$\pm 0.014780$	74.44	$\pm 0.014944$	74.85
2010 Best	78.80	$\pm 0.014003$	N/A	N/A	N/A
2010 Baseline	4.10	$\pm 0.006793$	N/A	N/A	N/A
Our Baseline	4.10	$\pm 0.006791$	8.93	$\pm 0.009769$	5.62
2010 Topline	99.80	$\pm 0.001531$	N/A	N/A	N/A
Our Topline	99.82	$\pm 0.001439$	99.33	$\pm 0.002804$	99.57

**Table 27. Non-Chinese treatment performance comparison of accuracy on SIGHAN 2010 traditional Chinese domain B (Computer) corpus.**

Configuration	$P$	$C_P$	$R$	$C_R$	$F$
6-tag	95.15	$\pm 0.002122$	93.20	$\pm 0.002487$	94.17
CNG	95.60	$\pm 0.002027$	93.16	$\pm 0.002494$	94.36
AVS	95.67	$\pm 0.002012$	93.83	<u><math>\pm 0.002378</math></u>	94.74
TCB	95.21	$\pm 0.002111$	93.25	$\pm 0.002480$	94.22
TCF	95.28	$\pm 0.002095$	93.42	$\pm 0.002450$	94.34
AVS+TCB	95.62	$\pm 0.002023$	93.72	$\pm 0.002398$	94.66
AVS+TCF	<b>95.74</b>	$\pm 0.001996$	93.83	<u><math>\pm 0.002378</math></u>	<b>94.77</b>
LRAVS	95.57	$\pm 0.002034$	93.79	$\pm 0.002384$	94.67
LRAVS+TCB	95.63	$\pm 0.002020$	<b>93.85</b>	$\pm 0.002373$	94.73
LRAVS+TCF	95.55	$\pm 0.002038$	93.81	$\pm 0.002381$	94.67
2010 Best	95.70	$\pm 0.001950$	94.80	$\pm 0.002130$	95.20
2010 Baseline	70.10	$\pm 0.004390$	87.30	$\pm 0.003193$	77.80
Our Baseline	70.15	$\pm 0.004522$	87.33	$\pm 0.003286$	77.80
2010 Topline	99.10	$\pm 0.000906$	98.80	$\pm 0.001044$	99.00
Our Topline	99.38	$\pm 0.000778$	98.85	$\pm 0.001055$	99.11

**Table 28. Non-Chinese-Pattern performance comparison of OOV on SIGHAN 2010 traditional Chinese domain B (Computer) corpus.**

Configuration	$R_{OOV}$	$C_{R_{OOV}}$	$P_{OOV}$	$C_{P_{OOV}}$	$F_{OOV}$
6-tag	58.79	$\pm 0.016769$	68.17	$\pm 0.015871$	63.14
CNG	61.77	$\pm 0.016556$	70.16	$\pm 0.015589$	65.70
AVS	60.59	$\pm 0.016649$	72.29	$\pm 0.015248$	65.93
TCB	59.09	$\pm 0.016751$	68.81	$\pm 0.015784$	63.58
TCF	59.34	$\pm 0.016735$	69.21	$\pm 0.015727$	63.89
AVS+TCB	60.89	$\pm 0.016626$	72.24	$\pm 0.015257$	66.08
AVS+TCF	61.35	$\pm 0.01659$	72.90	$\pm 0.015143$	66.63
LRAVS	61.67	$\pm 0.016564$	72.84	$\pm 0.015155$	66.79
LRAVS+TCB	<b>61.82</b>	$\pm 0.016552$	<b>73.07</b>	$\pm 0.015113$	<b>66.98</b>
LRAVS+TCF	61.55	$\pm 0.016574$	72.94	$\pm 0.015135$	66.76
2010 Best	66.60	$\pm 0.016069$	N/A	N/A	N/A
2010 Baseline	1.00	$\pm 0.003390$	N/A	N/A	N/A
Our Baseline	1.03	$\pm 0.003445$	0.55	$\pm 0.002515$	0.72
2010 Topline	99.60	$\pm 0.002150$	N/A	N/A	N/A
Our Topline	99.34	$\pm 0.002765$	99.41	$\pm 0.002609$	99.37



**Table 29. Non-Chinese treatment performance comparison of accuracy on SIGHAN 2010 traditional Chinese domain C (Medicine) corpus.**

Configuration	$P$	$C_P$	$R$	$C_R$	$F$
6-tag	94.70	$\pm 0.002170$	93.83	$\pm 0.002331$	94.26
CNG	95.35	$\pm 0.002039$	93.35	$\pm 0.002414$	94.34
AVS	95.28	$\pm 0.002055$	94.37	$\pm 0.002232$	94.82
TCB	94.76	$\pm 0.002158$	93.87	$\pm 0.002324$	94.31
TCF	94.88	$\pm 0.002135$	94.05	$\pm 0.002291$	94.46
AVS+TCB	95.33	$\pm 0.002044$	94.49	$\pm 0.002209$	94.91
AVS+TCF	95.33	$\pm 0.002043$	94.44	$\pm 0.002219$	94.88
LRAVS	<b>95.52</b>	$\pm 0.002003$	<b>94.60</b>	$\pm 0.002190$	<b>95.06</b>
LRAVS+TCB	95.36	$\pm 0.002038$	94.51	$\pm 0.002206$	94.93
LRAVS+TCF	95.42	$\pm 0.002025$	94.42	$\pm 0.002224$	94.91
2010 Best	95.70	$\pm 0.001950$	95.30	$\pm 0.002030$	95.50
2010 Baseline	81.00	$\pm 0.003764$	88.60	$\pm 0.003049$	84.60
Our Baseline	80.98	$\pm 0.003801$	88.63	$\pm 0.003075$	84.64
2010 Topline	98.90	$\pm 0.001001$	98.40	$\pm 0.001204$	98.60
Our Topline	98.91	$\pm 0.001006$	98.38	$\pm 0.001223$	98.64

**Table 30. Non-Chinese treatment performance comparison of OOV on SIGHAN 2010 traditional Chinese domain C (Medicine) corpus.**

Configuration	$R_{OOV}$	$C_{R_{OOV}}$	$P_{OOV}$	$C_{P_{OOV}}$	$F_{OOV}$
6-tag	74.79	$\pm 0.015086$	67.98	$\pm 0.016209$	71.22
CNG	77.16	$\pm 0.014586$	71.22	$\pm 0.015730$	74.07
AVS	76.13	$\pm 0.014810$	74.80	$\pm 0.015083$	75.46
TCB	75.60	$\pm 0.014922$	68.64	$\pm 0.016119$	71.95
TCF	75.79	$\pm 0.014883$	69.29	$\pm 0.016026$	72.39
AVS+TCB	76.72	$\pm 0.014683$	75.75	$\pm 0.014890$	76.23
AVS+TCF	77.22	$\pm 0.014572$	75.69	$\pm 0.014903$	76.44
LRAVS	<b>78.65</b>	$\pm 0.014237$	<b>76.37</b>	$\pm 0.014759$	<b>77.49</b>
LRAVS+TCB	77.75	$\pm 0.014451$	75.54	$\pm 0.014934$	76.63
LRAVS+TCF	78.03	$\pm 0.014385$	75.65	$\pm 0.014911$	76.82
2010 Best	79.80	$\pm 0.013949$	N/A	N/A	N/A
2010 Baseline	2.70	$\pm 0.005631$	N/A	N/A	N/A
Our Baseline	2.71	$\pm 0.005639$	4.34	$\pm 0.007082$	3.34
2010 Topline	99.20	$\pm 0.003095$	N/A	N/A	N/A
Our Topline	99.16	$\pm 0.003171$	98.73	$\pm 0.003891$	98.94

**Table 31. Non-Chinese treatment performance comparison of accuracy on SIGHAN 2010 traditional Chinese domain D (Finance) corpus.**

Configuration	$P$	$C_P$	$R$	$C_R$	$F$
6-tag	95.52	$\pm 0.001925$	95.46	$\pm 0.001937$	95.49
CNG	<b>96.13</b>	$\pm 0.001794$	95.04	$\pm 0.002020$	95.58
AVS	95.99	<u><math>\pm 0.001825</math></u>	95.79	$\pm 0.001868$	95.89
TCB	95.55	$\pm 0.001918$	95.51	$\pm 0.001927$	95.53
TCF	95.61	$\pm 0.001907$	95.57	$\pm 0.001915$	95.59
AVS+TCB	95.93	$\pm 0.001839$	95.77	$\pm 0.001874$	95.85
AVS+TCF	95.99	<u><math>\pm 0.001825</math></u>	<b>95.88</b>	$\pm 0.001850$	<b>95.93</b>
LRAVS	96.02	$\pm 0.001820$	95.73	$\pm 0.001881$	95.87
LRAVS+TCB	96.04	$\pm 0.001814$	95.82	$\pm 0.001862$	95.93
LRAVS+TCF	95.94	$\pm 0.001836$	95.71	$\pm 0.001885$	95.83
2010 Best	96.20	$\pm 0.001760$	96.40	$\pm 0.001720$	96.30
2010 Baseline	82.60	$\pm 0.003492$	88.80	$\pm 0.002905$	85.50
Our Baseline	82.56	$\pm 0.003531$	88.77	$\pm 0.002937$	85.55
2010 Topline	98.60	$\pm 0.001082$	98.10	$\pm 0.001258$	98.40
Our Topline	98.63	$\pm 0.001081$	98.10	$\pm 0.00127$	98.36

**Table 32. Non-Chinese treatment performance comparison of OOV on SIGHAN 2010 traditional Chinese domain D (Finance) corpus.**

Configuration	$R_{OOV}$	$C_{R_{OOV}}$	$P_{OOV}$	$C_{P_{OOV}}$	$F_{OOV}$
6-tag	80.45	$\pm 0.013488$	76.61	$\pm 0.014398$	78.48
CNG	<b>82.96</b>	$\pm 0.012787$	78.16	$\pm 0.014053$	80.49
AVS	81.33	$\pm 0.013253$	81.28	$\pm 0.013267$	81.30
TCB	80.99	<u><math>\pm 0.013346</math></u>	77.44	$\pm 0.014216$	79.17
TCF	80.92	$\pm 0.013363$	77.26	$\pm 0.014255$	79.05
AVS+TCB	80.99	<u><math>\pm 0.013346</math></u>	81.55	$\pm 0.013193$	81.27
AVS+TCF	80.99	<u><math>\pm 0.013346</math></u>	81.96	$\pm 0.013077$	81.47
LRAVS	82.62	$\pm 0.012889$	82.10	$\pm 0.013038$	<b>82.36</b>
LRAVS+TCB	82.18	$\pm 0.013016$	<b>82.44</b>	$\pm 0.012942$	82.31
LRAVS+TCF	81.86	$\pm 0.013105$	82.04	$\pm 0.013054$	81.95
2010 Best	81.20	$\pm 0.013288$	N/A	N/A	N/A
2010 Baseline	0.60	$\pm 0.002627$	N/A	N/A	N/A
Our Baseline	0.60	$\pm 0.002618$	2.28	$\pm 0.005078$	0.95
2010 Topline	99.70	$\pm 0.001860$	N/A	N/A	N/A
Our Topline	99.69	$\pm 0.001902$	98.54	$\pm 0.004076$	99.11

It has been observed that using any of the unsupervised features could create short patterns for the CRF learner, which might break more English words than using the *6-tag* approach alone. AVS, TCF, and TCB, however, resolve more overlapping ambiguities of Chinese words than the *6-tag* approach and CNG. Interestingly, even for the unsupervised feature without rank or overlapping information, TCB/TCF successfully recognizes “依靠 / 单位 / 的 / 纽带 / 来 / 维持,” while the *6-tag* approach sees this phrase incorrectly as “依靠 / 单位 / 的 / 纽 / 带来 / 维持.” TCB/TCF also saves more factoids, such as “一二九 · 九 / 左右” (129.9 / around) from scattered tokens, such as “一二九 / · / 九 / 左右” (129 / point / 9 / around).

The above observations suggest that the quality of a string as a word-like candidate should be an important factor for the unsupervised feature injected CRF learner. Relatively speaking, CNG probably brings in too much noise. Feature combinations of LRAVS and TCF usually improve  $F$  and  $F_{OOV}$ , respectively. Improvements are significant in terms of  $C_R$ ,  $C_P$ ,  $C_{Roov}$ , and  $C_{Poov}$ , which confirms the hypothesis mentioned at the end of Section 1.3 that, combining information from the outer pattern of a substring (*i.e.*, LRAVS) with information from the inner pattern of a substring (*i.e.*, TCF) into a compound of unsupervised feature could help improving CWS performance of supervised labeling scheme of CRF. Nevertheless, since AVS or TCB sometimes gain better results, fine-tuning of feature engineering according to different corpora and segmentation standards is necessary.

## 7. Conclusion and Future Work

This work provides a unified view of CRF-based CWS integrated with unsupervised features via frequent string, and it reasons that, since LRAVS comes with inner structure and TCF comes with outer structure of overlapping string, utilizing their compound features could be more useful than applying one of them solely. The thorough experimental results show that the compound features of LRAVS and TCF usually obtain competitive performance in terms of  $F$  and  $F_{OOV}$ , respectively. Sometimes, AVS and TCB may contribute more, but generally combining the outer pattern of a substring (*i.e.*, LRAVS or AVS) with the inner pattern of a substring (*i.e.*, TCF or TCB) into a compound of unsupervised features could help improve CWS performance of a supervised labeling scheme of CRF. Recommended future investigation is unknown word extraction and named entity recognition using AVS (Li *et al.*, 2010) and TCF/TCB (Chang & Lee, 2003; Zhang *et al.*, 2010) as features for more complicated CRF (Sun & Nan, 2010).

## Reference

- Chang, J.-S., & Su, K.-Y. (1997). An Unsupervised Iterative Method for Chinese New Lexicon Extraction. in *Proc. Computational Linguistics and Chinese Language Processing*, 2(2), 97-148.
- Chang, T.-H., & Lee, C.-H. (2003). Automatic Chinese unknown word extraction using small-corpus-based method. in *Proc. International Conference on Natural Language Processing and Knowledge Engineering*, 459-464.
- Chien, L.-F. (1997). PAT-tree-based Keyword Extraction for Chinese Information Retrieval. in *Proc. 20th Annual International ACM SIGIR Conference on Research and Development in Information Retrieval*, 50-58.
- Cohen, P., Adams, N., & Heeringa, B. (2007). Voting Experts: An Unsupervised Algorithm for Segmenting Sequences. *Intelligent Data Analysis*, 11(6), 607-625.
- Emerson, T. (2005). The Second International Chinese Word Segmentation Bakeoff. in *Proc. 4th SIGHAN Workshop on Chinese Language Processing*.
- Feng, H., Chen, K., Deng, X., & Zheng, W. (2004). Accessor Variety Criteria for Chinese Word Extraction. *Computational Linguistics*, 30(1), 75-93.
- Ha, L. Q., Seymour, R., Hanna, P., & Smith, F. J. (2005). Reduced N-Grams for Chinese Evaluation. *Computational Linguistics and Chinese Language Processing*, 10(1), 19-34.
- Harris, Z. S. (1970). Morpheme Boundaries within Words. Paper presented at the *Structural and Transformational Linguistics*.
- Huang, J. H., & Powers, D. (2003). Chinese Word Segmentation based on contextual entropy. in *Proc. 17th Asian Pacific Conference on Language, Information and Computation*, 152-158.
- Jiang, T.-J., Hsu, W.-L., Kuo, C.-H., & Yang, T.-H. (2011). Enhancement of Unsupervised Feature Selection for Conditional Random Fields Learning in Chinese Word Segmentation. in *Proc. 7th IEEE International Conference on Natural Language Processing and Knowledge Engineering*, 382-389.
- Jiang, T.-J., Liu, S.-H., Sung, C.-L., & Hsu, W.-L. (2010). Term Contributed Boundary Tagging by Conditional Random Fields for SIGHAN 2010 Chinese Word Segmentation Bakeoff. in *Proc. 1st CIPS-SIGHAN Joint Conf. on Chinese Language Processing*, Beijing, China.
- Jin, G., & Chen, X. (2007). The Fourth International Chinese Language Processing Bakeoff : Chinese Word Segmentation, Named Entity Recognition and Chinese POS Tagging. in *Proc. 6th SIGHAN Workshop on Chinese Language Processing*, 69-81.
- Kit, C., & Wilks, Y. (1999). Unsupervised learning of word boundary with description length gain. in *Proc. CoNLL-99*, 1-6.
- Lü, X., & Zhang, L. (2005). Statistical Substring Reduction in Linear Time. in *Proc. 1st Internal Joint Conference on Natural Language Processing*.
- Lafferty, J., McCallum, A., & Pereira, F. C. N. (2001). Conditional Random Fields

- Probabilistic Models for Segmenting and Labeling Sequence Data. in *Proc. ICML*, 282-289.
- Levow, G.-A. (2006). The Third International Chinese Language Processing Bakeoff Word Segmentation and Named Entity Recognition. in *Proc. 5th SIGHAN Workshop on Chinese Language Processing*, 108-117.
- Li, L., Li, Z., Ding, Z., & Huang, D. (2010). A Hybrid Model Combining CRF with Boundary Templates for Chinese Person Name Recognition. *International Journal Advanced Intelligent*, 2(1), 73-80.
- Li, M., Gao, J., Huang, C., & Li, J. (2003). Unsupervised Training for Overlapping Ambiguity Resolution in Chinese Word Segmentation. in *Proc. 2nd SIGHAN Workshop on Chinese Language Processing*, 17, 1-7.
- Lin, Y.-J., & Yu, M.-S. (2001). Extracting Chinese Frequent Strings without a Dictionary from a Chinese Corpus and its Applications. *J. Information Science and Engineering*, 17, 805-824.
- Ma, W.-Y., & Chen, K.-J. (2003). Introduction to CKIP Chinese Word Segmentation System for the First International Chinese Word Segmentation Bakeoff. in *Proc. 2nd SIGHAN Workshop on Chinese Language Processing*, 17, 168-171.
- Manber, U., & Myers, G. (1993). Suffix arrays: a new method for on-line string searches. *SIAM J. Computing*, 22(5), 935-948.
- O'Boyle, P. (1993). *A Study of an N-Gram Language Model for Speech Recognition*. (Ph.D.), Queen's University Belfast.
- Qiao, W., Sun, M., & Menzel, W. (2008). Statistical Properties of Overlapping Ambiguities in Chinese Word Segmentation and a Strategy for Their Disambiguation. in *Proc. Text, Speech and Dialogue*, 177-186.
- Ratnaparkhi, A. (1996). A Maximum Entropy Model for Part-of-Speech Tagging. in *Proc. Empirical Methods in Natural Language Processing*, 133-142.
- Sproat, R., & Emerson, T. (2003). The First International Chinese Word Segmentation Bakeoff. in *Proc. 2nd SIGHAN Workshop on Chinese Language Processing*, 17, 133-143.
- Stolcke, A. (2002). SRILM - An Extensible Language Modeling Toolkit. in *Proc. Spoken Language Processing*, 901-904.
- Sun, M., Huang, C. N., Lu, F., & Shen, D. Y. (1997). Using Character Bigram for Ambiguity Resolution In Chinese Word Segmentation (In Chinese). *Computer Research and Development*, 34(5), 332-339.
- Sun, W., & Xu, J. (2011). Enhancing Chinese Word Segmentation Using Unlabeled Data. in *Proc. Empirical Methods in Natural Language Processing*, 970-979.
- Sun, X., & Nan, X. (2010). Chinese base phrases chunking based on latent semi-CRF model. in *Proc. International Conference on Natural Language Processing and Knowledge Engineering*, 1-7.
- Sung, C.-L., Yen, H.-C., & Hsu, W.-L. (2008). Compute the Term Contributed Frequency. in

- Proc. 8th Int. Conference Intelligent System Design and Application*, 2, 325-328.
- Tanaka-Ishii, K. (2005). Entropy as an Indicator of Context Boundaries: An Experiment Using a Web Search Engine. in *Proc. Internal Joint Conference on Natural Language Processing*, 93-105.
- Tung, C.-H., & Lee, H.-J. (1994). Identification of Unkown Words from Corpus. *Computational Proc. Chinese and Oriental Languages*, 8, 131-145.
- Wallach, H. M. (2004). *Conditional Random Fields An Introduction*. (MS-CIS-04-21).
- Zhang, H., Huang, H., Zhu, C., & Shi, S. (2010). A pragmatic model for new Chinese word extraction. in *Proc. International Conference on Natural Language Processing and Knowledge Engineering*, 1-8.
- Zhang, R., Kikui, G., & Sumita, E. (2006). Subword-based Tagging for Confidence-dependent Chinese Word Segmentation. in *Proc. COLING/ACL*, 961-968.
- Zhao, H., Huang, C.-N., Li, M., & Lu, B.-L. (2010). A Unified Character-Based Tagging Framework for Chinese Word Segmentation. *ACM Trans. on Asian Language Information Processing*, 9(2).
- Zhao, H., & Kit, C. (2007). Incorporating Global Information into Supervised Learning for Chinese Word Segmentation. in *Proc. 10th PACLIC*, 66-74.
- Zhao, H., & Liu, Q. (2010). The CIPS-SIGHAN CLP2010 Chinese Word Segmentation Backoff. in *Proc. 1st CIPS-SIGHAN Joint Conf. on Chinese Language Processing*, 199-209.

## Appendix

**Table 33. Performance comparison of accuracy on SIGHAN 2003 AS corpus.**

Configuration	$P$	$C_P$	$R$	$C_R$	$F$
6-tag	<b>97.18</b>	$\pm 0.003024$	97.23	<u><math>\pm 0.002998</math></u>	<b>97.21</b>
CNG	97.05	$\pm 0.003091$	97.16	$\pm 0.003033$	97.11
AVS	97.06	$\pm 0.003086$	97.23	<u><math>\pm 0.002998</math></u>	97.14
TCB	97.16	$\pm 0.003037$	97.18	$\pm 0.003024$	97.17
TCF	97.15	$\pm 0.003042$	97.11	$\pm 0.003059$	97.13
AVS+TCB	97.04	$\pm 0.003098$	97.24	$\pm 0.002994$	97.14
AVS+TCF	97.07	$\pm 0.003081$	<b>97.30</b>	$\pm 0.002958$	97.19
LRAVS	96.89	$\pm 0.003172$	97.15	$\pm 0.003042$	97.02
LRAVS+TCB	97.03	$\pm 0.003103$	97.20	$\pm 0.003011$	97.12
LRAVS+TCF	96.94	$\pm 0.003147$	97.24	$\pm 0.002994$	97.09
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2003 Best	95.60	$\pm 0.003700$	96.60	$\pm 0.003300$	96.10
2003 Baseline	91.20	$\pm 0.005175$	91.70	$\pm 0.005040$	91.50
Our Baseline	91.23	$\pm 0.005168$	91.74	$\pm 0.005029$	91.48
2003 Topline	99.30	$\pm 0.001523$	99.00	$\pm 0.001818$	99.20
Our Topline	99.30	$\pm 0.001526$	99.02	$\pm 0.001804$	99.16

**Table 34. Performance comparison of OOV on SIGHAN 2003 AS corpus.**

Configuration	$R_{Oov}$	$C_{R_{Oov}}$	$P_{Oov}$	$C_{P_{Oov}}$	$F_{Oov}$
6-tag	77.13	$\pm 0.052294$	75.09	$\pm 0.053848$	<b>76.10</b>
CNG	73.64	$\pm 0.054857$	75.10	$\pm 0.053845$	74.36
AVS	70.93	<u><math>\pm 0.056540</math></u>	77.22	$\pm 0.052227$	73.94
TCB	76.74	$\pm 0.052603$	74.44	$\pm 0.054316$	75.57
TCF	<b>77.91</b>	$\pm 0.051658$	71.02	$\pm 0.056486$	74.31
AVS+TCB	70.93	<u><math>\pm 0.056540</math></u>	77.54	$\pm 0.051960$	74.09
AVS+TCF	70.93	<u><math>\pm 0.056540</math></u>	<b>77.87</b>	$\pm 0.051687$	74.24
LRAVS	69.77	$\pm 0.057185$	76.27	$\pm 0.052971$	72.87
LRAVS+TCB	69.38	$\pm 0.057391$	76.50	$\pm 0.052797$	72.76
LRAVS+TCF	70.16	$\pm 0.056975$	76.37	$\pm 0.052894$	73.13
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2003 Best	36.40	$\pm 0.059910$	N/A	N/A	N/A
2003 Baseline	0.00	$\pm 0.000000$	N/A	N/A	N/A
Our Baseline	0.00	$\pm 0.000000$	0.00	$\pm 0.000000$	0.00
2003 Topline	98.80	$\pm 0.013558$	N/A	N/A	N/A
Our Topline	98.84	$\pm 0.013348$	97.33	$\pm 0.020079$	98.08

**Table 35. Performance comparison of accuracy on SIGHAN 2003 CityU corpus.**

Configuration	$P$	$C_P$	$R$	$C_R$	$F$
6-tag	94.77	$\pm 0.002381$	94.79	$\pm 0.002377$	94.78
CNG	<b>95.24</b>	$\pm 0.002278$	<b>95.48</b>	$\pm 0.002222$	<b>95.36</b>
AVS	95.13	$\pm 0.002302$	95.20	$\pm 0.002286$	95.17
TCB	94.84	$\pm 0.002367$	94.87	$\pm 0.002360$	94.85
TCF	94.78	$\pm 0.002380$	94.77	$\pm 0.002382$	94.77
AVS+TCB	95.18	$\pm 0.002291$	95.24	$\pm 0.002278$	95.21
AVS+TCF	95.08	$\pm 0.002313$	95.19	$\pm 0.002288$	95.14
LRAVS	95.00	$\pm 0.002332$	95.21	$\pm 0.002284$	95.10
LRAVS+TCB	95.18	$\pm 0.002292$	95.33	$\pm 0.002256$	95.26
LRAVS+TCF	95.00	$\pm 0.002330$	95.27	$\pm 0.002271$	95.14
2003 Best	93.40	$\pm 0.002700$	94.70	$\pm 0.002400$	94.00
2003 Baseline	83.00	$\pm 0.004018$	90.80	$\pm 0.003092$	86.70
Our Baseline	82.97	$\pm 0.004021$	90.77	$\pm 0.003097$	86.69
2003 Topline	99.10	$\pm 0.001010$	98.60	$\pm 0.001257$	98.90
Our Topline	99.10	$\pm 0.001009$	98.62	$\pm 0.001249$	98.86

**Table 36. Performance comparison of OOV on SIGHAN 2003 CityU corpus.**

Configuration	$R_{Oov}$	$C_{R_{Oov}}$	$P_{Oov}$	$C_{P_{Oov}}$	$F_{Oov}$
6-tag	75.80	$\pm 0.017149$	66.07	$\pm 0.018969$	70.60
CNG	<b>77.25</b>	$\pm 0.016796$	<b>73.25</b>	$\pm 0.017735$	75.20
AVS	75.16	$\pm 0.017311$	71.79	$\pm 0.018030$	73.44
TCB	76.20	$\pm 0.017061$	66.63	$\pm 0.018891$	71.10
TCF	76.28	$\pm 0.017041$	66.38	$\pm 0.018927$	70.99
AVS+TCB	75.44	$\pm 0.017245$	72.06	$\pm 0.017977$	73.71
AVS+TCF	74.88	$\pm 0.017376$	71.66	$\pm 0.018055$	73.23
LRAVS	74.12	$\pm 0.017548$	72.01	$\pm 0.017987$	73.05
LRAVS+TCB	74.88	$\pm 0.017376$	72.92	$\pm 0.017804$	<b>73.89</b>
LRAVS+TCF	74.32	$\pm 0.017503$	72.23	$\pm 0.017943$	73.26
2003 Best	62.50	$\pm 0.019396$	N/A	N/A	N/A
2003 Baseline	3.70	$\pm 0.007563$	N/A	N/A	N/A
Our Baseline	3.69	$\pm 0.007555$	5.20	$\pm 0.008896$	4.32
2003 Topline	99.60	$\pm 0.002529$	N/A	N/A	N/A
Our Topline	99.60	$\pm 0.002533$	98.65	$\pm 0.004626$	99.12



**Table 37. Performance comparison of accuracy on SIGHAN 2003 PKU corpus.**

Configuration	$P$	$C_P$	$R$	$C_R$	$F$
6-tag	92.98	$\pm 0.003897$	93.67	$\pm 0.003713$	93.32
CNG	94.35	$\pm 0.003521$	94.70	$\pm 0.003417$	94.53
AVS	<b>94.39</b>	$\pm 0.003510$	94.70	$\pm 0.003417$	94.54
TCB	93.14	$\pm 0.003856$	93.69	$\pm 0.003709$	93.41
TCF	93.43	$\pm 0.003780$	93.58	$\pm 0.003739$	93.50
AVS+TCB	<b>94.43</b>	$\pm 0.003498$	<b>94.84</b>	$\pm 0.003376$	94.63
AVS+TCF	94.32	$\pm 0.003529$	94.83	$\pm 0.003377$	<b>94.58</b>
LRAVS	94.18	$\pm 0.003572$	94.71	$\pm 0.003415$	94.44
LRAVS+TCB	94.26	$\pm 0.003548$	94.81	$\pm 0.003383$	94.53
LRAVS+TCF	94.04	$\pm 0.003611$	94.62	$\pm 0.003441$	94.33
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2003 Best	94.00	$\pm 0.003600$	96.20	$\pm 0.002900$	95.10
2003 Baseline	82.90	$\pm 0.005743$	90.90	$\pm 0.004387$	86.70
Our Baseline	82.96	$\pm 0.005735$	90.87	$\pm 0.004392$	86.74
2003 Topline	99.60	$\pm 0.000963$	99.50	$\pm 0.001076$	99.50
Our Topline	99.63	$\pm 0.000930$	99.45	$\pm 0.001125$	99.54

**Table 38. Performance comparison of OOV on SIGHAN 2003 PKU corpus.**

Configuration	$R_{Oov}$	$C_{R_{Oov}}$	$P_{Oov}$	$C_{P_{Oov}}$	$F_{Oov}$
6-tag	60.22	$\pm 0.028389$	49.69	$\pm 0.029$	54.45
CNG	67.70	$\pm 0.027122$	63.24	$\pm 0.027966$	65.39
AVS	66.36	$\pm 0.027405$	64.94	$\pm 0.027676$	65.64
TCB	61.14	$\pm 0.028271$	51.49	$\pm 0.028988$	55.90
TCF	63.58	$\pm 0.027910$	54.74	$\pm 0.028870$	58.83
AVS+TCB	68.54	$\pm 0.026932$	<b>66.31</b>	$\pm 0.027414$	<b>67.41</b>
AVS+TCF	68.29	$\pm 0.026990$	65.22	$\pm 0.027624$	66.72
LRAVS	67.12	$\pm 0.027249$	64.56	$\pm 0.027743$	65.81
LRAVS+TCB	<b>68.46</b>	$\pm 0.026952$	64.91	$\pm 0.027681$	66.64
LRAVS+TCF	66.95	$\pm 0.027284$	63.02	$\pm 0.028$	64.93
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2003 Best	61.65	$\pm 0.025928$	N/A	N/A	N/A
2003 Baseline	5.00	$\pm 0.012641$	N/A	N/A	N/A
Our Baseline	4.96	$\pm 0.012596$	5.12	$\pm 0.01278$	5.04
2003 Topline	100.00	$\pm 0.000000$	N/A	N/A	N/A
Our Topline	100.00	$\pm 0.000000$	99.92	$\pm 0.001681$	99.96

**Table 39. Performance comparison of accuracy on SIGHAN 2003 CTB corpus.**

Configuration	$P$	$C_P$	$R$	$C_R$	$F$
6-tag	87.30	$\pm 0.003334$	86.83	$\pm 0.003385$	87.06
CNG	<b>89.61</b>	$\pm 0.003054$	<b>88.66</b>	$\pm 0.003175$	<b>89.13</b>
AVS	89.38	$\pm 0.003085$	88.06	$\pm 0.003246$	88.71
TCB	87.46	$\pm 0.003315$	86.86	$\pm 0.003382$	87.16
TCF	87.18	$\pm 0.003347$	86.45	$\pm 0.003426$	86.81
AVS+TCB	89.31	$\pm 0.003092$	88.08	<u><math>\pm 0.003244</math></u>	88.69
AVS+TCF	89.39	$\pm 0.003082$	88.17	$\pm 0.003233$	88.78
LRAVS	89.30	$\pm 0.003094$	88.21	$\pm 0.003228$	88.75
LRAVS+TCB	89.37	$\pm 0.003086$	88.09	$\pm 0.003243$	88.72
LRAVS+TCF	89.31	$\pm 0.003093$	88.07	<u><math>\pm 0.003244</math></u>	88.68
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2003 Best	87.50	$\pm 0.003300$	86.60	$\pm 0.003200$	88.10
2003 Baseline	66.30	$\pm 0.004731$	80.00	$\pm 0.004004$	72.50
Our Baseline	66.33	$\pm 0.004730$	80.01	$\pm 0.004003$	72.53
2003 Topline	98.80	$\pm 0.001090$	98.20	$\pm 0.001331$	98.50
Our Topline	98.84	$\pm 0.001072$	98.19	$\pm 0.001333$	98.52

**Table 40. Performance comparison of OOV on SIGHAN 2003 CTB corpus.**

Configuration	$R_{Oov}$	$C_{R_{Oov}}$	$P_{Oov}$	$C_{P_{Oov}}$	$F_{Oov}$
6-tag	69.85	$\pm 0.010805$	62.24	$\pm 0.011415$	65.83
CNG	<b>71.79</b>	$\pm 0.010596$	<b>71.31</b>	$\pm 0.010650$	<b>71.55</b>
AVS	70.59	$\pm 0.010728$	69.61	$\pm 0.010830$	70.09
TCB	70.23	$\pm 0.010766$	62.51	$\pm 0.011398$	66.14
TCF	69.49	$\pm 0.010841$	61.91	$\pm 0.011434$	65.48
AVS+TCB	70.73	$\pm 0.010714$	70.05	$\pm 0.010785$	70.39
AVS+TCF	70.95	$\pm 0.010690$	69.80	$\pm 0.010811$	70.37
LRAVS	70.35	$\pm 0.010753$	69.98	$\pm 0.010793$	70.16
LRAVS+TCB	70.58	$\pm 0.010730$	70.49	$\pm 0.010739$	70.53
LRAVS+TCF	70.24	$\pm 0.010765$	70.05	$\pm 0.010785$	70.15
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2003 Best	70.50	$\pm 0.010738$	N/A	N/A	N/A
2003 Baseline	6.20	$\pm 0.005678$	N/A	N/A	N/A
Our Baseline	6.24	$\pm 0.005694$	8.36	$\pm 0.006516$	7.14
2003 Topline	99.00	$\pm 0.002343$	N/A	N/A	N/A
Our Topline	99.02	$\pm 0.002324$	97.46	$\pm 0.003703$	98.23

**Table 41. Performance comparison of accuracy on SIGHAN 2006 AS corpus.**

Configuration	$P$	$C_P$	$R$	$C_R$	$F$
6-tag	94.57	±0.001499	95.76	±0.001333	95.16
CNG	95.13	±0.001424	96.16	±0.001271	95.64
AVS	95.25	±0.001407	96.18	±0.001267	95.71
TCB	94.74	±0.001477	95.87	±0.001316	95.30
TCF	94.80	±0.001468	95.85	±0.001319	95.32
AVS+TCB	95.32	±0.001398	96.23	±0.001260	95.77
AVS+TCF	95.33	±0.001395	96.21	±0.001263	95.77
LRAVS	95.24	±0.001408	96.25	±0.001256	95.74
LRAVS+TCB	<b>95.34</b>	±0.001394	<b>96.31</b>	±0.001247	<b>95.82</b>
LRAVS+TCF	95.12	±0.001424	95.97	±0.001300	95.55
2006 Best	95.50	±0.001371	96.10	±0.00128	95.80
2006 Baseline	87.00	±0.002224	91.50	±0.001844	89.20
Our Baseline	87.03	±0.002222	91.47	±0.001848	89.19
2006 Topline	98.70	±0.000749	98.00	±0.000926	98.30
Our Topline	98.68	±0.000754	97.98	±0.00093	98.33

**Table 42. Performance comparison of OOV on SIGHAN 2006 AS corpus.**

Configuration	$R_{Oov}$	$C_{R_{Oov}}$	$P_{Oov}$	$C_{P_{Oov}}$	$F_{Oov}$
6-tag	65.19	±0.015339	60.36	±0.015751	62.68
CNG	67.68	±0.01506	71.51	±0.014533	69.54
AVS	66.90	±0.015152	73.68	±0.01418	70.13
TCB	65.86	±0.015268	61.53	±0.015666	63.62
TCF	67.47	±0.015085	62.17	±0.015616	64.71
AVS+TCB	67.31	±0.015104	74.18	±0.014092	70.58
AVS+TCF	67.94	±0.015028	<b>74.33</b>	±0.014065	70.99
LRAVS	67.73	±0.015054	72.89	±0.014314	70.21
LRAVS+TCB	68.25	±0.014989	73.34	±0.014238	70.70
LRAVS+TCF	<b>69.62</b>	±0.014808	73.89	±0.014143	<b>71.69</b>
2006 Best	70.20	±0.014727	N/A	N/A	N/A
2006 Baseline	3.00	±0.005493	N/A	N/A	N/A
Our Baseline	2.98	±0.005476	5.86	±0.00756	3.95
2006 Topline	99.70	±0.001761	N/A	N/A	N/A
Our Topline	99.64	±0.001936	97.17	±0.005341	98.39

**Table 43. Performance comparison of accuracy on SIGHAN 2006 CityU corpus.**

Configuration	$P$	$C_P$	$R$	$C_R$	$F$
6-tag	96.92	$\pm 0.000736$	96.88	$\pm 0.000741$	96.90
CNG	97.26	$\pm 0.000696$	97.21	$\pm 0.000701$	97.23
AVS	97.31	$\pm 0.000690$	<b>97.34</b>	$\pm 0.000686$	97.32
TCB	96.95	$\pm 0.000733$	96.89	$\pm 0.000740$	96.92
TCF	96.96	$\pm 0.000732$	96.90	$\pm 0.000739$	96.93
AVS+TCB	97.32	$\pm 0.000689$	97.32	$\pm 0.000689$	97.32
AVS+TCF	<b>97.35</b>	$\pm 0.000685$	97.32	<u><math>\pm 0.000688</math></u>	97.33
LRAVS	<b>97.35</b>	$\pm 0.000684$	97.32	<u><math>\pm 0.000688</math></u>	<b>97.34</b>
LRAVS+TCB	97.34	$\pm 0.000686$	97.33	$\pm 0.000687$	<b>97.34</b>
LRAVS+TCF	97.23	$\pm 0.000700$	97.26	$\pm 0.000696$	97.24
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2006 Best	97.20	$\pm 0.000703$	97.30	$\pm 0.000691$	97.20
2006 Baseline	88.20	$\pm 0.002134$	93.00	$\pm 0.001687$	90.60
Our Baseline	88.22	$\pm 0.001374$	93.06	$\pm 0.001083$	90.57
2006 Topline	98.50	$\pm 0.000804$	98.20	$\pm 0.000879$	98.40
Our Topline	98.55	$\pm 0.00051$	98.19	$\pm 0.000568$	98.37

**Table 44. Performance comparison of OOV on SIGHAN 2006 CityU corpus.**

Configuration	$R_{Oov}$	$C_{R_{Oov}}$	$P_{Oov}$	$C_{P_{Oov}}$	$F_{Oov}$
6-tag	78.35	$\pm 0.008738$	69.60	$\pm 0.009759$	73.72
CNG	79.66	$\pm 0.008540$	76.97	$\pm 0.008932$	78.29
AVS	79.27	$\pm 0.008600$	78.08	$\pm 0.008777$	78.67
TCB	78.55	$\pm 0.008708$	69.97	$\pm 0.009725$	74.01
TCF	78.94	$\pm 0.008651$	69.94	$\pm 0.009728$	74.17
AVS+TCB	79.31	$\pm 0.008595$	77.93	$\pm 0.008798$	78.61
AVS+TCF	79.70	$\pm 0.008533$	78.30	$\pm 0.008745$	78.99
LRAVS	<b>79.84</b>	$\pm 0.008512$	78.32	$\pm 0.008742$	79.07
LRAVS+TCB	79.82	$\pm 0.008514$	78.57	$\pm 0.008706$	<b>79.19</b>
LRAVS+TCF	79.48	$\pm 0.008568$	<b>77.93</b>	$\pm 0.008798$	78.70
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2006 Best	78.70	$\pm 0.008686$	N/A	N/A	N/A
2006 Baseline	0.90	$\pm 0.002004$	N/A	N/A	N/A
Our Baseline	0.95	$\pm 0.002053$	2.47	$\pm 0.003293$	1.37
2006 Topline	99.30	$\pm 0.001769$	N/A	N/A	N/A
Our Topline	99.31	$\pm 0.001752$	95.22	$\pm 0.004526$	97.22

**Table 45. Performance comparison of accuracy on SIGHAN 2006 PKU corpus.**

Configuration	$P$	$C_P$	$R$	$C_R$	$F$
6-tag	92.51	$\pm 0.001338$	93.79	$\pm 0.001227$	93.14
CNG	93.54	$\pm 0.001250$	94.38	$\pm 0.001170$	93.96
AVS	93.43	$\pm 0.001259$	94.41	$\pm 0.001167$	93.92
TCB	92.54	<u><math>\pm 0.001335</math></u>	93.75	$\pm 0.001230$	93.14
TCF	92.54	<u><math>\pm 0.001335</math></u>	93.72	$\pm 0.001233$	93.13
AVS+TCB	93.43	$\pm 0.001259$	94.37	$\pm 0.001171$	93.90
AVS+TCF	93.42	$\pm 0.001260$	94.32	$\pm 0.001176$	93.87
LRAVS	<b>93.59</b>	$\pm 0.001245$	<b>94.44</b>	$\pm 0.001164$	<b>94.01</b>
LRAVS+TCB	93.54	$\pm 0.001250$	94.40	$\pm 0.001168$	93.97
LRAVS+TCF	93.40	$\pm 0.001262$	94.30	$\pm 0.001178$	93.85
2006 Best	92.60	$\pm 0.001330$	94.00	$\pm 0.001207$	93.30
2006 Baseline	79.00	$\pm 0.002694$	86.90	$\pm 0.002231$	82.80
Our Baseline	79.04	$\pm 0.002069$	86.87	$\pm 0.001717$	82.77
2006 Topline	97.60	$\pm 0.001012$	96.10	$\pm 0.00128$	96.80
Our Topline	97.59	$\pm 0.000779$	96.08	$\pm 0.000986$	96.83

**Table 46. Performance comparison of OOV on SIGHAN 2006 PKU corpus.**

Configuration	$R_{OOV}$	$C_{R_{OOV}}$	$P_{OOV}$	$C_{P_{OOV}}$	$F_{OOV}$
6-tag	70.51	$\pm 0.007834$	70.70	$\pm 0.00782$	70.60
CNG	74.97	$\pm 0.007442$	<b>78.04</b>	$\pm 0.007112$	76.47
AVS	74.57	$\pm 0.007481$	77.78	$\pm 0.007142$	76.14
TCB	70.73	$\pm 0.007817$	70.90	$\pm 0.007804$	70.81
TCF	70.96	$\pm 0.007799$	70.19	$\pm 0.007859$	70.57
AVS+TCB	74.51	$\pm 0.007487$	77.68	$\pm 0.007154$	76.06
AVS+TCF	74.14	$\pm 0.007522$	77.13	$\pm 0.007215$	75.61
LRAVS	<b>75.28</b>	$\pm 0.007411$	77.93	$\pm 0.007125$	<b>76.58</b>
LRAVS+TCB	75.13	$\pm 0.007427$	77.68	$\pm 0.007154$	76.38
LRAVS+TCF	74.53	$\pm 0.007486$	77.03	$\pm 0.007226$	75.76
2006 Best	70.70	$\pm 0.007819$	N/A	N/A	N/A
2006 Baseline	1.10	$\pm 0.001792$	N/A	N/A	N/A
Our Baseline	1.11	$\pm 0.001803$	3.42	$\pm 0.003124$	1.68
2006 Topline	98.90	$\pm 0.001792$	N/A	N/A	N/A
Our Topline	98.94	$\pm 0.001762$	92.56	$\pm 0.004507$	95.65

**Table 47. Performance comparison of accuracy on SIGHAN 2006 MSR corpus.**

Configuration	$P$	$C_P$	$R$	$C_R$	$F$
6-tag	<b>96.44</b>	$\pm 0.001169$	95.71	$\pm 0.001279$	96.08
CNG	96.19	$\pm 0.001208$	95.58	$\pm 0.001298$	95.88
AVS	96.30	$\pm 0.001191$	95.84	$\pm 0.001260$	96.07
TCB	96.40	<u><math>\pm 0.001177</math></u>	95.74	$\pm 0.001275$	96.07
TCF	96.35	$\pm 0.001183$	95.69	$\pm 0.001283$	96.02
AVS+TC	96.38	$\pm 0.001180$	95.87	$\pm 0.001256$	<b>96.12</b>
AVS+TCF	96.40	<u><math>\pm 0.001177</math></u>	95.73	$\pm 0.001276$	96.06
LRAVS	96.22	$\pm 0.001203$	95.85	<u><math>\pm 0.001259</math></u>	96.04
LRAVS+TCB	96.24	$\pm 0.001200$	<b>95.88</b>	$\pm 0.001255$	96.06
LRAVS+TC	96.16	$\pm 0.001213$	95.85	<u><math>\pm 0.001259</math></u>	96.01
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2006 Best	96.10	$\pm 0.001222$	96.40	$\pm 0.001176$	96.30
2006 Baseline	90.00	$\pm 0.001984$	94.90	$\pm 0.001455$	92.40
Our Baseline	90.03	$\pm 0.001891$	94.94	$\pm 0.001384$	92.42
2006 Topline	99.30	$\pm 0.000551$	99.10	$\pm 0.000625$	99.20
Our Topline	99.28	$\pm 0.000534$	99.08	$\pm 0.000603$	99.18

**Table 48. Performance comparison of OOV on SIGHAN 2006 MSR corpus.**

Configuration	$R_{Oov}$	$C_{R_{Oov}}$	$P_{Oov}$	$C_{P_{Oov}}$	$F_{Oov}$
6-tag	<b>66.57</b>	$\pm 0.016171$	55.62	$\pm 0.017031$	60.60
CNG	61.60	$\pm 0.016672$	58.23	$\pm 0.016906$	59.87
AVS	64.60	$\pm 0.016393$	60.83	$\pm 0.016733$	62.66
TCB	66.86	$\pm 0.016136$	55.95	$\pm 0.017018$	60.92
TCF	66.42	$\pm 0.016189$	54.67	$\pm 0.017065$	59.97
AVS+TCB	64.72	$\pm 0.016380$	<b>61.19</b>	$\pm 0.016705$	<b>62.91</b>
AVS+TCF	62.78	$\pm 0.016571$	59.86	$\pm 0.016803$	61.28
LRAVS	63.92	$\pm 0.016462$	59.94	$\pm 0.016797$	61.87
LRAVS+TCB	62.87	$\pm 0.016563$	60.40	$\pm 0.016765$	61.61
LRAVS+TCF	62.96	$\pm 0.016554$	59.56	$\pm 0.016824$	61.21
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2006 Best	61.20	$\pm 0.016704$	N/A	N/A	N/A
2006 Baseline	2.20	$\pm 0.005028$	N/A	N/A	N/A
Our Baseline	2.17	$\pm 0.004999$	11.13	$\pm 0.010780$	3.64
2006 Topline	99.90	$\pm 0.001083$	N/A	N/A	N/A
Our Topline	99.85	$\pm 0.001313$	99.24	$\pm 0.002975$	99.55

**Table 49. Performance comparison of accuracy on SIGHAN 2008 AS corpus.**

Configuration	$P$	$C_P$	$R$	$C_R$	$F$
6-tag	82.36	$\pm 0.002526$	83.25	$\pm 0.002475$	82.80
CNG	83.00	$\pm 0.002490$	83.77	$\pm 0.002444$	83.38
AVS	<b>83.09</b>	$\pm 0.002484$	<b>83.83</b>	$\pm 0.002440$	<b>83.46</b>
TCB	82.28	$\pm 0.002531$	83.20	$\pm 0.002478$	82.74
TCF	82.54	$\pm 0.002516$	83.37	$\pm 0.002468$	82.95
AVS+TCB	82.83	$\pm 0.002499$	83.62	$\pm 0.002453$	83.23
AVS+TCF	82.97	$\pm 0.002492$	83.80	<u><math>\pm 0.002442</math></u>	83.38
LRAVS	82.98	$\pm 0.002491$	83.78	$\pm 0.002443$	83.38
LRAVS+TCB	83.03	$\pm 0.002488$	83.80	<u><math>\pm 0.002442</math></u>	83.42
LRAVS+TCF	82.86	$\pm 0.002498$	83.72	$\pm 0.002447$	83.29
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2008 Best	94.40	$\pm 0.001527$	95.01	$\pm 0.001445$	94.70
2008 Baseline	82.32	$\pm 0.002534$	89.78	$\pm 0.002012$	85.69
Our Baseline	80.99	$\pm 0.002601$	89.29	$\pm 0.002050$	84.93
2008 Topline	98.80	$\pm 0.000723$	98.23	$\pm 0.000876$	98.52
Our Topline	98.53	$\pm 0.000796$	97.84	$\pm 0.000963$	98.19

**Table 50. Performance comparison of OOV on SIGHAN 2008 AS corpus.**

Configuration	$R_{Oov}$	$C_{R_{Oov}}$	$P_{Oov}$	$C_{P_{Oov}}$	$F_{Oov}$
6-tag	62.85	$\pm 0.011258$	55.49	$\pm 0.011580$	58.94
CNG	63.78	$\pm 0.011199$	<b>63.07</b>	$\pm 0.011245$	<b>63.42</b>
AVS	63.38	$\pm 0.011225$	62.50	$\pm 0.011280$	62.94
TCB	62.42	$\pm 0.011285$	55.61	$\pm 0.011576$	58.82
TCF	63.61	$\pm 0.011210$	56.22	$\pm 0.011560$	59.69
AVS+TCB	62.89	$\pm 0.011256$	60.88	$\pm 0.011371$	61.87
AVS+TCF	63.60	$\pm 0.011211$	61.80	$\pm 0.011321$	62.68
LRAVS	63.30	$\pm 0.01123$	62.19	$\pm 0.011298$	62.74
LRAVS+TCB	63.34	$\pm 0.011228$	62.27	$\pm 0.011294$	62.80
LRAVS+TCF	<b>62.81</b>	$\pm 0.011261$	61.71	$\pm 0.011326$	62.25
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2008 Best	74.04	$\pm 0.010215$	76.49	$\pm 0.009881$	75.24
2008 Baseline	2.08	$\pm 0.003325$	6.78	$\pm 0.005858$	3.19
Our Baseline	4.03	$\pm 0.004583$	8.08	$\pm 0.006348$	5.38
2008 Topline	99.32	$\pm 0.001915$	96.42	$\pm 0.004329$	97.84
Our Topline	99.40	$\pm 0.001795$	96.41	$\pm 0.004337$	97.88

**Table 51. Performance comparison of accuracy on SIGHAN 2008 CTB corpus.**

Configuration	$P$	$C_P$	$R$	$C_R$	$F$
6-tag	95.56	$\pm 0.001682$	95.51	$\pm 0.001691$	95.54
CNG	95.54	$\pm 0.001686$	95.53	$\pm 0.001688$	95.54
AVS	95.68	$\pm 0.001660$	95.71	$\pm 0.001655$	95.70
TCB	95.54	$\pm 0.001687$	95.54	$\pm 0.001687$	95.54
TCF	95.52	$\pm 0.001689$	95.54	$\pm 0.001685$	95.53
AVS+TCB	95.58	$\pm 0.001680$	95.61	$\pm 0.001674$	95.59
AVS+TCF	<b>95.98</b>	$\pm 0.001605$	<b>95.96</b>	$\pm 0.001609$	<b>95.97</b>
LRAVS	95.55	$\pm 0.001684$	95.56	$\pm 0.001682$	95.56
LRAVS+TCB	95.53	$\pm 0.001687$	95.56	$\pm 0.001683$	95.55
LRAVS+TCF	95.69	$\pm 0.001658$	95.72	$\pm 0.001653$	95.71
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2008 Best	95.96	$\pm 0.001386$	95.83	$\pm 0.001408$	95.89
2008 Baseline	84.27	$\pm 0.002563$	88.64	$\pm 0.002234$	86.40
Our Baseline	84.05	$\pm 0.002991$	88.86	$\pm 0.002570$	86.39
2008 Topline	98.25	$\pm 0.000923$	97.10	$\pm 0.001181$	97.67
Our Topline	98.42	$\pm 0.001018$	97.55	$\pm 0.001264$	97.98

**Table 52. Performance comparison of OOV on SIGHAN 2008 CTB corpus.**

Configuration	$R_{Oov}$	$C_{R_{Oov}}$	$P_{Oov}$	$C_{P_{Oov}}$	$F_{Oov}$
6-tag	77.63	$\pm 0.014611$	70.56	$\pm 0.01598$	73.92
CNG	76.28	$\pm 0.014915$	74.58	$\pm 0.015266$	75.42
AVS	77.69	$\pm 0.014597$	75.87	$\pm 0.015001$	76.77
TCB	77.69	<u><math>\pm 0.014597</math></u>	70.71	$\pm 0.015955$	74.04
TCF	77.69	<u><math>\pm 0.014597</math></u>	71.03	$\pm 0.015904$	74.21
AVS+TCB	77.20	$\pm 0.014710$	75.14	$\pm 0.015153$	76.16
AVS+TCF	<b>78.86</b>	$\pm 0.014316$	77.43	$\pm 0.014657$	<b>78.14</b>
LRAVS	77.11	$\pm 0.014731$	75.21	$\pm 0.015139$	76.15
LRAVS+TCB	77.04	$\pm 0.014745$	75.19	$\pm 0.015142$	76.11
LRAVS+TCF	78.15	$\pm 0.014488$	<b>76.50</b>	$\pm 0.014865$	77.32
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2008 Best	77.30	$\pm 0.014687$	77.61	$\pm 0.014615$	77.45
2008 Baseline	2.83	$\pm 0.005814$	7.69	$\pm 0.009341$	4.14
Our Baseline	1.54	$\pm 0.004313$	3.34	$\pm 0.006298$	2.10
2008 Topline	99.20	$\pm 0.003123$	97.07	$\pm 0.005913$	98.12
Our Topline	99.54	$\pm 0.002375$	97.56	$\pm 0.005409$	98.54



**Table 53. Performance comparison of accuracy on SIGHAN 2008 NCC corpus.**

Configuration	$P$	$C_P$	$R$	$C_R$	$F$
6-tag	93.55	$\pm 0.001259$	93.09	$\pm 0.001300$	93.32
CNG	<b>93.84</b>	$\pm 0.001232$	<b>93.90</b>	$\pm 0.001226$	<b>93.87</b>
AVS	93.69	$\pm 0.001246$	93.72	$\pm 0.001243$	93.71
TCB	93.60	$\pm 0.001254$	93.14	$\pm 0.001295$	93.37
TCF	93.46	$\pm 0.001267$	93.11	$\pm 0.001298$	93.28
AVS+TCB	93.79	$\pm 0.001237$	93.78	$\pm 0.001238$	93.78
AVS+TCF	93.75	<u><math>\pm 0.001240</math></u>	93.81	$\pm 0.001235$	93.78
LRAVS	93.76	<u><math>\pm 0.001240</math></u>	93.83	$\pm 0.001233$	93.79
LRAVS+TCB	93.78	$\pm 0.001238$	93.86	$\pm 0.001230$	93.82
LRAVS+TCF	93.73	$\pm 0.001242$	93.81	$\pm 0.001235$	93.77
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2008 Best	94.07	$\pm 0.001210$	94.02	$\pm 0.001214$	94.05
2008 Baseline	87.16	$\pm 0.001714$	92.00	$\pm 0.001390$	89.51
Our Baseline	87.18	$\pm 0.001713$	91.99	$\pm 0.001391$	89.52
2008 Topline	98.17	$\pm 0.000687$	97.35	$\pm 0.000823$	97.76
Our Topline	98.17	$\pm 0.000687$	97.35	$\pm 0.000823$	97.76

**Table 54. Performance comparison of OOV on SIGHAN 2008 NCC corpus.**

Configuration	$R_{oov}$	$C_{R_{oov}}$	$P_{oov}$	$C_{P_{oov}}$	$F_{oov}$
6-tag	62.32	$\pm 0.0114$	51.51	$\pm 0.011758$	56.40
CNG	60.43	$\pm 0.011504$	59.39	$\pm 0.011554$	59.90
AVS	59.76	$\pm 0.011537$	57.86	$\pm 0.011617$	58.79
TCB	<b>63.28</b>	$\pm 0.011341$	52.30	$\pm 0.011751$	57.27
TCF	62.86	$\pm 0.011367$	52.73	$\pm 0.011745$	57.35
AVS+TCB	60.30	$\pm 0.011511$	58.43	$\pm 0.011595$	59.35
AVS+TCF	59.91	$\pm 0.01153$	58.64	$\pm 0.011586$	59.27
LRAVS	60.08	$\pm 0.011522$	59.31	$\pm 0.011557$	59.69
LRAVS+TCB	60.32	$\pm 0.01151$	<b>59.49</b>	$\pm 0.011549$	<b>59.90</b>
LRAVS+TCF	60.23	$\pm 0.011514$	59.21	$\pm 0.011562$	59.72
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2008 Best	61.79	$\pm 0.011431$	59.84	$\pm 0.011533$	60.80
2008 Baseline	2.73	$\pm 0.003834$	18.58	$\pm 0.00915$	4.76
Our Baseline	2.73	$\pm 0.003831$	18.58	$\pm 0.009151$	4.75
2008 Topline	99.33	$\pm 0.001919$	92.03	$\pm 0.006372$	95.54
Our Topline	99.34	$\pm 0.001911$	92.04	$\pm 0.006368$	95.55

