Content-Based Book Recommending
Using Learning for Text Categorization

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ABSTRACT
Recommender systems improve access to relevant products and information by making personalized suggestions based on previous examples of a user’s likes and dislikes. Most existing recommender systems use social filtering methods that base recommendations on other users’ preferences. By contrast, content-based methods use information about an item itself to make suggestions. This approach has the advantage of being able to recommended previously unrated items to users with unique interests and to provide explanations for its recommendations. We describe a content-based book recommending system that utilizes information extraction and a machine-learning algorithm for text categorization. Initial experimental results demonstrate that this approach can produce accurate recommendations.

KEYWORDS: Recommender systems, information filtering, machine learning, text categorization

INTRODUCTION
There is a growing interest in recommender systems that suggest music, films, books, and other products and services to users based on examples of their likes and dislikes [13, 26, 11]. A number of successful startup companies like Firefly, Net Perceptions, and LikeMinds have formed to provide recommending technology. On-line book stores like Amazon and BarnesAndNoble have popular recommendation services, and many libraries have a long history of providing reader’s advisory services [3, 2]. Such services are important since readers’ preferences are often complex and not readily reduced to keywords or standard subject categories, but rather best illustrated by example. Digital libraries should be able to build on this tradition of assisting readers by providing cost-effective, informed, and personalized automated recommendations for their patrons.

Existing recommender systems almost exclusively utilize a form of computerized matchmaking called collaborative or social filtering. The system maintains a database of the preferences of individual users, finds other users whose known preferences correlate significantly with a given patron, and recommends to a person other items enjoyed by their matched patrons. This approach assumes that a given user’s tastes are generally the same as another user of the system and that a sufficient number of user ratings are available. Items that have not been rated by a sufficient number of users cannot be effectively recommended. Unfortunately, statistics on library use indicate that most books are utilized by very few patrons [13]. Therefore, collaborative approaches naturally tend to recommend popular titles, perpetuating homogeneity in reading choices. Also, since significant information about other users is required to make recommendations, this approach raises concerns about privacy and access to proprietary customer data.

Learning individualized profiles from descriptions of examples (content-based recommending [3]), on the other hand, allows a system to uniquely characterize each patron without having to match their interests to someone else’s. Items are recommended based on information about the item itself rather than on the preferences of other users. This also allows for the possibility of providing explanations that list content features that caused an item to be recommended; potentially giving readers confidence in the system’s recommendations and insight into their own preferences. Finally, a content-based approach can allow users to provide initial subject information to aid the system.

Machine learning for text-categorization has been applied to content-based recommending of web pages [25] and news-group messages [13]; however, to our knowledge has not previously been applied to book recommending. We have
been exploring content-based book recommending by applying automated text-categorization methods to semi-structured text extracted from the web. Our current prototype system, LIBRA (Learning Intelligent Book Recommending Agent), uses a database of book information extracted from web pages at Amazon.com. Users provide 1–10 ratings for a selected set of training books; the system then learns a profile of the user using a Bayesian learning algorithm and produces a ranked list of the most recommended additional titles from the system’s catalog.

As evidence for the promise of this approach, we present initial experimental results on several data sets of books randomly selected from particular genres such as mystery, science, literary fiction, and science fiction and rated by different users. We use standard experimental methodology from machine learning and present results for several evaluation metrics on independent test data including rank correlation coefficient and average rating of top-ranked books.

The remainder of the paper is organized as follows. Section 2 provides an overview of the system including the algorithm used to learn user profiles. Section 3 presents results of our initial experimental evaluation of the system. Section 4 discusses topics for further research, and section 5 presents our conclusions on the advantages and promise of content-based book recommending.

SYSTEM DESCRIPTION

Extracting Information and Building a Database

First, an Amazon subject search is performed to obtain a list of book-description URL’s of broadly relevant titles. LIBRA then downloads each of these pages and uses a simple pattern-based information-extraction system to extract data about each title. Information extraction (IE) is the task of locating specific pieces of information from a document, thereby obtaining useful structured data from unstructured text [16, 9]. Specifically, it involves finding a set of substrings from the document, called fillers, for each of a set of specified slots. When applied to web pages instead of natural language text, such an extractor is sometimes called a wrapper [14]. The current slots utilized by the recommender are: title, authors, synopses, published reviews, customer comments, related authors, related titles, and subject terms. Amazon produces the information about related authors and titles using collaborative methods; however, LIBRA simply treats them as additional content about the book. Only books that have at least one synopsis, review or customer comment are retained as having adequate content information. A number of other slots are also extracted (e.g. publisher, date, ISBN, price, etc.) but are currently not used by the recommender. We have initially assembled databases for literary fiction (3,061 titles), science fiction (3,813 titles), mystery (7,285 titles), and science (6,177 titles).

Since the layout of Amazon’s automatically generated pages is quite regular, a fairly simple extraction system is sufficient. LIBRA’s extractor employs a simple pattern matcher that uses pre-filler, filler, and post-filler patterns for each slot, as described by [9]. In other applications, more sophisticated information extraction methods and inductive learning of extraction rules might be useful [7].

The text in each slot is then processed into an unordered bag of words (tokens) and the examples represented as a vector of bags of words (one bag for each slot). A book’s title and authors are also added to its own related-title and related-author slots, since a book is obviously “related” to itself, and this allows overlap in these slots with books listed as related to it. Some minor additions include the removal of a small list of stop-words, the preprocessing of author names into unique tokens of the form first-initial-last-name and the grouping of the words associated with synopses, published reviews, and customer comments all into one bag (called “words”).

Learning a Profile

Next, the user selects and rates a set of training books. By searching for particular authors or titles, the user can avoid scanning the entire database or picking selections at random. The user is asked to provide a discrete 1–10 rating for each selected title.

The inductive learner currently employed by LIBRA is a bag-of-words naïve Bayesian text classifier [22] extended to handle a vector of bags rather than a single bag. Recent experimental results [10, 20] indicate that this relatively simple approach to text categorization performs as well or better than many competing methods. LIBRA does not attempt to predict the exact numerical rating of a title, but rather just a total ordering (ranking) of titles in order of preference. This task is then recast as a probabilistic binary categorization problem of predicting the probability that a book would be rated as positive rather than negative, where a user rating of 1–5 is interpreted as negative and 6–10 as positive. As described below, the exact numerical ratings of the training examples are used to weight the training examples when estimating the parameters of the model.

Specifically, we employ a multinomial text model [7], in which a document is modeled as an ordered sequence of word events drawn from the same vocabulary, V. The “naïve Bayes” assumption states that the probability of each word event is dependent on the document class but independent of the word’s context and position. For each class, c_j, and word or token, w_k ∈ V, the probabilities, P(c_j) and P(w_k|c_j) must be estimated from the training data. Then the posterior probability of each class given a document, D, is computed using Bayes rule:

$$P(c_j|D) = \frac{P(c_j)}{P(D)} \prod_{i=1}^{|D|} P(a_i|c_j)$$  \hspace{1cm} (1)

where a_i is the i-th word in the document, and |D| is the length of the document in words. Since for any given docu-
In our case, since books are represented as a vector of “documents,” \( d_m \), one for each slot (where \( s_m \) denotes the \( m \)th slot), the probability of each word given the category and the slot, \( P(w_k|c_j, s_m) \), must be estimated and the posterior category probabilities for a book, \( B \), computed using:

\[
P(c_j|B) = \frac{P(c_j)}{P(B)} \prod_{m=1}^{S} \prod_{i=1}^{|d_m|} P(a_{mi}|c_j, s_m) \tag{2}
\]

where \( S \) is the number of slots and \( a_{mi} \) is the \( i \)th word in the \( m \)th slot.

Parameters are estimated from the training examples as follows. Each of the \( N \) training books, \( B_e \) (\( 1 \leq e \leq N \)) is given two real weights, \( 0 \leq \alpha_{ej} \leq 1 \), based on scaling its user rating, \( r \) (\( 1 \leq r \leq 10 \)): a positive weight, \( \alpha_{e1} = (r-1)/9 \), and a negative weight \( \alpha_{e0} = 1 - \alpha_{e1} \). If a word appears \( n \) times in an example \( B_e \), it is counted as occurring \( \alpha_{e1}n \) times in a positive example and \( \alpha_{e0}n \) times in a negative example. The model parameters are therefore estimated as follows:

\[
P(c_j) = \sum_{e=1}^{N} \frac{\alpha_{ej}}{N} \tag{3}
\]

\[
P(w_k|c_j, s_m) = \sum_{e=1}^{N} \alpha_{ej} n_{kem}/L(c_j, s_m) \tag{4}
\]

where \( n_{kem} \) is the count of the number of times word \( w_k \) appears in example \( B_e \) in slot \( s_m \), and

\[
L(c_j, s_m) = \sum_{e=1}^{N} \alpha_{ej} |d_m| \tag{5}
\]

denotes the total weighted length of the documents in category \( c_j \) and slot \( s_m \).

These parameters are “smoothed” using Laplace estimates to avoid zero probability estimates for words that do not appear in the limited training sample by redistributing some of the probability mass to these items using the method recommended in [3]. Finally, calculation with logarithms of probabilities is used to avoid underflow.

The computational complexity of the resulting training (testing) algorithm is linear in the size of the training (testing) data. Empirically, the system is quite efficient. In the experiments on the Lit11 data described below, the current Lisp implementation running on a Sun Ultra 1 trained on 20 examples in an average of 0.4 seconds and on 840 examples in an average of 11.5 seconds, and probabilistically categorized new test examples at an average rate of about 200 books per second. An optimized implementation could no doubt significantly improve performance even further.

A profile can be partially illustrated by listing the features most indicative of a positive or negative rating. Table 1 presents the top 20 features for a sample profile learned for recommending science books. Strength measures how much more likely a word in a slot is to appear in a positively rated book than a negatively rated one, computed as:

\[
Strength(w_k, s_j) = \log(P(w_k|c_1, s_j)/P(w_k|c_0, s_j)) \tag{6}
\]

### Table 1: Sample Positive Profile Features

| Slot          | Word         | Strength |
|---------------|--------------|----------|
| WORDS         | ZUBRIN       | 9.85     |
| WORDS         | SMOLIN       | 9.39     |
| WORDS         | TREPIL       | 8.77     |
| WORDS         | DORF         | 8.67     |
| SUBJECTS      | COMPARATIVE  | 8.39     |
| AUTHOR        | D.GOLDSMITH  | 8.04     |
| WORDS         | ALH          | 7.97     |
| WORDS         | MANNED       | 7.97     |
| RELATED-TITLES | SETTLE      | 7.91     |
| RELATED-TITLES | CASE        | 7.91     |
| AUTHOR        | R.ZUBRIN     | 7.63     |
| AUTHOR        | R.WAGNER     | 7.63     |
| AUTHOR        | H.MORAVECE   | 7.63     |
| RELATED-AUTHORS | D.GREGORIO  | 7.63     |
| RELATED-AUTHORS | A.RADFORD   | 7.63     |
| WORDS         | LEE          | 7.57     |
| WORDS         | MORAVECE     | 7.57     |
| WORDS         | WAGNER       | 7.57     |
| RELATED-TITLES | CONNECTIONIST| 7.51     |
| RELATED-TITLES | BELOW       | 7.51     |

### Producing, Explaining, and Revising Recommendations

Once a profile is learned, it is used to predict the preferred ranking of the remaining books based on posterior probability of a positive categorization, and the top-scoring recommendations are presented to the user.

The system also has a limited ability to “explain” its recommendations by listing the features that most contributed to its high rank. For example, given the profile illustrated above, LIBRA presented the explanation shown in Table 2. The strength of a cue in this case is multiplied by the number of times it appears in the description in order to fully indicate its influence on the ranking. The positiveness of a feature can in turn be explained by listing the user’s training examples that most influenced its strength, as illustrated in Table 3 where “Count” gives the number of times the feature appeared in the description of the rated book.

After reviewing the recommendations (and perhaps disreccommendations), the user may assign their own rating to examples they believe to be incorrectly ranked and retrain the
The Fabric of Reality: The Science of Parallel Universes- And Its Implications by David Deutsch recommended because:

| Slot     | Word    | Strength |
|----------|---------|----------|
| WORDS    | MULTIVERSE | 75.12   |
| WORDS    | UNIVERSES | 25.08   |
| WORDS    | REALITY   | 22.96   |
| WORDS    | UNIVERSE  | 15.55   |
| WORDS    | QUANTUM   | 14.54   |
| WORDS    | INTELLECT | 13.86   |
| WORDS    | OKAY      | 13.75   |
| WORDS    | RESERVATIONS | 11.56 |
| WORDS    | DENIES    | 11.56   |
| WORDS    | EVOLUTION | 11.02   |
| WORDS    | WORLDS    | 10.10   |
| WORDS    | SMOLIN    | 9.39    |
| WORDS    | ONE       | 8.50    |
| WORDS    | IDEAS     | 8.35    |
| WORDS    | THEORY    | 8.28    |
| WORDS    | IDEA      | 6.96    |
| SUBJECTS | REALITY   | 6.78    |
| TITLE    | PARALLEL  | 6.76    |
| WORDS    | IMPLY     | 6.47    |
| WORDS    | GENIUSES  | 6.47    |

Table 2: Sample Recommendation Explanation

The word UNIVERSES is positive due to your ratings:

| Title                     | Rating | Count |
|---------------------------|--------|-------|
| The Life of the Cosmos    | 10     | 15    |
| Before the Beginning : Our Universe and Others | 8    | 7     |
| Unveiling the Edge of Time | 10   | 3     |
| Black Holes : A Traveler’s Guide | 9    | 3     |
| The Inflationary Universe | 9     | 2     |

Table 3: Sample Feature Explanation

system to produce improved recommendations. As with relevance feedback in information retrieval [27], this cycle can be repeated several times in order to produce the best results. Also, as new examples are provided, the system can track any change in a user’s preferences and alter its recommendations based on the additional information.

EXPERIMENTAL RESULTS

Methodology

Data Collection Several data sets were assembled to evaluate LIBRA. The first two were based on the first 3,061 adequate-information titles (books with at least one abstract, review, or customer comment) returned for the subject search “literature fiction.” Two separate sets were randomly selected from this dataset, one with 936 books and one with 935, and rated by two different users. These sets will be called LIT1 and LIT2, respectively. The remaining sets were based on all of the adequate-information Amazon titles for “mystery” (7,285 titles), “science” (6,177 titles), and “science fiction” (3,813 titles). From each of these sets, 500 titles were chosen at random and rated by a user (the same user rated both the science and science fiction books). These sets will be called MYST, SCI, and SF, respectively.

In order to present a quantitative picture of performance on a realistic sample; books to be rated where selected at random. However, this means that many books may not have been familiar to the user, in which case, the user was asked to supply a rating based on reviewing the Amazon page describing the book. Table 4 presents some statistics about the data and Table 5 presents the number of books in each rating category. Note that overall the data sets have quite different ratings distributions.

Performance Evaluation To test the system, we performed 10-fold cross-validation, in which each data set is randomly split into 10 equal-size segments and results are averaged over 10 trials, each time leaving a separate segment out for independent testing, and training the system on the remaining data [22]. In order to observe performance given varying amounts of training data, learning curves were generated by testing the system after training on increasing subsets of the overall training data. A number of metrics were used to measure performance on the novel test data, including:

- **Classification accuracy** (Acc): The percentage of examples correctly classified as positive or negative.
- **Recall** (Rec): The percentage of positive examples classified as positive.
- **Precision** (Pr): The percentage of examples classified as positive which are positive.
- **Precision at Top 3** (Pr3): The percentage of the 3 top ranked examples which are positive.
- **Precision at Top 10** (Pr10): The percentage of the 10 top ranked examples which are positive.
- **F-Measure** (F): A weighted average of precision and recall frequently used in information retrieval:

\[ F = (2 \cdot Pr \cdot Rec) / (Pr + Rec) \]
**Rating of Top 3** (Rt3): The average user rating assigned to the 3 top ranked examples.

**Rating of Top 10** (Rt10): The average user rating assigned to the 10 top ranked examples.

**Rank Correlation** ($r_s$): Spearman’s rank correlation coefficient between the system’s ranking and that imposed by the users ratings ($-1 \leq r_s \leq 1$); ties are handled using the method recommended by [1].

The top 3 and top 10 metrics are given since many users will be primarily interested in getting a few top-ranked recommendations. Rank correlation gives a good overall picture of how the system’s continuous ranking of books agrees with the user’s, without requiring that the system actually predict the numerical rating score assigned by the user. A correlation coefficient of 0.3 to 0.6 is generally considered “moderate” and above 0.6 is considered “strong.”

### Basic Results

The results are summarized in Table 6, where $N$ represents the number of training examples utilized and results are shown for a number of representative points along the learning curve. Overall, the results are quite encouraging even when the system is given relatively small training sets. The SF data set is clearly the most difficult since there are very few highly-rated books.

The “top n” metrics are perhaps the most relevant to many users. Consider precision at top 3, which is fairly consistently in the 90% range after only 20 training examples (the exceptions are LIT1 until 70 examples and SF until 450 examples). Therefore, Libra’s top recommendations are highly likely to be viewed positively by the user. Note that the “% Positive” column in Table 4 gives the probability that a randomly chosen example from a given data set will be positively rated. Therefore, for every data set, the top 3 and top 10 recommendations are always substantially more likely than random to be rated positively, even after only 5 training examples.

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**Table 6: Summary of Results**

| Data | N  | Acc | Rec | Pr  | Pr3 | Pr10 | F  | Rt3 | Rt10 | $r_s$ |
|------|----|-----|-----|-----|-----|------|----|-----|------|------|
| LIT1 | 5  | 63.5| 49.0| 50.3| 63.3| 62.0 | 46.5| 5.87 | 6.02  | 0.31 |
| LIT1 | 10 | 65.5| 51.3| 53.3| 86.7| 76.0 | 49.7| 6.63 | 6.65  | 0.35 |
| LIT1 | 20 | 73.4| 64.8| 62.6| 86.7| 81.0 | 62.6| 7.53 | 7.20  | 0.62 |
| LIT1 | 40 | 73.9| 65.1| 63.6| 86.7| 81.0 | 63.4| 7.40 | 7.32  | 0.64 |
| LIT1 | 100| 79.0| 70.7| 71.1| 96.7| 86.0 | 70.5| 8.03 | 7.44  | 0.69 |
| LIT1 | 840| 79.8| 62.8| 75.9| 96.7| 94.0 | 68.5| 8.57 | 8.03  | 0.74 |
| LIT2 | 5  | 59.0| 57.6| 52.4| 70.0| 74.0 | 53.3| 6.80 | 6.82  | 0.31 |
| LIT2 | 10 | 65.0| 64.5| 56.7| 80.0| 82.0 | 59.2| 7.33 | 7.33  | 0.48 |
| LIT2 | 20 | 69.5| 67.2| 63.2| 93.3| 91.0 | 64.1| 8.20 | 7.84  | 0.59 |
| LIT2 | 40 | 74.3| 72.1| 68.9| 93.3| 91.0 | 69.0| 8.53 | 7.94  | 0.69 |
| LIT2 | 100| 78.0| 78.5| 71.2| 96.7| 94.0 | 74.4| 8.77 | 8.22  | 0.72 |
| LIT2 | 840| 80.2| 71.9| 78.6| 96.7| 94.0 | 81.5| 9.13 | 8.48  | 0.77 |
| MYST | 5  | 73.2| 83.4| 82.1| 86.7| 89.0 | 81.5| 8.20 | 8.40  | 0.36 |
| MYST | 10 | 75.6| 87.9| 82.4| 90.0| 90.0 | 83.8| 8.40 | 8.40  | 0.40 |
| MYST | 20 | 81.6| 89.3| 86.4| 96.7| 91.0 | 87.3| 8.23 | 8.43  | 0.46 |
| MYST | 40 | 85.2| 95.4| 85.9| 96.7| 94.0 | 90.3| 8.37 | 8.52  | 0.50 |
| MYST | 100| 86.6| 95.2| 87.2| 93.3| 94.0 | 90.9| 8.70 | 8.69  | 0.55 |
| MYST | 450| 85.8| 93.2| 88.1| 96.7| 98.0 | 90.5| 8.97 | 8.97  | 0.61 |
| SCI  | 5  | 62.8| 63.8| 46.3| 73.3| 60.0 | 51.1| 6.97 | 6.17  | 0.35 |
| SCI  | 10 | 67.6| 61.9| 51.2| 80.0| 67.0 | 54.3| 7.30 | 6.32  | 0.37 |
| SCI  | 20 | 75.4| 66.0| 64.2| 96.7| 80.0 | 63.1| 8.37 | 7.03  | 0.51 |
| SCI  | 40 | 79.6| 69.5| 68.7| 93.3| 80.0 | 68.3| 8.43 | 7.23  | 0.59 |
| SCI  | 100| 81.8| 74.4| 72.2| 93.3| 83.0 | 72.3| 8.50 | 7.29  | 0.65 |
| SCI  | 450| 85.2| 79.1| 76.8| 93.3| 89.0 | 77.2| 8.57 | 7.71  | 0.71 |
| SF   | 5  | 67.0| 38.3| 32.9| 40.0| 29.0 | 28.2| 5.23 | 4.34  | 0.02 |
| SF   | 10 | 64.6| 49.0| 28.9| 53.3| 36.0 | 31.5| 5.83 | 4.72  | 0.15 |
| SF   | 20 | 71.8| 45.8| 37.4| 66.7| 37.0 | 37.8| 6.23 | 5.04  | 0.21 |
| SF   | 40 | 72.6| 58.9| 40.1| 70.0| 43.0 | 43.0| 6.47 | 5.26  | 0.39 |
| SF   | 100| 76.4| 65.7| 46.2| 80.0| 56.0 | 52.4| 7.00 | 5.75  | 0.40 |
| SF   | 450| 79.2| 82.2| 49.1| 90.0| 63.0 | 60.6| 7.70 | 6.26  | 0.61 |

1References to performance at 70 and 300 examples are based on learning curve data not included in the summary in Table 6.
Considering the average rating of the top 3 recommendations, it is fairly consistently above an 8 after only 20 training examples (the exceptions again are Lit1 until 100 examples and SF). For every data set, the top 3 and top 10 recommendations are always rated substantially higher than a randomly selected example (cf. the average rating from Table 4).

Looking at the rank correlation, except for SF, there is at least a moderate correlation (\(r_s \geq 0.3\)) after only 10 examples, and SF exhibits a moderate correlation after 40 examples. This becomes a strong correlation (\(r_s \geq 0.6\)) for Lit1 after only 20 examples, for Lit2 after 40 examples, for Sci after 70 examples, for Myst after 300 examples, and for SF after 450 examples.

Results on the Role of Collaborative Content
Since collaborative and content-based approaches to recommending have somewhat complementary strengths and weaknesses, an interesting question that has already attracted some initial attention [3, 4] is whether they can be combined to produce even better results. Since Libra exploits content about related authors and titles that Amazon produces using collaborative methods, an interesting question is whether this collaborative content actually helps its performance. To examine this issue, we conducted an “ablation” study in which the slots for related authors and related titles were removed from Libra’s representation of book content. The resulting system, called Libra-NR, was compared to the original one using the same 10-fold training and test sets. The statistical significance of any differences in performance between the two systems was evaluated using a 1-tailed paired t-test requiring a significance level of \(p < 0.05\).

Overall, the results indicate that the use of collaborative content has a significant positive effect. Figures 1, 2, and 3 show sample learning curves for different important metrics for a few data sets. For the Lit1 rank-correlation results shown in Figure 1, there is a consistent, statistically-significant difference in performance from 20 examples onward. For the Myst results on precision at top 10 shown in Figure 2, there is a consistent, statistically-significant difference in performance from 40 examples onward. For the SF results on average rating of the top 3, there is a statistically-significant difference at 10, 100, 150, 200, and 450 examples. The results shown are some of the most consistent differences for each of these metrics; however, all of the datasets demonstrate some significant advantage of using collaborative content according to one or more metrics. Therefore, information obtained from collaborative methods can be used to improve content-based recommending, even when the actual user data underlying the collaborative method is unavailable due to privacy or proprietary concerns.

FUTURE WORK
We are currently developing a web-based interface so that Libra can be experimentally evaluated in practical use with a larger body of users. We plan to conduct a study in which each user selects their own training examples, obtains recommendations, and provides final informed ratings after reading one or more selected books.
Another planned experiment is comparing LIBRA’s content-based approach to a standard collaborative method. Given the constrained interfaces provided by existing on-line recommenders, and the inaccessibility of the underlying proprietary user data, conducting a controlled experiment using the exact same training examples and book databases is difficult. However, users could be allowed to use both systems and evaluate and compare their final recommendations.

Since many users are reluctant to rate large number of training examples, various machine-learning techniques for maximizing the utility of small training sets should be utilized. One approach is to use unsupervised learning over unrated book descriptions to improve supervised learning from a smaller number of rated examples. A successful method for doing this in text categorization is presented in [23]. Another approach is active learning, in which examples are acquired incrementally and the system attempts to use what it has already learned to limit training by selecting only the most informative new examples for the user to rate [8]. Specific techniques for applying this to text categorization have been developed and shown to significantly reduce the quantity of labeled examples required [17, 18].

A slightly different approach is to advise users on easy and productive strategies for selecting good training examples themselves. We have found that one effective approach is to first provide a small number of highly rated examples (which are presumably easy for users to generate), running the system to generate initial recommendations, reviewing the top recommendations for obviously bad items, providing low ratings for these examples, and retraining the system to obtain new recommendations. We intend to conduct experiments on the existing data sets evaluating such strategies for selecting training examples.

Studying additional ways of combining content-based and collaborative recommending is particularly important. The use of collaborative content in LIBRA was found to be useful, and if significant data bases of both user ratings and item content are available, both of these sources of information could contribute to better recommendations [3, 4]. One additional approach is to automatically add the related books of each rated book as additional training examples with the same (or similar) rating, thereby using collaborative information to expand the training examples available for content-based recommending.

A list of additional topics for investigation include the following.

- Allowing a user to initially provide keywords that are of known interest (or disinterest), and incorporating this information into learned profiles by biasing the parameter estimates for these words [24].
- Comparing different text-categorization algorithms: In addition to more sophisticated Bayesian methods, neural-network and case-based methods could be explored.
- Combining content extracted from multiple sources: For example, combining information about a title from Amazon, BarnesAndNoble, on-line library catalogs, etc.
- Using full-text as content: A digital library should be able to efficiently utilize the complete on-line text, as well as abstracted summaries and reviews, to recommend items.

CONCLUSIONS

The ability to recommend books and other information sources to users based on their general interests rather than specific enquiries will be an important service of digital libraries. Unlike collaborative filtering, content-based recommending holds the promise of being able to effectively recommend unrated items and to provide quality recommendations to users with unique, individual tastes. LIBRA is an initial content-based book recommender which uses a simple Bayesian learning algorithm and information about books extracted from the web to recommend titles based on training examples supplied by an individual user. Initial experiments indicate that this approach can efficiently provide accurate recommendations in the absence of any information about other users.

In many ways, collaborative and content-based approaches provide complementary capabilities. Collaborative methods are best at recommending reasonably well-known items to users in a communities of similar tastes when sufficient user data is available but effective content information is not. Content-based methods are best at recommending unpopular items to users with unique tastes when sufficient other user data is unavailable but effective content information is easy to obtain. Consequently, as discussed above, methods for integrating these approaches will perhaps provide the best of both worlds.

Finally, we believe that methods and ideas developed in machine learning research [22] are particularly useful for content-based recommending, filtering, and categorization, as well as for integrating with collaborative approaches [5, 6]. Given the future potential importance of such services to digital libraries, we look forward to an increasing application of machine learning techniques to these challenging problems.

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