IMPLEMENTATION AND EVALUATION OF SCALABLE APPROACHES FOR AUTOMATIC CHINESE TEXT CATEGORIZATION

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Abstract

The purpose of this research is to identify scalable approaches that can handle large amount of training data such as several years of news articles, and automatically assign predefined category to Chinese free text documents. Our approach consists of the following processes: (i) term extraction, (ii) term selection, and (iii) document classification. The approach first builds a recently developed SB-tree to identify all repeated substrings, called patterns, from the text. We then proceed to identify possible boundary of terms appearing in the identified patterns. After terms are extracted from the training articles, we run term selection algorithms to select the most significant terms and to reduce the number of terms to an acceptable level. The selected terms are used by the classifier to assign a predefined category to each text document. Our current experiment uses CNA one year news as training data, which consists of 73,420 articles and is far more than previous related research. In the experiment, we implement and compare four term selection methods, the odds ratio method, the mutual information method, the information gain method and the $\chi^2$-test method, when they are combined with the naive Bayes classifier.

Keywords: Text Categorization, Term Selection, Naive Bayes Classifier, Information Retrieval.

1 Introduction

Text categorization is the problem of automatically assigning predefined categories to free text documents, and is gaining more and more importance as the amount of text data available on World Wide Web grows dramatically. A well classified text database will be very helpful for a user to identify interesting data from the huge collection of texts. There are many studies about the text categorization as well as web-page classification [11, 3, 7, 8, 21, 25, 26, 18, 6, 5, 2, 10]. While there are a great number of researches on automatic text categorization for English texts, text categorization for Asian languages such as Chinese, Japanese, Korean and Thai has not been studied seriously until recently [17, 29, 1].

It is well known that written Asian language consists of strings of ideograph separated by punctuation signs. An ideograph (or character) can function as a word with meaning(s), or it can act as an alphabet to form a "word" with one or more adjacent characters. Determining the boundaries of single or multi-character words in a string, a process called segmentation [4], is very difficult because no delimiter or white space is used in the text and one has to rely on the context.
Because text segmentation is not straightforward, 1-grams, 2-grams and n-grams have been used as indexing terms to represent documents in Asian languages. Among them, 1-gram-based approaches is the simplest one that uses single characters as indexing terms, and should be good for recall in information retrieval (IR) because it guarantees that if there are correct word matches between queries and documents, there will be 1-gram matches. However, single characters (1-grams) are ambiguous in meaning, which results in low precision in IR. A number of research have proposed to use n-grams, instead of 1-grams, as indexing terms. An n-gram is a sequence of n contiguous characters in the text. The 1-gram-based approaches [23] simply use every single character as a single term, and the 2-gram-based approaches use every 2 contiguous characters as indexing terms, and the general n-gram-based approaches use all 1-grams, 2-grams, 3-grams, ..., n-grams as indexing terms. Although 2-gram and n-gram perform similarly well as indicated in our experiment, in this research, we take n-grams, 1 ≤ n ≤ 10, as indexing terms because n-grams can catch the concept of a document. Notice that the possible number of n-grams in Chinese is dramatically huge, and furthermore many of them are meaningless and non-informative for text categorization. The major challenge is to develop approach that can reduce the number of n-grams to an acceptable level, while at the same time maintains similar categorization accuracy.

The purpose of this research is to identify scalable approaches that can handle large amount of training data such as several years of news articles, and automatically assign predefined category to Chinese free text documents. Our approach consists of the following processes: (i) term extraction, (ii) term selection, and (iii) document classification. Identifying terms, or so-called word segmentation, from text documents is one of the most difficult problems in processing Chinese texts. In this research, we develop a scalable approach to identify terms from large amount of text data, which does not use a dictionary. The approach first builds a recently developed SB-tree [9, 4, 19] to identify all repeated substrings, called patterns, from the texts. We believe important terms will appear repeatedly in the articles. The SB-tree also gives the information such as the frequency of a pattern, the documents and the locations where a pattern appears which are then used to identify possible boundary of terms appearing in the same pattern, and to remove meaningless patterns which are substrings of some terms. Term boundaries are used to partition patterns into terms. After terms are extracted from the training articles, we run term selection algorithms to select the most representative terms and to reduce the number of terms to an acceptable level. The selected terms are used by the classifier to assign a predefined category to each text document.

Our current experiment uses CNA one year news as training data, which consists of 73,420 articles and is far more than previous related research which use either one month news or sampled articles from the whole year news. Notice that although sampling methods are very interesting research issues, most of the commercial systems prefer to extract information from the original whole-set data as done in the recent data mining applications. We believe the whole year training data can make conclusions from our experiment more reliable than previous research. We implement and compare four term selection methods, the odds ratio method, the mutual information method, the information gain method and the $\chi^2$-test method, when they are combined with the naive Bayes classifier [22]. Our experiment shows that $\chi^2$-test achieve the best performance.

The remainder of this paper is organized as follows. Section 2 describes the process to remove meaningless and non-informative substrings, and to select the most representative terms. Section 3 introduces the naive Bayes classifier. Section 4 gives our experimental results. Section 5 gives conclusion and further remarks. Throughout this paper, we assume 2 ≤ n ≤ 10 when n-gram is mentioned.
2 Term Selection

To avoid the segmentation problem and extract meaningful terms efficiently, we use n-gram-based approach which is based on simple statistics rather than complex syntax and semantic analysis. It is very important to reduce the number of n-grams generated from the original data. In the section, we describe how to reduce the number of n-grams generated from the original data. The process consists of two main steps: substring removal and term selection. Substring removal is to remove patterns that are substrings of other identified terms, and term selection is to select the most representative terms. Two common term selection methods, odd ratio method and information gain method, are implemented and compared in this research.

2.1 Substring Removal

For Chinese, it is very important to remove the redundant substrings because there are \( n(n + 1)/2 \) substrings derived from each n-gram and, furthermore, most of the substrings are meaningless and non-informative. For example, the substrings of "stock market" are listed in the table below. The substrings "stock", "market", "market" derived from "stock market" are not meaningful "words" in Chinese, and should be removed from the term set.

| 1-gram  | 股,票,市,場 |
|---------|------------|
| 2-gram  | 股票(stock),票市( ),市場( ) |
| 3-gram  | 股票市( ),票市場( ) |
| 4-gram  | 股票市場 |

The method that removes the meaningless substrings is motivated by the method developed by Chein [4]. Let \( T \) denote the total set of n-grams, and \( T = \{t_1, t_2, \ldots, t_k\} \). Our observation is that if the string \( t_j \) is a substring of \( t_i \), and the term frequency ratio of \( t_i \) and \( t_j \) is almost equal to 1.0, say \( \geq 0.9 \), then we can assume \( t_j \) is a redundant substring generated from \( t_i \), and remove \( t_j \) from the term set. In this experiment, we remove the substring \( t_j \) when the ratio of term frequency of \( t_j \) over the term frequency of \( t_i \) is greater than or equal to 0.9. The original number of n-grams (\( n \leq 10 \)), whose term frequency \( \geq 5 \), generated our training data is 935734. After the substring removal the number is reduced to 425903.

2.2 Term selection methods

Substring removal is just to remove redundant substrings. The number of remained n-grams is still very large. Most of them are not significant for the purpose of categorizing text documents. Term selection, or so-called feature selection, is the process to select most significant terms, and to reduce the number of terms to an acceptable level as the time and space required by current classifiers greatly depend on the size of the term set. In addition, the noise, i.e. the non-significant terms, can reduce the precision achieved by a classifier. Several term selection methods have been proposed for occidental languages [20, 16, 15, 10, 27]. In this experiment, we implement the odds ratio method, the mutual information method, the information gain method and the \( \chi^2 \)-test method, and compare their performance when they are combined with the naive Bayes classifier. We next review them.

For convenience of the definition of feature selection, we claims that the two-way contingency table of a term \( t \) and a category \( c \), where \( A \) is the number of times \( t \) and \( c \) co-occur, \( B \) is the number of time the \( t \) occurs without \( c \), \( C \) is the number of times \( c \) occurs without \( t \), and \( N \) is the total number of documents. We summarized above statements as
2.2.1 Odds Ratio(OR)

The odds ratio value of term $t$ for each class (category) is different. For each term $t$, the value of odds ratio to class $C_k$ is defined as follows[10].

$$OddsRatio(t, C_k) = \log \frac{Odds(t|C_k)}{Odds(t|C_{neg})} = \log \frac{P(t|C_k)(1 - P(t|C_{neg}))}{(1 - P(t|C_k)P(t|C_{neg}))},$$

where $P(t|C_k)$ is the conditional probability of term $t_j$ occurring given the class value 'k', $P(t|C_{neg})$ is the conditional probability of term $t$ occurring given the class value $\neq k$, and the odds function of $X_i$ is defined as follows.

$$Odds(X_i) = \begin{cases} \frac{1}{N^2} & P(X_i) = 0 \\ \frac{1}{1 - N^2} & P(X_i) = 1 \\ \frac{P(X_i)}{1 - P(X_i)} & P(X_i) \neq 0 \land P(X_i) \neq 1 \end{cases}$$

Where $N$ is the number of training documents. Notice that the value of odds ratio of one term which just appear in only one class would be very large no matter term frequency is low or high. It happens that the term selection via the score of odds ratio maybe suffer from low hit frequency of selected term when apply testing documents.

2.2.2 Mutual Information(MI)

The difference between the information uncertainty before adding $t$ and after adding $t$ measures the gain in information due to the Class c. This information is called mutual information and is naturally defined as[27]

$$MI(t, c) = \log \left[ \frac{1}{P(c)} \right] - \log \left[ \frac{1}{P(c|t)} \right] = \log \left[ \frac{P(c|t)}{P(c)} \right] = \log \left[ \frac{P(t,c)}{P(t)p(c)} \right] = MI(c; t)$$

If the two probabilities $p(t)$ and $P(t|c)$ are the same, then we have gained no information and the mutual information is zero. In practical, the score of $MI(t, c)$ is strongly influenced by the marginal probabilities of terms. For terms with an equal conditional probability $P(t|c)$, the term with low term frequency will have a higher score than common terms. The MI can be estimated using

$$MI(t, c) \approx \log \frac{A \times N}{(A + C) \times (A + B)}$$
2.2.3 Information Gain (IG)

Information Gain is frequently employed as a method of feature scoring in the field of machine learning [22]. Let $|c|$ denote the number of categories. The information gain of term $t$ is defined as

$$IG(t; C) = E(C) - E(C|t) = \sum_k P(C_k) \log P(C_k) + P(t = 1) \sum_{k=1}^{|c|} P(C_k|t = 1) \log P(C_k|t = 1) + P(t = 0) \sum_{k=1}^{|c|} P(C_k|t = 0) \log P(C_k|t = 0)$$

$IG$ can be proven equivalent to the weighted average of the mutual information and is called average mutual information. $IG$ makes a use of information about the term absence, while MI ignores such information. Furthermore, $IG$ normalizes the mutual information scores using the joint probabilities while MI uses the non-normalized scores [27]. Notice that the number of score for each term measured by $IG$ is just one.

2.2.4 $\chi^2$-test (CHI)

The $\chi^2$-test measures the lack of independence between $t$ and $c$, and can be computed to the $\chi^2$ distribution with one degree of freedom to judge extremeness. The $\chi^2$-test measure is defined as [14]

$$\chi^2(t, c) = \frac{N \times (AD - CB)^2}{(A + C) \times (B + D) \times (A + B) \times (C + D)}$$

3 Naive Bayes Classifier

There are several well known classification methods in machine learning or image processing field, such as decision tree method, k-nearest-neighbors (KNN), Neural network method, Rocchio algorithm and Naive Bayes classifier [22, 13]. In this research, we implement the naive Bayes classifier for its simplicity and scalability. We are ready to implement other classifiers and measure their performance when they are combined with various term selection methods. The Naive Bayes classifier is one highly practical learning method and is based on the simplifying assumption that the probabilities of terms occurrences are conditionally independent of each other given the class value [22], though this is often not the case. The naive Bayes approach classifies a new document $Doc$ to the most probable class, $C_{NB}$ defined below.

$$C_{NB} = \arg\max_{C_k \in C} P(C_k|Doc)$$

By Bayes' theorem [12], the $P(C_k|Doc)$ can be represented as

$$P(C_k|Doc) = \frac{P(Doc|C_k)P(C_k)}{\sum_{C_i \in C} P(Doc|C_i) P(C_i)}$$

Where $P(C_k) = |C_k|/\sum_{C_i \in C} |C_i|$ is the probability of the class $C_k$, and $|C_k|$ is the number of training documents in class $C_k$. 

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To estimate $P(Doc|C_k)$ is difficult since it is impossible to collect a sufficiently large number of training examples to estimate this probability without prior knowledge or further assumptions. However, the estimation become possible due to the assumption that a word's(term) occurrence is independent on the class the document comes from, but that it occurs independently of the other words(terms) in the document. Therefore, the $P(Doc|C_k)$ can be written as follows [13]:

$$P(Doc|C_k) = \prod_{j=1}^{|Doc|} P(t_j|C_k)$$

where $|Doc|$ is the number of words (terms) in document $Doc$, and $P(t_j|C_k)$ is the conditional probability of $t_j$ given Class $C_k$. Given the term $T = (t_1, t_2, \ldots, t_n)$ that describe the document $Doc$, the estimation of $P(Doc|C_k)$ is reduce to estimating each $P(t_j|C_k)$ independently. Notice above equation works well when every term appears in every document; otherwise, the product becomes 0 when some terms do not appear in that document. We use the following to approximate $P(t_j|C_k)$ to avoid the possibility that the product becomes 0, and still keeps the meaning of the equation.

$$P(t_j|C_k) = \frac{1 + TF(t_j, C_k)}{|T| + \sum_j |T|TF(t_j, C_k)}$$

where $TF(t_j, C_k)$ is the frequency of term $t_j$ in documents having class value $k$, $|T|$ is the number of all distinct terms used in the domain of document representation. The formula used to predict probability of class value $C_k$ for a given document $Doc$ is as the following :

$$P(C_k|Doc) = \frac{P(C_k) \prod_{t_j \in Doc} P(t_j|C_k)^{TF(t_j, Doc)}}{\sum_t P(C_t) \prod_{t_j \in Doc} P(t_j|C_t)^{TF(t_j, Doc)}}$$

## 4 Experimental Results

The amount of training&testing data of previous related experiments [28, 4, 23] are thousands of news articles which were just within one month or sampling from several months. In order to close the reality of the term distribution of Chinese corpus, we select 12 Central News Agency (CNA) news group from 1991/1/1 to 1991/12/31, which contains 73420 news articles and 23680756 Chinese characters, and chose 21 days out of the next month (January 1992) as testing news. The statistics of training&testing news are listed in Table 1.

### 4.1 Comparison : 1-gram, 2-gram, 3-gram and n-gram

There are discussions to chose 1-gram, 2-gram(bigram) or n-gram to be basic indexing unit of Chinese texts [17, 24, 1] in Information Retrieval. The character-based approach (1-gram) is good for recall in IR, but not for precision. In [23], they developed a Chinese news filtering agents using character-based approach, and got the result of filtering news efficiently, but the precision of the filtering news is quite low. There is the limitations of character-based approach. For example, considering the order of the Chinese character, the two words 高中 (junior high school) and 中国 (China) make no difference via character-based approach. In [17], some reference states that the major of the modern Chinese words are bisyllable. Therefore, they take a lot of experiments and conclude that 2-gram indexing is effective and performs as well as short-word indexing in IR. Notice that the number of 3-grams is more than the number of 2-grams no matter before or after the
| CNA News Group    | #Train | #Test |
|-------------------|--------|-------|
| 1 政治            | 23516  | 422   |
| 2 經済            | 10160  | 219   |
| 3 交通            | 3423   | 70    |
| 4 文教            | 6064   | 94    |
| 5 體育            | 4929   | 73    |
| 6 社會            | 5679   | 107   |
| 7 股市            | 3313   | 42    |
| 8 軍事            | 4646   | 79    |
| 9 農業            | 3217   | 54    |
| 10 宗教           | 1315   | 22    |
| 11 財政           | 3622   | 59    |
| 12 教育           | 3536   | 66    |

| Total             | 73420  | 1307  | 1442  | 1599  |

Table 1: CNA News : Training & Testing

substring removal for terms with frequency \( \geq 5 \). This observation is different from the statements in [17] (see table 2). Notice that the number of the n-grams is the number after substring removal.

Let the top \( k \) measure denote the percentage of the correct category is in the first \( k \) categories when all the categories are sorted according to their probabilities computed by the naive Bayes classifier. Namely, the top 1 measure denotes the percentage that the news are assigned to their pre-defined categories. Notice that the top \( k \) measure will be very meaningful in a semi-automatic system when the number of categories is large as it can quickly identify the most possible \( k \) categories. We choose the n-gram, \( 2 \leq n \leq 10 \), as the basic indexing unit. Table 3 gives the accuracy achieved when 1-gram, 2-gram, and n-gram are used as term unit and no term selection is performed for n-grams. In the top 1 measure, the gap between the 1-gram-based and n-gram-based approach is about 8%, about 68% and 76%, respectively. The gap decreases as \( k \) increases. In top 3 measure, the gap becomes about 3%. The 1-gram-based approach uses only 3089 distinct characters; however, the n-gram-based approach uses 299386 terms. Although the 2-gram-based and the n-gram-based approaches achieve similar accuracy, we use n-grams to measure the difference performed of odds ratio and information gain methods because n-grams can catch the concept of an article and can be assigned as keyword. This can be important in other area of information retrieval.

### 4.2 Term Selection Comparison : OR, MI, IG and CHI

In this experiment we implement and compare four methods, \( OR, IG, CHI \) and \( MI \) [10, 27], which require much less computation time and are more scalable. All methods compute scores to all terms. Terms are selected according to their scores. Let the top \( k \) measure denote the percentage of the correct category is in the first \( k \) categories when all the categories are sorted according to their
### Table 2: Term Length Distribution

| Term Length | tf>=5 | Percent | tf>=5+(sub90) | Percent |
|-------------|-------|---------|---------------|---------|
| 1           | 4134  | 0.4%    | 3628          | 0.9%    |
| 2           | 129938| 13.9%   | 84441         | 19.8%   |
| 3           | 212764| 22.7%   | 113249        | 26.6%   |
| 4           | 172807| 18.5%   | 89472         | 21.0%   |
| 5           | 122745| 13.1%   | 51296         | 12.0%   |
| 6           | 88384 | 9.4%    | 33573         | 7.9%    |
| 7           | 66787 | 7.1%    | 20759         | 4.9%    |
| 8           | 53640 | 5.7%    | 14388         | 3.4%    |
| 9           | 45101 | 4.8%    | 9694          | 2.3%    |
| 10          | 39414 | 4.2%    | 5403          | 1.3%    |
| 11          | 935734|         | 425903        |         |

### Table 3: Accuracy Comparison: 1-gram, 2-gram, 3-gram and n-gram

| Top1       | 1-gram | #Term | 1/1-1/17 | 1/11-1/17 | 1/21-1/27 |
|------------|--------|-------|----------|-----------|-----------|
|            | 1-gram | 3089  | 68.94    | 68.72     | 65.23     |
|            | 2-gram | 103072| 76.36    | 75.66     | 72.23     |
|            | 3-gram | 153558| 76.21    | 75.56     | 72.73     |
|            | (2+...+10)-gram | 295910 | 77.12 | 76.63 | 72.67 |

| Top2       | 1-gram | #Term | 1/1-1/17 | 1/11-1/17 | 1/21-1/27 |
|------------|--------|-------|----------|-----------|-----------|
|            | 1-gram | 3089  | 86.61    | 84.67     | 82.74     |
|            | 2-gram | 103072| 91.43    | 89.04     | 87.49     |
|            | 3-gram | 153558| 90.97    | 88.49     | 87.37     |
|            | (2+...+10)-gram | 295910 | 92.04 | 88.7    | 87.99 |

| Top3       | 1-gram | #Term | 1/1-1/17 | 1/11-1/17 | 1/21-1/27 |
|------------|--------|-------|----------|-----------|-----------|
|            | 1-gram | 3089  | 92.35    | 90.78     | 90.06     |
|            | 2-gram | 103072| 95.72    | 93.62     | 92.87     |
|            | 3-gram | 153558| 94.72    | 92.86     | 91.81     |
|            | (2+...+10)-gram | 295910 | 95.56 | 92.93 | 92.62 |

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probabilities computed by the naive Bayes classifier. Let the HitAvg denote the average number of the selected terms been found in testing news and use to see the popularity of selected terms. As in Table 4 shows, the accuracy of top 1 measure of the CHI method is from 71.61% to 77.43% as the number of selected term from each class increases from 100 to 10000. The performance of the IG method is similar to the performance of the CHI method while IG prefer the terms whose term frequency are high. The HitAvg of IG and CHI are 43.77 and 26.36 respectively when the number of selected terms from each class is 500. Notice that the accuracy of top 2 measure of CHI is about 90% and is very meaningful in a semi-automatic system. In Table 4 CHI is the best and achieves 75.90% accuracy in top 1 measure when the number of selected terms from each class is 500. That is, the number of n-gram can be reduced from 295910 to 5918 while the accuracy only lose less 2% accuracy as compared with Table 3. Both the performance of OR and MI are worse than CHI’s because both of them prefer to select term whose term frequency is low such that their HitAvg are 4.43 and 2.68 respectively. This observation is consistent with previous theoretic assumption in section 2.2.1&2.2.2. Notice that OR achieve 78.04 in top 1 measure, better than CHI’s 77.43% when the number of selected terms from each class is 10000, but the number of total selected term by OR is 91745, larger than CHI’s 79202.

To illustrate the effectiveness of selected term by term selection of CHI method, for example, we have 20 top score terms selected from four classes respectively in the table 5. To state the characteristic of n-gram, there are significant terms such as "Council for Economic Planning and Development of Executive for R.O.C", "Taiwan Railway Administration" and "The Department of Education, Taiwan Provincial Goverment" chose from "(cna.economics.*)", "(cna.transport.*)" and "(cna.edu.*)" classes respectively. Notice that using n-gram are more meaningful and informative than using 1-gram or 2-gram(bigram).

5 Conclusions and Further Remarks

In this paper, we sketch an implementation of approaches that can handle large amount of training data such as several years of news articles, and automatically assign predefined category to Chinese free text documents. We implement a SB-tree-based approach to extract terms from the original text data, and develop a simple approach to remove redundant substrings. We also compare four term selection methods, the odds ratio method, the mutual information method, the information gain method and the $\chi^2$-test method, and use the naive Bayes classifier to evaluate their performance. Among four feature selection method, $\chi^2$-test achieve the best performance. Our current experiment uses CNA one year news as training data, which consists of 73,420 articles and is far more than previous related research. We believe the whole year training data can make conclusions from our experiment more reliable than previous research. The experiment shows that the character-based approach performs poorly in the top 1 measure; however is quite competitive in the top 3 measure. Notice that the top $k$ measure will be very meaningful in a semi-automatic system when the number of categories is large as it can quickly identify the most possible $k$ categories. This paper present an initial experimental study of Chinese text categorization. There are a lot of work to be proceeded in the future. The naive Bayes classifier is a basic approach in the probability model. There are many other classifiers in the vector model such as KNN and Rocchio algorithm.
| The number of selected terms from each class | The number of total selected terms | Feature Selection Method | Top1   | Top2   | Top3   | HitAvg |
|---------------------------------------------|-----------------------------------|--------------------------|--------|--------|--------|--------|
| 100                                         | 1200                              | OR                       | 56.85  | 69.32  | 74.29  | 1.68   |
| 100                                         | 1200                              | IG                       | 69.85  | 87.22  | 91.97  | 19.41  |
| 100                                         | 1200                              | CHI                      | 71.61  | 86.92  | 92.43  | 12.66  |
| 100                                         | 1200                              | MI                       | 42.08  | 57.77  | 65.42  | 0.56   |
| 500                                         | 6000                              | OR                       | 67.25  | 76.97  | 82.40  | 4.43   |
| 500                                         | 6000                              | IG                       | 72.69  | 89.36  | 93.57  | 43.77  |
| 500                                         | 6000                              | CHI                      | 75.90  | 90.90  | 94.49  | 26.36  |
| 500                                         | 6000                              | MI                       | 55.62  | 72.61  | 78.73  | 2.68   |
| 1000                                        | 12000                             | OR                       | 69.24  | 79.27  | 84.93  | 6.84   |
| 1000                                        | 12000                             | IG                       | 73.37  | 89.14  | 94.26  | 58.60  |
| 1000                                        | 11770                             | CHI                      | 76.28  | 91.28  | 95.03  | 35.79  |
| 1000                                        | 12000                             | MI                       | 61.82  | 77.81  | 83.09  | 4.99   |
| 2000                                        | 23991                             | OR                       | 73.14  | 82.71  | 87.83  | 12.61  |
| 2000                                        | 24000                             | IG                       | 74.67  | 89.82  | 93.96  | 71.24  |
| 2000                                        | 23075                             | CHI                      | 76.28  | 90.67  | 95.03  | 47.95  |
| 2000                                        | 23990                             | MI                       | 68.32  | 81.64  | 86.76  | 11.08  |
| 5000                                        | 57726                             | OR                       | 76.13  | 88.14  | 93.34  | 46.47  |
| 5000                                        | 60000                             | IG                       | 76.36  | 89.44  | 93.50  | 81.51  |
| 5000                                        | 52399                             | CHI                      | 76.97  | 90.74  | 94.95  | 70.25  |
| 5000                                        | 57161                             | MI                       | 74.60  | 87.22  | 92.59  | 41.55  |
| 10000                                       | 91745                             | OR                       | 78.04  | 90.36  | 93.57  | 71.79  |
| 10000                                       | 120000                            | IG                       | 76.66  | 89.44  | 93.88  | 84.64  |
| 10000                                       | 79202                             | CHI                      | 77.43  | 90.21  | 93.73  | 80.30  |
| 10000                                       | 91024                             | MI                       | 77.58  | 90.21  | 94.34  | 69.58  |

Table 4: Feature Selection Comparison: Testing News(1992/1/1-1992/1/7)
Table 5: 20 top score terms using CHI method

| Rank | Term                          | Score |
|------|-------------------------------|-------|
| 1    | 經濟部                         |       |
| 2    | 行政院                         |       |
| 3    | 航空局                         |       |
| 4    | 政黨                           |       |
| 5    | 行政院經濟建設委員會           |       |
| 6    | 政院                           |       |
| 7    | 經理                           |       |
| 8    | 民政                           |       |
| 9    | 領袖                           |       |
| 10   | 二院                           |       |
| 11   | 選舉                           |       |
| 12   | 中央                           |       |
| 13   | 國民                           |       |
| 14   | 日名                           |       |
| 15   | 外交                           |       |
| 16   | 秘書                           |       |
| 17   | 國代                           |       |
| 18   | 人民                           |       |
| 19   | 民政                           |       |
| 20   | 貿易                           |       |

We will do experiment to understand their performance in Chinese text categorization. In addition, the category structure in this experiment is flat. However, most of the information search engines provides hierarchical structures. We will do experiment on web information, and study approaches that takes advantages of the hierarchical structures provided in search engines.

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