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A model for book inquiry history analysis and book-acquisition recommendation of libraries

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ABSTRACT

In the era of knowledge economy, the libraries play an important role for library users to maintain and provide a large number of book resources. In order to satisfy requirements of borrowers, the libraries have to purchase all kinds of new books on a regular time schedule. However, the borrowers' demands cannot be satisfied simply because of the limited number of librarians and thus the libraries require useful suggestions for book-acquisition. Traditionally, the book-acquisition recommendation applications are collected by library consultants and then evaluated by librarians. Under the circumstance, several pitfalls (e.g., only partial library borrowers realize the book-acquisition recommendation procedure or a lot of time and human efforts required) might occur. Therefore, this paper focuses on the development of a book-acquisition recommendation model for libraries to acquire the various library borrowers' demands based on book inquiry history under a library system.

In addition to the book-acquisition recommendation model, a Web-based book-acquisition recommendation system is also developed and a demonstration case is applied to verify the performance of the proposed approach. Under the book-acquisition recommendation platform, the librarians can automatically derive the book-acquisition recommendation list to fit borrowers' requirements and the complicated recommendation processes for borrowers can also be reduced. The attempt of this research is to enhance the accuracy and efficiency of book-acquisition performance and therefore the book-acquisition tasks in library can be efficiently accomplished.
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1. Introduction

Libraries are established to provide a means of learning. In order to satisfy most user demands, a library should collect a diversified range of books in order to handle the borrowers' needs. Taking a university library as an example, borrowers are able to search for specific books via the book search function within the library system, which is based on the developed Internet. However, book storage in the library is limited and not all borrower requirements can be fully satisfied. Therefore, when borrowers cannot find their required books, they may recommend a list of books to be purchased for the library by filling in forms or by contacting book consultants. To fill in forms, the borrowers login to the library system, fill in the appropriate forms and upload the information to the system. In addition, the borrowers are able to contact the book consultant with their recommendations. The book consultants then integrate the lists of recommended books and pass them on to the librarians for acquisition.

As regards the above two methods, the librarians gather all of the lists of recommended books, and then check to ensure that the recommended books in the book list have been purchased or collected. After this has been confirmed, they integrate all the recommended lists for book-acquisition. The current book-acquisition recommendation process of libraries, i.e., AS-IS model for book-acquisition recommendation of libraries, is shown in Fig. 1.

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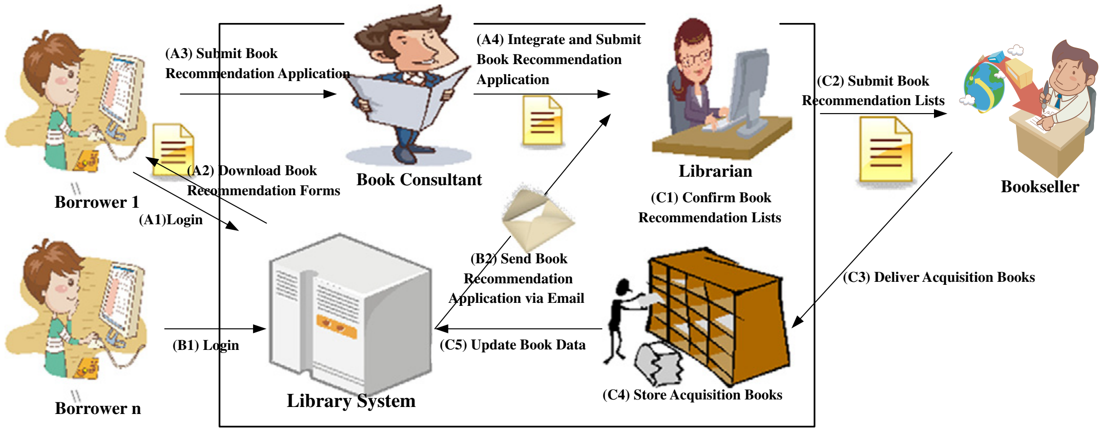


Fig. 1. AS-IS model for book-acquisition recommendation of libraries.

As shown in Fig. 1, although the library systems of some libraries provide book recommendation services, the libraries have not properly advertised this recommendation mechanism, so only some borrowers know that they can request the acquisition of books. In addition, some borrowers are unwilling to execute the book recommendation function because the process is too complicated and the purchasing time is too long.

This paper states the following major problems with regard to the current book-acquisition recommendation process used in libraries.

- ➢ Although the books are recommended by borrowers, only some borrowers are aware of this recommendation process; thus, not all the borrowers' requirements can be satisfied.
- ➢ The overall book-acquisition process needs to operate more quickly, efficiently and electronically.

This paper attempts to develop a book-acquisition recommendation model based on text mining technology and Internet technology in order to provide librarians with suggestions for book-acquisition. The proposed model collects the book inquiry history from cases where borrowers have not found books within the library system by using keyword extraction. The extracted keywords match the book database of the bookseller in order to obtain the recommended books; the librarians are then able to purchase the books based on the book-acquisition recommendation list. The process developed by this paper is a system-based active recommendation process where the book list does not need to be collected artificially. Moreover, the recommendation list can meet most borrowers' requirements with increased efficiency. The To-Be model for library book-acquisition recommendation is given in Fig. 2.

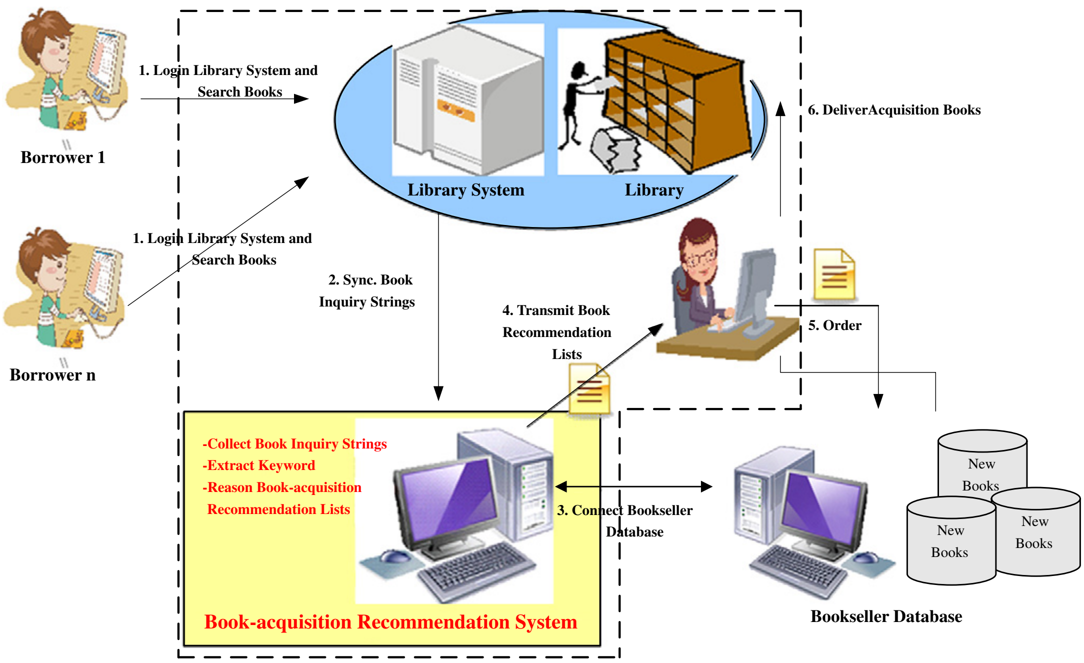


Fig. 2. TO-BE model for library book-acquisition recommendation.

2. Literature review

Based on the book-acquisition recommendation of libraries, the proposed model consists of three typical issues including data mining, keyword extraction and book-acquisition recommendation. The previous studies related to these three topics are reviewed in this section.

2.1. Data mining

A great number of data mining methodologies have been developed for data clustering, classification and association (Giudici & Passerone, 2002; Kamimura, Bicciato, Shimizu, Alford, & Stephanopoulos, 2000). The methodologies commonly employed are decision tree (Breault, Goodall, & Fos, 2002), CHAID approach (Rygielski, Wang, & Yen, 2002) and C4.5 tree algorithm (Chae, Ho, Cho, Lee, & Ji, 2001; Coppola & Vanneschi, 2002). Several heuristic approaches that simulate the thinking processes of human beings are also employed for data analysis including the neural network approach (Leu, Chen, & Chang, 2001), generic algorithm (Kamrani, Rong, & Gonzalez, 2001; Sorensen & Janssens, 2003) and fuzzy approach (Honga, Lin, & Wang, 2003; Nikravesh & Aminzadeh, 2001). The above methodologies have been widely applied for analysis of personal profiles and business operation intelligence.

Besides the abovementioned basic methodologies, on-line data bases have been widely used in recent years, the data storage forms can be divided into concentrated storage in one single data warehouse, distributed storage or storage in operating system. The On Line Analytical Processing (OLAP) can help users segment and analyze data to find out the needed information (Ganti & Gehrke, 2002). Relevant theories are proposed to improve the accuracy and efficiency of data analysis, such as the Rough Set Theory (Ananthanarayana, Murty, & Subramanian, 2003) and the stochastic model (Jenamani, Mohapatra, & Ghose, 2003), which are developed to make up the deficiencies in the abovementioned theories.

2.2. Keyword extraction

Owing to the booming growth of Internet technology, to enhance the performance for enterprises to derive the required information from massive documents and domain knowledge has become a key issue for enterprise knowledge management. Many researches focus on keyword extraction technology to select the keywords from the documents.

Keyword frequency is considered a critical feature of keywords in many keyword extraction algorithms, such as KEIFES (Keyword Extraction and Information Filtering System). This KEIFES first utilizes "Co-occurring Frequency" of fuzzy theory to calculate the correlation coefficients between each two words. The words with larger "Co-occurring Frequency" can be regarded as the keywords for the documents (Wakami, Mizutani, Kataoka, & Imanaka, 1997). In addition, a model for document keyword extraction on the basis of keyword correlation thesaurus is proposed (Hou & Chan, 2003). This keyword correlation determination algorithm is developed based on the keyword frequency and location in the specified documents. The keywords with high correlation can be integrated to represent documents content better. Therefore, the problem that the words with similar meaning are recognized as different keywords for these documents simultaneously can be avoided.

Many approaches apply natural language processing technology to extract keywords. These approaches combine the Parsing and Generation functions of natural language processing program, and use UTA (Uniform Tabular Algorithm) as the kernel model to analyze the semantics of the sentences. UTA can analyze the character string or derive relevant vocabularies based on semantic expression by the data structure of sentence inputted by the users. Thus, the implicit information of the sentence can be correctly analyzed (Neumann, 1998). In addition, Chan (2004) extracts the keywords based on keyword correlation. This approach uses the salient pattern of the sentence to distinguish the semantics and utilizes network structure to express the correlation among the keywords to establish the semantic correlation model. Finally, the keywords can be extracted via Lexical Cohesion and Contextual Coherence of the natural language.

Besides the above keyword extraction methodologies, PAT-Tree-Based algorithm is applicable to Chinese keyword extraction. First of all, PAT-Tree can be used as the data structure for quick-access of N-Gram. Then, a Significance Estimation Function can be built based on Mutual Information concept to delete the relatively uncompleted words and to reserve the integrated words. PAT-Tree's advantage is that PAT-Tree-Based algorithm can extract Chinese keywords without relying on term database or grammar. Also, PAT-Tree-Based algorithm can dispose some specific terms, such as, "names", "science and technology," etc. (Chien, 1997). On the other hand, PAT-Tree algorithm is applicable to automatic keyword extraction technology with Bi-Gram model. First of all, all the two-word terms of the documents can be selected via Bi-Gram model; then, PAT-Tree structure is established based on two-word term sets. Finally, the keywords can be extracted based on the distribution of PAT-Tree structure (Horng & Yeh, 2000).

2.3. Book-acquisition recommendation

Libraries are confronted with reduced book funds and increased book ordering costs now, therefore, how libraries satisfy readers' requirements with limited funds is really a major issue to library servers. Take university libraries as an example, the government reduces the subsidies for public and private universities yearly. With the limited funds of universities, the administrative units cannot reduce the teaching study budget to increase the book funds, therefore, the inadequate budget is a major difficulty in the operation of university libraries in Taiwan (Yu, 2004). In addition, Tsao (2002) uses the On Line Analytical Processing (OLAP) to analyze the readers' borrowing records and generate association rules as the basis of recommended collection, so that the librarians could give opinions on purchasing of core and hot collected books. Finally, Lin (2005) investigates the reading behaviors of on-line readers, the influence of article length, positive aspiring articles and negative reports on readers' favor is investigated to figure out the preference of most readers from the survey of the reading habits of users; this research result can be used as a suggestion for booksellers to store books or for libraries to purchase and collect books.

Besides the abovementioned reduced book funds of libraries, the book purchasing timeliness of libraries and suppliers is also paid attention to gradually. In order to shorten the response time of booksellers and simplify the complicated process of book purchasing, the book suppliers set up a book data access system for prompt dealings. In this system, the seller only needs to input the book name to make comparison in the database of the book supplier, list the coincident book information, and finally send it back to the seller side, so that the consumers can know the book information timely as a reference (Lin, 2007). In addition, the libraries and suppliers have taken the purchasing method of Electronic Data Interchange (EDI) now, the difference between the EDI purchasing and traditional library purchasing process is that the libraries, booksellers and publishers are connected on line through computers, this method can not only reduce the contact cost and purchasing time, but also avoid the difference between the data formats in purchase orders and delivery orders (Hsueh, 1995). Furthermore, long-term ordering is one mode of book ordering, due to some books in the library are of series published serially, it is not feasible to order after the whole series of books are published, the library always needs to adopt continuous ordering, so that the collection will not go so far as to be interrupted by any lost ordering (Wang, 2000).

Finally, some rare or infrequent books are needed by only the minority of readers, therefore, this type of books is seldom inquired, so that there is no opinion on this type of books, furthermore, as the book funds are limited, this type of books is likely to be traded off by purchasers of libraries, so that some users' rights are neglected. Therefore, in order to improve the service quality of libraries, this type of books shall be paid the equivalent attention to (Zeugner, 2002).

3. Book-acquisition recommendation model

In the book-acquisition recommendation model, the book inquiry strings from borrowers should be collected for keyword extraction via the *Keyword Density Thesaurus* (KDT) and the *Keyword Sequence Thesaurus* (KST). Based on the extracted keyword, the *Keyword-Book Mapping* (KBM) model can provide the recommendation list for book-acquisition (as shown in Fig. 3).

3.1. Keyword Density Thesaurus

The KDT proposed in this paper uses the book inquiry strings entered by borrowers for comparison with the keyword set (established by domain experts) and non-keyword set (e.g., *of*, *and*) for candidate keyword extraction. After each candidate keyword density is calculated and compared with the predefined threshold, a new keyword can be extracted from the candidate keyword set and the density keyword set can be established.

The symbols used in the algorithm are defined as follows.

BDS The density keyword threshold for judgment of density keyword
CKW. The candidate keyword set

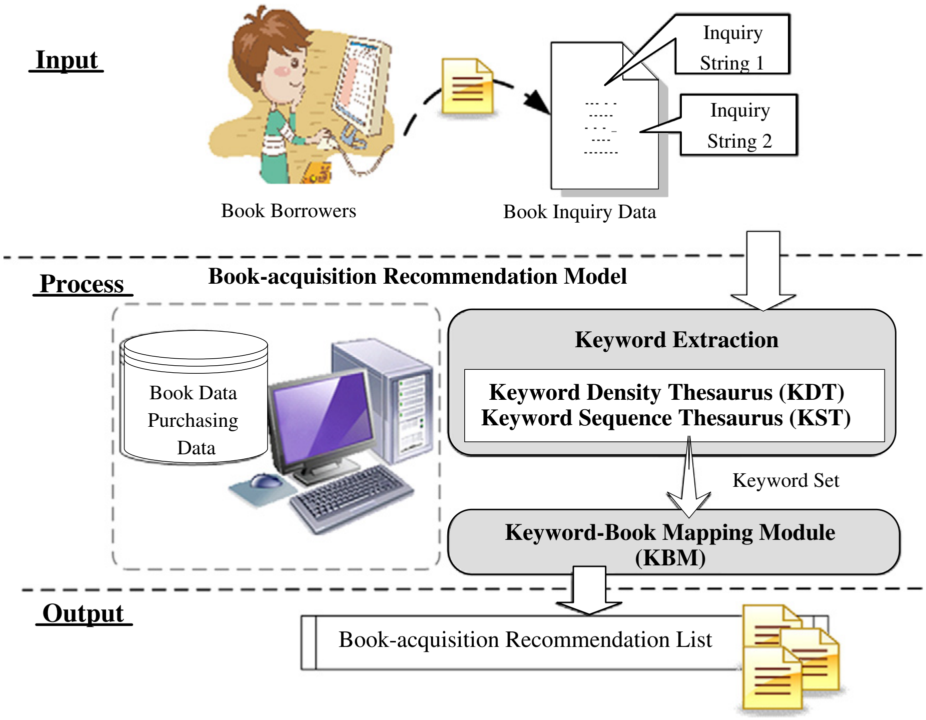


Fig. 3. The book-acquisition recommendation model proposed in this paper.

CKW_i The i'th candidate keyword in CKW.
$CKW^*_\bullet$ The candidate keyword set after candidate keyword merging
CKW^*_i The i'th merged candidate keyword in $CKW^*_\bullet$
DKW The density keyword set
$DCKW^*_i$ The density of merged candidate keyword CKW^*_i, namely, the proportion of the frequency of CKW^*_i to frequency of $CKW^*_\bullet$
KW The keyword set
$N(CKW^*_i)$ The frequency of CKW^*_i
NKW The non-keyword set

3.1.1. Step (A1): extraction of candidate keywords

First of all, this algorithm collects all the book inquiry strings entered by users in the library system. Then, each book inquiry string is segmented and all the segmented words are compared with the established keyword database (KW) and non-keyword database (NKW) via word comparison methodology. After the keywords and non-keywords are deleted from the segmented words, the reserved words are recognized as the candidate keywords. In this step, the candidate keywords $CKW_\bullet = \{CKW_1, CKW_2, \ldots, CKW_i\}$ from book inquiry history are extracted.

For example, the inquiry string is "Economy of free". After the keyword deletion (delete non-keywords such as "of"), words "economy" and "free" become the candidate keywords.

3.1.2. Step (A2): mergence of candidate keyword

Some of the candidate keywords might be identical (i.e., $CKW_i = CKW_j$ and $i \neq j$). The identical keywords should be merged to be distinct keywords. After merging the all identical candidate keywords, the merged candidate keyword set can be obtained, i.e., $CKW^*_\bullet = \{CKW^*_1, CKW^*_2, \ldots, CKW^*_i\}$ and the merged candidate keyword frequencies ($N(CKW^*_i)$) within CKW also can be calculated.

For example, the query times by all users of the candidate keyword "free" during the inquiry string collection period (presumably a month) can be accumulated.

3.1.3. Step (A3): calculation of the density of candidate keyword

This algorithm calculates the density of each merged candidate keyword in Step (A3). That is, the keyword frequency proportion of the i'th merged candidate keyword to the candidate keyword set can be derived via Eq. (1).

$$DCKW^*_i = \frac{N(CKW^*_i)}{\sum_{alli} N(CKW^*_i)} \tag{1}$$

For example, during the string collection period, all candidate keywords have been inquired for 100 times. Candidate keyword "free" has been inquired for twice, and thus the keyword density of "free" can be obtained ($2/100 = 0.02$).

3.1.4. Step (A4): establishment of density keyword set

The density values of all merged candidate keywords are compared with the predefined density threshold (BDS). If $DCKW^*_i$ is larger than or equal to BDS, the merged candidate keyword CKW^*_i is regarded as a keyword. The density keyword set DKW can be obtained (as shown in Eq. (2)).

$$\text{If } DCKW^*_i \geq BDS \text{ then } CKW^*_i \in DKW \tag{2}$$

For example, candidate keyword "free" keyword density is 0.02, which is greater than the preset threshold value of 0.01. Therefore, candidate keyword "free" can be categorized as the density keyword.

3.2. Keyword Sequence Thesaurus

The inquiry sequence of each book inquiry string should be recorded first in KST. In addition, after the inquiry strings are compared with the keywords, the relative inquiry sequences of all inquiry strings to keywords can be calculated. The identical inquiry strings with the same relative sequence should be merged (the merged inquiry strings are defined as the critical inquiry word) and accumulated according to the frequency of each critical inquiry word. Finally, critical inquiry word frequency is compared with the predefined threshold to determine a new keyword, i.e., sequence keyword.

The symbols used in the algorithm are defined as follows.

BNS The sequence keyword threshold for judgment of density keyword
$IKW^*_{k,m}$ After keyword comparison, $IKW^*_{k,m}$ is denoted as $IKW_{k,}m$ that exists in KW
$IKW_{k,}m$ The k'th inquiry string collected in the m'th inquiry string collection period

$IKW_{k,m}[L]$The relative inquiry sequence L ($L = k - h$) between $IKW_{k,}m$ and $IKW^{*}_{h,m}$
$N(QKW_i)$ The critical inquiry word frequency of QKW_i
QKW. The critical inquiry word set
QKW_i The i'th critical inquiry word in QKW.
SKW The sequence keyword set

3.2.1. Step (B1): collection of inquiry strings and record of inquiry sequence

This algorithm collects the book inquiry strings entered by users during each book inquiry collection period and records corresponding inquiry sequence. That is, the inquiry string with the k'th inquiry order $IKW_{k,}m$ collected in the m'th inquiry period can be obtained.

For example, the query sequence of all inquiry strings during this inquiry period by the user can be recorded (as shown in columns "Inquiry string" and "Sequence" of Table 1,). The query sequence of "Meteorology" is 2.

3.2.2. Step (B2): comparison with keyword

In Step (B2), each $IKW_{k,}m$ is compared with the established keyword set. If the $IKW_{k,}m$ exists in keyword set, the corresponding inquiry string $IKW_{k,}m$ is denoted as $IKW^{*}_{k,m}$.

3.2.3. Step (B3): calculation of relative inquiry sequence

The relative inquiry sequence L ($L = k - h$) of each inquiry word $IKW_{k,}m$ (the k'th inquiry sequence, $k = 1,2,\ldots$) to keyword $IKW_{h,}m^{*}$ (the h'th inquiry sequence, $h = 0,1,2,\ldots k$) collected in the m'th collection period is calculated, and the inquiry word $IKW_{k,}m[L]$ with relative sequence L can be obtained.

For example, if the inquiry string collection period is one month and the query of each user is used as the data collection cycle, then the query frequency of same inquiry string at same relative sequence can be accumulated. As shown in Table 1, the user query strings in the following sequence are "Jesus", "Meteorology", "Free" etc. "Meteorology" and "Radiation" are keywords; therefore, the relative sequence of "News" against "Meteorology" is 6 ($8 - 2 = 6$) (see the third column), the relative sequence against "radiation" is 4 ($8 - 4 = 4$) (see the fourth column). If other users use the inquiry string of "News" for query, and the relative sequence against the keyword is 6 or 4, then, add 1 to the frequency, otherwise the frequency is not accumulated.

3.2.4. Step (B4): mergence of inquiry words

As all the relative sequences are determined, some inquiry words collected in difference collection periods might be identical (i.e., $IKW_{k,m}[L] = IKW_{p,h}[G]$ and $L = G$, means the book inquiry string $IKW_{k,m}$ is identical to $IKW_{p,h}$ and the relative sequence L is equal to G); therefore, the specific inquiry words should be merged and accumulated inquiry frequency. Otherwise, if some inquiry words are identical with different relative sequences, the two words are regarded as different inquiry words. All the inquiry words with relative sequences are compared with each other to obtain the distinct words (i.e., critical inquiry words). Finally, the critical inquiry word set ($QKW = \{QKW_1, QKW_2, \ldots\ldots\}$) can be obtained and the frequency of each critical inquiry word ($N(QCK_i)$) can be accumulated.

3.2.5. Step (B5): establishment of sequence keyword set

The critical inquiry word frequency $N(QKW_i)$ is compared with the sequence keyword threshold (BNS). If the frequency value is lager than or equal to the predefined threshold BNS, the critical inquiry word QKW_i is regarded as a keyword. After that, the sequence keyword set SKW can be obtained (as shown in Eq. (3)).

$$\text{If } N\left(QKW_i\right) \geq BNS \text{ then } QKW_i \in SKW \tag{3}$$

For example, during the inquiry string collection period, the accumulated frequency of the inquiry string of "News" is 3, which is greater than the predefined threshold BNS (valued at 2). Thus, the word "News" can be regarded as the sequential keyword.

Table 1
Sequence and relative sequence of inquiry string.

Inquiry string	Sequence	Relative sequence (I)	Relative sequence (II)
Jesus	1	−1	−3
Meteorology	2	0	−2
Free	3	1	−1
Radiation	4	2	0
Political Science	5	3	1
Chang'an	6	4	2
Tomb-raider	7	5	3
News	8	6	4

3.3. Keyword-Book Mapping module

The Keyword-Book Mapping module of this paper uses the *density keyword set* (DKW, extracted via KDT), the *sequence keyword set* (SKW, extracted via KST) and the *system keyword set* (SysKW, established by domain experts and then provided via KDT and KST) as the analysis data for determining the book-acquisition recommendation list. At first, these three kinds of keywords should be attached to the book classification attributes. Then, the keyword quantity of each book category and the relative scale between each book category can be calculated. After that, the book-acquisition recommendation list can be populated via the proposed Keyword-Book Mapping module. In this section, the density keyword set is taken as an example for determining the book-acquisition recommendation list.

3.3.1. Attachment of book category attribute of keyword set

According to the *Classification Scheme for Chinese Libraries* (CSCL), ten book categories can be derived. The keywords within the book outline/content and book title from the list of categories can be extracted and ten book category keyword sets can be established. After that, as a density keyword exists in the specific book category keyword set, this density keyword is attached to the corresponding category attribute. Finally, the proportions of ten book categories are determined based on the number of attached book category keywords.

The symbols used in the algorithm are defined as follows.

D_T_j The keyword set of the j'th book category extracted from DKW
$N(D\_T_j)$ Number of keywords in D_T_j
$N(S\_T_j)$ Number of keywords in T_T_j
$N(Sys\_T_j)$ Number of keywords in Sys_T_j
$P(D\_T_j)$ The proportion of the keyword number of D_T_j to the keyword number of all book categories D_T_j ($j=1,2,\ldots,10$)
S_T_j The keyword set of the j'th book category extracted from SKW
Sys_T_j The keyword set of the j'th book category established from system keyword set
T_CL_j The keyword set of the j'th book category extracted from book databases of booksellers
T_j The j'th book category based on Classification Scheme for Chinese Libraries

3.3.1.1. Step (C1-1): establishment of book category keyword set. In this algorithm, domain experts should establish each book category keyword set T_CL_j (as shown in Table 2) according to the "Classification Scheme for Chinese Libraries" at first.

For example, domain experts set 1000 keywords of each book category. The keywords of the book category "Philosophy" are set as: value, contribution, talent, hardship, library etc. (contained in T_CL_2).

3.3.1.2. Step (C1-2): comparison of keywords. In this step, the density keyword set (DKW) and each established book category keyword set T_CL_j are intersected to derive the density keyword set D_T_j of each book category (as shown in Eq. (4)). The density keyword numbers of book categories ($N(D\_T_j)$) also can be calculated.

$$D\_T_j = DKW \cap T\_CL_j \quad j = 1, 2, \ldots, 10 \tag{4}$$

For example, 100 density keywords generated during the string collection period including "model", "platform", "library" etc. are compared with the book category keywords. If density keyword "library" is in the book keyword set of "Philosophy", then the relationship is marked as 1.

3.3.1.3. Step (C1-3): calculation of the proportion of each book category. The proportion $P(D\_T_j)$ of the specific book category to all book categories according to the keyword number of each category can be calculated via Eq. (5). The results of the book

Table 2
Establishment of book category keyword set.

T_j	Book categories	Book category keyword set
T_1	General	T_CL_1
T_2	Philosophy	T_CL_2
T_3	Religion	T_CL_3
T_4	Science	T_CL_4
T_5	Applied Science	T_CL_5
T_6	Social Science	T_CL_6
T_7	Historical and Geography I	T_CL_7
T_8	Historical and Geography II	T_CL_8
T_9	Chinese	T_CL_9
T_{10}	Fine Arts	T_CL_{10}

Table 3
Book classification attribute attachment and proportion calculation.

Keyword set	Book classification keyword	Book category proportion
Density Keyword Set (DKW)	$D\_T_j = DKW \cap T\_CL_j$	$P(D\_T_j) = \frac{N(D\_T_j)}{\sum_{allj} N(DT_j)} \times 100\%$
Sequence keyword set (SKW)	$S\_T_j = SKW \cap T\_CL_j$	$P(S\_T_j) = \frac{N(S\_T_j)}{\sum_{allj} N(S\_T_j)} \times 100\%$
System keyword set (SysKW)	$Sys\_T_j = SysKW \cap T\_CL_j$	$P(Sys\_T_j) = \frac{N(Sys\_T_j)}{\sum_{allj} N(Sys\_T_j)} \times 100\%$

classification attribute attachment and the proportions of book categories of these three keyword sets are summarized in Table 3.

$$P\left(D\_T_j\right) = \frac{N\left(D\_T_j\right)}{\sum_{j=1}^{10} N\left(D\_T_j\right)} \times 100\% \tag{5}$$

For example, the relationships of book categories “General” and “Philosophy” are summarized for 23 and 10 times respectively. Then, if the 100 density keywords are distributed in 10 book categories in number of 23 and 10, then the percentage of the book category “General” is 23/100, the percentage of the book category “Philosophy” is 10/100 (as shown in Table 4).

3.3.2. Matching of book-acquisition recommendation list

The D_T_j established in the above section are matched with the book databases of booksellers to derive the candidate books. Then, the candidate books of each book category are ranked according to the publication date or sales volume in order to derive the book-acquisition recommendation list.

The symbols used in the algorithm are defined as follows.

A_j The candidate book set of the j'th book category
$A_j[B_i]$ The i'th candidate book in A_j
BBS The candidate book threshold for determination of the candidate book
$KB_{j,i,k}$ The proportion of word number of the i'th keyword to the k'th book title in the j'th book category
$N(D\_T_{i,j})$ The word number of the i'th keyword in D_T_j
$N(T_j[B_k])$ The word number of the k'th book title in T_j
$T_j[B_k]$ The k'th book in T_j
$P[A_j]$ The book recommendation list of the j'th book category according to book popularity (i.e., sales volume)
$R_{Sales}[A_j[B_i]]$
The rank value of $A_j[B_i]$ based on popularity (i.e., sales volume)
$R_{Time}[A_j[B_i]]$
The rank value of $A_j[B_i]$ based on publication date
S The total book-acquisition amount
$S(D\_T_j)$ The book-acquisition amount of D_T_j
$T[A_j]$ The book recommendation list of the j'th book category according to book publication date

Table 4
Proportion of each book category.

Keywords	Book categories				
	General	Philosophy	…	Science	…
Model	0	0	…	…	…
Platform	1	0	…	…	…
…			…	…	…
Library	0	1	…	…	…
…	…	…	…	…	…
…	…	…	…	…	…
Sum	23	10	…	5	…
Percentage	23/100	10/100	…	5/100	…

Table 5
The rank value of each candidate book in A_j.

Candidate book ($A_j[B_i]$)		Aj[B1]	Aj[B2]	…	Aj[Bi]	…
Rank	Publication date	$R_{Time}[A_j[B_1]]$	$R_{Time}[A_j[B_2]]$	…	$R_{Time}[A_j[B_i]]$	…
	Sales volume	$R_{Sales}[A_j[B_1]]$	$R_{Sales}[A_j[B_2]]$	…	$R_{Sales}[A_j[B_i]]$	…

3.3.2.1. Step (C2-1): calculation of the word number proportion of keyword to book title. In this step, the i'th keyword ($D\_T_{i,j}$) in D_T_j is compared with k'th book title ($T_j[B_k]$) of book categories (T_j) one by one. If the book title contains the keywords, the word number proportion ($KB_{j,i,k}$) of the keyword to the book title can be calculated via Eq. (6).

$$\text{If } D\_T_{i,j} \subset T_j\,[B_k]\ \forall \text{ all i and } \forall \text{ all } k \text{ then } KB_{j,i,k} = \frac{N\left(D\_T_i,j\right)}{N\left(T_j[B_k]\right)} \tag{6}$$

For example, for the book entitled “Let the Heart be Free” of book category “General”, the density keyword “Free” accounts for 2/5 = 0.4 of the book title.

3.3.2.2. Step (C2-2): comparison with candidate book threshold. The proportion ($KB_{j,i,k}$) calculated in Step (C2-1) is compared with the predefined candidate book threshold (BBS). If the $KB_{j,i,k}$ is larger than or equal to the predefined candidate book threshold (BBS), the corresponding book ($T_j[B_k]$) is listed in the candidate book list set (A_j) via Eq. (7).

$$\text{If } KB_{j,i,k} \geq BBS \text{ then } \quad T_j[B_i] \in A_j \tag{7}$$

For example, the percentage of the keyword “Free” at 0.4 is greater than the book list candidate threshold (BBS) value at 0.2. Book “Let the Heart be Free” can be included on the list of candidate books.

3.3.2.3. Step (C2-3): calculation of the rank value of each candidate book. In this step, all candidate books ($A_j[B_i]$) are ranked according to publication date or popularity (sales volume). The ranks $R_{Time}[A_j[B_i]]$ of candidate books are arranged from late to early publication date (as shown in Table 5). In the same way, the ranks $R_{Sales}[A_j[B_i]]$ are arranged from large to small sales volume (as shown in Table 5).

For example, regarding the book category “General”, the list of candidate books includes 10 books such as “The Aesthetic Economics of World's Top Museums” and “Let the Heart be Free”. The priority can be determined by sales volume and publishing date. The sales volume and publishing date ranks of “Let the Heart be Free” is 9 and 2 (see Table 6).

3.3.2.4. Step (C2-4): calculation of the book-acquisition amount of each book category. The $P(D\_T_j)$ obtained in Eq. (5) is multiplied by the total book-acquisition amount (S) to derive the book-acquisition amount of each book category $S(D\_T_j)$ (as shown in Eq. (8)).

$$S\left(D\_T_j\right) = P\left(D\_T_j\right) \times S \tag{8}$$

For example, it is known that 20 books will be purchased during the string collection period. Therefore, the percentage of books demand for book category “General” is 0.23 (obtained from Eq. (5)) and the demand for book category “General” is 20*0.23 = 4.6.

Table 6
Rank value of each candidate book.

Book title	Sales volume	Publishing date	Rank (sales)	Rank (date)
The Aesthetic Economics of World's Top Museums	300	2009/8/6	8	2
Let the Heart be Free	200	2009/7/31	9	4
My Bible Rhapsody	100	2009/8/1	10	3
Meteorological Theories and Applications	400	2006/6/1	5	8
Atomic Radiation and Protection Character Biographies	350	2004/3/21	7	10
Political Science (Synopsis) —National College Entrance Exam, Local Entrance Exam	900	2006/8/14	1	7
Livelihoods and Urban Policies of Chang'an in Tang Dynasty	680	2007/6/1	2	6
Millennium Tomb-raider Notes—Discovering Civilization	555	2010/8/6	4	1
Internet-based Journalism: The Application of New Media—Practice and Prospects	670	2004/8/8	3	9
Basic Pencil Sketch Techniques	400	2009/4/1	6	5

Table 7
Book-acquisition recommendation lists based on DKW, SKW and SysKW.

Keyword set	Book-acquisition recommendation list	
Density keyword set (DKW)	Publication date	$T[A_j]=\{A_j[B_i]\|R_{Time}[A_j[B_i]]\le S(D\_T_j)\}$
	Sales volume	$P[A_j]=\{A_j[B_i]\|R_{Sales}[A_j[B_i]]\le S(D\_T_j)\}$
Sequence keyword set (SKW)	Publication date	$T[A_j]=\{A_j[B_i]\|R_{Time}[A_j[B_i]]\le S(S\_T_j)\}$
	Sales volume	$P[A_j]=\{A_j[B_i]\|R_{Sales}[A_j[B_i]]\le S(S\_T_j)\}$
System keyword set (SysKW)	Publication date	$T[A_j]=\{A_j[B_i]\|R_{Time}[A_j[B_i]]\le S(Sys\_T_j)\}$
	Sales volume	$P[A_j]=\{A_j[B_i]\|R_{Sales}[A_j[B_i]]\le S(Sys\_T_j)\}$

3.3.2.5. Step (C2-5): derivation of the book-acquisition recommendation list. In Step (C2-5), two types of book-acquisition recommendation list are derived with reference to the rank values of candidate books in Table 7. First of all, if the rank value ($R_{Time}[A_j[B_i]]$, $R_{Sales}[A_j[B_i]]$) is less than the book-acquisition amount of each book category ($S(D\_T_j)$), this book ($A_j[B_i]$) is listed in book-acquisition recommendation list ($T[A_j]$, $P[A_j]$) (as shown in Eqs. (9) and (10)). The book-acquisition recommendation lists based on DKW, SKW and SysKW are summarized in Table 7.

$$T\left[A_j\right] = \left\{A_j[B_i]\middle|R_{Time}\left[A_j[B_i]\right]\le S\left(DT_j\right)\right\} \tag{9}$$

$$P\left[A_j\right] = \left\{A_j[B_i]\middle|R_{Sales}\left[A_j[B_i]\right]\le S\left(DT_j\right)\right\} \tag{10}$$

For example, for book category “General”, the list of recommended books by sales includes “Political Science (Synopsis) —National College Entrance Exam, Local Entrance Exam”, “Livelihoods and Urban Policies of Chang'an in Tang Dynasty”, “Internet-based Journalism: The Application of New Media-Practice and Prospects” and “Millennium Tomb-raider Notes-Discovering Civilization” (ranking value below 4.6). The list of recommended books by sales volume can be generated by the same way.

3.4. Summary

As a whole, according to the requirements of a library's book acquisition goals, the book-acquisition recommendation model proposed in this paper utilizes all borrowers' book inquiry histories entered into the library system for keyword extraction, i.e., KDT and KST. Then, in the KBM, the extracted keywords and system keywords are attached to book category attributes in order to calculate the book-acquisition amount of each book category. After that, based on the book databases of booksellers, the recommended books corresponding to each book category can be derived. In this proposed book-acquisition recommendation model, all of the borrowers' demands can be taken into account; moreover, the book-acquisition recommendation time can also be shortened and the human resources economized.

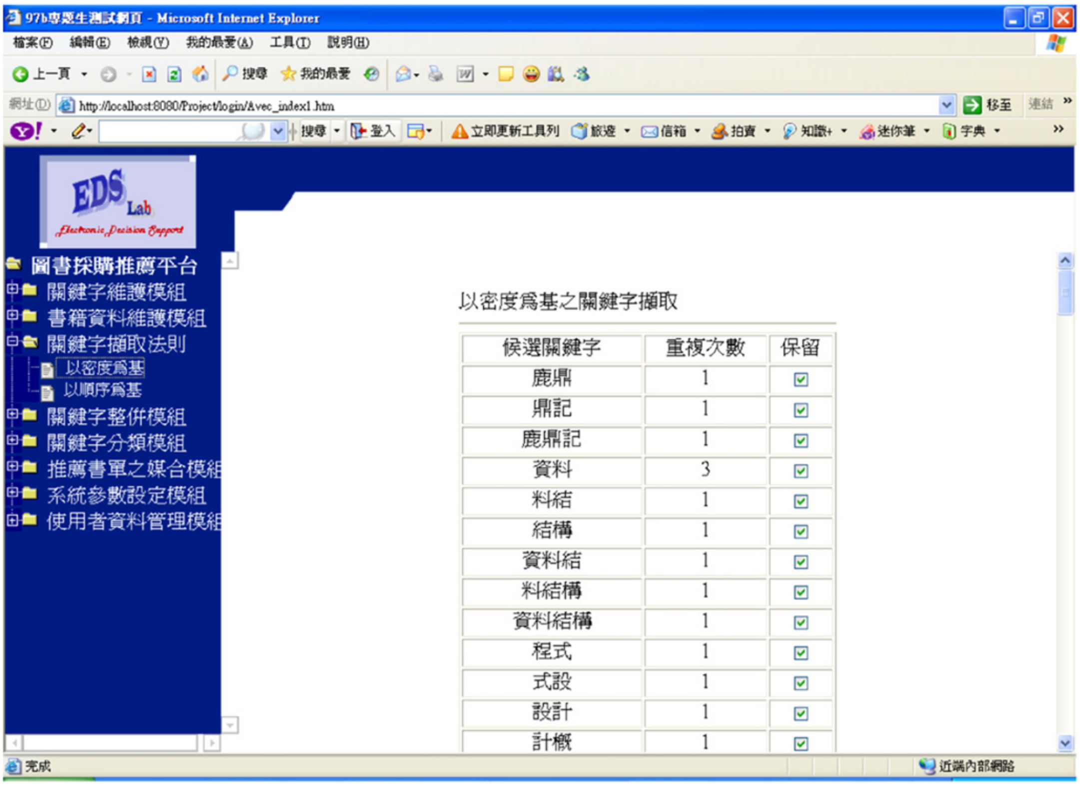
4. Book-acquisition recommendation system

In order to demonstrate the feasibility of the proposed algorithms for book-acquisition recommendation, a Web-based portal (namely a book-acquisition recommendation system) is developed for book recommendation in libraries. Under this system, the book inquiry history and book data can be maintained and the user demands properly managed, such that the book-acquisition recommendation can be accurately provided to the staff.

Based on the user login information, the book-acquisition recommendation system recognizes the user category (i.e., system administrator, librarian and common user) and provides the corresponding functions to the user. Within the system, common users can search for their required books via a book searching function. Furthermore, the book inquiry strings entered by common users can be maintained within the system to increase the book inquiry history (i.e., analysis data) and to improve the reasoning performance of the three kernel modules. After importing the book inquiry history, the keywords can be extracted via keyword analysis functions including KDT and KST functions performed by librarians (Figs. 4 and 5). In addition, librarians can review, check and modify the book-acquisition recommendation list and then download the corresponding Excel files via a Keyword-Book Mapping module (Fig. 6). Furthermore, librarians can also generate distinct book-acquisition recommendation lists by setting different weighting values, including keyword extraction thresholds, book recommendation thresholds or book-acquisition amounts based on their experience (Fig. 7). Finally, in addition to the above modules, system administrators can also execute book data maintenance modules, keyword maintenance modules and user profile maintenance modules (Figs. 8 and 9).

5. Case study

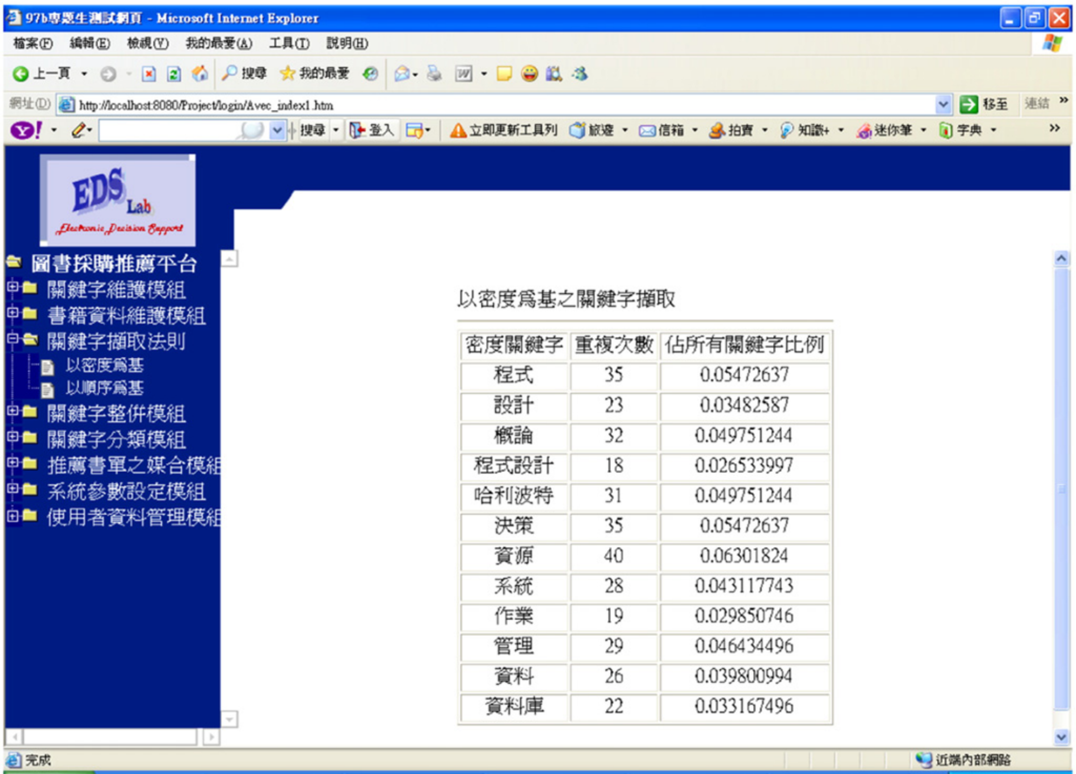
In order to demonstrate the applicability of the developed book-acquisition recommendation system, this paper selected 50 students randomly from an educational institution to fill in book inquiry questionnaires, in order to replace the book inquiry history since inquiry strings entered by users under library system are difficult to capture. A total of 1250 inquiry strings of 50



候選關鍵字	重複次數	保留
鹿鼎	1	☑
鼎記	1	☑
鹿鼎記	1	☑
資料	3	☑
料結	1	☑
結構	1	☑
資料結	1	☑
料結構	1	☑
資料結構	1	☑
程式	1	☑
式設	1	☑
設計	1	☑
計概	1	☑

Fig. 4. Results of keyword extraction (1).

books were gathered, and the collected data were used for system performance evaluation. The performance evaluation procedure included a system training stage and a system testing stage. The performance evaluation process, indices and results are sequentially introduced as follows.



密度關鍵字	重複次數	佔所有關鍵字比例
程式	35	0.05472637
設計	23	0.03482587
概論	32	0.049751244
程式設計	18	0.026533997
哈利波特	31	0.049751244
決策	35	0.05472637
資源	40	0.06301824
系統	28	0.043117743
作業	19	0.029850746
管理	29	0.046434496
資料	26	0.039800994
資料庫	22	0.033167496

Fig. 5. Results of keyword extraction (2).

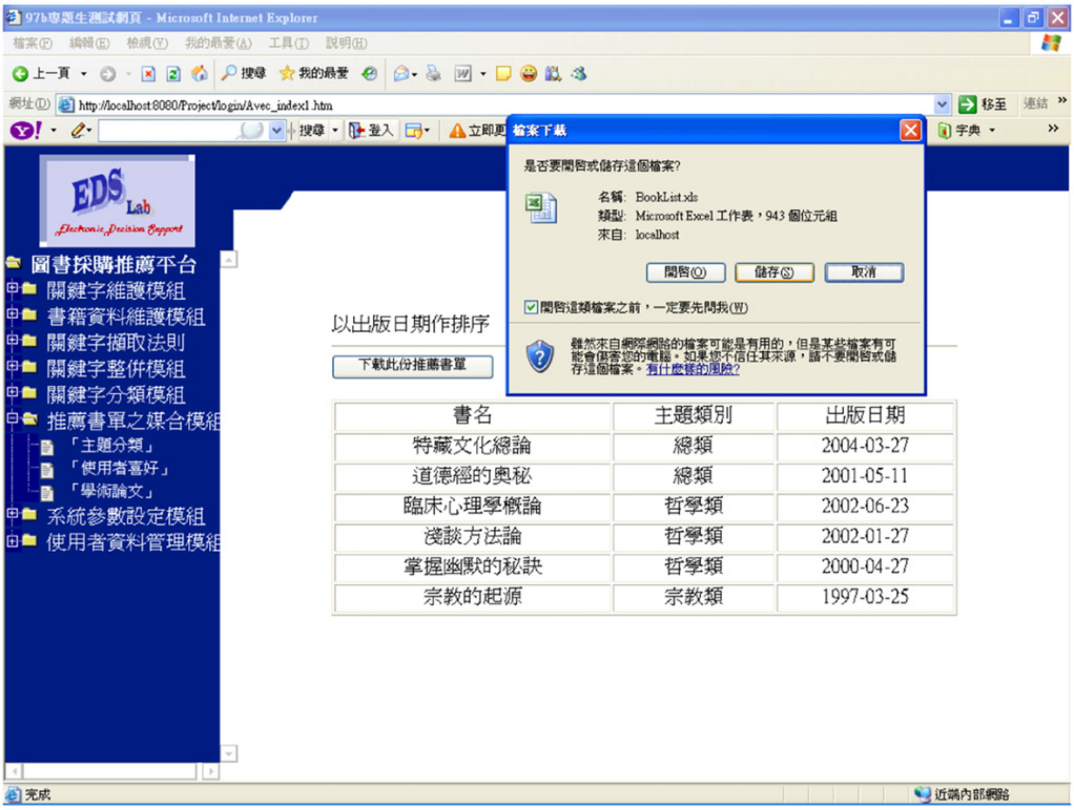


Fig. 6. Results of book recommendation and download the corresponding book list.

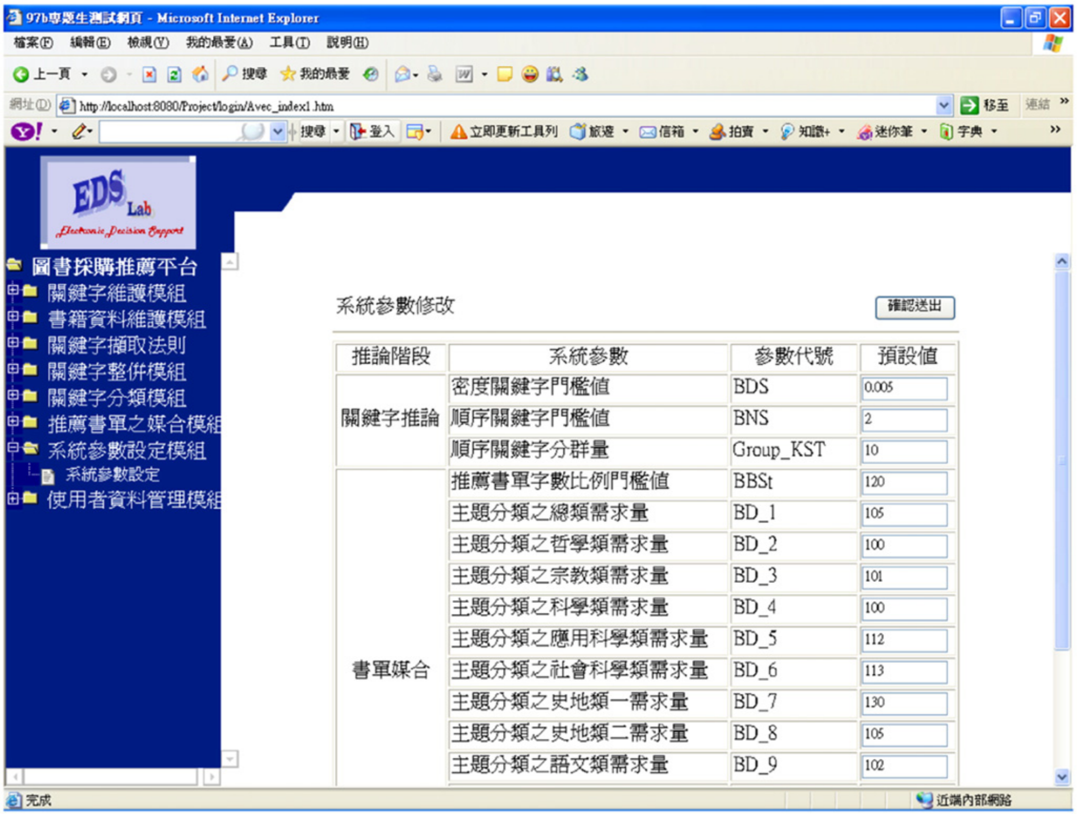


Fig. 7. Maintenance of system thresholds.

Fig. 8. Maintenance of keywords.

5.1. Performance evaluation process

In the designed questionnaires of this book inquiry, we selected five books randomly from each of the ten categories of the CSCL: *General*, *Philosophy*, *Religion*, *Science*, *Applied Science*, *Social Science*, *History and Geography I*, *History and Geography II*, *Chinese*, and *Fine Arts* (50 books in all). Each respondent (50 students in all) selected five books from 50 pre-selected books and

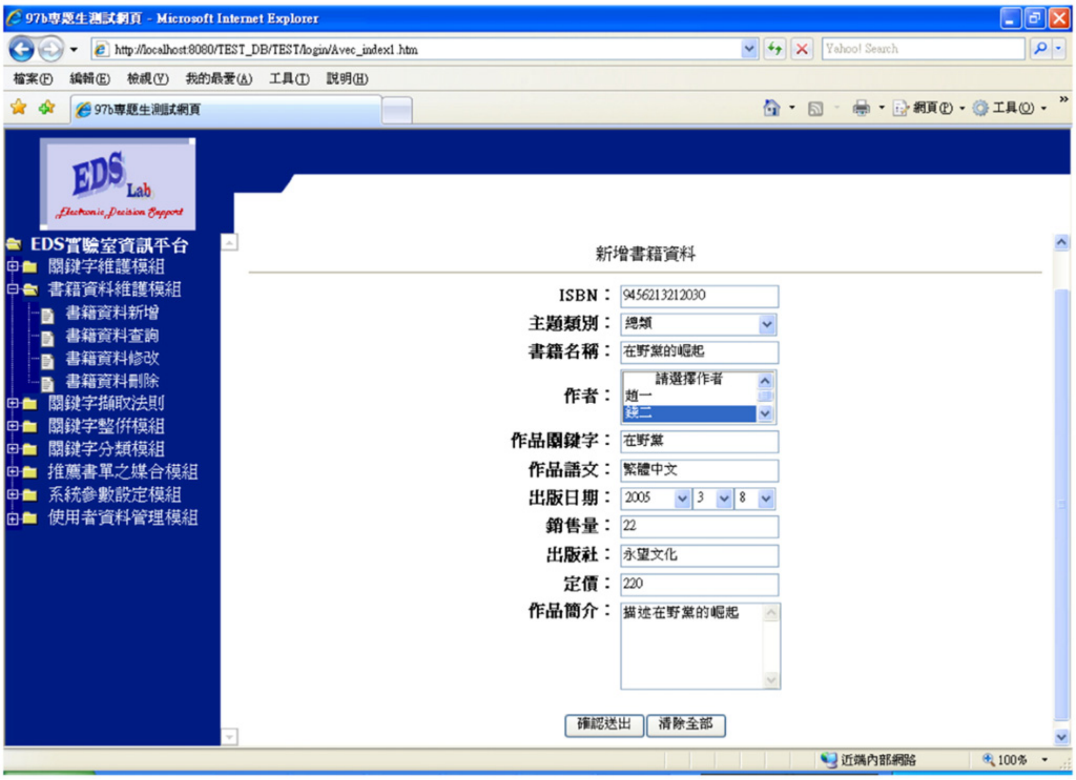


Fig. 9. Maintenance of book data.

Table 8
System testing data.

Book category	Inquiry string		Book title
General	Museum	Economics	*The Aesthetic Economics of World's Top Museums*
Philosophy	Calm	Free	*Let the Heart be Free*
Religion	Bible	Jesus	*My Bible Rhapsody*
Science	Meteorological theories	Meteorology	*Meteorological Theories and Applications*
Applied Science	Atom	Radiation	*Atomic Radiation and Protection Character Biographies*
Social Science	Politics	Political Science	*Political Science (Synopsis) —National College Entrance Exam, Local Entrance Exam*
History and Geography I	Tang Dynasty	Chang'an	*Livelihoods and Urban Policies of Chang'an in Tang Dynasty*
History and Geography II	Millennium	Tomb-raider	*Millennium Tomb-raider Notes—Discovering Civilization*
Chinese	Internet	News	*Internet-based Journalism: The Application of New Media—Practice and Prospects*
Fine Arts	Pencil	Sketch	*Basic Pencil Sketch Techniques*

filled in five inquiry strings. Therefore, 25 inquiry strings generated by all of the students could be collected from each book, and 1250 inquiry strings of 50 books were integrated.

After that, we selected 350 inquiry strings from 1250 inquiry strings as the system training data. The proposed three kernel modules (including KDT, KST and KBM) of the book-acquisition recommendation system were used for keyword extraction and book-acquisition recommendation reasoning in order to obtain the relations between extracted keywords and recommended books. Also, one book (10 books in all) and two inquiry strings (20 inquiry strings in all) were selected randomly from each of the ten book categories as the system testing data (as shown in Table 8). The book list of these 20 inquiry strings is populated from the inquiry strings and the relations between keywords and books are derived from the *density keyword set* (DKW), *sequence keyword set* (SKW) and *system keyword set* (SysKW) in the system training stage. Finally, the difference between the system-reasoned books and the nominal books (i.e., the selected 10 testing books) could be observed to validate the correctness of the proposed model.

5.2. Definition of performance evaluation indices

The performance indices, including book recall rate and accuracy, are introduced prior to the performance evaluation of this developed system. After that, distributions of recall rate and reasoning accuracy of the system are evaluated and investigated.

The book recall rate R_i is the ratio $\left(R_i = \frac{m_i}{n_i}\right)$ of the number of correctly reasoned results (m_i) to the number of nominal books (n_i) of the i'th inquiry string. In addition, the reasoning accuracy A_i is the ratio $\left(A_i = \frac{m_i}{c_i}\right)$ of the number of correctly reasoned results (m_i) to the number of the reasoned books (c_i) of the i'th inquiry string.

5.3. Performance evaluation

Seven periods with different inquiry string numbers are used (350 inquiry strings are imported onto the system during the first period, and 150 inquiry strings are imported at each following period) to investigate the learning behavior of the proposed model.

After importing the training inquiry strings of each period, the keywords can be extracted via keyword extraction algorithms under each period. Then, taking 20 inquiry strings picked in the above section as the testing inquiry strings, the recommended books of the testing inquiry strings can be determined based on DKW, SKW and SysKW. In order to evaluate and investigate distributions of performance indices, including recall rate and reasoning accuracy, the performance indices of these three keyword sets are summarized in Table 9 and learning behavior is illustrated in Fig. 10.

As shown in Table 9 and Fig. 10, for the book recommendation list reasoned with DKW, the book recall rate and the accuracy increase from 25% to 35% during the first two periods (i.e., training data are increased from 350 to 500). These indices go up to

Table 9
Book recall rate and accuracy of three keyword sets in different periods.

Keyword extraction	Keyword set	Evaluation index	# of training inquiry strings						
		Average	350	500	650	800	950	1100	1250
KDT	DKW	Book recall rate	25%	35%	30%	0%	0%	0%	0%
		Book accuracy	23%	30%	30%	15%	0%	0%	0%
KST	SKW	Book recall rate	70%	25%	15%	0%	5%	5%	0%
		Book accuracy	68%	25%	10%	10%	5%	5%	0%
System keywords	SysKW	Book recall rate	0%	15%	25%	40%	50%	70%	75%
		Book accuracy	0%	13%	20%	38%	48%	55%	73%

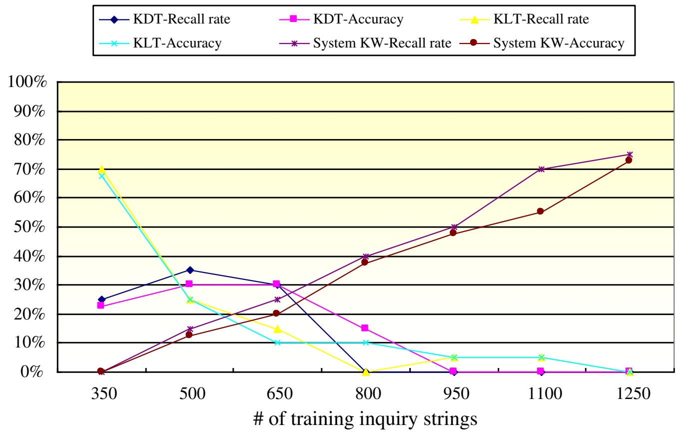


Fig. 10. Performance distributions of three keyword sets in different periods.

30.0% at the third period and then converge to 0% after the fourth period (i.e., training data are increased from 650 to 800). That is, these two indices grow negatively.

Second, for the book recommendation list reasoned with SKW, the book recall rate and the book accuracy decrease from 70% to 25% between the first period and the second period (i.e., training data are increased from 350 to 500). Then, though the indices maintain about 5% during the fourth period to the sixth period (i.e., training data are increased from 800 to 1100), the indices are all down to 0% as the training data are increased during the seventh period. Therefore, the indices still grow negatively.

Finally, for the book recommendation list reasoned with SysKW, the book recall rate and book accuracy are 0% during the first period and increase to about 15% during the second period (i.e., training data are increased from 350 to 500). The indices improve an average of 10% from the second to the sixth period, and the indices increase to about 75% during the 7th period. Therefore, the recall rate and accuracy of this keyword set obviously improves as training data are imported.

5.4. Analysis and discussion of performance evaluation

Concerning the performance evaluation results of book-acquisition recommendation lists reasoned with DKW, SKW and SysKW, it can be observed that the two performance indices, book recall rate and book accuracy, exhibit optimal performance and better learning behavior in SysKW because the keywords of SysKW are first established by domain experts. Then, as the training inquiry strings are increased, the feedback keywords extracted via the two keyword extraction algorithms are increased. Therefore, the system can obtain the keywords from the book inquiry strings entered by users and maintained in keyword database; the recall rate and accuracy steadily improve as the training data are imported (i.e., keywords are continuously increased and maintained in the system). Otherwise, the indices with SKW and DKW exhibit the worst system performance.

As a whole, when the training inquiry strings are imported into the system (i.e., training inquiry strings are less than 350) in the first period, the repeat rate of relative sequences of book inquiry strings is above the repeat rate of inquiry strings. Therefore, it is better to use the SKW to obtain the book recommendation list. In addition, when the training inquiry strings are imported into the system between the second and the third periods (training data are increased from 500 to 650), it is better to use the DKW to derive the book recommendation list. Finally, when a large amount of training inquiry strings is imported after the fourth period (i.e., training inquiry strings are above 800), the keyword set extracted via KDT and KST clearly is not growing as the training inquiry strings increase and repeat; therefore, it is better to use the SysKW to obtain the book-acquisition recommendation list.

In addition to performance evaluation, in order to emphasize the contributions and benefits of this paper for users, the value of this paper is discussed in three different perspectives including "theoretical approach", "technology development" and "practical applications".

5.4.1. Theoretical approach

This paper proposes a book-acquisition recommendation model including keyword extraction module and book-acquisition list generating module to provide book-acquisition recommendations to libraries.

5.4.2. Technological development

This paper establishes the technological development for the book-acquisition recommendation platform, and integrates functions including keyword extraction and book-acquisition list generating in a Web-based system. These functions can speed up the matching of the list of recommended books and provide recommended books for libraries to reduce operational time and save human resource, and thus improving the book-acquisition efficiency of libraries.

5.4.3. Practical application

Since inquiry strings entered by users under library system are difficult to capture, this paper uses the questionnaire on "book inquiry strings" filled by users to represent the original data to confirm the feasibility of the proposed algorithm and system.

6. Conclusion

This paper utilizes text mining and classification technologies to develop a model for book-acquisition recommendation, including keyword extraction algorithms and Keyword-Book Mapping algorithms. Notably, in keyword extraction algorithms, including the *Keyword Density Thesaurus* (KDT) and the *Keyword Sequence Thesaurus* (KST), the keywords can automatically be extracted from the book inquiry history. In the context of the *Keyword-Book Mapping* (KBM) algorithm, the relationship between keywords and book categories can be developed, and then the book-acquisition recommendation list can be determined. In addition to the book-acquisition recommendation model, a Web-based book-acquisition recommendation system is also developed to automatically extract keywords and determine a book-acquisition recommendation list to improve the performance of book-acquisition tasks. That is, under the book-acquisition recommendation platform, librarians are able to automatically populate the book-acquisition recommendation list to fit borrowers' requirements, and the complicated recommendation processes for borrowers can be simplified.

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