Journal of Artificial Intelligence Research, vol. 1, no.1, pp. 10-16, OCTOBER 2024

Digital Library Book Recommendation System Based on Tag Mining

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ARTICLE INFO

Keywords:
book recommendation
digital library
personalized service
content similarity
collaborative filtering

ABSTRACT

Aiming at the problem of low utilization of library resources in the current network information-flooded environment, this paper designs a book recommendation system framework suitable for digital libraries. In the book recommendation system, the recommended candidate set of books is selected by using the reader's borrowing record combined with the collaborative filtering model. Then, the book and the target reader are labeled. And the content similarity is calculated according to the content characteristics of the book and the reader's comment information. Finally, the final recommendation result is obtained according to the calculation result and the library collection information. Providing book recommendation services in digital libraries can effectively help users enhance their reading interest and optimize the reader's experience.

1. Introduction

In contemporary society, marked by information and intelligence, technologies such as artificial intelligence (AI), big data, and cloud computing have driven a new wave of technological revolution [19, 5]. Library services have also evolved towards digitization, intelligence, and personalization. Notably, during the past few years of the global pandemic, digital services have become an essential component of library operations [18]. As early as the 1990s, with the advent and advancement of computer technology, physical libraries began their journey toward digital transformation. This involved digitizing collections, automating library management processes, and enabling individual libraries to establish their own databases and management systems using computer-based tools.

With the maturation of entity extraction [36], digital twins [48], sentiment analysis [43] and social network analysis [20], interconnectivity between different libraries' digital resources became possible, allowing readers to access various library resources online. By the late 1990s, the National Library of China took the lead in several digital library initiatives, marking the beginning of the country's library digitization efforts. After more than two decades of development, digital libraries have not only expanded significantly but also enhanced their specialization and diversity, achieving higher levels of sophistication and functionality.

Since the widespread adoption of mobile internet, mobile libraries have gained extensive use. Unlike traditional physical and digital libraries, mobile libraries provide users with dynamic services accessible anytime and anywhere. The rise of big data technologies has further laid the foundation for the intelligent, innovative, and personalized development of mobile libraries. However, the increasing volume of digital library resources has also led to the problem of "information overload". Effective solutions to this challenge include information retrieval and personalized recommendation systems [16]. Information retrieval involves the proactive search for useful information by users, while personalized recommendation leverages algorithms to suggest potentially relevant information to users based on their preferences and behavior patterns.

To enhance the utilization of library resources and increase readers' interest in reading, offering personalized book recommendation features in digital libraries has become an effective approach, aligning with the trend toward personalized services. Introducing book recommendation systems in libraries and ensuring their effectiveness has also become a focal point of research in the field of library science. Jomsri applied association rule techniques to explore the relationships between readers' interests and available books based on book categories, facilitating book search and efficient utilization of library resources [12]. Similarly, Tsuji et al. integrated book characteristics–such as title similarity, alignment with NDC (Nippon Decimal Classification) categories, and borrowing records–into an SVM classifier to recommend books to university library users [34]. Existing research on book recommendations continues to focus primarily on leveraging available library data, such as borrowing records and bibliographic information [33, 9, 27, 47]. However, there is limited exploration of utilizing reader feedback, such as reviews and user-generated tags, for recommendation purposes. Although the current infrastructure of most digital libraries restricts access to reader feedback, online book review platforms–such as Douban–host a wealth of user-generated content that could be mined for book recommendations.

Based on a comprehensive review of the key elements of book recommendation systems in digital libraries, this paper proposes a recommendation approach that integrates library borrowing records, book content information, and external book review data. By analyzing content information, such as book summaries, along with reader reviews, books can be processed and assigned relevant tags. Similarly, the

DOI: https://doi.org/10.70891/JAIR.2024.100022
ISSN of JAIR: 3078-5529

tags of books previously borrowed by readers can serve as indicators of their interests, functioning as personalized reader tags. This approach enables the efficient calculation of similarity between reader and book tags, facilitating the generation of personalized book recommendations for individual readers.

2. Literature Review

The primary function of recommendation systems is to personalize results by analyzing users' historical behavior to uncover implicit preferences, helping users discover latent interests and guiding them to fulfill their information needs [29]. Since the introduction of the email-based recommendation system Tapestry, research and applications of recommendation systems have been continuous. With the advancement of internet technologies, personalized recommendation has become an essential component in various fields, such as news, music, and social networks [14, 4, 30]. On one hand, to improve the accuracy of recommendations, scholars have continuously refined algorithms and conducted experiments. Early recommendation algorithms were based on content-based filtering, collaborative filtering, and machine learning models. With the widespread application of deep learning, newer algorithms leveraging models such as deep neural networks, recurrent neural networks (RNNs), and graph neural networks (GNNs) have emerged [31, 44], providing effective solutions for handling multi-source heterogeneous data [26, 42]. On the other hand, recommendation diversity has become a growing area of interest among researchers. Wei et al. proposed an improved probabilistic propagation model [38], while Peña et al. combined topic models with matrix factorization techniques [23]. These approaches successfully enhance the overall diversity of recommendations without compromising accuracy.

In the field of library and information science, recommendation systems are also a critical area of research. One notable example is the Fab recommendation system, part of Stanford University's digital library project, which combines the advantages of content-based filtering and collaborative filtering to recommend webpages that align with users' potential interests from a vast pool of online information [3]. Later, the Citeseer system shifted the focus toward recommending academic papers by analyzing and predicting users' preferences for webpages, offering URLs they might find relevant. As recommendation technologies have matured, there has been a growing focus on developing and applying recommendation systems for academic resources. Platforms like WoS (Web of Science) and Google Scholar now suggest literature related to users' current or past search topics [45]. Researchers further enhance these systems by leveraging various data points, such as keywords, citation and co-citation relationships, and co-authorship networks, to recommend papers, collaborators, and datasets to scholars [28, 10, 32, 39]. In the realm of book recommendations, online bookstores have adopted these systems extensively. Platforms such as Amazon and Dangdang utilize users' browsing, purchasing, and rating histories to recommend books that may capture their interest. Scholars have also studied user profiling, interest sequences, and preference shifts, integrating these elements into recommendation systems to provide personalized book recommendations [40, 25, 21].

Similarly, research on book recommendations within the context of physical library borrowing scenarios has been emerging continuously. The widespread application of big data technologies has prompted scholars to explore how these technologies can empower both digital and mobile libraries. Peska and Vojtas proposed a personalized book recommendation algorithm that integrates time-sequential collaborative filtering with students' learning trajectories [25]. Wayesa et al. utilized a combination of content-based filtering (CBF) and collaborative filtering (CF) enhanced with semantic relationships to generate knowledge-based book recommendations for readers in a digital library [37]. Lin designed an improved item-based collaborative filtering algorithm, which merges a mean model representation with a user-based collaborative filtering approach to enhance recommendation performance [15]. Additionally, Anoop and Ubale developed a cloud-based library recommendation system that applies a collaborative filtering algorithm [2]. In this system, administrators categorize books and recommend top-rated books (with 5-star ratings) to users, further enhancing the personalized recommendation experience.

The integration of digital libraries with big data technologies is a key strategy for delivering more accurate and personalized information services. One of the most effective ways to achieve this is by introducing personalized recommendation systems. This approach not only enhances the user experience of digital library patrons but also increases the library's appeal and engagement with its readers.

3. Elements of Digital Library Recommendation Systems

Recommendation systems function within specific contexts, and an information system must consist of certain essential elements to be recognized as a recommendation system. Each element plays a distinct role in the recommendation process. In the context of digital library recommendation systems, the fundamental elements include readers, book resources, and the digital library platform. Readers and books, as the users and recommended objects of the system, are indispensable components of any book recommendation system. The digital library platform records the interaction data between readers and books, with the completeness and reliability of this data being critical to the system's effectiveness and the quality of recommendations [8].

3.1. Readers

The core element of any recommendation system is the user, as the primary goal of the system is to provide personalized recommendations tailored to users. In book recommendation systems, the main users are library patrons.

A recommendation system relies on the analysis of users' characteristics and historical behavior data to identify their interests and generate relevant recommendations. Therefore, users form the foundation of the system. User profiling is one of the commonly employed methods in recommendation systems for analyzing user-related data. Through user profiles, the system can uncover users' latent needs and support precise targeting strategies [46]. For example, Wang proposed a set of accurate reading recommendation strategies based on student profiles [35]. Similarly, Duan combined user profiling techniques with collaborative filtering algorithms, performing multi-type, real-time, and in-depth analysis of large datasets [6]. Guided by user behavior patterns and interest attributes, Duan's approach classifies user preferences and book categories to construct a precise library recommendation model tailored to readers' interests. Jia and Li further elaborated on the characteristics and requirements of personalized intelligent services in libraries [11]. They integrated user profiling into the personalized service system and designed a framework for personalized intelligent services within libraries, centered on user profiles.

3.2. Book Resources

Book resources are the core assets of a library, with all library activities and services centered around them. In a book recommendation system, the objects recommended to readers are also these resources. Typically, library databases store bibliographic information such as book titles, authors, and publication dates. In the context of digitalization, users can search for books using subject keywords, and assess whether the search results–through titles, abstracts, and other metadata–meet their needs [41]. Similarly, recommendation systems can employ these subject keywords as features to calculate similarities between books or between books and users' preferences. Mathew et al. performed content-based filtering by extracting book categories and subcategories, using them to filter transactions according to user preferences [17]. Pera and Ng developed K3Rec, a recommendation system designed to differentiate books aimed at younger readers (K-3) from those for more mature audiences [24]. This system takes into account various attributes, including grade levels, content, illustrations, topics, and additional features such as length and writing style, to align books with the interests, preferences, and reading abilities of emergent readers.

3.3. Digital Library Platform

In different contexts, recommendation systems have varying focuses and objectives. In the environment of a digital library, the primary goal of recommendations is to encourage readers to borrow books. The interaction data between readers and books, such as borrowing records, are stored in electronic format within the library's database. Additionally, both reader and book information are stored in their respective databases. Furthermore, data related to readers' search queries, browsing history, and downloads are also recorded. The presence of a recommendation system enables digital libraries to leverage stored data effectively, facilitating precise recommendations and personalized services. Most current digital library platforms provide functional services such as catalog searches, access to digital resources like journals, and promotional content such as news and announcements. However, these platforms have yet to fully adopt data-centric business models. As society becomes increasingly data-intensive, digital libraries must transition towards data-driven knowledge services. Managing and utilizing vast, heterogeneous datasets will undoubtedly become a critical area of growth for digital libraries [13]. The core of recommendation systems lies in leveraging big data technologies to discover associations within data. For example, Duan and Wang applied data mining techniques in university libraries to develop personalized services, proposing a system architecture that covers data processing, mining algorithms, and the application of mined results [7]. Thus, as a key element of book recommendation systems, digital libraries–supported by big data technologies–can more efficiently and accurately achieve the goal of providing personalized services to readers.

4. Book Recommendation Process

This study divides the process of recommending books to readers–based on their historical borrowing data–into two steps: candidate selection and ranking. Traditional recommendation algorithms, such as collaborative filtering, can complete both steps using only readers' borrowing data. However, the recommendation algorithm in this study incorporates external data, specifically Douban book data, to enrich the available book information and enhance the effectiveness of the recommendations. The flow of the book recommendation process is illustrated in Figure 1.

4.1. Candidate Selection

A preliminary candidate set for book recommendations can be generated based on readers' historical borrowing records using the collaborative filtering approach. Collaborative filtering is a classic algorithm in the field of recommendation systems. Its fundamental principle is that users with similar behaviors are likely to have similar interests [22]. Applying this concept, the system identifies other readers with borrowing patterns that resemble those of the target reader. Books borrowed by these similar readers–but not yet borrowed by the target reader–are included in the candidate set.

In a recommendation system, let the set of readers be denoted as U and the set of books as B. For any reader $\circ u_i \in U$ (where $i = 0, 1, \cdots, m$), if they have borrowed a book $\circ b_j \in B$ (where $j = 0, 1, \cdots, n$), it can be inferred that the reader u_i is interested in that book b_i . The relationship between the reader set U and the book set B can be represented by a reader-book matrix $m * n$. If a reader u_i is interested in a book b_j (i.e., has borrowed it), the corresponding matrix entry is recorded as 1 ($r_(i, j) = 1$); if the reader u_i has not borrowed the book, the entry is recorded as 0. Using the constructed reader-book matrix, the similarity between different

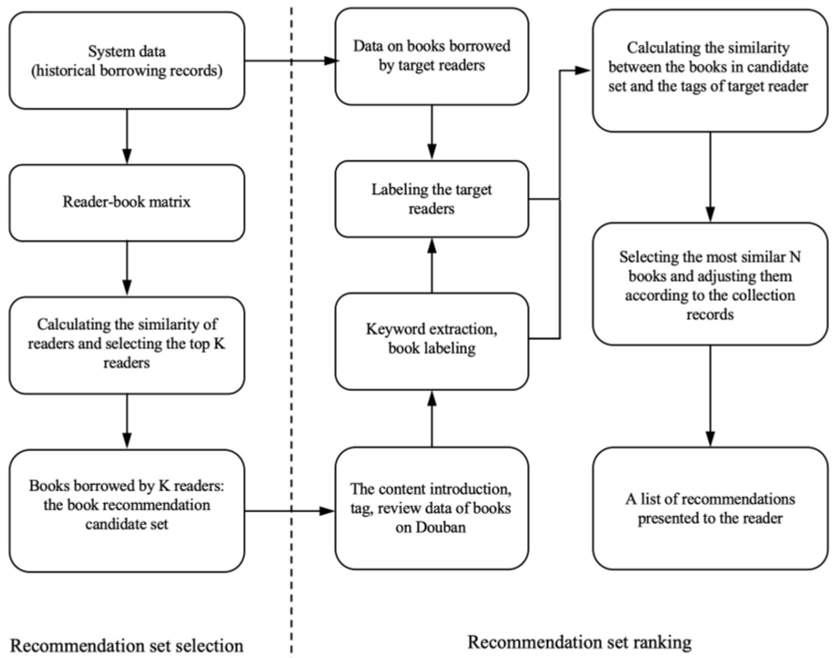

Figure 1: Process of book recommendation.

readers can be computed. Various similarity measures can be applied in recommendation systems, with cosine similarity being one of the most widely used methods. The formula for calculating cosine similarity is as follows:

$$sim(i, j) = \frac{i \cdot j}{\|i\| \cdot \|j\|} \tag{1}$$

In a book recommendation system, let i and j represent the vectors of books corresponding to readers u_i and u_j in the matrix. By calculating the similarity between these vectors, the system identifies the top K readers whose borrowing behavior is most similar to that of the target reader. The set of books borrowed by these K similar readers forms a potential collection of books that the target reader may also find interesting. To generate a personalized recommendation candidate set for the target reader, books that the reader has already borrowed–indicating known interest–are excluded from this collection. The remaining books constitute the recommendation candidate set, containing new books that the target reader has not yet explored but is likely to find appealing.

4.2. Candidate Set Ranking

Since the number of books that can be displayed to readers is limited, whether on mobile platforms or web interfaces, and readers' patience for browsing is finite, further filtering and ranking of the candidate set is essential. The goal is to display the books most likely to interest the reader prominently on the recommendation interface. In the classic collaborative filtering algorithm, the ranking process can be carried out using borrowing records. For each book in the candidate set, the system predicts the target reader's level of interest, and the books are sorted according to these predicted scores. While this method is computationally efficient and relies on simple data sources and structures, ranking solely based on borrowing behavior is somewhat coarse-grained.

Digital library systems store not only basic bibliographic information such as titles and holdings but also more detailed metadata like classification codes and authorship. Additionally, external sources such as the book module on Douban provide even richer information, including book summaries, user-generated tags, and reviews. These datasets contain both objective book attributes and subjective user perceptions, offering a more comprehensive view of a book's characteristics. Thus, in this study, we incorporate Douban's book information to measure similarity between books. By doing so, we can recommend books with the highest similarity to those in the reader's borrowing history, ensuring that the recommendations are more relevant and aligned with the reader's preferences.

To calculate similarity using book features, it is first necessary to tag both the target reader and the books in the candidate set. For books in the candidate set, keywords can be extracted from content summaries and reader reviews, combined with user-generated tags from Douban, forming a comprehensive set of tags for each book. For the target reader, the combined tag set of all previously borrowed books serves as the reader's tags. Keyword extraction techniques have become increasingly mature. For this task, Latent Dirichlet Allocation (LDA) can be used to extract relevant keywords from text data. Once both the target reader and the books in the candidate set are labeled, the similarity between the two sets of tags can be calculated. The N books

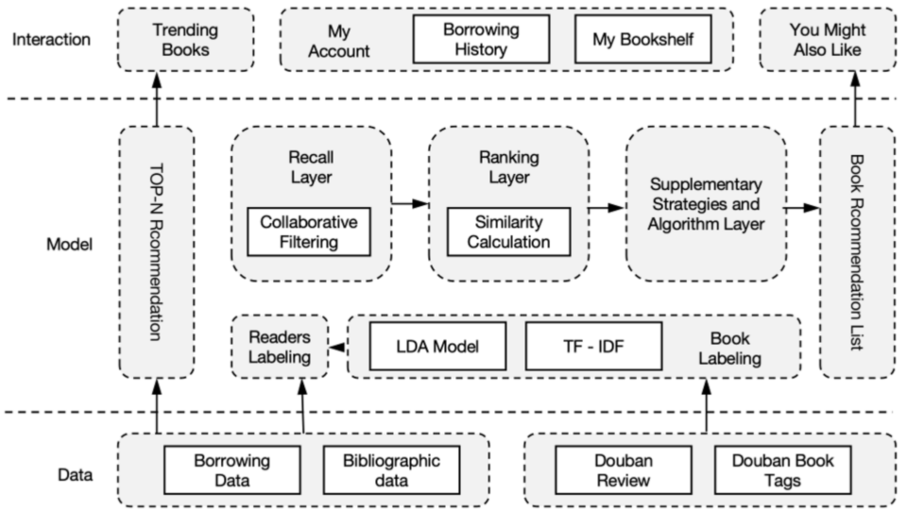

Figure 2: The structure of book recommender systems.

with the highest similarity to the target reader's tags are then selected to form the final recommendation list.

Assume that the tag set of reader u_i is $\{l_{i1}, l_{i2}, l_{i3}, \cdots, l_{im}\}$, the tag set of book $b_j$is $\{l_{j1}, l_{j2}, l_{j3}, \cdots, l_{jn}\}$ and $v = min(m, n)$, the tag similarity between the reader and the book can be calculated as:

$$sin\left(u_i, b_j\right) = \sum_{k=0}^{v} \frac{l_{ik} \times l_{jk}}{\sqrt{\sum_{k=0}^{v} l_{ik}^2}} \sqrt{\sum_{k=0}^{v} l_{jk}^2} \tag{2}$$

Based on the results of tag similarity calculations, the N books with the highest similarity scores are sorted in descending order and recommended to the target reader. The value of NN is typically determined by the presentation format of the platform. For example, on Douban's web platform, NN is set to 10, while on the mobile platform, users can initially view 10 recommended books and access the full list through the "View All" option.

Given the unique requirement of physical book borrowing in offline libraries, it is essential to align the recommendation system with real-time holdings data. Books that are currently unavailable or checked out should either be marked or removed from the recommendation list, facilitating readers identify books available for immediate offline borrowing.

4.3. Design of the Book Recommendation System

The book recommendation system designed in this study functions as an integral part of the digital library. The system architecture is outlined in Figure 2, consisting of three key components: the data layer, the model layer (algorithm layer), and the interaction layer. Firstly, the data layer forms the foundation of the architecture. It consolidates internal data, such as borrowing records and bibliographic data from the library, along with external data, including reviews and user-generated tags from Douban. Secondly, the model layer is the core of the recommendation system. It processes and analyzes data from various sources to generate personalized book recommendation lists for readers. Thirdly, the interaction layer handles the user interface, displaying recommended books to readers. It also enables users to search for books, save favorites, and view their borrowing history, fostering seamless interaction between readers and the recommendation system.

5. Evaluation of the Recommendation System

Evaluating the effectiveness of a recommendation system is a challenging task. In recommendation algorithm research, quantifiable metrics such as accuracy and recall are commonly used to assess the system's performance. In practical applications, however, additional factors become relevant. These include the coverage of recommendations, the diversity and popularity of recommended items, and the novelty and surprise factor that contribute to a positive user experience and satisfaction [1]. Furthermore, the real-time performance and robustness of the system during operation are critical dimensions for evaluation and are frequently considered in assessing the overall quality of recommendation systems.

5.1. Quantifiable Evaluation Metrics

Let $R(u)$ represent the list of books recommended to the target reader, and $T(u)$ denote the list of books the target reader actually borrows after receiving the recommendations. The precision and recall of the recommendation results can be defined as follows:

$$Precision = \frac{\sum_u |R(u) \cap T(u)|}{\sum_u |R(u)|} \tag{3}$$

$$Recall = \frac{\sum_u |R(u) \cap T(u)|}{\sum_u |T(u)|} \tag{4}$$

Precision measures the proportion of books in the recommendation list that the reader actually borrows; recall measures the proportion of the books the reader eventually borrows that were included in the recommendation list.

5.2. User Experience Evaluation Metrics

The goals of a recommendation system vary for service providers across different scenarios, such as improving click-through rates, conversion rates, or video watch time. On the user side, the primary objective is to enhance the user experience by filtering information and helping users discover valuable content. When user experience is optimized, the service provider's goals are also more likely to be achieved, making the two goals mutually reinforcing. User experience is therefore a critical aspect of evaluating recommendation systems. Beyond accuracy, users also value the element of surprise–whether the system can recommend unexpected yet desirable items. While these aspects are challenging to quantify through data alone, they remain essential indicators of a recommendation system's effectiveness.

6. Conclusion and Future Work

This paper proposes a personalized book recommendation system for digital libraries. The system is based on the collaborative filtering approach, extracting a candidate set from readers' borrowing records. It then integrates content information and reader reviews from Douban to generate a recommendation list tailored to the target reader's interests. Finally, the system incorporates library holdings data to display a refined recommendation list to readers. By combining borrowing records unique to libraries with content-based features and user feedback, this system offers a novel approach to enhancing personalized services in digital libraries.

However, there are still some challenges. The candidate ranking method relies on mature external platforms, such as Douban, which may present practical difficulties during implementation. To ensure the smooth operation of the personalized recommendation system, digital libraries must further enhance their infrastructure, offering more diverse information sources and richer interactive features for users. Additionally, this recommendation method does not address the cold-start problem for new users and new books. Future research should explore complementary recommendation strategies tailored to these scenarios to ensure the system can effectively handle cases where limited user or book data is available.

Acknowledgement

The authors declare that there is no funding and no conflict of interest.

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