

Chinese Word Segmentation and Named Entity Recognition: A Pragmatic Approach

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This paper presents a pragmatic approach to Chinese word segmentation. It differentiates from most of the previous approaches mainly in three respects. First of all, while theoretical linguists have defined Chinese words with various linguistic criteria, Chinese words in this study are defined pragmatically as segmentation units whose definition depends on how they are used and processed in realistic computer applications. Secondly, we propose a pragmatic mathematical framework in which segmenting known words and detecting unknown words of different types (i.e. morphologically derived words, factoids, named entities, and other unlisted words) can be performed simultaneously in a unified way. These tasks are usually conducted separately in other systems. Finally, we do not assume the existence of a universal word segmentation standard which is application independent. Instead, we argue for the necessity of multiple segmentation standards due to the pragmatic fact that different NLP applications might require different granularities of Chinese words.

*These pragmatic approaches have been implemented in an adaptive Chinese word segmenter, called **MSRSeg** which will be described in detail. It consists of two components: (1) a generic segmenter that is based on the framework of linear mixture models, and provides a unified approach to the five fundamental features of word-level Chinese language processing: lexicon word processing, morphological analysis, factoid detection, named entity recognition, and new word identification; and (2) a set of output adaptors for adapting the output of the former to different application-specific standards. Evaluation on five test sets with different standards shows that the adaptive system achieves state-of-the-art performance on all the test sets.*

1. Introduction

This paper is intended to address two fundamental issues in Chinese natural language processing (NLP) with a unified and *pragmatic* approach: what is a word in Chinese, and how does a computer identify Chinese words automatically. Our approach is distinguished from most of the previous approaches by the following three unique components which are integrated into a single model: a taxonomy of Chinese words, a unified approach to word breaking¹ and unknown word detection, and a customizable display of word segmentation. We will describe each of them in turn.

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1 In this paper, we differentiate the terms *word breaking* and *word segmentation*. Word breaking refers to the process of segmenting known words that are pre-defined in a lexicon. Word segmentation refers to the process of both lexicon word segmentation and unknown word detection.

Chinese word segmentation is challenging partly due to the fact that it is often difficult to define what constitutes a word in Chinese. Theoretical linguists have tried to define Chinese words with various linguistic criteria (e.g. Packard 2000). While each of those criteria provides valuable insights to the “word-hood” in Chinese, they do not always lead us to the same conclusions when applied to some specific cases. Fortunately, this may not be a serious issue in computational linguistics where the definition of words can vary and can depend to a large degree upon how one uses and processes these words in computer applications (Sproat and Shih 2002).

In this paper, we define Chinese words from the viewpoint of computational linguistics. We develop a taxonomy where Chinese words can be categorized into one of the following five types: lexicon words, morphologically derived words, factoids, named entities, and new words.² These five types of words have different computational properties, and are processed in different ways in our system, as will be described in detail in Section 3. Two of these five types, factoids and named entities, are not important to theoretical linguists but are significant in NLP.

Chinese word segmentation involves mainly two research issues, word boundary disambiguation and unknown word identification. In most of the current systems, these two tasks are considered as separate ones and dealt with using different components in a cascaded or consecutive manner.

However, we believe that these two problems are not separable in nature, and are better solved simultaneously. In this paper, we present a unified approach to the five fundamental features of word-level Chinese NLP (corresponding to the five types of words described above): (1) word breaking, (2) morphological analysis, (3) factoid detection, (4) named entity recognition (NER), and (5) new word identification (NWI). This approach is based on a mathematical framework of linear mixture models where component models are inspired by the source-channel models of Chinese sentence generation. There are basically two types of component models: a source model and a set of channel models. The source model is used to estimate the generative probability of a word sequence, in which each word belongs to one word type. For each word type, a channel model is used to estimate the likelihood of a character string given the word type. So there are multiple channel models. We shall show that this framework is flexible enough to incorporate a wide variety of linguistic knowledge and statistical models in a unified way.

In computer applications, we are more concerned with *segmentation units* than *words*. While words are supposed to be unambiguous and static linguistic entities, segmentation units are expected to vary from application to application. In fact, different Chinese NLP-enabled applications may have different requirements that request different granularities of word segmentation. For example, automatic speech recognition (ASR) systems prefer “longer words” to achieve higher accuracy whereas information retrieval (IR) systems prefer “shorter words” to obtain higher recall rates, etc. (Wu 2003).

Therefore, we do not assume that there exists a universal word segmentation standard which is application independent. Instead, we argue for the existence of multiple segmentation standards, each for a specific application. It is undesirable to develop a set of application-specific segmenters. A better solution is to develop a generic segmenter with customizable output, which is able to provide alternative segmenta-

² New words in this paper refer to out-of-vocabulary words that are neither recognized as named entities or factoids nor derived by morphological rules. These words are mostly domain-specific and/or time-sensitive (see Section 5.5 for details).

tion units according to the specification which is either pre-defined or implied in the application data. To achieve this, we present a Transformation-Based Learning (TBL, Brill 1995) method, as will be described in Section 6.

The pragmatic approach to Chinese word segmentation, as described above, has been implemented in an adaptive Chinese word segmenter, called **MSRSeg**. It consists of two components: (1) a generic segmenter that is based on the linear mixture model framework of word breaking and unknown word detection, and can adapt to domain-specific vocabularies, and (2) a set of output adaptors for adapting the output of the former to different application-specific standards. Evaluation on five test sets with different standards shows that the adaptive system achieves state-of-the-art performance on all the test sets. It thus demonstrates the possibility of a single adaptive Chinese word segmenter that is capable of supporting multiple user applications.

The remainder of this paper is organized as follows. Section 2 presents previous work in this field. Section 3 introduces the taxonomy of Chinese words, and describes the corpora we used in our study. Section 4 presents some theoretical background on which our unified approach is based. Section 5 outlines the general architecture of the Chinese word segmenter, **MSRSeg**, and describes each of the components in detail, presenting separate evaluation of each component where appropriate. Section 6 presents the TBL method of standards adaptation. While in Section 5 we presume the existence of an annotated training corpus, we focus in Section 7 on the methods of creating training data in an (semi-)automatic manner with minimal or no human annotation. We thus demonstrate the possibilities of unsupervised learning of Chinese words. Section 8 presents several evaluations of the system on the different corpora, each corresponding to a different segmentation standard, in comparison with other state-of-the-art systems. Finally, we conclude the paper in Section 9.

2. Previous Work

2.1 Approaches to Word Segmentation

Many methods of Chinese word segmentation have been proposed: reviews include (Wu and Tseng 1993; Sproat and Shih 2002; Sun and Tsou 2001). These methods can be roughly classified into dictionary-based methods and statistical-based methods, while many state-of-the-art systems use hybrid approaches.

In dictionary-based methods, given an input character string, only words that are stored in the dictionary can be identified. One of the most popular methods is Maximum Matching (MM), usually augmented with heuristics to deal with ambiguities in segmentation. Papers that use this method or minor variants include (Chen et al. 1999; Nie, Jin and Hannan 1994; etc.). The performance of these methods thus depends to a large degree upon the coverage of the dictionary, which unfortunately may never be complete because new words appear constantly. Therefore, in addition to the dictionary, many systems also contain special components for unknown word identification. In particular, statistical methods have been widely applied because they utilize a probabilistic or cost-based scoring mechanism, instead of the dictionary, to segment the text. These methods, however, suffer from three drawbacks. First, some of these methods (e.g. Lin et al. 1993; Chang and Su 1997) identify OOV (out-of-vocabulary) words without identifying their types. For instance, one would identify a string as a unit, but fail to identify whether it is a person name. This is not always sufficient. Second, many current statistical methods suffer from the difficulty in incorporating linguistic knowledge effectively into segmentation. For example, Teahan et al. (2000) and Dai et al. (1999) do not use any linguistic knowledge. Thus, the identified OOV words

are likely to be linguistically implausible, and consequently, additional manual checking is needed for some subsequent tasks such as parsing. Third, in many current segmenters, OOV identification is considered as a separate process from segmentation (e.g. Chen 2003; Wu and Jiang 2000; Chen and Bai 1998). For instance, Chen (2003) assumes that OOV words are usually two or more characters long and are often segmented into single characters. He then uses different components to detect OOV words of different types in a cascaded manner after the basic word segmentation.

We believe that the identification of OOV words should not be defined as a separate problem from word segmentation. Integrating them would benefit both. We thus propose a unified approach which solves both problems simultaneously. One previous work along this line is Sproat et al. (1996), which is based on weighted finite-state transducers (FSTs). Our approach is motivated by the same inspiration, but is based on a different mechanism: linear mixture models. As we shall see, the models provide a more flexible framework to incorporate various kinds of lexical and statistical information. Many types of OOV words that are not covered in Sproat's system can be dealt with in our system. The linear models we used are originally derived from linear discriminant functions widely used for pattern classification (Duda, Hart and Stork 2001), and have been recently introduced into NLP tasks by Collins and Duffy (2001). Other frameworks of Chinese word segmentation, which are similar to the linear models, include maximum entropy models (Xue 2003) and conditional random fields (Peng, Feng and McCallum 2004). They also use a unified approach to word breaking and OOV identification.

2.2 More on New Word Identification

In this paper, new words refer to OOV words other than named entities, factoids and morphologically derived words. These words are mostly domain-specific terms (e.g. 蜂窝式 'cellular') and time-sensitive political, social or cultural terms (e.g. 三通 'Three Links', 非典 'SARS'). There have been two general approaches to NWI. The first is to acquire new words from large corpora in an off-line manner and put them into a dictionary before word segmentation starts (e.g. Fung and Wu 1994; Nie, Jin and Hannan 1994; Chien 1997; Gao et al. 2002). The other is to detect new words online, i.e. to spot new words in a sentence on the fly during the process of word segmentation (e.g. Chen 2003; Wu and Jiang 2000). These two approaches complement each other, and we use both of them in our system.

There have been quite a few methods proposed for the off-line approach. The basic assumption is that a Chinese word should appear as a stable sequence in the corpus. So these methods use metrics that are based on statistical features such as mutual information, term frequency or their variants. They require a reasonably large training corpus. The new words detected are mostly proper nouns and other relatively frequent words. Unfortunately, new words in our definition may not be frequent.

There has been less previous work on the latter, and this is the focus of our research reported in this paper. Some recent advances on online NWI explore the use of machine learning approaches. For example, Li et al. (2003) define NWI as a binary classification problem, and use Support Vector Machines (SVM) to combine various linguistically-motivated features to determine whether a Chinese character sequence is a word. Our method is an extension of Li et al.'s in that NWI is not a stand-alone process in our system, but an integral part of word segmentation. We shall show experimentally the benefit of the integration in Section 5.5.

2.3 Standards Adaptation

As described earlier, while Chinese words are supposed to be well-defined, unambiguous and static linguistic entities, we are more concerned with *segmentation units* which are expected to vary among different computer applications. This inspires the development of an adaptive Chinese word segmenter.

However, most of the previous segmenters have been developed according to some standard that assumes a single *correct* segmentation. The only adaptive system³, to the best of our knowledge, is the customizable segmenter described in (Wu 2003), where the display of the segmentation output can be customized by users. The adaptation method we will describe in Section 6 can be viewed as an improved version in that the adaptation rules (or transformations) are acquired automatically from application data via the TBL method (Gao et al. 2004). Though the use of TBL for Chinese word segmentation is not new i.e. see (Palmer 1997; Hockenmaier and Brew 1998), none of them is aimed at standards adaptation.

2.4 Evaluation

Performance of Chinese word segmenters is generally reported in terms of precision and recall. However, a comparison across systems could be very difficult due to the following two reasons. First of all, the “correct” segmentation is not clearly defined. It is common that for a given sentence, there are multiple plausible word segmentations. As shown in (Sproat et al. 1996), the rate of agreement between two human judges is less than 80%. To deal with this problem, Fung and Wu (1994) suggest a procedure called *nk-blind* that uses n blind judges’ standards. If we set $k = 1$, it is sufficient for a segmentation to be considered correct if it agrees with at least one of the n judges. If $k = n$, all judges must agree. Therefore, *nk-blind* gives a more representative performance measure by taking into account multiple judges. Similarly, Sproat et al. (1996) also uses multiple human judges. In Section 8.2, we will present our method for cross-system comparison. We do not use multiple human judges. Instead, we only consider a set of measures that are lexicon-independent and less ambiguous among different human judges and systems.

The second concerns the use of different test sets and ground-rules by many research papers. For example, some papers report precision and recall rates of 98% or 99%. But they either count only the words that are stored in the dictionary, or use unrealistically simple data with a very low OOV rate. Recently, the ACL-SIGHAN-sponsored First International Chinese Word Segmentation Bakeoff alleviates the situation to some degree (Sproat and Emerson 2003). The Bakeoff releases four datasets, each corresponding to a different standard, and consistent train-test splits. We shall evaluate our segmenter on the four datasets in Sections 6.2 and 8.3.

3. Chinese Words

This section defines Chinese words at three levels. We begin with a taxonomy, where Chinese words are categorized into five main types according to the way they are processed and used in realistic systems. Second, we develop the MSR standard, which is a set of specific rules to guide human annotators in segmenting Chinese sentences. Finally, we describe the development of a gold test set and how we evaluate Chinese word segmenters. Below, we use the term “gold test set” to represent the manually

³ Huang et al. (1997) also proposed an adaptive, three-level standard.

Table 1
Taxonomy of Chinese words used in developing MSRSeg.

LW	Lexical Word	
MDW (see Figure 1 for details)	Morphologically Derived Word	
MP_*, MS_*	Affixation (Prefix, Suffix)	朋友们
MR_*	Reduplication	高高兴兴
ML_*	Splitting	吃了饭
MM_*	Merging	上下班
MHP_*	Head + Particle	走出去
FT	Factoid word	
Dat	Date	10月11日
Dur	Duration	20多分钟
Tim	Time	十二点三十分
Per	Percent and fraction	60%, 1/8
Mon	Money	25000美元
NUMBER	Frequency, integer, decimal, ordinal, rate, etc.	三次, 三个, 12.2亿, 第二个
MEASURE	Age, weight, length, area, capacity, speed, temperature, angle, etc.	78岁, 700公斤, 2亿公里, 1.8亿公顷, 78亿立方米, 每秒2.89米, 9摄氏度, 5度
Ema	E-mail	jfgao@microsoft.com
Pho	Phone, fax, telex	62617711
www	WWW	www.microsoft.com
NE	Named Entity	
P	Person name	李俊生, 亚历山大
L	Location name	蒙特利尔, 圣海伦岛公园
O	Organization name	中央民族乐团, 华加索博物馆
NW	New Word	三通, 非典

- (a) 朋友们/十二点三十分/高高兴兴/地/到/李俊生/教授/家/吃饭
(Friends happily go to professor Li Junsheng's home for lunch at twelve thirty.)
- (b) [朋友+们] MA_S [十二点三十分 12:30 tim] [高兴 MR_AABB] [地][到] [李俊生 P] [教授]
[家] [吃饭]

Figure 1

A Chinese sentence is in (a), where slashes indicating word boundaries. An output of our word segmentation system is in (b), where square brackets indicate word boundaries. + indicates a morpheme boundary.

annotated corpus, according to the MSR standard, on top of the “test corpus” which is the raw text corpus.

3.1 Taxonomy

The taxonomy of Chinese words is summarized in Table 1, where Chinese words are categorized into the five types: entries in a lexicon (or lexicon words, LW), morphologically derived words (MDW), factoids (FT), named entities (NE), and new words (NW). These five types of words have different functions in Chinese NLP, and are processed in different ways in our system. For example, a plausible word segmentation for the sentence in Figure 1(a) is shown in the same figure. Figure 1(b) is the output of our system, where words of different types are processed in different ways:

- For LW, word boundaries are detected such as 教授 ‘professor’.

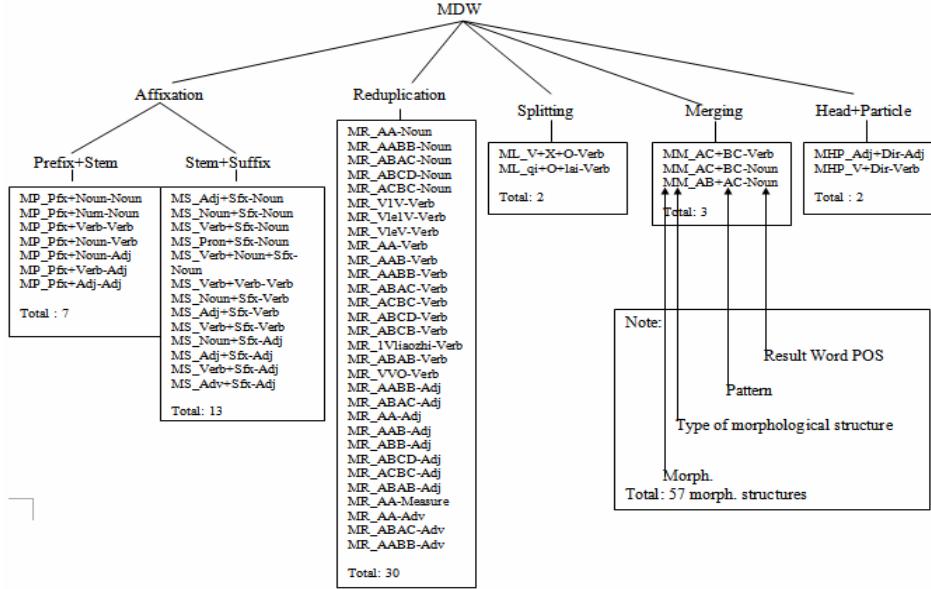
- For MDW, their morphological patterns and stems are detected, e.g. 朋友们 ‘friend+s’ is derived by affixation of the plural affix 们 to the noun (stem) 朋友 (MA_S indicates a suffixation pattern), and 高高兴兴 ‘happily’ is a reduplication of the stem 高兴 ‘happy’ (MR_AABB indicates an AABB reduplication pattern).
- For FT, their types and normalized forms are detected, e.g. 12:30 is the normalized form of the time expression 十二点三十分 (“tim” indicates a time expression).
- For NE, their types are detected, e.g. 李俊生 ‘Li Junsheng’ is a person name.

As one of the reviewers pointed out, the five types of words cannot be defined by any consistent classification criteria (e.g. the relation between MDW and LW depends on the lexicon being used), the taxonomy therefore does not give a clear definition of Chinese words. In this paper, we do not intent to give a standard definition of Chinese words. Instead, we treat Chinese word segmentation as a preprocessing where the best *segmentation units* depend on how they are used in the consequential applications. The five word types are not the definition of Chinese words. They represent five typical processes of Chinese words in most applications. This is one of the reasons that we title this paper “a pragmatic approach”. We focus on two tasks in the approach: how to achieve different Chinese words processing (of the five types) using a unified framework that can be jointly optimized (Sections 4 and 5); and how to adapt our system to different applications (Section 6). Now, we describe each of the five word types in Table 1 in detail.

LW (lexicon words): While some previous research suggested Chinese word segmentation without the use of dictionaries (e.g.: Sproat and Shih 1990; Sun, Shen and Tsou 1998), we believe that a dictionary is an essential component of many applications. For example, in a machine translation system, it is desirable to segment a sentence into LW as much as possible so that the candidate translations of these words can be looked up from a bilingual dictionary. Similarly, we would also like to segment a sentence into LW in a Chinese text-to-speech (TTS) system because the pronunciations stored in the dictionary are usually much more precise than those generated dynamically (for instance by character-to-sound rules). In our system, we used a lexicon containing 98,668 words, including 22,996 Chinese characters stored as single-character words. This lexicon is a combination of several dictionaries that are defined by Chinese linguists and used in different Microsoft applications. Thus, all LW in theory are similar to those described in Packard (2000), i.e. linguistic units that are “salient and highly relevant to the operation of the language processor”.

MDW (morphologically derived words): Chinese words of this type have the following two characteristics. First, MDW can be generated from one or more LW (called stems) via a productive morphological process. For example, in Figure 2, the MDW 高高兴兴 ‘happily’ is generated from a stem 高兴 ‘happy’ via an AABB reduplication process. As shown in Table 1, there are five main categories of morphological processes, each of which has several subcategories, as detailed in Figure 2 (see Wu (2003) for a detailed description):

- **Affixation (MP and MS):** 朋友们 (friend - plural) ‘friends’;
- **Reduplication (MR):** 高兴 ‘happy’ → 高高兴兴 ‘happily’;
- **Splitting (MS)** (i.e. a set of expressions that are separate words at the syntactic level but single words at the semantic level): 吃了饭 ‘already ate’, where

**Figure 2**

Taxonomy of morphologically derived words (MDW) in MSRSeg.

the bi-character word 吃饭 ‘eat’ is split by the particle 了 ‘already’;

- **Merging (MM)**: 上班 ‘on duty’ + 下班 ‘off duty’ → 上下班 ‘on-off duty’; and
- **Head Particle (MHP)** (i.e. expressions that are verb + comp): 走 ‘walk’ + 出去 ‘out’ → 走出去 ‘walk out’.

Second, MDW form stable Chinese character sequences in the corpus. That is, the components within the MDW are strongly correlated (of high co-occurrence frequency), while the components at both ends have low correlations with words outside the sequence. We shall describe in Section 5.2 how the ‘stability’ of a Chinese sequence is measured qualitatively, and how to construct a morph-lexicon for Chinese morphology analysis.

FT (factoids): There are ten categories of factoid words, such as time and date expressions, as shown in Table 1. All FT can be represented as regular expressions. Therefore, the detection and normalization of FT can be achieved by Finite State Machines.

NE (named entities): They refer to those frequently-used Chinese names, including person names, location names and organization names. One cannot develop a regular grammar that rejects or accepts the constructions of NE with a high accuracy, as we can do with most FT. In Section 5.3, we shall describe how we use both heuristics and statistical models for NER.

NW (new words): They refer to OOV words that are neither recognized as named entities or factoids nor derived by morphological rules. In particular, we are focusing on low-frequency new words in this paper. They are newly coined words, occasional words, and mostly time-sensitive words (Wu and Jiang 2000). Many current segmenters simply ignore those new words, assuming that they are often of little significance

in most of applications. However, we argue that the identification of those words is critical because a single unidentified word can cause segmentation errors in the surrounding words. For those NLP applications that require full-parsing, this is even more critical because a single error would cause a whole sentence to fail.

3.2 MSR Standard

The above taxonomy has been specified in detail in the MSR standard. There are two general guidelines for the development of the standard:

1. The standard should be applicable to a wide variety of NLP tasks, of which some representative examples are Chinese text input, IR, TTS, ASR, and MT.
2. The standard should be compatible with existing standards, of which representative examples are the Chinese NE standards in ET/ER-99⁴, the Mainland standard (GB/T), the Taiwan's ROCLING standard (CNS14366, Huang et al. 1997), and the UPenn Chinese Treebank (Xia 1999), as much as possible.

We are seeking a standard that is “linguistically felicitous, computationally feasible, and must ensure data uniformity” (Huang et al. 1997; Sproat and Shih 2002). The MSR standard consists of a set of specific rules that aims at unambiguously determining the word segmentation of a Chinese sentence, given a reference lexicon. The development of the standard is an iterative procedure, interacting with the development of a gold test set (which we will describe in the next section). We began with an initial set of segmentation rules, based on which four human annotators label a test corpus. Whenever an inter-annotator conflict is detected (automatically), we resolve it by revising the standard (e.g. mostly by adding more specific rules). The process is iterated until no conflict is detected. For example, we begin with the rule of detecting MDW: “if a character sequence can be derived from a LW via a morphological process, then the sequence is treated as a MDW candidate.” We then observe that both 吃了饭 ‘already ate’ and 吃了一顿饭 ‘already had a meal’ are derived from the LW 吃饭 ‘eat’ via the morphological process of splitting. While 吃了饭 is a reasonable MDW, 吃了一顿饭 is debatable. We then add a rule: “MDW candidate with complex internal structures should be segmented.” We also add a set of specific rules to define what a complex internal structure is. An example of those rules is “for MDW candidate of the type MS, we only consider sequences that are less than four characters long.”

One drawback of the approach is that the standard would become very complicated as we continue to add such specific rules, and people would start making clerical errors. We do not have any systematic solution currently. The complexity has to be controlled manually. That is, all new added rules are recompiled by a linguist so that the total number of rules is manageable.

3.3 MSR Gold Test Set and Training Set

There were several questions to be answered when we were developing the gold test set for evaluation.

1. How to construct a test corpus for reliable evaluation?
2. Does the segmentation in the gold test set depend on a particular lexicon?

⁴ MET is a Chinese named entity standard defined in the MUC (message understanding conference, http://www.itl.nist.gov/iaui/894.02/related_projects/muc/). ER99 is an extension of MET though it is not as universally used as MET (http://www.nist.gov/speech/tests/ie-er/er_99/er_99.htm).

Table 2
Domain/style distribution in the MSR test corpus.

Domain \ Style (MB)	Descriptive writing	Expository writing	Narrative writing	Practical ⁵ writing	Spoken	Total (%)
Culture		2.2	49.6	12.2		64 (6)
Economic		10.6	102.6	55.1	12.7	181 (17)
Literature	33.1	13.2	6.3			52.6 (5)
Military			42.1			42.1 (4)
Politics		36.2	102.9	88.8	100.8	328.7 (31)
Science&Tech.	7.3	14.7	85.8	2.1	9.4	119.3 (11)
Society	4.5	6.2	56.9	23.9		91.5 (8)
Sport		10.5	33.7		8.3	52.5 (5)
Computer		24.8	65.6			90.4 (9)
Law		2.1	26.3			28.4 (3)
Total (%)	44.9 (4)	120.5 (12)	571.8 (54)	182.1 (17)	131.2 (13)	1,051 (100)

/一批/优异/的/运动/成绩/、/一/条/清晰/的/改革/思路/、/一/笔/巨大/的/精神财富/，/这是/本届/运动会/对/我们/的/赠予/。/对于/正在/为/岁/
/[dat MET 本世纪]/最后/一/簇/全运会/圣火/燃灭/了/，/愿/体育/健儿/从/新/的/起点/上/，/去/迎接/[MS_Noun+Sfx-Adj 世纪/性]/的/挑战/。
/[P 李铁映]/分别/参加/[O 政协]/小组/讨论/提出/
/促进/体育/事业/走上/科学化/轨道/，/用/科技/提高/国民经济/整体/素质/
/[O 新华社]/(北京)/[dat 2/月/28日]/电/，/记者/[曲志红]/、/[P 李斌]/) / [O 中共中央/政治局]/委员/、/国务委员/[P 李铁映]/，/
/[P 李铁映]/首先/感谢/[MS_Noun+Sfx-Noun 委员]/们/对/体育/工作/提出的/宝贵/建议/，/他/表示/要/回去/研究/，/切实/改进/有关/工作/。
/[P 李铁映]/强调/，/体育/事业/是/建设/社会主义/精神文明/的/重要/组成部分/，/体育/改革/必须/坚持/社会主义/方向/，/适应/社会主义/市
[P 温家宝]/在/参加/科技界/小组/讨论/时/强调/，/广大/科技/工作者/要/运用/科学技术/，/提高/国民经济/的/整体/素质/，/提高/经济/增长/的/质量/和/效益/
/[P 温家宝]/还/谈/了/[int 两/人/点/意见/，/第一/，/要/运用/科学技术/，/提高/国民经济/的/整体/素质/，/提高/经济/增长/的/质量/和/效益/
/[O 全国/政协]/[MP_Pfx+Noun-Noun 副/主席]/[P 孙孚凌]/、/[P 朱光亚]/也/分别/参加了/体育界/和/科技界/委员/的/讨论/。
/武林/常青/树/-/一/伤/著名/武术/教练/[P 吴彬]/，/附/图片/1/张/ /
/本报记者/ //[P 王霞光]/
/[P 吴彬]/属/牛/，/下/个/月/他/就要/过/[age 60/岁]/生日/。/按理/说/，/这/头/老黄牛/也/该/喘/口/[MS_Noun+Sfx-Noun 气儿]/了/，/可/实
/作为/我国/著名的/国家级/武术/教练/，/[P 吴彬]/[MPH_V+Dir-Verb 培养/出]/了一大批/全国冠军/。/[dat MET 当年]/主演/电影/《[L_ms_]
/[P 吴彬]/有/众多/的/头衔/，/[MPH_V+Dir-Verb 并/在]/最/前头/的/乃是/[O 北京/武术/院]/院长/、/[O 北京/武术/队]/总教练/，/其次/才是/[
[P 吴彬]/早年/在/[O 北京/体院]/零/的/是/举重/，/后/因/具备/习武/天资/，/经/系/主任/[P 张文广]/教授/批准/[M 转/到]/武术/专业/。/如
/[MPH_V+Dir-Verb 培养/出]/无数/武术/人才/的/[O 北京/武术/队]/堪称/[P 吴彬]/的/得意/之/作/，/但/[P 吴彬]/从来/也/没有"/得意忘形/"/
/为了/武术/运动/的/正常/发展/，/[P 吴彬]/曾/呼吁/公平/竞争/。/他/说/：'/'/10 中国/武/协/1/主席/[P 李杰]/上任/后/，/一直/强调/狠抓/赛
/精力/充沛/的/[P 吴彬]/脑子/里/想/的/全/是/武术/的/事儿/。/对/武术/发展/的/前景/，/[P 吴彬]/很/有些/自己/的/看法/。/他/认为/，/一
/"/为/寻/古/树/繁萦/路/，/不/数/征人/[ten 半/步]题/。'/'/10 中国/武/协/[MP_Pfx+Noun-Noun 副/主席]/[P 番凤凰]/如此/评价/[P 吴彬]/。
/手/握/[M 体育/法]/--/[I 中国]/群众/体育/全面发展/·法制/篇/，/全民/健身/ / /

Figure 3
Fragments of the MSR gold test set.

Table 3
Words in the MSR gold test set.

Word type	N
LW	205,162
MDW	3,746
FT	6,630
NE	Person name 4,347
	Location name 5,311
	Organization name 3,850

3. Should we assume a single correct segmentation for a sentence?
4. What are the evaluation criteria?
5. How to perform a fair comparison across different systems using the gold test set?

5 Chinese writing is normally divided into the first three: descriptive, expository, and narrative. Practical writing is just an umbrella term for all the writing for practical purposes such as notes, letters, emails, marriage announcements, etc.

Table 4
Standards and corpora.

Corpora (standards)	Abbrev.	# Tr. Word	# Te. Word	OOV
MSR standard	MSR	20M	226K	.002
Beijing University	PK	1.1M	17K	.069
U. Penn Chinese Treebank	CTB	250K	40K	.181
Hong Kong City U.	HK	240K	35K	.071
Academia Sinica	AS	5.8M	12K	.021

We answer the first three questions in this section, and leave the rest for Section 3.5. First of all, to conduct a reliable evaluation, we select a test corpus that contains approximately half a million Chinese characters that have been proofread and balanced in terms of domains and styles. The distributions are shown in Table 2. The gold test set is developed by annotating the test corpus according to the MSR standard via the iterative procedure, described in Section 3.2. The statistics are shown in Table 3. Some fragments of the gold test set are shown in Figure 3, where the notation is presented in Tables 1.

As discussed in Section 3.1, we believe that the lexicon is a critical component of many applications. The segmentation of the gold test set depends upon a reference lexicon, which is the combination of several lexicons that are used in Microsoft applications, including Chinese text input system (Gao et al. 2002), ASR (Chang et al. 2001), TTS (Chu et al. 2003) and the MSR-NLP Chinese parser (Wu and Jiang 2000). The lexicon consists of 98,668 entries. On the basis of this, we also developed a *morph-lexicon*, which contains 50,963 high-frequency MDW. We will describe how the morph-lexicon was constructed in Section 5.2.

Regarding the third question, though it is common that there are multiple plausible segmentations for a given Chinese sentence, we keep only a single gold segmentation for each sentence for two reasons. The first is its simplicity. The second is due to the fact that we currently do not know any effective way of using multiple segmentations in the above-mentioned applications. In particular, we segment each sentence as much as possible into words that are stored in the reference lexicon. When there are multiple segmentations for a sentence, we keep the one that contains the fewest number of words.

We have also manually developed a training set according to the MSR standard. It contains approximately 40 million Chinese characters from various domains of text such as newspapers, novels, magazines etc. In our experiments, 90% of the training set is used for model parameter estimation, and the remaining 10% is a held-out set for tuning.

3.4 SIGHAN’s Bakeoff Standards and Corpora

As mentioned in Section 1, **MSRSeg** is designed as an adaptive segmenter that consists of two components: (1) a generic segmenter that can adapt to different domain vocabularies, and (2) a set of output adaptors, learned from application data, for adapting to different application-specific standards.

Therefore, we evaluate **MSRSeg** using five corpora, each corresponding to a different standard, and consistent train-test splits, as shown in Table 4. **MSR** is described in previous sections, and the other four are standards used in SIGHAN’s First International Chinese Word Segmentation Bakeoff (or Bakeoff for brevity, (Sproat and Emer-

son 2003). In the Bakeoff corpora, OOV is defined as the set of words in the test corpus not occurring in the training corpus.

In experiments, we always consider the following adaptation paradigm. Suppose we have a “general” pre-defined standard, according to which we create a *large* amount of training data. We then develop a *generic* word segmenter. Whenever we deploy the segmenter for any application, we customize the output of the segmenter according to an application-specific standard, which can be partially acquired from a given *small* amount of application data (called adaptation data).

MSR is used as the general standard in our experiments, on which the generic segmenter has been developed. The four Bakeoff standards are used as “specific” standards into which we wish to adapt the general standard. We notice in Table 4 that the adaptation data sets (i.e. training corpora for the four Bakeoff standards) are much smaller than the **MSR** training set. Thus, the experimental setting is a good simulation of the adaptation paradigm described above. In the rest of the paper, we shall by default report results on the **MSR** dataset unless otherwise stated.

3.5 Evaluation Methodology

As described earlier, we argue that Chinese words (or segmentation units) cannot be defined independently of the applications, and hence a more flexible system (i.e. an adaptive segmenter such as **MSRSeg**) should be adopted. However, we are faced with the challenge of how to perform an objective and rigorous evaluation of such a system.

The evaluation of NLP systems in general concerns two issues: the criteria and the standard data sets. In this paper we argue that **MSRSeg** is a better system in two aspects. First, the generic segmenter provides not only word segmentation but also word-internal structures (e.g. the tree structures of MDW, FT and NE, as will be described in Section 6) which cover all possible segmentations. Ideally, such a segmenter provides a “superset” of segmentation units where each different application can find the “subset” it needs. Second, the output adaptors of **MSRSeg** can automatically pick different subsets (i.e. segmentation units) from the superset according to different applications. Therefore, there are two criteria for evaluating an adaptive segmenter: how complete the superset is, and how effective the adaptation is. The real evaluation will require some application data sets (i.e. segmented texts used by different applications). However, such application data is not available yet and no other system has undergone such evaluation, so there is no way to compare our system against others in this fashion. The evaluation methodology we adopted in this paper is a simulation. On the one hand, we developed a generic standard and a corresponding gold test set which simulates the generic superset that attempts to cover as many applications as possible. We then evaluate on the data set the completeness of the generic segmenter. On the other hand, we will show that we can effectively adapt the generic segmenter to the four different bakeoff data sets, each of which simulates an application subset.

The evaluation measures we use in this study are summarized in Table 5. The performance of **MSRSeg** is measured through multiple precision-recall (P/R) pairs, and F-measures (defined as $2PR/(P+R)$), each for one word type. Riv is the recall of in-vocabulary words. Roov is the recall of OOV words. They are used to measure the segmenter’s performances in resolving ambiguities in word segmentation and detecting unknown words, respectively. We also test the statistical significance of results, using the criterion proposed by Sproat and Emerson (2003).

Table 5

Evaluation measures for Chinese word segmenter.

Measures	Remarks
P/R/F	Multiple pairs, each for one type of words (i.e. LW, MDW, FT, NE); P/R/F of NER are used for cross-system comparison
Roov	Test the performance of detecting unknown words
Riv	Test the performance of resolving ambiguities in word segmentation
# OAS errors	Similar to cross-bracketing, used for cross-system comparison
# CAS errors	Test on a set of 70 high-frequency CASs in our study
Significant test	See (Sproat and Emerson 2003).

In addition to Riv, the number of OAS (overlap ambiguity string) and CAS (combination ambiguity string) errors are used to measure the segmenter's performance of resolving ambiguities in word segmentation in more detail. Liang (1987) defines OAS and CAS as follows.

Definition 1 *A character string ABC is called an **overlap ambiguity string** (OAS) if it can be segmented into two words either as AB/C or A/BC (not both) depending on different context.*

Definition 2 *A character string AB is called a **combination ambiguity string** (CAS), if A, B, and AB are words.*

Liang (1987) reports that the relative frequency of OAS is 1.2 per 100 characters in Chinese text, and the relative frequency of CAS is 12 times lower than that of OAS. However, according to the above definition, the relative frequency of CAS can be much higher because most single characters in Chinese can be words by themselves, and as a result, almost all bi-character words can be CASs. However, this is not desirable. Consider the word 高度 'altitude'. Though both 高 'high' and 度 'degree' are words by themselves, the segmentation 高/度 almost never occurs in reality. To remedy this problem, Sun and Tsou (2001) revise the definition as follows:

Definition 3 *A character string AB is called a **combination ambiguity string** (CAS), if A, B, and AB are words, and there is at least one context under which the segmentation A/B is plausible both semantically and syntactically.*

Though the revision clarifies the definition in principle, it requires a judgment of the syntactic and semantic sense of the segmentation – a task where an agreement cannot be reached easily among different human annotators. Therefore, we only use the measure of CAS in a pilot study. As will be described in Section 7, the number of CAS errors is estimated by counting the wrong segmentations of the pre-defined 70 high-frequency CASs.

While all measures in Table 5 can be used in evaluating **MSRSeg**, most of them cannot be used in cross-system comparisons. For example, since the **MSR** gold test set is based on a reference lexicon, some of the measures are meaningless when we compare our system to other segmenters that use different lexicons. So in comparing different systems, we consider only the P/R/F of NER and the number of OAS errors (i.e. crossing brackets), because these measures are lexicon independent and there is always a single unambiguous answer.

Table 6

Context model, word classes, class models and feature functions.

Word class	Model	Feature functions, $f(\mathbf{s}, \mathbf{w})$
Context model	Word class trigram, $P(\mathbf{w})$.	$\log(P(\mathbf{w}))$
LW	Lexicon TRIE	Number of LW in \mathbf{w} .
MDW	Morph-lexicon TRIE	Number of MDW in \mathbf{w} .
NE	Character/word bigram, each for one type, $P(\mathbf{s}' NE)$, where \mathbf{s}' is a substring of \mathbf{s} , and forms an NE.	$\sum_{\mathbf{s}' \in A} \log(P(\mathbf{s}' NE))$, where A is the set of substrings that are NE of a particular type in \mathbf{w} .
FT	FSA, each for one type	Number of FT (of a particular type) in \mathbf{w} .
NW	SVM classifier	Score of SVM classifier

4. Theoretical Background

This section provides some theoretical background on the basis of which **MSRSeg** has been developed. We first present in Section 4.1 a Chinese word segmentation framework that uses source-channel models of Chinese sentence generation. Then, in section 4.2, we generalize source-channel models as linear mixture models in which a wide variety of linguistic knowledge and statistical models can be incorporated in a unified way. These models are constructed via two basic modeling tools: (1) n -gram language models (LM, Chen and Goodman 1999), and (2) finite state automata (FSA, Roche and Schabes 1997). More specifically, the LM we used are bigram and trigram backoff models, where the parameters are estimated using maximum-likelihood estimation (MLE) with a particular smoothing method, called Modified Absolute Discounting described in (Gao, Goodman and Miao 2001). LM are used to capture statistical information, such as the likelihood of word or character sequence. FSA are used to represent (1) the lexicon, (2) the rules for detecting FT, and (3) the rules for generating NE candidates.

4.1 Source-Channel Models

The task of **MSRSeg** is to detect not only word boundaries but also word types so that words of different types can be processed accordingly, as shown in Figure 1. Therefore, following the Chinese word taxonomy in Table 1, we define a Chinese *word class* as a group of words that are supposed to be generated according to the same distribution (or processed in the same manner) as follows:

1. Each LW is defined as a class;
2. Each MDW is defined as a class;
3. Each type of FT (e.g. time expression) is defined as a class;
4. Each type of NE (e.g. person names) is defined as a class; and
5. All NW belong to a class.

Notice that both LW and MDW are open sets, and we need to assign a floor-value to those words that are not stored in the lexicons. In particular, we define six unknown word classes as follows. One class is used to represent all unknown LW and all unknown MDW whose type cannot be detected. The other five classes are used to represent unknown MDW, one for each of the five types listed in Table 1, i.e. MP/MS, MR, MS, MM and MHP. The probabilities of these unknown word classes are estimated using the Good-Turing method.

Let $\mathbf{w} = w_1 w_2 \dots w_n$ be a word class sequence, and \mathbf{s} be a Chinese sentence which is character sequence. A segmenter's job is to choose the most likely word class sequence \mathbf{w}^* among all possible candidates into which \mathbf{s} could have been segmented:

$$\mathbf{w}^* = \arg \max_{\mathbf{w} \in \text{GEN}(\mathbf{s})} P(\mathbf{w} | \mathbf{s}) = \arg \max_{\mathbf{w} \in \text{GEN}(\mathbf{s})} P(\mathbf{w})P(\mathbf{s} | \mathbf{w}) \quad (1)$$

where $\text{GEN}(\mathbf{s})$ denotes the candidate set given \mathbf{s} .

Equation (1) is the basic form of source-channel models for Chinese word segmentation. The models assume that a Chinese sentence \mathbf{s} is generated as follows: First, a person chooses a sequence of concepts (i.e., word classes \mathbf{w}) to be output, according to the probability distribution $P(\mathbf{w})$; then the person attempts to express each concept by choosing a sequence of characters, according to the probability distribution $P(\mathbf{s} | \mathbf{w})$.

The source-channel models can be interpreted in another way as follows: $P(\mathbf{w})$ is a stochastic model estimating the probability of word class sequence. It indicates, given a context, how likely a word class occurs. For example, person names are more likely to occur before a title such as 教授 'professor'. Consequently, we also refer to $P(\mathbf{w})$ as a *context model* afterwards. $P(\mathbf{s} | \mathbf{w})$ is a generative model estimating how likely a character string is generated given a word class. For example, the character string 李俊生 is more likely to be a person name than 里俊生 'Li Junsheng' because 李 is a common family name in China while 里 is not. So $P(\mathbf{s} | \mathbf{w})$ is also referred to as *class model* afterwards. In our system, we use only one context model (i.e., a trigram language model) and a set of class models of different types, each of which is for one class of words, as shown in Table 6.

It should be noted that different class models are constructed in different ways (e.g. NE models are n -gram models trained on corpora whereas FT models use derivation rules and have binary values). The dynamic value ranges of different class model probabilities can be so different (some are not *probabilities* but *scores*) that it is inappropriate to combine all models through simple multiplication as in Equation (1). One way to balance these score quantities is to introduce for each class model (i.e. channel model) a model weight λ to adjust the class model score $P(\mathbf{s} | \mathbf{w})$ to $P(\mathbf{s} | \mathbf{w})^\lambda$. In our experiments, these weights are optimized so as to minimize the number of word segmentation errors on training data under the framework of linear models, as described in Section 4.2. It is worth noticing that the source-channel models are the rationale framework behind our system, e.g. the decoding process described in Section 5.6 follows the framework. Linear models are just another representation based on which we describe the optimization algorithm of class model weights.

4.2 Linear Models

The framework of linear models is derived from linear discriminant functions widely used for pattern classification (Duda, Hart and Stork 2001), and has been recently introduced into NLP tasks by Collins and Duffy (2001). It is also related to (log-)linear models described in (Berger, Della Pietra and Della Pietra 1996; Xue 2003; Och 2003; Peng, Feng and McCallum 2004).

We use the following notation in the rest of the paper.

- Training data is a set of example input/output pairs. In Chinese word segmentation we have training samples $\{\mathbf{s}_i, \mathbf{w}_i^R\}$, for $i = 1 \dots M$, where each \mathbf{s}_i is an input Chinese character sequence and each \mathbf{w}_i^R is the reference segmentation (i.e. word class sequence) of \mathbf{s}_i .

- We assume a set of $D + 1$ features $f_d(\mathbf{s}, \mathbf{w})$, for $d = 0 \dots D$. The features are arbitrary functions that map (\mathbf{s}, \mathbf{w}) to real values. Using vector notation, we have $\mathbf{f}(\mathbf{s}, \mathbf{w}) \in \mathbb{R}^{D+1}$, where $\mathbf{f}(\mathbf{s}, \mathbf{w}) = \{f_0(\mathbf{s}, \mathbf{w}), f_1(\mathbf{s}, \mathbf{w}), \dots, f_D(\mathbf{s}, \mathbf{w})\}$. As shown in Table 6, $f_0(\mathbf{w})$ is called the base feature and is defined as the logarithm probability of the context model (i.e. word class trigram model). $f_d(\mathbf{s}, \mathbf{w})$, for $d = 1 \dots D$, are defined for D word classes, respectively (i.e., they are basically derived from class models). Their values are either the summation of the logarithm of the probabilities of the corresponding probabilistic models, or assigned heuristically. Below, for those features that are only defined on \mathbf{w} , we will omit \mathbf{s} and denote them as $f(\mathbf{w})$.
- Finally, the parameters of the model are a vector of $D + 1$ parameters, each for one feature function, $\lambda = \{\lambda_0, \lambda_1, \dots, \lambda_D\}$. $\lambda_1, \dots, \lambda_D$ are in fact class model weights described in Section 4.1. The likelihood score of a word class sequence \mathbf{w} can be written as

$$\text{Score}(\mathbf{w}, \mathbf{s}, \lambda) = \lambda \mathbf{f}(\mathbf{w}, \mathbf{s}) = \sum_{d=0}^D \lambda_d f_d(\mathbf{w}, \mathbf{s}). \quad (2)$$

We see that Equation (2) is yet another representation of the source-channel models described in Section 4.1 by introducing class weights (i.e. adjust $P(\mathbf{s} | \mathbf{w})$ to $P(\mathbf{s} | \mathbf{w})^\lambda$) and taking logarithm of all probabilities. The decision rule of Equation (1) can then be rewritten as

$$\mathbf{w}^* = \arg \max_{\mathbf{w} \in \text{GEN}(\mathbf{s})} \text{Score}(\mathbf{w}, \mathbf{s}, \lambda). \quad (3)$$

In what follows, we will describe the way of estimating λ under the framework of gradient descent: an iterative procedure of adjusting the parameters λ in the direction that minimizes the segmentation errors with respect to a loss function. We will present in turn the loss function and the optimization algorithm.

4.2.1 Loss Function. Assume that we can measure the number of segmentation errors in \mathbf{w} by comparing it with a reference segmentation \mathbf{w}^R using an error function $Er(\mathbf{w}^R, \mathbf{w})$ (i.e. editing distance in our case). The training criterion that directly minimizes the segmentation errors over the training data is

$$\lambda^* = \arg \min_{\lambda} \sum_{i=1 \dots M} Er(\mathbf{w}_i^R, \mathbf{w}(\mathbf{s}_i, \lambda)), \quad (4)$$

where $\mathbf{w}(\mathbf{s}_i, \lambda)$ is the segmentation determined by Equation (3) where it is denoted as \mathbf{w}^* . Equation (4) is referred to as the Minimum Sample Risk (MSR, Gao et al. 2005) criterion afterwards. Notice that without knowing the “true” distribution of the data, the best λ can be chosen approximately based on training samples – known as the principle of Empirical Risk Minimization (ERM, Vapnik 1998): If the segmenter were trained using exactly the MSR criterion, it would converge to a Bayes risk performance (minimal error rate) as the training size goes to infinity.

However, $Er(\cdot)$ is a piecewise constant function of the model parameter λ , and thus a poor candidate for optimization by any simple gradient-type numerical search. For example, the gradient cannot be computed explicitly because $Er(\cdot)$ is not differentiable with respect to λ , and there are many local minima on the error surface. Therefore, we use an alternative loss function, minimum squared error (MSE) in Equation (5), where $Score(\cdot)$ is defined in Equation (2) where \mathbf{s} has been suppressed for simplicity. $MSELoss(\lambda)$ is simply the squared difference between the score of the correct segmentation and the score of the incorrect one, summing over all training samples.

ALGORITHM: PERCEPTON-TRAINING

Input: Training samples $\{\mathbf{s}_i, \mathbf{w}_i^R\}$, for $i = 1 \dots M$, with feature vectors $\mathbf{f}(\mathbf{s}, \mathbf{w}^R)$. # of iteration round T .

Initialization: $\lambda_i = 1$, $i = 0, 1, \dots, M$.

1. **for** $t \leftarrow 1$ **to** T
2. **for** $i \leftarrow 1$ **to** M
3. $\mathbf{w}_i = \text{argmax}_{\mathbf{w} \in \text{GEN}(\mathbf{s}_i)} \lambda^{t-1} \mathbf{f}(\mathbf{s}_i, \mathbf{w})$
4. **for** $d \leftarrow 1$ **to** D
5. $\lambda_d \leftarrow \lambda_d^{t-1} - \eta G(\lambda_d^{t-1})$, where $G(\lambda_d^{t-1})$ is calculated by Equation (8), and $\eta = 0.001$.

Output: Final parameter setting λ^T

Figure 4

The perceptron training algorithm for Chinese word segmentation.

$$\text{MSELoss}(\lambda) = \sum_{i=1 \dots M} (\text{Score}(\mathbf{w}_i^R, \lambda) - \text{Score}(\mathbf{w}_i, \lambda))^2. \quad (5)$$

It is useful to note that the MSE solution, under certain conditions, leads to approximations to maximum likelihood solution. The quality of the approximation depends upon the form of the linear discriminant functions (e.g. Equation (2)). Due to its appealing theoretical properties, the MSE criterion has received considerable attention in the literature, and there are many solution procedures available (Duda, Hart and Stork 2001).

4.2.2 Optimization Algorithm. This section discusses the *delta rule*, a training algorithm of an unthresholded perceptron, following the description in (Mitchell 1997). The delta rule in its component form is

$$\lambda_d = \lambda_d - \eta G(\lambda_d), \quad (6)$$

where η is the step size⁶, and G is the gradient of MSELoss. G can be estimated by differentiating the loss function of Equation (7) with respect to λ_d as

$$G(\lambda_d) = \frac{\partial \text{MSELoss}(\lambda)}{\partial \lambda_d} = \sum_{i=1 \dots M} (\text{Score}(\mathbf{w}_i^R, \lambda) - \text{Score}(\mathbf{w}_i, \lambda)) (f_d(\mathbf{w}_i^R) - f_d(\mathbf{w}_i)). \quad (7)$$

However, the objective function of Equation (5) in the context of our task (i.e. Chinese word segmentation) has many local minima, and thus gradient descent cannot guarantee finding the global minimum. We therefore use a *stochastic approximation* to gradient descent. Whereas the gradient descent computes parameter updates after summing over all training samples as shown in Equation (7), the stochastic approximation method updates parameters incrementally, following the calculation of the error for each individual training sample, as shown in Equation (8).

$$G(\lambda_d) = (\text{Score}(\mathbf{w}_i^R, \lambda) - \text{Score}(\mathbf{w}_i, \lambda)) (f_d(\mathbf{w}_i^R) - f_d(\mathbf{w}_i)) \quad (8)$$

The stochastic approximation method can be viewed as optimizing a distinct loss function $\text{MSELoss}_i(\lambda)$ defined for each individual training sample i as follows

$$\text{MSELoss}_i(\lambda) = (\text{Score}(\mathbf{w}_i^R, \lambda) - \text{Score}(\mathbf{w}_i, \lambda))^2. \quad (9)$$

⁶ η is usually taken as a time-decreasing function (e.g. Su and Lee 1994) to have a fast convergence-speed in the beginning and a small variance in final iterations. We have tested this approach in our study, resulting in very limited improvement.

The optimization algorithm we used in our experiments is shown in Figure 4. It takes T passes over the training set. All parameters are initially set to be 1. The context model parameter λ_0 does change during training. Class model parameters are updated in a simple additive fashion: parameters are altered according to the gradient with respect to $\text{MSELoss}_i(\lambda)$.

In our implementation, we approximate \mathbf{w}^R as the \mathbf{w} in $\text{GEN}(\mathbf{s})$ with the fewest errors, so $\text{Score}(\lambda, \mathbf{s}, \mathbf{w}^R) - \text{Score}(\lambda, \mathbf{s}, \mathbf{w}) \leq 0$, where the equality holds only when $\mathbf{w}^R = \mathbf{w}$. That is, the model parameters are updated when the sentence is wrongly segmented. The update rule increases the parameter values for word classes whose models were “underestimated” (i.e. expected feature value $f(\mathbf{s}, \mathbf{w})$ is less than observed feature value $f(\mathbf{s}, \mathbf{w}^R)$), and decreases the parameter values whose models were “overestimated” (i.e. $f(\mathbf{s}, \mathbf{w})$ is larger than $f(\mathbf{s}, \mathbf{w}^R)$). Empirically, the sequence of these updates, when iterated over all training samples, provides a reasonable approximation to descending the gradient with respect to the original loss function of Equation (5). Although this method cannot guarantee a globally optimal solution, it is chosen for our modeling because of its efficiency and because it achieved the best results in our experiments.

The algorithm is similar to the perceptron algorithm described in (Collins 2002). The key difference is that, instead of using the delta rule of (8) (as shown in Line 5 of Figure 4), Collins (2002) updates parameters using the rule: $\lambda_d^{t+1} \leftarrow \lambda_d^t + f_d(\mathbf{w}_i^R) - f_d(\mathbf{w}_i)$. Our pilot study shows that our algorithm achieves slightly better results.

4.3 Discussions on Robustness

The training methods described in Section 4.2 aims at minimizing errors in a training set. But test sets can be different. The *robustness* issue concerns how well the minimal error rate in the training set preserves in the test set. According to (Dudewicz and Mishra 1988), the MSE function in general is not very robust because it is not bounded, and can be contaminated from those training samples far away from the decision boundary. One of many possible solutions of improving the robustness is to introduce *margin* in the training procedure of Figure 4. The basic idea is to enlarge the score difference (or score margin) between a correct segmentation (i.e. \mathbf{w}^R) and its competing incorrect segmentations (i.e. $\{\mathbf{w}; \mathbf{w} \in \text{GEN}(\mathbf{s}), \mathbf{w} \neq \mathbf{w}^R\}$). According to Equation (8), the perceptron training algorithm of Figure 4 does not adjust parameters if the sentence is segmented correctly. The robustness could be improved if we continued to enlarge the score margin between the correct segmentation and the top competing candidate even if the input sentence had been correctly segmented, until the margin has exceeded a preset threshold. More specially, we can modify Equation (8) as follows

$$G(\lambda_d) = (\text{Score}(\mathbf{w}_i^R, \lambda) - \text{Score}(\mathbf{w}_i, \lambda) - \delta)(f_d(\mathbf{w}_i^R) - f_d(\mathbf{w}_i)) \quad (10)$$

where δ is the desired margin which can either be an absolute value or a quantity proportional to the score of the correct segmentation (Su and Lee 1994). The modified training algorithm is similar to the *perceptron algorithm with margins*, proposed by Krauth and Mèzard (1987). We leave the evaluation of the algorithm to future work. Readers can also refer to (Duda, Hart and Stork 2001) for a detailed description of margin-based learning algorithms.

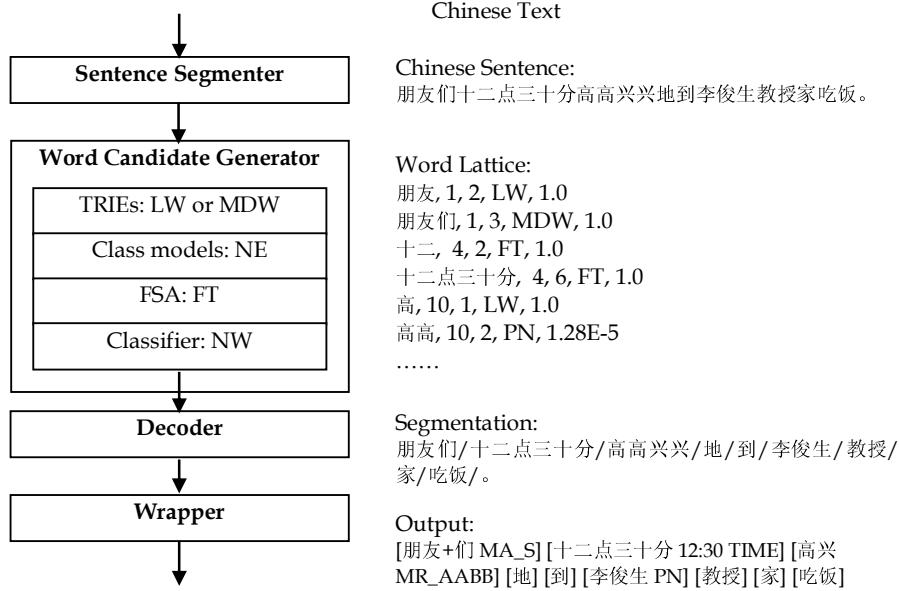


Figure 5
Overall architecture of **MSRSeg**.

5. System Description

5.1 Architecture Overview

MSRSeg consists of two components: a generic segmenter and a set of output adaptors. We describe the first component in this section, and leave the second to Section 6. The generic segmenter has been developed on the basis of the mathematical models described in Section 4. It consists of several components as shown in Figure 5.

- (1) **Sentence Segmenter:** to detect sentence boundaries using punctuation clues such as 。 ? !.
- (2) **Word Candidate Generator:** given an input string s , to generate all word candidates and store them in a word lattice. Each candidate is assigned to its word class and the class model score, e.g. $\log P(s' | w)$ where s' is any substring of s .
- (3) **Decoder:** to select the best (or the N best) word segmentation (i.e. word class sequence w^*) from the lattice according to Equations (4) and (5), using the Viterbi (or A^*) search algorithm.
- (4) **Wrapper:** to output segmentation results using some pre-defined canonic forms, e.g. MDW and FT are of their normalized form, as described in Section 3.1.

Below, we will describe candidate generators for different word classes. They are (1) the lexicon (and morph lexicon) TRIEs to generate LW (or MDW) candidates, (2) the NE class models to generate NE candidates, (3) the finite-state automaton (FSA) to generate FT candidates, and (4) the classifier to generate NW candidates.

5.2 Lexicon Representation and Morphological Analysis

Lexicon words are represented as a set of TRIEs (Frakes and Baeza-Yates 1992), which is a particular implementation of FSA described in Section 4. Given a character string, all its prefix strings that form lexical words can be retrieved by browsing the TRIE whose root represents its first character.

Though there are well-known techniques for English morphology analysis (i.e. finite-state morphology), they are difficult to extend to Chinese for two reasons. First, Chinese morphological rules are not as *general* as their English counterparts. For example, in most cases English plural nouns can be generated using the rule “noun + s → plural noun”. But only a small subset of Chinese nouns can be pluralized (e.g. 朋友们 ‘friends’) using its Chinese counterpart “noun + 们 → plural noun” whereas others (e.g. 南瓜 ‘pumpkins’) cannot⁷. Secondly, the operations required by Chinese morphological analysis such as copying in reduplication, merging and splitting, cannot be implemented using the current finite-state networks⁸.

Our solution is extended lexicalization. We simply collect all MDW of the five types described in Section 3.1 and incorporate them into the TRIE lexicon, called *morph-lexicon*. The TRIEs are essentially the same as those used for lexical words, except that not only the MDW’s identity but also its morphological pattern and stem(s) are stored.

The procedure of lexicalization involves three steps: **(1) Candidate generation.** It is done by applying a set of morphological rules to both the word lexicon and a large corpus. For example, the rule ‘noun + 们 → plural noun’ would generate candidates like 朋友们. **(2) Statistical filtering.** For each candidate, we obtain a set of statistical features such as frequency, mutual information, left/right context dependency from a large corpus. We then use an information-gain-like metric described in (Chien 1997; Gao et al. 2002) to estimate how likely a candidate is to form a morphologically derived word, and remove the “bad” candidates. The basic idea behind the metric is that a Chinese word should appear as a stable sequence in the corpus. That is, the components within the word are strongly correlated, while the components at both ends should have low correlations with words outside the sequence. **(3) Linguistic selection.** We finally manually check the remaining candidates, and construct the morph-lexicon, where each entry is tagged with its morphological pattern and stem(s). The resulting morph-lexicon contains 50,963 MDW.

5.3 Named Entities

We consider four types of named entities: person names (PN), location names (LN), organization names (ON), and transliterations of foreign names (FN). Because any character strings can in principle be named entities of one or more types, in order to limit the number of candidates for a more effective search, we generate named entity candidates given an input string in two steps: First, for each type, we use a set of constraints (which are compiled by linguists and are represented as FSA) to generate only those “most likely” candidates. Second, each of the generated candidates is assigned a class model probability. These class models are defined as generative models which

⁷ We do not consider those special cases, such as in a children’s fairy story, where the magic pumpkins can even talk.

⁸ There are some types of copying operations that can be implemented by FSMs (e.g. Spoart 1992), but the implementation is not trivial. Because the size of MDW is manageable, storing them as a list (as in our paper) is not much more expensive than storing them as a finite-state network, in terms of space and access speed, our implementation can be viewed as a pragmatic solution, easy to implement and maintain.

are estimated on their corresponding named entity lists using MLE, together with a backoff smoothing schema, as described in Section 4.1.1. We will describe briefly the constraints and the class models below. The Chinese person name model is a modified version of that described in Sproat et al. (1996). Other NE models are novel, though they share some similarities with the Chinese person name model.

5.3.1 Chinese Person Names. There are two main constraints. (1) PN patterns: We assume that a Chinese PN consists of a family name F and a given name G , and is of the pattern $F+G$. Both F and G are of one or two characters long. (2) Family name list: We only consider PN candidates that begin with an F stored in the family name list (which contains 373 entries in our system).

Given a PN candidate, which is a character string s , the class model probability $P(s|PN)$ is computed by a character bigram model as follows: (1) Generate the family name sub-string s_F , with the probability $P(s_F|F)$; (2) Generate the given name sub-string s_G , with the probability $P(s_G|G)$ (or $P(s_{G1}|G1)$); and (3) Generate the second given name, with the probability $P(s_{G2}|s_{G1}, G2)$. For example, the generative probability of the string 李俊生 given that it is a PN would be estimated as $P(\text{李俊生}|PN) = P(\text{李}|F)P(\text{俊}|G1)P(\text{生}|俊, G2)$.

5.3.2 Location Names. Unlike PN, there are no patterns for LN. We assume that a LN candidate is generated given s (which is less than 10 characters long), if one of the following conditions is satisfied: (1) s is an entry in the LN list (which contains 30,000 LNs); (2) s ends in a keyword in a 120-entry LN keyword list such as 市 ‘city’⁹.

The probability $P(s|LN)$ is computed by a character bigram model. Consider a string 夏米尔河 ‘Shamir river’. It is a LN candidate because it ends in a LN keyword 河 ‘river’. The generative probability of the string given it is a LN would be estimated as $P(\text{夏米尔河}|LN) = P(\text{夏}|\langle LN \rangle)P(\text{米}|\text{夏})P(\text{尔}|\text{米})P(\text{河}|\text{尔})P(\langle LN \rangle|\text{河})$, where $\langle LN \rangle$ and $\langle /LN \rangle$ are symbols denoting the beginning and the end of a LN, respectively.

5.3.3 Organization Names. ON are more difficult to identify than PN and LN because ON are usually nested named entities. For example, the ON 中国国际航空公司 ‘Air China Corporation’ contains an LN 中国 ‘China’.

Like the identification of LN, an ON candidate is only generated given a character string s (less than 15 characters long), if it ends in a keyword in a 1,355-entry ON keyword list such as 公司 ‘corporation’. To estimate the generative probability of a nested ON, we introduce word class segmentations of s , w , as hidden variables. In principle, the ON class model recovers $P(s|ON)$ over all possible C : $P(s|ON) = \sum_w P(s,w|ON) = \sum_w P(w|ON)P(s|w,ON)$. Since $P(s|w,ON) = P(s|w)$, we have $P(s|ON) = \sum_w P(w|ON)P(s|w)$. We then assume that the sum is approximated by a single pair of terms $P(w^*|ON)P(s|w^*)$, where w^* is the most probable word class segmentation discovered by Equation (5). That is, we also use our system to find w^* , but the source-channel models are estimated on the ON list.

Consider the earlier example. Assuming that $w^* = LN/\text{国际}/\text{航空}/\text{公司}$, where 中国 is tagged as a LN, the probability $P(s|ON)$ would be estimated using a word class bigram model as: $P(\text{中国国际航空公司}|ON) \approx P(LN/\text{国际}/\text{航空}/\text{公司}|ON)P(\text{中国}|LN) = P(LN|\langle ON \rangle)P(\text{国际}|LN)P(\text{航空}|\text{国际})P(\text{公司}|\text{航空})P(\langle /ON \rangle|\text{公司})P(\text{中国}|LN)$.

⁹ For a better understanding, the constraint is a simplified version of that used in MSRSeg.

$| LN)$, where $P(\text{中国} | LN)$ is the class model probability of 中国 given that it is a LN, and <ON> and </ON> are symbols denoting the beginning and the end of a ON, respectively.

5.3.4 Transliterations of Foreign Names. As described in Sproat et al. (1996): FN are usually transliterated using Chinese character strings whose sequential pronunciation mimics the source language pronunciation of the name. Since FN can be of any length and their original pronunciation is effectively unlimited, the recognition of such names can be tricky. Fortunately, there are only a few hundred Chinese characters that are particularly common in transliterations.

Therefore, an FN candidate would be generated given s , if it contains only characters stored in a transliterated name character list (which contains 618 Chinese characters). The probability $P(s | FN)$ is estimated using a character bigram model. Notice that in our system a FN can be a PN, a LN, or an ON, depending on the context. Then, given a FN candidate, three named entity candidates, each for one category, are generated in the lattice, with the class probabilities $P(s | PN)=P(s | LN)=P(s | ON)=P(s | FN)$. In other words, we postpone the determination of its type to the decoding phase where the context model is used.

5.3.4 Abbreviations. For the sake of completeness, we describe below the basic ideas of tackling NE abbreviations within our framework. This is on-going research, and we do not have conclusive results yet. Readers can refer to (Zhu et al. 2003; Sun, Zhou and Gao 2003) for more details, where marginal improvements have been reported.

For different types of NE, different strategies can be adopted. We find that most abbreviations of Chinese PN and LN are single-character NE. The PN and LN models described previously cannot handle them very well because (1) single-character NE are generated in a way different from that of multi-character NE, and (2) the context of single-character NE is different from multi-character ones. For example, single-character NE usually appears adjacently such as 中 and 俄 in 中俄贸易 ‘China-Russia trade’. But this is not the case for multi-character NE.

We thus define single-character PN and LN as two separate word classes, denoted by SCPN and SCLN, respectively. We assume that a character is a candidate of SCPN (or SCLN) only when it is included in a pre-defined SCPN (or SCLN) list, which contains 151 (or 177) characters. The class model probabilities are assigned by unigram models as

$$P(s | SCPN) = \frac{C(s)}{\sum_{i=1 \dots N} C(s_i)}, \quad P(s | SCLN) = \frac{C(s)}{\sum_{i=1 \dots N} C(s_i)}, \quad (11)$$

where $C(s)$ is the count of the SCPN (or SCLN) s in an annotated training set and N is the size of SCPN (or SCLN) list. In the context model, we also differentiate between PN (or LN) and SCPN (or SCLN). Therefore, SCPN and SCLN should be labeled explicitly in the training data.

It is much more difficult to detect abbreviations of ON (denoted by ONA) because ONA are usually multiple-character strings, and can be generated from their original ON arbitrarily. For example, the abbreviation of 清华大学 ‘Tsinghua University’ is 清华 while the abbreviation of 北京大学 ‘Peking University’ is 北大. We assume that an ONA candidate is only generated given a character string s (less than 6 characters long), if both of the following conditions are satisfied: (1) An ON has been detected in the same document, and (2) s can be derived from the ON using a generative pattern defined in Table 7. Since there is no training data for the ONA class model, we

Table 7

Generative patterns of ONA, where s_{ij} denotes the j -th character of the i -th word of ON (Sun, Zhou and Gao 2003)

Condition (ON)	Generated patterns (ONA)	Examples
$ON = w_1 \dots w_N$ ($N \geq 2$)	$ONA = s_{11}s_{21},$ or $ONA = s_{11}s_{21}s_{31},$ or ... $ONA = s_{11}s_{21} \dots s_{N1}$	北京/邮电/大学 → 北邮 北京/邮电/大学 → 北邮大
$ON = w_1w_2,$ and w_1 is not a LN	$ONA = w_1$	清华/大学 → 清华
$ON = w_1w_2w_3,$ and w_1 is not a LN	$ONA = w_1,$ or $ONA = w_1w_2$	苹果/电脑/公司 → 苹果 苹果/电脑/公司 → 苹果/电脑
$ON = w_1w_2w_3,$ and w_1 is a LN	$ONA = w_2$	北京/国安/队 → 国安

Table 8

FT detection results on MSR gold test set. The row of ‘All’ is the results of detecting all 10 types of factoids, as described in Table 1, which amount to 6630 factoids, as shown in Table 3.

	All (P/R)	dat (P/R)	tim (P/R)	mea (P/R)	mon (P/R)
FSA	0.906/0.905	0.967/0.870	0.967/0.967	0.911/0.919	0.991/0.975
MSRSeg	0.908/0.896	0.980/0.851	0.973/0.967	0.913/0.898	0.994/0.975

construct a score function to assign each ONA candidate a class model score. Consider a string 北大. The generative probability of the string given it is an ONA would be as approximated as $P(\text{北大} | \text{ONA}) \approx P(\text{北京大学} | \text{ON}) P(\text{北大} | \text{北京大学}, \text{ON})$, where $P(\text{北大} | \text{北京大学}, \text{ON})$ is defined as a constant (0.8 in our experiments) if 北大 can be derived from 北京大学 using any generative pattern of Figure 7, 0 otherwise. If there are more than one ON that are detected previously in the same document and can derive the ONA candidate (e.g. 北方大学 ‘North University’), only the closest ON is taken into account. We also notice that ONA and ON occur in similar context. So we do not differentiate them in the context model.

5.4 Factoids

The types of factoids handled in **MSRSeg** are shown in Table 1 of Section 3.1. For each type of factoid, we generate a grammar of regular expressions. The ten regular expressions are then compiled into a single FSA. Given an input string s , we scan it from left to right, and output a FT candidate when a substring matches one of the ten regular expressions. We also remove those FT candidates that are substrings of any other candidates of the same type. Consider the example in Figure 1, only the string 十二点三十分 is accepted as a FT candidate (time expression), but not the substrings such as 十二点 or 十二点三十。

The use of FSA is motivated by the fact that the detection of most FT is based exclusively on their internal properties and without relying on context. This can be in principle justified by experiments. As shown in Table 8, the overall performance of FT detection using only FSA is comparable with that of using **MSRSeg** where the contextual information of FT is considered (i.e. in **MSRSeg**, FSA are used as feature functions, and the FT are detected simultaneously with other words). If we read the results carefully, we can see that the use of context information (in **MSRSeg**) achieves a higher precision but a lower recall – a small but significant difference.

5.5 New Words

New words in this section refer to OOV words that are neither recognized as named entities or factoids nor derived by morphological rules. These words are mostly domain-specific and/or time-sensitive, such as 三通‘Three Links’, 非典 ‘SARS’. The identification of such new words has not been studied extensively before. It is an important issue that has substantial impact on the performance of word segmentation. For example, approximately 30% of OOV words in the SIGHAN’s PK corpus in Table 4 are new words of this type. There has been previous work on detecting Chinese new words from a large corpus in an off-line manner and updating the dictionary before word segmentation. However, our approach is able to detect new words on-line, i.e. to spot new words in a sentence on the fly during the process of word segmentation where widely-used statistical features such as mutual information or term frequency are not available.

For brevity of discussion, we will focus on the identification of 2-character new words, denoted as NW_11. Other types of new words such as NW_21 (a 2-character word followed with a character) and NW_12 can be detected similarly (e.g. by viewing the 2-character word as an inseparable unit, like a character). These 3 types amount to 85% of all NWs in the PK corpus. Below, we shall describe the class model and context model for NWI, and the creation of training data by sampling.

5.5.1 Class Model. We use a classifier ($\text{SVM}^{\text{light}}$ (Joachims 2002) in our experiments) to estimate the likelihood of two adjacent characters forming a new word. Of the great number of features with which we experimented, four linguistically-motivated features are chosen due to their effectiveness and availability for on-line detection. They are *Independent Word Probability* (IWP), *Anti-Word Pair* (AWP), *Word Formation Analogy* (WFA), and *Morphological Productivity* (MP). Below we describe each feature in turn. In Section 5.5.2, we shall describe the way the training data (new word list) for the classifier is created by sampling.

IWP (Independent Word Probability) is a real valued feature. Most Chinese characters can be used either as independent words or component parts of multi-character words, or both. The IWP of a single character is the likelihood for this character to appear as an independent word in texts (Wu and Jiang 2000):

$$\text{IWP}(x) = \frac{C(x, W)}{C(x)} \quad (12)$$

where $C(x, W)$ is the number of occurrences of the character x as an independent word in training data, and $C(x)$ is the total number of x in training data. We assume that the IWP of a character string is the product of the IWPs of the component characters. Intuitively, the lower the IWP value, the more likely the character string forms a new word. In our implementation, the training data is word-segmented.

AWP (Anti-Word Pair) is a binary feature derived from IWP. For example, the value of AWP of an NW_11 candidate ab is defined as: $\text{AWP}(ab)=1$ if $\text{IWP}(a)>\theta$ or $\text{IWP}(b)>\theta$, 0 otherwise. $\theta \in [0, 1]$ is a pre-set threshold. Intuitively, if one of the component characters is very likely to be an independent word, it is unlikely to be able to form a word with any other characters. While IWP considers all component characters in a new word candidate, AWP only considers the one with the maximal IWP value.

WFA (Word Formation Analogy) is a binary feature. Given a character pair (x, y) , a character (or a multi-character string) z is called the *common stem* of (x, y) if at least one of the following two conditions hold: (1) character strings xz and yz are lexical words (i.e. x and y as prefixes); and (2) character strings zx and zy are lexical words (i.e. x and

y as suffixes). We then collect a list of such character pairs, called *affix pairs*, of which the number of common stems is larger than a pre-set threshold. The value of WFA for a given NW_11 candidate ab is defined as: $WFA(ab) = 1$ if there exist an affix pair (a, x) (or (b, x)) and the string xb (or ax) is a lexical word, 0 otherwise. For example, given an NW_11 candidate 下岗 (xia4-gang3, ‘be laid off’), we have $WFA(\text{下岗}) = 1$ because (上, 下) is an affix pair (they have 32 common stems such as _任, _游, _台, _车, _面, _午, _班) and 上岗 (shang4-gang3, ‘take over a shift’) is a lexical word.

MP (Morphological Productivity) is a real-valued feature. It is a measure of the productivity of a particular construction, as defined below (Baayen 1989):

$$MP(x) = \frac{n_1(x)}{N(x)} \quad (13)$$

MP is strongly related to the Good-Turing estimate. Here N is the number of tokens of a particular construction found in a corpus, e.g. the number of tokens of all nouns ending in -们, and n_1 is the number of types of that construction, e.g. the number of unique nouns ending in -们. Intuitively, a higher value of MP indicates a higher probability that (one of) the component parts of a multi-character string appears to be a word. For example, Sproat and Shih (2002) show that the MP values of Chinese noun affix -们 and verb affix -过 are 0.20 and 0.04, respectively, indicating -们 that is a much more productive affix, while the MP value of single-character nouns which belong to a closed and non-productive class is close to 0. These results are in agreement with our intuition. Similarly, we find some very productive characters with high MP values. For example, in our training set, there are 236 words that contains the character 帽, among which 13 occur only once.

5.5.2 Context Model. The motivations of using context model for NWI are two-fold. The first is to capture useful contextual information. For example, new words are more likely to be nouns than pronouns, and POS tagging is context-sensitive. The second is more important. As described in Section 4, with a context model, NWI can be performed simultaneously with other word segmentation tasks (e.g.: word breaking, NER and morphological analysis) in a unified approach.

However, it is difficult to develop a training corpus where new words are annotated because “we usually do not know what we don’t know”. Our solution is Monte Carlo simulation. We sample a set of new words from our dictionary according to the distribution – the probability that any lexical word w would be a new word $P(NW|w)$. We then generate a new-word-annotated corpus from a word-segmented text corpus.

Now we describe the way $P(NW|w)$ is estimated. It is reasonable to assume that new words are those words whose probability to appear in a new document is lower than general lexical words. Let $P_i(k)$ be the probability of word w_i that occurs k times in a document. In our experiments, we assume that $P(NW|w_i)$ can be approximated by the probability of w_i occurring less than K times in a new document:

$$P(NW|w_i) \approx \sum_{k=0}^{K-1} P_i(k), \quad (14)$$

where the constant K (7 in our experiments) is dependent on the size of the document: The larger the document, the larger the value. $P_i(k)$ can be estimated using several term distribution models (Chapter 15.3 in Manning and Schütze (1999)). Following (Gao and Lee 2000), we use K-Mixture (Katz 1996) which estimate $P_i(k)$ as

$$P_i(k) = (1 - a)\delta_{k,0} + \frac{a}{\beta+1} \left(\frac{\beta}{\beta+1}\right)^k, \quad (15)$$

where $\delta_{k,0}=1$ if $k=0$, 0 otherwise. α and β are parameters that can be fit using the observed mean λ and the observed inverse document frequency IDF as follow:

$$\begin{aligned} \lambda &= \frac{cf}{N}, \quad IDF = \log \frac{N}{df}, \\ \beta &= \lambda \times 2^{IDF} - 1 = \frac{cf - df}{df}, \text{ and } a = \frac{\lambda}{\beta}, \end{aligned} \quad (16)$$

where cf is the total number of occurrence of word w_i in training data, df is the number of documents in training data that w_i occurs in, and N is the total number of documents. In our implementation, the training data contain approximately 40 thousand documents that have been balanced among domain, style and time.

5.5.3 Evaluation Results. The NWI component has been constructed as an SVM classifier. This section discusses two factors that we believe have the most impact on the performance of NWI. First, we investigate the relative contribution of the four linguistically-motivated features in NWI. Second, we compare methods where we use the NWI component (i.e. an SVM classifier) as a post-processor versus as a feature function in the linear models of Equation (4).

The NWI results on the PK test set are shown in Tables 9 and 10. We turned off the features one at a time and recorded the scores of each ablated NWI component. It turns out that in cases of both NW_11 and NW_12, IWP is obviously the most effective feature.

Tables 11 and 12 show results of NWI on four Bakeoff test sets. We can see that unified approaches (i.e. using NWI component as a feature function) significantly outperform consecutive approaches (i.e. using NWI component as a post-processor) consistently, in terms of both Roov and P/R/F of the overall word segmentation. This demonstrates empirically the benefits of using the context model for NWI and the unified approach to Chinese word segmentation, as described in 5.5.2.

5.6 Decoder

The decoding process follows the source-channel framework. It consists of three steps:

Step 1: Throughout the process, we maintain an array of word class candidates, called lattice, which is initialized to be empty.

Step 2: Given a Chinese sentence, all possible words of different types are generated simultaneously by corresponding channel models described in Sections 5.2 to 5.5. For example, as shown in Table 6, the lexicon TRIE generates LW candidates; the SVM classifier generates NW candidates, and so on. All the generated candidates are added to the lattice. Each element in the lattice is a 5-tuple (w, i, l, t, s) , where w is the word candidate, i is the starting position of w in the sentence, l is the length of w , t is the word class tag, and s is the class model score of w assigned by its feature function in Table 6. Some examples are shown in Figure 5.

Step 3: The Viterbi (or A*) algorithm is used to search for the best word class sequence, among all candidate segmentations in the lattice, according to Equations (2) and (3).

Table 9

NW_11 identification results on PK test set

	P	R	F
All features	0.565	0.788	0.658
w/o IWP	0.395	0.835	0.536
w/o AWP	0.508	0.723	0.596
w/o MP	0.556	0.771	0.646
w/o WFA	0.561	0.779	0.652

Table 10

NW_21 identification results on PK test set

	P	R	F
All features	0.420	0.811	0.553
w/o IWP	0.104	0.973	0.188
w/o AWP	0.338	0.730	0.462
w/o MP	0.398	0.716	0.512
w/o WFA	0.401	0.797	0.534

Table 11

NWI results on PK and CTB corpora, NWI as post-processor versus unified approach

MSRSeg	PK				CTB			
	Roov	F	P	R	Roov	F	P	R
w/o NWI	.741	.956	.949	.963	.690	.892	.875	.910
w/ NWI (post-processor)	.746	.953	.947	.960	.722	.899	.886	.912
w/ NWI (unified approach)	.781	.955	.952	.959	.746	.904	.895	.914

Table 12

NWI results on HK and AS corpora, NWI as post-processor versus unified approach

MSRSeg	HK				AS			
	Roov	F	P	R	Roov	F	P	R
w/o NWI	.694	.947	.937	.958	.436	.951	.958	.943
w/ NWI (post-processor)	.728	.952	.944	.959	.549	.955	.950	.959
w/ NWI (unified approach)	.746	.954	.948	.960	.584	.958	.955	.961

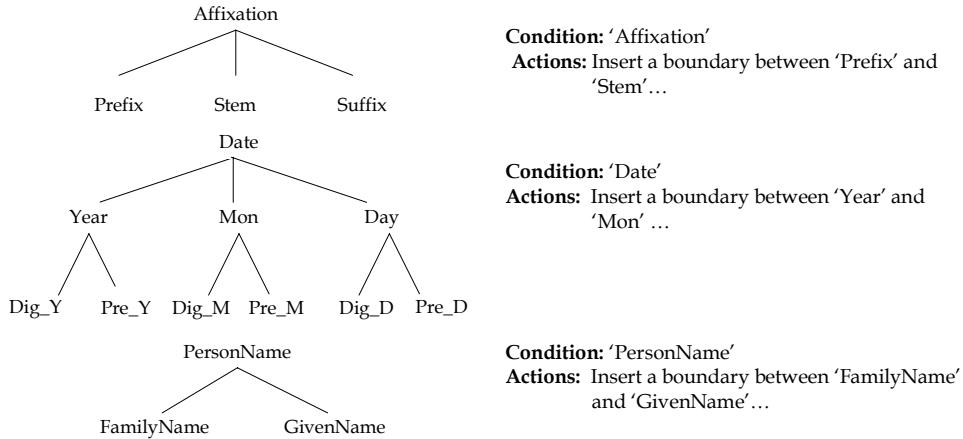
For efficiency, we sometimes need to control the search space. Given an input sentence s , all word candidates are ranked by their normalized class model score $\lambda f(\cdot)$. Thus, the number of candidates (i.e. the size of the lattice) is controlled by two parameters:

- Number threshold – the maximum number of candidates cannot be larger than a given threshold;
- Score threshold – the difference between the class model score of the top-ranked candidates and the bottom-ranked candidates cannot be larger than a given threshold.

6. Standards Adaptation

This section describes the second component of **MSRSeg**: a set of adaptors for adjusting the output of the generic segmenter to different application-specific standards.

We consider the following standards adaptation paradigm. Suppose we have a *general* standard pre-defined by ourselves. We have also created a large amount of training data which are segmented according to this general standard. We then develop a *generic* word segmenter, i.e. the system described in Section 5. Whenever we deploy the segmenter for any application, we need to customize the output of the segmenter according to an application-specific standard, which is not always explicitly defined. However, it is often implicitly defined in a given amount of application data (called adaptation data) from which the specific standard can be partially acquired.

**Figure 6**

Word internal structure and class-type transformation templates.

6.1 Transformation-Based Learning Approach

In **MSRSeg**, standards adaptation is conducted by a postprocessor which performs an ordered list of transformations on the output of the generic segmenter – removing extraneous word boundaries, and inserting new boundaries – to obtain a word segmentation that meets a different standard.

The method we use is Transformation-Based Learning (TBL, Brill (1995)), which requires an initial segmentation, a goal segmentation into which we wish to transform the initial segmentation and a space of allowable transformations (i.e. transformation templates). Under the abovementioned adaptation paradigm, the initial segmentation is the output of the generic segmenter. The goal segmentation is adaptation data. The transformation templates can make reference to words (i.e. lexicalized templates) as well as some pre-defined types (i.e. class-type based templates), as described below.

We notice that most variability in word segmentation across different standards comes from those words that are not typically stored in the dictionary. Those words are dynamic in nature and are usually formed through productive morphological processes. In this study, we focus on three categories: MDW, NE and FT.

For each word class that belongs to these categories, we define an internal structure similar to (Wu 2003). The structure is a tree with 'word class' as the root, and 'component types' as the other nodes. There are 30 component types. As shown in Figure 6, the word class Affixation has three component types: Prefix, Stem and Suffix. Similarly, PersonName has two component types and Date has nine – 3 as non-terminals and 6 as terminals. These internal structures are assigned to words by the generic segmenter at run time. The transformation templates for words of the above three categories are of the form:

Condition: word class

Actions:

- Insert – place a new boundary between two component types.
- Delete – remove an existing boundary between two component types.

Table 13

Comparison scores for PK open and CTB open.

	PK (# of Tr. Word = 1.1M)					CTB (# of Tr. Word = 250K)				
	P	R	F	Roov	Riv	P	R	F	Roov	Riv
1. MSRSeg w/o adaptation	.824	.854	.839	.320	.861	.799	.818	.809	.624	.861
2. MSRSeg	.952	.959	.955	.781	.972	.895	.914	.904	.746	.950
3. FMM w/ adaptation	.913	.946	.929	.524	.977	.805	.874	.838	.521	.952
4. Rank 1 in Bakeoff	.956	.963	.959	.799	.975	.907	.916	.912	.766	.949
5. Rank 2 in Bakeoff	.943	.963	.953	.743	.980	.891	.911	.901	.736	.949

Table 14

Comparison scores for HK open and AS open

	HK (# of Tr. Word = 240K)					AS (# of Tr. Word = 5.8M)				
	P	R	F	Roov	Riv	P	R	F	Roov	Riv
1. MSRSeg w/o adaptation	.819	.822	.820	.593	.840	.832	.838	.835	.405	.847
2. MSRSeg	.948	.960	.954	.746	.977	.955	.961	.958	.584	.969
3. FMM w/ adaptation	.818	.823	.821	.591	.841	.930	.947	.939	.160	.964
4. Rank 1 in Bakeoff	.954	.958	.956	.788	.971	.894	.915	.904	.426	.926
5. Rank 2 in Bakeoff	.863	.909	.886	.579	.935	.853	.892	.872	.236	.906

Since the application of the transformations derived from the above templates are conditioned on word class and make reference to component types, we call the templates *class-type transformation templates*. Some examples are shown in Figure 6.

In addition, we also use *lexicalized transformation templates* as:

- Insert – place a new boundary between two lemmas.
- Delete – remove an existing boundary between two lemmas.

Here, lemmas refer to those basic lexical words that cannot be formed by any productive morphological process. They are mostly single characters, bi-character words, and 4-character idioms.

6.2 Evaluation Results

The results of standards adaptation on four Bakeoff *open* test sets¹⁰ are shown in Tables 13 and 14. A set of transformations for each standard is learnt using TBL from the corresponding Bakeoff training set. For each test set, we report results using our system with and without standards adaptation (Rows 1 and 2). It turns out that performance improves dramatically across the board in all four test sets.

For comparison, we also include in each table the results of using the FMM (forward maximum matching) greedy segmenter¹¹ as a generic segmenter (Row 3), and the top 2 scores (sorted by F) that are reported in SIGHAN’s First International Chinese Word Segmentation Bakeoff (Rows 4 and 5). We can see that with adaptation, our generic segmenter can achieve state-of-the-art performance on different standards, showing its superiority over other systems. For example, there is no single segmenter in the Bakeoff which achieved top-2 ranks in all four test sets (Sproat and Emerson 2003).

¹⁰ See Section 8.3 for the definitions of open test and close test.

¹¹ FMM algorithm processes through the sentence from left to right, taking the longest match with the lexicon entry at each point. Similarly, BMM (backward maximum matching) algorithm processes the sentence from right to left.

Table 15

Size of training data set and the adaptation results on AS open

Size of training set (# words)	R	P	F	R oov	R iv
5.8 M	.961	.956	.958	.603	.968
2.9 M	.959	.950	.954	.623	.966
1.1 M	.954	.945	.949	.591	.962
.25 M	.947	.935	.941	.595	.955
w/o adaptation	.832	.838	.835	.405	.847

We notice in Tables 13 and 14 that the quality of adaptation seems to depend largely upon the size of adaptation data (indicated by # of Tr. Word in the tables): we outperformed the best bakeoff systems in the **AS** set because of the large size of the adaptation data while we are worse in the **CTB** set because of the small size of the adaptation data. To verify our hypothesis, we evaluated the adaptation results using subsets of the **AS** training set of different sizes, and observed the same trend, as shown in Table 15. However, even with a much smaller adaptation data set (e.g. 250K words), we still outperform the best Bakeoff results.

7. Training Data Creation

This section describes (semi-)automatic methods of creating the training data based on which the class model probability $P(\mathbf{w})$ (i.e. trigram probability) in Equation (1) is estimated. Ideally, given an annotated corpus, where each sentence is segmented into words which are tagged by their classes, the trigram word class probabilities can be calculated using MLE. Unfortunately, building such annotated training corpora is very expensive.

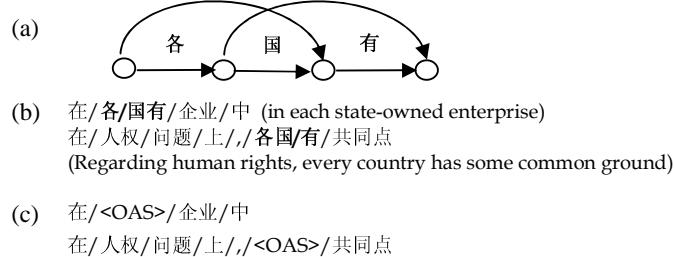
7.1 Bootstrapping Approach and Beyond

Our basic solution is the bootstrapping approach described in Gao et al. (2002). It consists of three steps: (1) Initially, we use a greedy word segmenter¹² to annotate the corpus, and obtain an initial context model based on the initial annotated corpus; (2) we re-annotate the corpus using the obtained models; and (3) re-train the context model using the re-annotated corpus. Steps 2 and 3 are iterated until the performance of the system converges. This approach is also named Viterbi iterative training – an approximation of EM training.

In the above approach, the quality of the context model depends to a large degree upon the quality of the initial annotated corpus, which is however not satisfied due to two problems. First, the greedy segmenter cannot deal with the segmentation ambiguities, and even after many iterations, these ambiguities can only be partially resolved. Second, many factoids and named entities cannot be identified using the greedy word segmenter which is based on the dictionary.

To solve the first problem, we use two methods to resolve segmentation ambiguities in the initially segmented training data. We classify word segmentation ambiguities into two classes: overlap ambiguity (OA), and combination ambiguity (CA), corresponding respectively to OAS and CAS defined in Section 3.5.

12 The greedy word segmenter is based on a FMM algorithm.

**Figure 7**

A Chinese OAS 各国有 in (a). Two sentences in the training set, which contain the OAS (b) and whose OAS have been replaced with the single tokens <OAS> (c). (Li et al. 2003)

To resolve OA, we identify all OAS in the training data and replace them with a single token <OAS>. An example is shown in Figure 7. By doing so, we remove the portion of training data that are likely to contain OA errors. We thus train a context model using the reduced training set which does not contain any OAS. Intuitively, the resulting context model would resolve the ambiguities. The method has been tested on the MSR test set. Our main results are shown in Table 16. We can see that the FMM (or Backward Maximum Matching – BMM) method can only resolve 73.1% (or 71.1%) of OA, while using our method, the resulting context model can resolve 94.3% of the OA. Our method is different from previous ones that use lexicalized rules to resolve OAS. For example, Sun and Zuo (1998) report that over 90% of OA can be disambiguated simply by rules. We re-implemented their method in our experiments, and find that 90.7% (or 91.3%) of the OA in the MSR test set can be resolved. The result is similar to Sun and Zou's, but still not as good as ours. Therefore, we conclude that our method significantly outperforms the rule-based approaches. Another advantage of our method is that it is an unsupervised approach that requires no human annotation. Readers can refer to (Li et al. 2003) for more details.

To resolve CA, we select 70 high-frequency two-character CASs (e.g. 才能 ‘talent’ and 才/能 ‘just able’), as shown in Figure 8. For each CAS, we train a binary classifier using sentences that contains the CAS and have been segmented using the greedy segmenter. Then for each occurrence of a CAS in the initial segmented training data, the corresponding classifier is used to determine whether the CAS should be segmented. Our experiments show that 95.7% of the CAs can be resolved. Detailed results are shown in Figure 8, where ‘Voting’ indicates the accuracy of the baseline method that always chooses the more frequent case of a given CAS, and ‘VSM’ indicates the accuracy of the VSM-inspired (vector space model) binary classifier¹³, which will be described below. Suppose for a given CAS, s , whose position in a sentence is i , we use its six surrounding words w in positions $i-3, i-2, i-1, i+1, i+2$ and $i+3$ as features. We then define a set of feature functions to simulate the TF-IDF scores. Each feature function is a mapping $f(s, w) \in \mathcal{R}$. In particular, let $\text{TF1}(s, w)$ (or $\text{TF2}(s, w)$) be the term frequency of w in the case that s is a 1-word (or 2-word) string. Similarly, let $\text{IDF1}(s, w)$ (or $\text{IDF2}(s, w)$) be 1 if w only occurs in the case that s is a 1-word (or 2-word) string. If w occurs in both cases, let $\text{IDF1}(s, w) = \text{IDF2}(s, w) = 0.25$. We also assign weight λ for

¹³ The VSM-inspired classifier for resolving CA was mainly proposed and implemented by Wenfeng Yang, when he was visiting Microsoft Research Asia.

Table 16

Methods of resolving OAs in word segmentation, on the MSR test set

Methods	Accuracy
FMM	73.1%
BMM	71.5%
Rule + FMM	90.7%
Rule + BMM	91.3%
Ours	94.3%

才能 与其 人为 着手 上将 将来 穿着 不过 成人 处在 到底 到手 得出 的话 上来 正当 中将 总会 等到 等同 等于 低下 地带 都会 多年 一度 一道 高等 上人 高地 个人 上前 过夜 和局 业已 回家 口水 后退 来使 中人 会同 中共 家当 马上 中和 口气 中游 家人 为人 教会 人手 人称 可靠 理事 全能 天下 在场 天才 市区 着眼 条约 应对 是非 正在 内在 名将 将就 同行 同一 使女
Overall accuracy of Voting: 81.7%
Overall accuracy of ME: 94.1%
Overall accuracy of VSM: 95.7%

Figure 8

Results of 70 high-frequency 2-character CASs. ‘Voting’ indicates the accuracy of the baseline method that always chooses the more frequent case of a given CAS. ‘ME’ indicates the accuracy of the maximum-entropy classifier. ‘VSM’ indicates the accuracy of the method of using VSM for disambiguation.

each position empirically (i.e. in our experiments, we have $\lambda_3=\lambda_{+3}=1$, $\lambda_2=\lambda_{+2}=4$, and $\lambda_1=\lambda_{+1}=7$). Then, we can calculate the score of \mathbf{s} to be 1-word or 2-word by Equations (18) and (19), respectively. The CAS is a single word if $\text{Score1}(\mathbf{s}) > \text{Score2}(\mathbf{s})$, two words otherwise.

$$\text{Score 1}(\mathbf{s}) = \sum_{i=-3\dots+3, i \neq 0} \text{TF 1}(\mathbf{s}, w_i) \text{IDF 1}(\mathbf{s}, w_i) \lambda_i \quad (17)$$

$$\text{Score 2}(\mathbf{s}) = \sum_{i=-3\dots+3, i \neq 0} \text{TF 2}(\mathbf{s}, w_i) \text{IDF 2}(\mathbf{s}, w_i) \lambda_i \quad (18)$$

Our experiments show that the VSM-inspired classifier outperforms other well-known classifiers for this particular task. For example, a maximum entropy classifier using the same features achieved an overall accuracy of 94.1%.

For the second problem of NE and FT detection, though we can simply use the FSA-based approach, as described in Section 5.4, to detect FT in the initial segmented corpus, our method of NER in the initial step (i.e. step 1) is a little more sophisticated. First, we manually annotate named entities on a small subset (call *seed set*) of the training data. Then, we obtain a context model on the seed set (called *seed model*). We thus improve the context model which is trained on the initial annotated training corpus by interpolating it with the seed model. Finally, we use the improved context model in steps 2 and 3 of the bootstrapping. We shall show in the next subsection that a relatively small seed set (e.g. 150K words) is enough to get a reasonably good context model for initialization.

7.2 Evaluation Results

To justify the methods described above, we built a large number of context models using different initial corpora. For each of the initial corpora, a context model is trained using the Viterbi iterative procedure until convergence, i.e. the improvement

Table 17

Comparison of performance of **MSRSeg**: the versions that are trained using (semi-)supervised iterative training with different initial training sets (Rows 1 to 8) versus the version that is trained on annotated corpus of 20 million words (Row 9).

	Initial training set	Word segmentation			FT		PN		LN		ON		
		F	P	R	P	R	P	R	P	R	P	R	
1	FMM	.877	.833	.927									
2	1 + OA	.886	.841	.936									
3	1 + FT	.919	.894	.946	.903	.887							
4	2 + FT	.927	.903	.954	.902	.886							
5	4 + NE	0.15	.961	.955	.968	.900	.889	.835	.818	.897	.865	.780	.681
6	Seed set	0.35	.967	.962	.973	.903	.891	.840	.820	.900	.866	.794	.680
7	(M word)	0.50	.967	.962	.972	.905	.895	.844	.821	.900	.863	.800	.678
8		1.00	.968	.963	.973	.905	.895	.854	.826	.903	.865	.802	.679
9	MSR training set	.974	.969	.979	.905	.899	.870	.906	.892	.855	.816	.654	

Table 18

Precision of person name recognition on the **MSR** test set, using Viterbi iterative training, initialized by four seed sets with different sizes

Seed set (M char)	w/o iteration	w/ 1 iteration	w/ 2 iterations
0.15	.745	.790 (+1.6%)	.800 (+0.7%)
0.35	.757	.796 (+1.8%)	.802 (+0.5%)
0.50	.783	.824 (+5.2%)	.835 (+1.3%)
1.00	.815	.835 (+2.5%)	.840 (+0.6%)

Table 19

Precision of location name recognition on the **MSR** test set, using Viterbi iterative training, initialized by four seed sets with different sizes

Seed set (M char)	w/o iteration	w/ 1 iteration	w/ 2 iterations
0.15	.883	.895 (+1.4%)	.897 (+0.2%)
0.35	.893	.901 (+0.9%)	.900 (-0.1%)
0.50	.894	.901 (+0.8%)	.900 (-0.1%)
1.00	.895	.902 (+0.8%)	.903 (+0.1%)

Table 20

Precision of organization name recognition on the **MSR** test set, using Viterbi iterative training, initialized by four seed sets with different sizes

Seed set (M char)	w/o iteration	w/ 1 iteration	w/ 2 iterations
0.15	.695	.770 (+10.8%)	.780 (+1.3%)
0.35	.737	.786 (+6.6%)	.794 (+1.0%)
0.50	.745	.790 (+6.0%)	.800 (+1.3%)
1.00	.757	.796 (+5.2%)	.802 (+0.8%)

of the word segmentation performance of the resulting system is less than a pre-set threshold. The results are shown in Table 17, where Row 1 (FMM) presents the segmentation results of using the initial corpus segmented by a greedy word segmenter – the basic solution described above; in Row 2, we resolve segmentation (overlap) ambiguities on top of the corpus in Row 1; we then tag FT in Rows 3 and 4. From Rows 5 to 8, several NE annotated seed sets of different sizes are used, showing the tradeoff between performance and human cost. In Rows 1 to 8, we use the raw training set containing approximately 50 million characters. For comparison, we also include in

Row 9, the results of **MSRSeg**, whose context model has been trained on 20-million-word manually annotated corpus. The experimental results reveal several facts.

- Although the greedy segmenter (FMM) can resolve around 90% of ambiguities in word segmentation, as shown in Table 16, the resulting segmenter is still much worse than **MSRSeg** because a large number of unknown words cannot be detected correctly even after Viterbi iterative learning.
- The method of resolving OA brings marginal improvements. Since the method does not require any human annotation, Row 2 shows the best results we achieved in our experiments using unsupervised learning approaches.
- Factoid rules, although simple, bring substantial improvements.
- The Viterbi iterative training method does not turn out to be an effective way of resolving ambiguities in word segmentation, nor detecting new words. In Rows 1 to 4, the word segmentation performance always saturates after 2 or 3 iterations with little improvement. For example, FMM (Row 1) achieves an initial segmentation F-measure of 0.8771, and after two iterations, it saturates and ends up with 0.8773.
- The Viterbi iterative training is effective in boosting the precision of NER without great sacrifices for a recall (e.g. the recall remains almost the same when using the seed set of Row 5 in Table 17, or becomes a little worse when using the seed sets of Rows 6 to 8). As shown in Tables 18 to 20, we start with a series of seed sets of different sizes and achieve a reasonable accuracy of NER, which is comparable with that of **MSRSeg**, after two iterations.
- The use of a small NE annotated seed set (e.g. in Row 5) would achieve the best tradeoff between performance and human effort, because after 2 iterations, the accuracy of NER is very close to that of using larger seed sets, while the human effort of creating the seed set is much less.

Table 21
MSRSeg system results for the MSR test set

Segmenter	Word segmentation		FT		PN		LN		ON	
	P	R	P	R	P	R	P	R	P	R
1 FMM	.837	.927								
2 Baseline	.863	.947								
3 2 + FT	.913	.961	.904	.898						
4 3 + PN	.950	.972	.905	.898	.790	.905				
5 4 + LN	.955	.975	.905	.899	.858	.906	.794	.860		
6 5 + ON	.969	.979	.905	.899	.870	.906	.892	.855	.816	.654

8. System Evaluation

8.1 System Results

Our system is designed so that components such as the FT detector and NE recognizer can be ‘switched on or off’, so that we can investigate the relative contribution of each component to the overall word segmentation performance. To date, we have not done a separate evaluation of MDW recognition. We leave it to future work.

The main results are shown in Table 21. For comparison, we also include in the table (Row 1) the results of using the greedy segmenter (FMM) described in Section 7. Row 2 shows the baseline results of our system, where only the lexicon is used. It is interesting to find, in Rows 1 and 2, that the dictionary-based methods already achieve quite good recall, but the precisions are not very good because they cannot correctly identify unknown words that are not in the lexicon such factoids and named entities. We also find that even using the same lexicon, our approach that is based on the linear mixture models outperforms the greedy approach (with a slight but statistically significant different) because the use of context model resolves more ambiguities in segmentation. The most promising property of our approach is that the linear mixture models provide a flexible framework where a wide variety of linguistic knowledge and statistical models can be combined in a unified way. As shown in Rows 3 to 6, when components are switched on in turn by activating corresponding class models, the overall word segmentation performance increases consistently.

We also conduct an error analysis, which shows that 85% of errors come from NER and factoid detection, especially the NE abbreviations, although the tokens of these word types amount to only 8.3% in the MSR test set. The rest 15% of errors are mainly due to new words.

8.2 Comparison with Other Systems using MSR Test Set

We compare our system with three other Chinese word segmenters¹⁴ on the MSR test set:

1. The **MSWS** system is one of the best available products. It is released by Microsoft® (as a set of Windows APIs). **MSWS** first conducts the word breaking using MM (augmented by heuristic rules for disambiguation), then conducts factoid detection and NER using rules.

¹⁴ The three systems are well-known in mainland China, but to our knowledge no standard evaluations on Chinese word segmentation have been published by press time. Although our comparison evaluations are limited to NER and crossing bracket (described below), we think the comparison we draw is still informative.

Table 22

Cross-system comparison results

Segmenters	# OAS errors	LN			PN			ON		
		P	R	F	P	R	F	P	R	F
MSWS	63	.935	.442	.600	.907	.744	.818	.642	.469	.600
LCWS	49	.854	.720	.782	.945	.781	.856	.713	.131	.222
PBWS	20	.767	.736	.752	.780	.787	.784	.817	.216	.342
MSRSeg	7	.876	.864	.870	.830	.897	.862	.799	.617	.696

2. The **LCWS** system is one of the best research systems in mainland China. It is released by Beijing Language University. The system works similarly to **MSWS**, but has a larger dictionary containing more PN and LN.
3. The **PBWS** system is a rule-based Chinese parser (Wu and Jiang 2000), which can also output word segmentation results. It explores high-level linguistic knowledge such as syntactic structure for Chinese word segmentation and NER.

As mentioned above, to achieve a fair comparison, we compare the above four systems only in terms of NER precision-recall and the number of OAS errors. However, we find that due to the different annotation specifications used by these systems, it is still very difficult to compare their results automatically. For example, 北京市政府 ‘Beijing city government’ has been segmented inconsistently as 北京市/政府 ‘Beijing city’ + ‘government’ or 北京/市政府 ‘Beijing’ + ‘city government’ even in the same system. Worse still, some LNs tagged in one system are tagged as ONs in another system. Therefore, we have to manually check the results. We picked 933 sentences at random containing 22,833 words (including 329 PNs, 617 LNs, and 435 ONs) for testing. We also did not differentiate LNs and ONs in evaluation. That is, we only checked the word boundaries of LNs and ONs and treated both tags as interchangeable. The results are shown in Table 22. We can see that in this small test set **MSRSeg** achieves the best overall performance of NER and the best performance of resolving OAS.

8.3 Evaluations on Bakeoff Test Sets

Table 23 presents the comparison results of **MSRSeg** on four SIGHAN’s Bakeoff test sets with others reported previously. The layout of the table follows (Peng, Feng and McCallum 2004). SX indicates participating sites in the 1st SIGHAN International Chinese Word Segmentation Bakeoff (Sproat and Emerson 2003). CRFs indicates the word segmenter reported in (Peng, Feng and McCallum 2004), which uses models of linear-chain conditional random fields (CRFs). Entries contain the F-measure of each segmenter on different open runs, indicated by XXo, with the best performance in bold. Column Site-Avg is the average F-measure over the datasets on which a segmenter reported results of open runs, where a bolded entry indicates the segmenter outperforms **MSRSeg**. Column Our-Avg is the average F-measure of **MSRSeg** over the same datasets, where a bolded entry indicates that **MSRSeg** outperforms the other segmenter. For completeness, we also include in Table 23 the results of closed runs, indicated by XXc. In a closed test, one can only use training material from the training data for the particular corpus being testing on. No other material was allowed (Sproat and Emerson 2003). Since **MSRSeg** uses the MSR corpus for training, our results are of

Table 23

Comparisons against other segmenters: In Column 1, SX indicates participating sites in the 1st SIGHAN International Chinese Word Segmentation Bakeoff, and CRFs indicates the word segmenter reported in (Peng et al. 2004). In Columns 2 to 5, entries contain F-measure of each segmenter on different open runs, with the best performance in bold. Column Site-Avg is the average F-measure over the datasets on which a segmenter reported results of open runs, where a bolded entry indicates the segmenter outperforms **MSRSeg**. Column Our-Avg is the average F-measure of **MSRSeg** over the same datasets, where a bolded entry indicates that **MSRSeg** outperforms the other segmenter.

	ASo	ASc	CTBo	CTBc	HKo	HKc	PKo	PKc	Site-Avg	Our-Avg
S01			.881	.881		.901	.953	.951	.917	.930
S02				.912	.874				.912	.904
S03	.872		.829			.886		.925	.878	.943
S04							.937	.939	.937	.955
S05				.732				.894		
S06				.829		.924		.924		
S07							.940		.940	.955
S08						.956	.904	.938	.936	.947
S09									.946	
S10		.961								
S11			.901	.831					.930	.930
S12			.884			.879		.886		.888
CRFs	.957	.956	.894	.849	.946	.928	.946	.941	.936	.943
MSRSeg	.958		.904		.954		.955			.943

open tests¹⁵.

Several conclusions can be drawn from Table 23. First of all, for the same system, open tests generally achieve better results than close tests due to the use of additional training material¹⁶. Second, there is no single segmenter that performs best in all four datasets. Third, **MSRSeg** achieves consistently high performance across all four datasets. For example, **MSRSeg** achieves better average performance than the other three segmenters that report results on all four datasets (i.e. S03, S11, CRF). In particular, **MSRSeg** outperforms them on every dataset. There are two segmenters that achieve better average F-measure than ours. One is S02, which reported results on CTB only. The other is S10, which reported results on CTB and PK. From these results, we conclude that **MSRSeg** is an adaptive word segmenter that achieves state-of-the-art performance on different datasets, corresponding to different domains and standards.

As described in Section 2.1, most segmenters, including the ones in Table 23, can be roughly grouped into two categories: ones that use a rule-based approach, and ones that use a statistical approach. **MSRSeg** is a hybrid system that takes advantages of both. Though rule-based systems (e.g. S08, S10 and S11 in Table 23) can achieve reasonably good results, they cannot effectively make use of increasingly large training data, and are weak in unknown word detection and adaptation. Some statistical segmenters (e.g. S01 and S07 in Table 23) use generative models, such as HMM, for Chi-

¹⁵ It would be more informative if the comparison could be conducted in close tests, which implies that dictionaries and models of **MSRSeg** should be generated solely on the given training data. We leave it for future work.

¹⁶ It is interesting to see that, in AS, close tests achieve better performance than open tests, although among different systems. It is because that the training data of AS is much larger than the other 3 corpora, and those segmenters that apply statistical approaches, such as S09 (Xue 2003) and CRFs, have been well trained.

nese word segmentation. However, it is very difficult to incorporate linguistic knowledge into the (approximated or assumed) generation process of Chinese sentence, underneath which the models are developed. Discriminative models (e.g. the linear models in **MSRSeg**, where though all components models are derived from generative models, they are combined using discriminatively trained weights) are free from this issue, and provide a flexible mathematical framework to incorporate arbitrary linguistic knowledge. They do not assume any underlying generation process. Instead, they assume that the training and test sets are generated from the same distribution, but the form of the distribution (i.e. generative process) is unknown. If we view Chinese word segmentation as a classification problem i.e. to discriminate between “good” segmentations and “bad” ones, we may prefer discriminative models to generative models. Intuitively, it is sufficient to find directly the desired features that can differentiate good segmentations from bad ones (as in discriminative models). It is, however, not necessary to estimate the distributions of generating Chinese sentences (or segmentations) first, and then use the estimated distributions to construct the desired features (as in generative models). As pointed out by Vapnik (1998): “when solving a given problem, solve it directly and try to avoid solving a more general problem as an intermediate step.”

Our models is similar to maximum entropy models in (Xue 2003) and CRFs in (Peng, Feng and McCallum 2004) in that all these models give flexibility to incorporate arbitrary features, and can be discriminatively-trained. Our models are novel in that many feature functions are derived from probabilistic or heuristic models inspired by source-channel models of Chinese sentence generation, as described in Section 4.3. Therefore, these feature functions are not only potentially more reasonable but also much more informative than for instance the binary features used in standard maximum entropy models in NLP.

We also notice that many segmenters (e.g. S03 and S04 in Table 23) separate unknown word detection from word segmentation. Though this would make the development of the segmenter easier, it seems to be a flawed solution in nature, as we discussed earlier. The benefits of integrating both tasks can also been shown empirically in Table 23.

9. Conclusions

This paper presents a *pragmatic* approach to Chinese word segmentation. Our main contributions are three-fold. First, we view Chinese words as *segmentation unit* whose definition is pragmatic in nature and depends on how they are used and processed (differently) in realistic applications, while theoretical linguists define *words* with purely linguistic criteria. Second, we propose a pragmatic mathematical framework for Chinese word segmentation, where various problems of word segmentation (i.e. word breaking, morphological analysis, factoid detection, NER and NWI) are solved in a unified approach. The approach is based on linear models where component models are inspired by source-channel models of Chinese sentence generation. Third, we describe in detail an adaptive Chinese word segmenter, **MSRSeg**. This pragmatic system consists of two components: (1) a generic segmenter that is based on the mathematical framework of word segmentation and unknown word detection, and can adapt to different domain-specific vocabularies, and (2) a set of output adaptors for adapting the output of the former to different application-specific standards. Evaluation on five test sets with different standards shows that the adaptive system achieves state-of-the-art performance on all the test sets.

One area of our future work is to apply **MSRSeg** in a wide range of practical applications. We believe that some application-specific features can also be integrated into the framework. For instance, in MT, it would be interesting to investigate how to jointly optimize the performances of both word segmentation and word alignment.

As one of the reviewers pointed out, though the reliable high performance of **MSRSeg** is impressive, it is by far one of the most complex systems with access to the richest resources. Hence, another interesting area of our future work is to explore whether the performance is attributed to a superior architecture or simply to the richer resources. We have developed a simplified version of **MSRSeg**, called **S-MSRSeg**. It does not use the morph-lexicon, and is trained using one fifth of the **MSR** training data in Table 4, which are only partially labeled (i.e. LW are not annotated). Interestingly, **S-MSRSeg** achieves very similar (or slightly worse) performance on the five test sets in Table 4. This demonstrates again the potential of our *pragmatic* approach to Chinese word segmentation. Needless to say, the work reported in this paper represents not an end, but a beginning of yet another view of Chinese word segmentation. Towards this end **S-MSRSeg** and its training and test datasets are publicly available (e.g. at <http://research.microsoft.com/~jfgao>), for the sake of encouraging others to improve upon the work we have done.

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