A Multi-Class SVM Classification System Based on Methods of Self-Learning and Error Filtering

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***Abstract*—In this paper, the technique of Support Vector Machine has been used to deal with multi-class Chinese text classification. Several data retrieving techniques including word segmentation, term weighting and feature extraction are adopted to implement our system. To improve classification accuracy, two revised methods, self-learning and error filtering, for straight forward SVM results are proposed. The method of self-learning uses misclassified documents to retrain classification system, and the method of error filtering filters out possibly misclassified documents by analyzing the decision values from SVM. The experiment result on real-world data set shows the accuracy of basic SVM classification system is about 79% and the accuracy of improved SVM classification system can reach 83%.**

***Index Terms*—Document Classification, Support Vector Machine (SVM), Multi-Class SVM, Error Filtering**

I. Introduction

With more and more articles and documents in the information system, how to automatically classify information becomes a main research subject. The methods for document classification can be divided into two major types, retrieving semantic meaning of the document content and calculating the statistical similarity of documents. The second type is much popular because the first type is more time-consuming to deal with large set of semantic information. SVM classification system is based on the second approach.

Document classification can be taken into two steps, text preprocessing and classifier training. Figure 1 is an overview of our document classification system. Text preprocessing involves data retrieving techniques, includes segmenting a long sentence to serval shorter terms (word segmentation), eliminating the meaningless keywords (feature extraction), computing the weight of keywords (term weighting), and representing a document in Vector Space Model (VSM). In feature extraction, it computes the weights of all keywords, then eliminates some keywords with weights lower than a predefined threshold. To compute the weight of each keyword, three methods, Term Frequency (TF), Term Frequency * Inverse Document Frequency (TFIDF), and Information Gain (IG)[6], are adopted in our system. Two normalization techniques, L1 and L2 normalization[16], are also applied in term weighting to compare the performance difference.

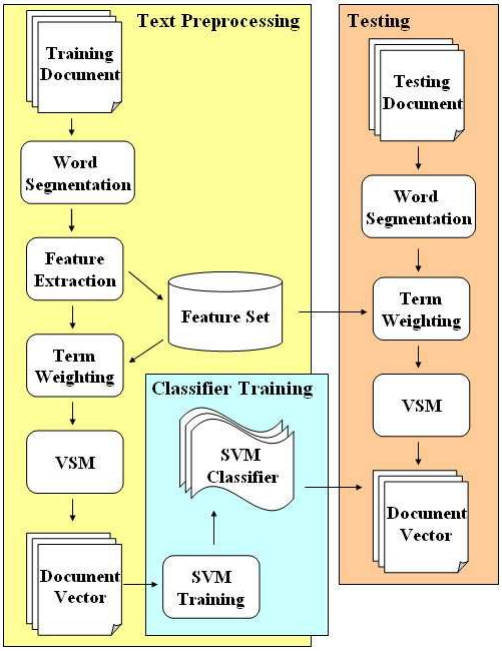


Fig. 1. SVM system for Text Preprocessing ,Classifier Training, and Classification.

Some well-known classification methods like K-Nearest Neighbors (KNN)[15], Support Vector Machines (SVM)[5][3][7], Naive Bayes[10], and neural network[14] have been well studied recently. We chooses SVM as our basic classifier

because SVM has been proven very effective in many research results and is able to deal with large dimensions of feature space. SVM is a statistic classification method proposed by Cortes and Vapnik in 1995 [7]. It is originally designed for binary classification. The derived version, a multi-class SVM, is a set of binary SVM classifiers able to classify a document to a specific class.

In addiction to use the basic classification techniques, we propose two revised methods, self-learning and error filtering, to increase the accuracy of multi-class SVM classification. The idea of these two methods is as follows:

1) The method of self-learning
   The classifier will retrain itself by combining the original training set and the misclassified documents to a new training set. This method avoids misclassifying similar documents again.
2) The method of error filtering
   The system will identify documents which are difficult to be differentiated from all classes. If a document is marked as "indistinct", it means the document has high probability to be misclassified. To avoid misclassifying, the document should be reclassified by other classification methods.

Our experiment uses 6000 official documents of the National Chung Cheng University from the year 2002 to 2005. These documents have a commonly special property that there are seldom words in their contents. The average number of keywords in each document is nearly 10. This leads to a challenge on the accuracy of the classification system. In order to compare performance, our experiment implements several data retrieving techniques, TF, TFIDF, and IG as the feature extraction scheme and TF, TFIDF with L1 and L2 normalization as the term weighting scheme. We also adjust the filtering level of feature extraction to find out the best strategy. The filtering level is a percentage threshold of feature extraction. The experiment shows the best strategy is to take IG with filtering level 0.9 as the scheme of feature extraction and TFIDF with L2 normalization as the scheme of term weighting. The accuracy is about 79.83%. When adopting the method of self-learning, the average accuracy raises 1.64%. Adopting the method of error filtering, the average accuracy is up 4.45%. Combining the methods of self-learning and error filtering, the average accuracy improves 5.54% higher.

The rest of the paper is organized as follows: Chapter 2 briefly introduces some multi-class SVM classifications. Chapter 3 presents the procedure of the classification system in this work. Chapter 4 presents the two methods of self-learning and error filtering. Chapter 5 shows the experiment performance of the classification system. Chapter 6 summarizes the main idea of this paper.

II. Related works

The first process of classifying documents is to weight terms in documents. There are several popular methods like Mutual Information (MI), Chi Square Statistic (CHI), Term Frequency * Inverse Document Frequency (TFIDF), Information Gain (IG), etc. Based on these weights, it's easier to decide which terms are significant and which terms should be filtered. Then, our classification procedure is to represent documents in Vector Space Model (VSM) and classify vectors by SVM classifier.

Support Vector Machine (SVM) is a statistical classification system proposed by Cortes and Vapnik in 1995[7]. The simplest SVM is a binary classifier, which is mapping to a class and can identify an instance belonging to the class or not. To produce a SVM classifier for class C, the SVM must be given a set of training samples including positive and negative samples. Positive samples belong to C and negative samples do not. After text preprocessing, all samples can be translated to n-dimensional vectors. SVM tries to find a separating hyper-plane with maximum margin to separate the positive and negative examples from the training samples.

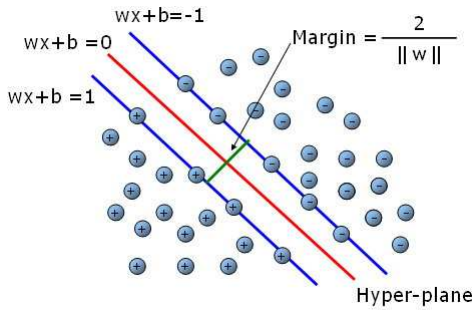


Fig. 2. Support vector machine

There are two kinds of multi-class SVM system[5], one-against-all(OAA) and one-against-one(OAO). The OAA SVM must train k binary SVMs where k is the number of classes. The ith SVM is trained with all samples belonging to ith class as positive samples, and takes other examples to be negative samples. These k SVMs could be trained in this way, and then k decision functions are generated. After setting up all SVMs with positive and negative samples, it trains all k SVMs. Then it can get k decision functions. For a testing data, we compute all the decision values by all decision functions and choose the

maximum value and the corresponding class to be its resulting class.

$$\text{The class of input data x} = arg \max_{i=1...k} (w_i \cdot x + b)$$

The OAO SVM is that for every combination of two classes i and j, it must train a corresponding SVM_{ij}. Therefore, it will train $k(k-1)/2$ SVMs and get $k(k-1)/2$ decision functions. For an input data, we compute all the decision values and use a voting strategy to decide which class it belongs to. If sign($w_{ij} \cdot x + b_{ij}$) shows x belongs to ith class, then the vote for the ith class is added by one. Otherwise, the jth class is added by one. Finally, x is predicted to be the class with the largest vote. This strategy is also called the "Max Wins" method.

There is no theoretic proof that which kind of multi-class SVM is better, and they are often compared by experiment. In [5][16], it shows the average accuracy of OAA SVM is better than the OAO SVM.

There are some researches for multi-class SVM classification. In [16], it presents a new algorithm to deal with noisy training data, which combines multi-class SVM and KNN method. The result shows that this algorithm can greatly reduce the influence of noisy data on SVM classifier. In [9], it compares OAO SVM, OAA SVM, DAG SVM (Directed Acyclic Graph SVM), and two all together SVM. An all together SVM means it trains a SVM classifier by solving a single optimization problem. Experiments show that OAO and DAG method may be more suitable for practical use. In [8], it reduces training data by using KNN method before the procedure of SVM classification. The mean idea is to speed up the training time. The experiment compares OAO SVM, DAG SVM, and the proposed hybrid SVM. It shows the accuracy are similar for three methods but the training time of hybrid SVM outperforms the other two methods. In [12], it compares SVM and Naive Bayes in multi-class classification. They both use a method, called "error correcting output code (ECOC)", to decide the class label of input data. The experiment shows the accuracy of SVM is better than Naive Bayes method.

III. Classification system

A classification system is composed of three phases, Text preprocessing, SVM training, and Performance testing.

- Text preprocessing. Text preprocessing is taken into three steps, Word segmentation, Feature extraction, and Term weighting.
  1) Word segmentation. Sentences in documents should be segmented to several shorter terms. Especially, it's much difficult to segment Chinese sentence because there is no natural delimiter between Chinese words. In our implementation, we adopt a Chinese word segmentation tool [18], developed by Institute of Information Science in Academia Sinica. It's obvious that the result of Chinese word segmentation has large influence on accuracy of classification systems.
  2) Feature extraction. The following methods are compared experimentally in our system.
     - TF, the weight of term i is defined as $w(t_i) = tf_i$, where tf_i is the number of occurrences of the ith term.
     - TFIDF, $w(t_i) = tf_i \times \log \frac{N}{n_i}$, N is the number of all documents, n_i is the number of documents where term i occurs.
     - Information Gain,

$$w(t_i) = -\sum_{j=1}^{m} p(c_j) \log p(c_j)$$

$$+p(t_i) \sum_{j=1}^{m} p(c_j|t_i) \log p(c_j|t_i)$$

$$+p(\widehat{t_i}) \sum_{j=1}^{m} p(c_j|\widehat{t_i}) \log p(c_j|\widehat{t_i}) \qquad (1)$$

     $p(c_j)$ is the probability that terms occur in category j, $p(t_i)$ is the probability that term i occurs, $p(c_j|t_i)$ is the probability that term i occurs in category j, $p(\widehat{t_i})$ is the probability that term i does not occur, $p(c_j|\widehat{t_i})$ is the probability that the term i doesn't occur in category j.

     It is difficult to define the threshold for the three methods. We use a percentage threshold instead, named filtering level (FL). Assume n is the number of keywords, let $0 < FL \leq 1$, then it reserves ($n * FL$) keywords and eliminates the others. The remaining keywords are features and we use them to represent document vector. To simplify the notation, we use TFIDF$^{0.8}$ to denote the TFIDF with filtering level 0.8.
  3) Term weighting. We compared 2 weighting methods with 2 normalization methods.
     - TF with L1 normalization (TF$_{L1}$), $d = (\frac{tf_1}{S}, \frac{tf_2}{S}, \ldots, \frac{tf_n}{S})$, where tf_i is the

number of occurrences of the ith term and $S = \sum_{i=1}^{n} t_i$.

- TF with L2 normalization (TF_{L2}), $d = (\frac{tf_1}{S}, \frac{tf_2}{S}, \ldots, \frac{tf_n}{S})$, where tf_i is the number of occurrences of the ith term and $S = \sqrt{\sum_{i=1}^{n} tf_i^2}$.
- TFIDF with L1 normalization ($TFIDF_{L1}$), $d = (\frac{v_1}{S}, \frac{v_2}{S}, \ldots, \frac{v_n}{S})$, where $v_i = tf_i \times \log \frac{N}{n_i}$, N is the total number of documents in training set, n_i is the number of documents in training set where term i occurs, and $S = \sum_{i=1}^{n} tf_i \times \log \frac{N}{n_i}$.
- TFIDF with L2 normalization ($TFIDF_{L2}$), $d = (\frac{v_1}{S}, \frac{v_2}{S}, \ldots, \frac{v_n}{S})$, where $v_i = tf_i \times \log \frac{N}{n_i}$, N is the total number of documents in training set, n_i is the number of documents in training set where term i occurs, and $S = \sqrt{\sum_{i=1}^{n} (tf_i \times \log \frac{N}{n_i})^2}$.

- SVM training. The OAA SVM is chosen to be our classification system, that is k binary SVMs will be trained and predict the class label of an input data with the maximum decision value. Considering the performance of SVM, a SVM tool, SVM^{light} [17], developed by Thorsten Joachims, is adopted.
  In SVM training, all training data are separated at first. For example, in figure 3, there are six documents in the training set. Document *a1* belongs to class *A*, document *b1* and *b2* belong to class *B*, and document *c1*, *c2*, and *c3* belong to class C. For the SVM classifier in *C*, *a1* is in the positive set and other five documents belong to the negative set. For the SVM classifier in *B*, *b1* and *b2* are in the positive set and other four documents belong to the negative set. For the SVM classifier in *C*, *c1*, *c2*, and *c3* are in the positive set and other three documents belong to the negative set. Then SVM^{light} is executed to train SVM A,B, and C and outputs three trained SVMs. We use the trained SVMs to classify documents.

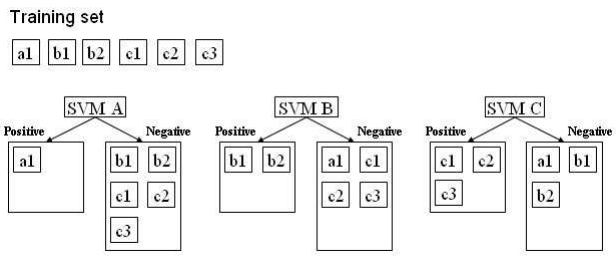


Fig. 3. Set up training set

- Performance testing. After all classifiers are trained, our system could predict the class label, the class in which the SVM classifier generates the maximum decision value, of the input data. For a set of testing data, the way to evaluate accuracy is defined as

$$\text{accuracy} = \frac{\text{number of correctly classified documents}}{\text{number of total documents}} \quad (2)$$

- An example of system flow.

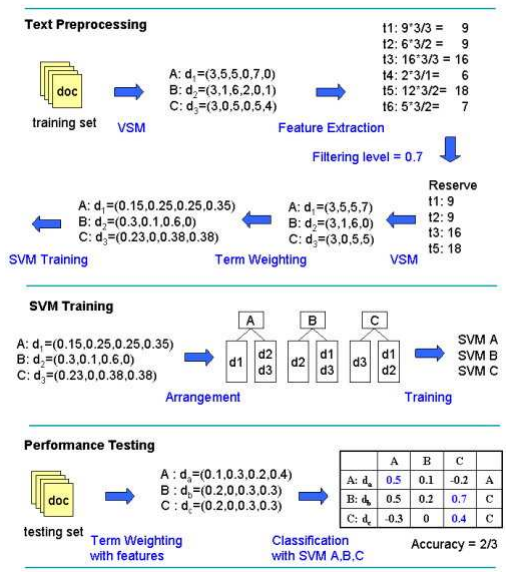


Fig. 4. An example of system flow

Figure 4 is an example of system flow. At first, it needs a training set. Assume there are three documents d_1, d_2, and d_3, and they belong to classes A, B, and C, respectively.

1) Text preprocessing. Long sentences should be segmented to shorter terms. The Chinese word segmentation system [18] is used in our implementation. Assume there are six keywords (t_1, t_2, ..., t_6) after word segmentation in our example. Then $A : d_1 = (3, 5, 5, 0, 7, 0)$ means d_1 belongs to class A and contains 3 term t_1, 5 term t_2, 5 term t_3 and 7 term t_5. It uses TFIDF of feature extraction with filtering level 0.7 ($TFIDF^{0.7}$). The weight of t_1 is $(3 + 3 + 3) \times \frac{3}{3} = 9$, the weight of t_2 is $(5 + 1 + 0) \times \frac{3}{2} = 9$, and so on. Using the filtering level, $6 \times 0.7 = 4.2 \simeq 4$ keywords will be reserved. After feature extraction, it reserves t_1, t_2, t_3 and t_5. Then TF with L1 normalization (TF_{L1}) of term weighting is adopted. For example, the weight of t_1 in d_1 is $\frac{3}{3+5+5+7} = 0.15$.
2) SVM training. The positive and negative samples for all SVMs should be separated. For example, SVM A takes all samples of class A, d_1, to be positive

set and all other samples, d_2 and d_3, to be negative set. Then we use the SVM^{light}[17] tool to be our classification system.

3) Performance testing. Assume there are three testing documents, d_a, d_b, and d_c, belonging to class A, B, and C, respectively. After the procedure of Text preprocessing, these three documents could be classified by all trained SVMs and calculated decision values. Our classification system predicts the class label, the class in which the SVM classifier generate the maximum decision value, of the document. In our example, the decision values are given arbitrarily and the accuracy is 66.67%.

IV. The Improvement of System

A. The method of self-learning

If the class labels of testing data are verified, the system can learn from these data. Not all input data are suitable to retrain system, specific misclassified data could be taken into consideration. After retraining the system by misclassified data, it would probably not misclassify the similar data. This method is called "Learning from Misclassified Data (LMD)". The following describes the LMD.

1) Verifying all classified data.
2) For each misclassified data of class A and its predicted class X, showed in figure 5, adding it to the positive set of the SVM in class A and adding to the negative set of the SVM in class X.
3) Retraining these two SVMs in which the training set has been modified.

That is a easy concept, and indeed it can effectively increase the accuracy of the system.

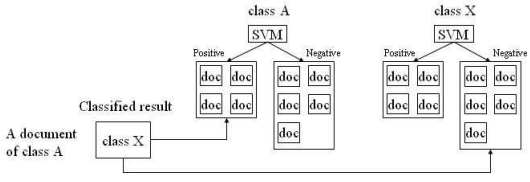


Fig. 5. Learning from Misclassified Data (LMD)

B. The method of error filtering

Our classification system chooses the class label, the class in which the SVM generates the maximum decision value, of the input data. But all those decision values could be negative. It means the input data does not belong to any class. It probably leads to misclassification. In the other case, the maximum and second maximum values could be very close. It means the input data is hard to be differentiated from the two most possible classes. It also leads to misclassification.

To avoid above situations, we define two variables and two thresholds for decision values. Result_Value(RV) is the maximum decision value which means how close the input data is to the predicted class. Difference_Value(DV) is the difference between maximum and second maximum value which means how the input data can be clearly separated from two most possible classes.

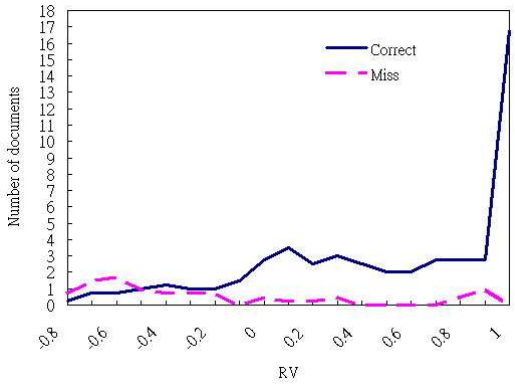


Fig. 6. The distribution of RV of documents

In figure 6, the x-axis is RV of documents and the y-axis is the number of documents. The solid line is the average RV distribution of correctly classified documents. The dotted line is the average RV distribution of misclassified documents. We can find that if a RV is larger than 0, the threshold, the input data has lots of probability belonging to the corresponding class and we return the class straightforward in our method. The threshold is named "RV bound" (RVB). If the RV is smaller than RVB, we use DV to differentiate the document.

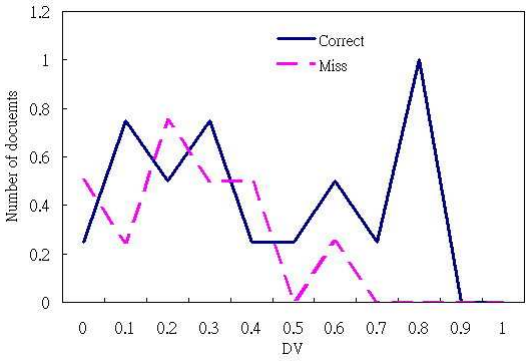


Fig. 7. The distribution of DVs of documents which RVs are smaller than RVB

In figure 7, it is showed the DV distribution of documents with RVs smaller than RVB. In our

method, if the DV is bigger than a threshold, named "Difference_Value bound" (DVB), the system will predict the class label of the testing data, or a indistinguishable message otherwise.

An input document is either distinguishable or indistinguishable.
(a) Distinguishable
1) RV $\geq$ RVB
2) RV $<$ RVB and DV $\geq$ DVB
(b) Indistinguishable
1) RV $<$ RVB and DV $<$ DVB

Now the problem is how to define the two thresholds, RVB and DVB. For the binary classifier in each class, RVB and DVB are individually decided by learning from training data. For a class A and all documents which are classified to class A, the RVB is computed by following formulation

$$RVB = Cor\_RV\_Avg \times (1 - \frac{Cor\_Num}{Total}) + Mis\_RV\_Avg \times (1 - \frac{Mis\_Num}{Total}) \quad (3)$$

where Cor_RV_Avg is the average RV of correctly classified data, Cor_Num is the number of correctly classified data, Mis_RV_Avg is the average RV of misclassified data, Mis_Num is the number of misclassified data, and $Total = Cor\_Num + Mis\_Num$. After determining the RVB, we compute DVB by documents with RVs smaller than RVB. The formulation is defined as

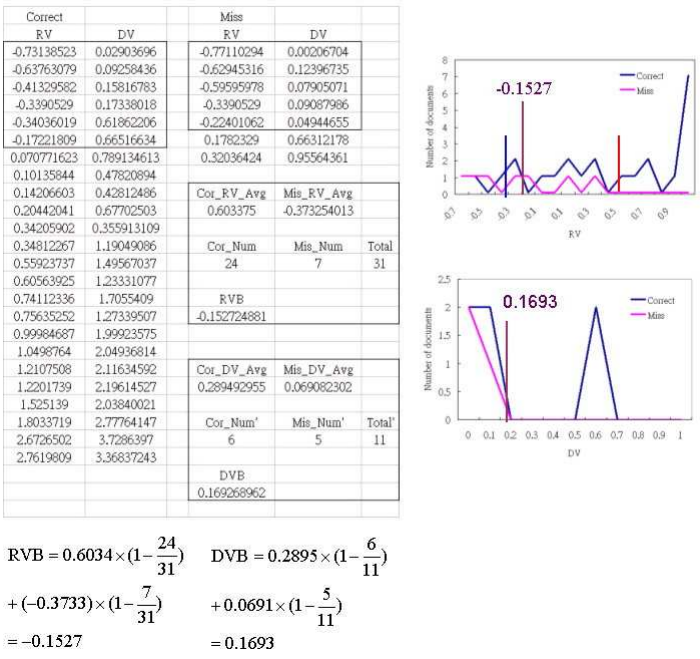
$$DVB = Cor\_DV\_Avg \times (1 - \frac{Cor\_Num'}{Total'}) + Mis\_DV\_Avg \times (1 - \frac{Mis\_Num'}{Total'}) \quad (4)$$

where Cor_DV_Avg is the average DV of correctly classified data, Cor_Num' is the number of correctly classified data, Mis_DV_Avg is the average DV of misclassified data, Mis_Num' is the number of misclassified data, and $Total' = Cor\_Num' + Mis\_Num'$.

The RVB and the DVB will clearly separate the correctly classified and misclassified data. Figure 8 is an example of computing RVB and DVB. The left two columns is the RV and DV of correctly classified data. The right two columns is the RV and DV of misclassified data. The RVB and DVB can be calculated by the two formulations.

C. Combining self-learning and error filtering

In section IV, a method of self-learning, LMD is proposed. LMD chooses the misclassified data to retrain the system. But through separating indistinguishable data from the classified data, there is one strategy to choose which data to



Correct		Miss	
RV	DV	RV	DV
-0.73138523	0.02903696	-0.77110294	0.00206704
-0.63763079	0.09258436	-0.62945316	0.12396735
-0.41329582	0.15816783	-0.59595978	0.07905071
-0.3390529	0.17338018	-0.3390529	0.09087986
-0.34036019	0.61862206	-0.22401062	0.04944655
-0.17221809	0.66516634	0.1782329	0.66312178
0.070771623	0.789134613	0.32036424	0.95564361
0.10135844	0.47820894		
0.14206603	0.42812486	Cor_RV_Avg	Mis_RV_Avg
0.20442041	0.67702503	0.603375	-0.373254013
0.34205902	0.355913109		
0.34812267	1.19049086	Cor_Num	Mis_Num Total
0.55923737	1.49567037	24	7 31
0.60563925	1.23331077		
0.74112336	1.7055409	RVB	
0.75635252	1.27339507	-0.152724881	
0.99984687	1.99923575		
1.0498764	2.04936814		
1.2107508	2.11634592	Cor_DV_Avg	Mis_DV_Avg
1.2201739	2.19614527	0.289492955	0.069082302
1.525139	2.03840021		
1.8033719	2.77764147	Cor_Num'	Mis_Num' Total'
2.6726502	3.7286397	6	5 11
2.7619809	3.36837243		
		DVB	
		0.169268962	

$$RVB = 0.6034 \times (1 - \frac{24}{31}) + (-0.3733) \times (1 - \frac{7}{31}) = -0.1527$$

$$DVB = 0.2895 \times (1 - \frac{6}{11}) + 0.0691 \times (1 - \frac{5}{11}) = 0.1693$$

Fig. 8. An example of computing RVB and DVB

retrain the system. Because the predicted class label of some indistinguishable data are correct, they worth to be learned. The indistinguishable data and misclassified data are used to retrain the system, called "Learning from Misclassified and Indistinguishable Data (LMID)". The following describes the LMID.

1) Varifying all classified data.
2) For each misclassified data with the correct class label A and the predicted class label X, the dotted line in figure 9, adding it to the positive set of the SVM in class A and to the negative set of the SVM in class X.
3) For each indistinguishable data with the correct class label A and the predicted class label A, the solid line in figure 9, adding it to the positive set of the SVM in class A.
4) Retraining the SVMs which training set has been modified.

The only difference between LMD and LMID is the step 3 in LMID. LMD and LMID are compared experimentally in section V.

V. Experiment Results

The experiment uses the official documents of the National Chung Cheng University from the year 2002 to 2005. We take 20 units (classes), 150 documents for each unit (class) as training data, and 150 documents for each unit (class) as testing data. Totally we have 6000 documents for experiment. There is a common characteristic among official documents, seldom words in the contents. The average number of keywords in

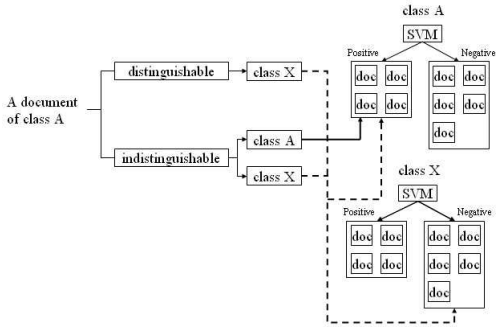


Fig. 9. Learning from Misclassified and Indistinguishable Data (LMID).

each document is nearly 10. That leads to a challenge on the accuracy of the classification system.

The way to evaluate accuracy is defined as

$$\text{accuracy} = \frac{\text{number of correctly classified documents}}{\text{number of total documents}}$$

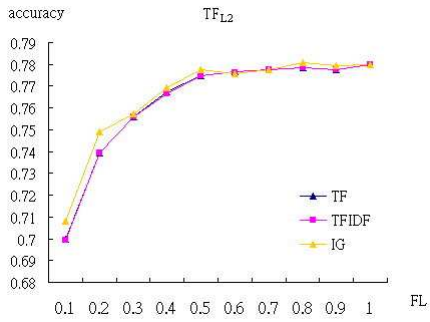


Fig. 10. he accuracy of TF, TFIDF, and IG of feature extraction with TF_{L2} of term weighting

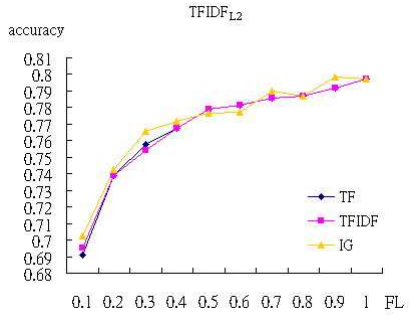


Fig. 11. The accuracy of TF, TFIDF, and IG of feature extraction with $TFIDF_{L2}$ of term weighting

Figure 10 is the result of using TF_{L2} as term weighting scheme and three kinds of feature extraction with increasing filtering level from 0 to 1. Figure 11 is the result of using $TFIDF_{L2}$ as term weighting scheme. We can find out the IG is better than TFIDF and TF when the filtering level is decreasing but the differentiation is not so obvious because of the characteristic of seldom words in document content.

Then we compare TF_{L1}, TF_{L2}, $TFIDF_{L1}$, and $TFIDF_{L2}$ as term weighting scheme.

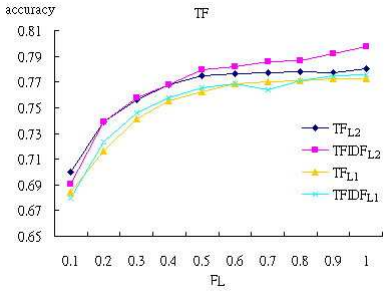


Fig. 12. TF_{L1}, TF_{L2}, $TFIDF_{L1}$, and $TFIDF_{L2}$ of term weighting with TF of feature extraction

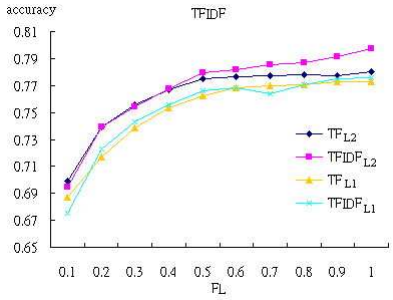


Fig. 13. TF_{L1}, TF_{L2}, $TFIDF_{L1}$, and $TFIDF_{L2}$ of term weighting with TFIDF of feature extraction

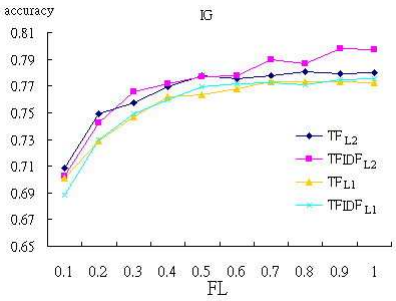


Fig. 14. TF_{L1}, TF_{L2}, $TFIDF_{L1}$, and $TFIDF_{L2}$ of term weighting with IG of feature extraction

Figure 12, 13, and 14 are the results of comparing TF_{L1}, TF_{L2}, $TFIDF_{L1}$, and $TFIDF_{L2}$ as term weighting scheme with TF, TFIDF, and IG as feature extraction scheme. It is observed $TFIDF_{L2}$ outperforms the others. In our experiment, we found the best strategy of our classification system for the input data is $IG^{0.9}$ as feature extraction scheme with $TFIDF_{L2}$ as term weighting scheme, and the accuracy of classification is 79.83%.

Table II is the result of using self-learning (LMD) method mentioned in section IV-A. The

	Basic SVM	LMD SVM
Data set	Accuracy	Accuracy
T1	–	–
T2	0.7817	0.79
T3	0.785	0.8017
T4	0.77	0.7883
T5	0.8017	0.81
Average	0.7846	0.7975

TABLE I
THE ACCURACY OF USING THE METHOD OF SELF-LEARNING (LMD)

Accuracy	Basic SVM	EF SVM
T1	0.8	0.8263
T2	0.7817	0.8109
T3	0.785	0.8185
T4	0.77	0.7996
T5	0.8017	0.8272
Average	0.78168	0.8165

TABLE II
THE ACCURACY OF USING THE METHOD OF ERROR FILTERING (EF)

testing data are divided into 5 sets. For each class,there are 30 documents belonging to each set. Totally there are 600 document in each set. We compare results with basic SVM and LMD SVM. Here we use the TFIDF$_{L2}$ as term weighting scheme and TF$^{1.0}$ as feature extraction scheme. After classifying each testing data set, the system will automatically be retrianed by itself. Therefore, beside of T1, the other testing sets will have different accuracy. We can find the average accuracy of LMD SVM is better than basic SVM and is 1.64% improvement on accuracy.

Table IV-C and Table IV-C are the results of using error filtering(EF) method mentioned in section IV-B. We compare the "Basic SVM" and "EF SVM", they show the average accuracy of "Basic SVM" is 78.168% and "EF SVM" is 81.65% with 94.634% distinguish ability. We can find that "EF SVM" has 4.45% improvement on average accuracy.

Table IV-C and IV-C show the result of using the methods of combining error filtering and self-learning, which is mentioned in section IV-C. It is found that both accuracy and distinguish ability are arising. LMD SVM and LMID SVM has

Distinguish ability	EF SVM
T1	0.95
T2	0.9517
T3	0.9367
T4	0.0.9483
T5	0.945
Average	0.94634

TABLE III
THE DISTINGUISH ABILITY OF USING THE METHOD OF ERROR FILTERING (EF)

Accuracy	Basic SVM	EF SVM	LMD EF SVM	LMID EF SVM
T1	0.8	0.8263	0.8263	0.8263
T2	0.7817	0.8109	0.8191	0.8134
T3	0.785	0.8185	0.8473	0.847
T4	0.77	0.7996	0.8277	0.8234
T5	0.8017	0.8272	0.9363	0.8339
Average	0.78168	0.8165	0.83134	0.82898

TABLE IV
THE ACCURACY OF USING THE METHOD OF COMBINING SELF-LEARNING AND ERROR FILTERING

Distinguish ability	EF SVM	LMD EF SVM	LMID EF SVM
T1	0.95	0.95	0.95
T2	0.9517	0.94	0.467
T3	0.9367	0.9167	0.915
T4	0.9483	0.9383	0.9483
T5	0.945	0.9467	0.9533
Average	0.94634	0.93834	0.94266

TABLE V
THE DISTINGUISH ABILITY OF USING THE METHOD OF COMBINING SELF-LEARNING AND ERROR FILTERING

5.54% and 5.24% improvement, respectively. The accuracy of LMD is better than LMID SVM but LMID SVM has higher distinguish ability.

VI. CONCLUSION

In this paper, soem data retrieving techniques and multi-class SVM classifiers are introduced. After the procedure of Text preprocessing and SVM training, a classification system could be built and then automatically classify documents. Our experiment shows the best strategy is to adopt IG$_{0.9}$ as feature extraction scheme with TFIDF$_{L2}$ as term weighting scheme, and the accuracy of classification is 79.83%. The influence on feature extraction is not obvious because of the characteristic of document contents, few words on average. In order to improve the accuracy of the system, we propose two methods, self-learning and error filtering. In self learning (LMD), it is observed that the accuracy of LMD SVM has 1.64% improvement compared to the basic SVM. In error filtering (EF SVM), there is 4.45% improvement on average accuracy . After combining the methods of self-learning and error filtering, the experiment shows the accuracy of LMD and LMID has 5.54% and 5.24% improvement, respectively.

VII. FUTURE WORKS

There are still many other ways to implement feature extraction. We can apply some new methods to the system and compare their experimental results. In section III, there is a short description on word segmentation. Chinese word segmentation is difficult to deal with, and there still is room to improve the influence of word segmentation. After filtering out possibly misclassified data, our classification system does not deal with them. We will figure out other classification methods which

are good at these kind of data in order to improve the accuracy and distinguish ability.

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