# Reading Recommendation Technology in Digital Libraries Based on Readers' Social Relationships and Readers' Interests

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***Abstract*—In recent years, the construction of digital libraries has contributed to the advancement of smart lending services. The challenge of suggesting appropriate books for readers from a vast collection of books remains a primary obstacle in the current construction of digital libraries. A fusion method for recommending content to readers with diverse interests is proposed. The method initially extracts short-term borrowing behavior characteristics and simultaneously considers the social similarity characteristics of readers, resulting in the recommendation of content through target ranking search. Aiming to cater to long-term readers, a reading recommendation method that integrates readers' reading behaviors is proposed to model readers' interests through the attention mechanism. It constructs readers' preference models by using synergistic metrics, and finally achieves content recommendation through preference fusion. The proposed model attained the swiftest convergence and the minimum logarithmic loss of 1.85 in recommending readings for multi-interest readers. Additionally, the accuracy of the proposed model in recommending science reading scenarios was 97.24%, surpassing other models. In the reading recommendation experiments for extended borrowings, the suggested model demonstrated superior performance with regard to recall and precision, which were 0.198 and 0.062, respectively. Lastly, after comparing the recommendation errors of different reading models, the proposed model exhibited a root-mean-square error and an average absolute error of 0.731 and 0.721, respectively. These results denote the most precise recommendation accuracy among the three models. The proposed model demonstrates excellent recommendation effectiveness in real-world reading recommendation scenarios. This research offers significant technical references for the advancement of related recommendation technology and the development of digital libraries.**

***Keywords*—Digital library; recommend; behavioral characteristics; interest; attention mechanism***

## I. INTRODUCTION

In recent years, the development of smart lending services has rapidly increased with the rise of digital library (DL). As a novel type of library, it offers readers a unique reading experience due to its convenient access and extensive reading resources. For instance, it provides a user-friendly online reading feature that enables readers to access and read books via electronic devices at any time and from any location. Secondly, it has rich and diverse reading resources, covering books in various fields, which meets the diverse needs of readers [1]. Retrieval and search functions are available to quickly locate and recommend suitable books for readers. This presents a significant challenge in construction [2]. The traditional recommendation technology relies heavily on the user's historical behavioural data or content similarity, disregarding the reader's multitude of interests and social similarity features (SSF), resulting in limited accuracy and personalization of the recommendation results [3]. Liang X et al. researched current recommendation techniques and found that the current recommendation systems used in teaching had poor balance and couldn’t meet the actual teaching needs. Therefore, based on trust relationships, a balanced recommendation technique for educational resources was proposed, which determined the relationship between data and recommendation sites by extracting resource feature data. The actual results showed that this technology could significantly improve the recommendation effect of teaching resources, which was superior to traditional recommendation techniques [4]. To address the shortcomings of conventional recommendation techniques in the context of library book recommendations, researchers have turned their attention to the development of reading recommendation techniques that integrate diverse interests and SSF. For multi-interest reader (MIR), the study proposes a fusion multi-interest RR method. The RR model is constructed by extracting readers' short-term borrowing behavior and SSF. For long-term readers (LTR), the study proposes an RR method that integrates readers' reading behaviors and models readers' long-term and short-term interests through the attention mechanism.

The study puts forth a novel approach to RR that incorporates a multitude of interests and SSF. The recommendation results are more accurate and personalized when the characteristics of readers' long- and short-term borrowing behaviours and their SSF are taken into account. Additionally, the attention mechanism and preference fusion further improve the content recommendation effect. The construction of DL will further improve readers' reading experience and provide important technical references for the digitalization of libraries and the improvement of recommended technologies.

The research is organized into six sections. Introduction is given in Section I. Section II focuses on the latest technology in library recommendation and its applications. Section III constructs two RR models, one based on MIR and the other on long-term borrowing readers to understand the reading characteristics of the patrons. Section IV applies the aforementioned technologies to specific scenarios to validate the effectiveness of the library recommendation model in real-life situations. Discussion is given in Section V. Section VI provides an analysis of the entire study and outlines the direction for future research improvement.

## II. Related Work

Recommendation technology is a comprehensive data mining method that provides personalized recommendation services to users based on their historical behaviors, preferences, and other characteristics. Anwar T found that recommendation systems had a wide range of applications in various fields, especially in providing recommendation services based on interests and hobbies, greatly improving user experience. Therefore, to improve the reading effect of library users, a book recommendation method that collected knowledge from multiple domains was proposed. This technology utilized user search term retrieval and searches for similar semantic analysis. The results showed that this technology had excellent application effects and significantly improved the reading efficiency of the library [5]. Swaminathan B et al. proposed a four-layer architectural model which alone contained network, sensors, services and applications to help deploy smart agricultural systems with limited energy consumption. In the study, focusing on the application layer a deep learning algorithm was proposed to build a fertilizer recommendation system that conforms to expert opinion for farmers. Applying this technology to agricultural production scenarios, this technology could effectively help farmers' select appropriate fertilizers and improve the effectiveness of agricultural management [6]. Yu K et al.'s study focused on the application of IoT AI in social computing. However, the current recommendation technology was mainly based on partial feature capture, ignoring implicit preference feedback, which affected the final recommendation effect. In response, an improved collaborative Bayesian network model was proposed in the study, which was used for the social recommendation process. Through a large number of experiments, the proposed technique had good robustness and met the users' social service needs [7].

The application of recommender systems in the field of digital books solves the problem of reading information as well as content selection for readers, and through advanced digital service technology, it can more accurately promote suitable book information for readers. Anwar K et al. studied the existing book recommender systems in order to solve the problem of information overload in recommender systems. The study focused on exploring the machine learning techniques used in book recommendation systems and examined the evaluation metrics to assess the recommendation techniques. Book recommendation categories were identified through the analysis and a converged digital book recommendation technique was given. Applying the technology to specific library scenarios, the technology could provide personalized promotion services for readers, which was better than the related recommendation technology [8]. Ko H et al. found that existing recommendation techniques were unable to capture readers' implicit feedback and social information, resulting in a recommendation service that failed to meet the reading needs of customers. In this regard, a personalized fusion recommendation system was proposed by comparing the differences in different recommendation technologies. The system could collect readers' diversified characteristic information and determine the reading scope according to readers' interests and preferences, so as to provide readers with accurate RR services. Through relevant experiments, it showed that this technology could provide personalized recommendation services for readers according to their preferences, which was better than related technologies [9]. Cong H et al. found that existing recommender systems need to solve the problem of matching massive information data. Thus, a book personalized recommendation algorithm based on intelligent classification algorithm was proposed in the study. The algorithm utilized collaborative filtering recommendation technology to achieve the initial screening of information, and finally used convolutional neural network for further filtering, input user data and video data. It realized the content recommendation through scoring ranking. The corresponding experiments showed that the proposed recommendation technology had good personalized recommendation capability, and the recommendation accuracy was better than that of the same period recommendation model [10]. The research of Da'u et al. aimed to solve the cold-start and data sparsity problems in book recommendations. A Kitchemen-ham based systematic literature review method was adopted to study and analyze the current state-of-the-art recommendation technologies. Moreover, a recommendation system integrating a deep learning framework was finally proposed to obtain the main feature data by capturing the features of the user and the target object and to realize the recommendation of the content through the scoring. Through experiments, it was found that the proposed technology could effectively solve the problems of sparse information and inaccurate book recommendations, and significantly improve the effect of the reader's reading experience [11].

In conclusion, the preceding research has examined and analyzed the most recent advancements in recommendation technologies. It is evident that these technologies have a profound impact across a multitude of domains, effectively enhancing users' target selection efficacy and enriching the user experience. However, current recommendation technologies still face problems such as information overload and insufficient recommendation accuracy. In book recommendations, most technologies are based on user preference information, lacking attention to user social information and implicit preference feedback. Therefore, to improve the selection effect of reading books, an intelligent digital book recommendation technology is proposed. This research will contribute to the improvement of the user reading experience and the enhancement of the effectiveness of DL construction.

## III. Modeling Reading Recommendations in Digital Libraries on Readers' Social Relationships and Reader Interests

This part mainly analyzes the RR service of digital reading scenarios, considers different readers' needs, and constructs the RR model of MIR and the RR model of long-term borrowing readers to realize the RR for different objects.

### A. *Modeling Reading Recommendations Based on Multi-Interest Reader*

In recent years, the advancement of information industry technology has prompted a shift towards digital development in traditional libraries. This transition is driven by the need to provide readers with personalized and diversified services.

Among them, providing readers with high-quality and efficient RR services is an important goal of the construction. In the construction, a number of services such as borrowing, recommending, book management and so on will be provided for readers, so as to meet the personalized reading experience of readers [12]. The system structure framework is shown in Fig. 1.

In Fig. 1, it provides customers with multi-end service requirements, and meets customers' online and offline related reading service requirements through the recommendation service module. However, the traditional book recommendation system mainly carries out RR service for readers' reading behavior data, which cannot meet the reading needs of multiple readers. Therefore, considering the factors of readers' multiple reading interests, a recommendation technology based on multiple interest reading is proposed. Firstly, in the RR system, it is necessary for the system to recommend suitable books for each reader. Additionally, the system must analyse the data of readers' historical borrowing, historical collection and historical flipping. This allows the system to obtain short-term behavioral data sequences that satisfy readers' reading interests. [13]. At the same time, readers' interests will change during short-term reading, such as science students and arts students will have obvious differences in reading interests during exam time. In this regard, in the RR service, data mining will be performed on reading groups with SSF. The personalized recommendation of experimental content will be made by calculating the characteristics of different social groups.

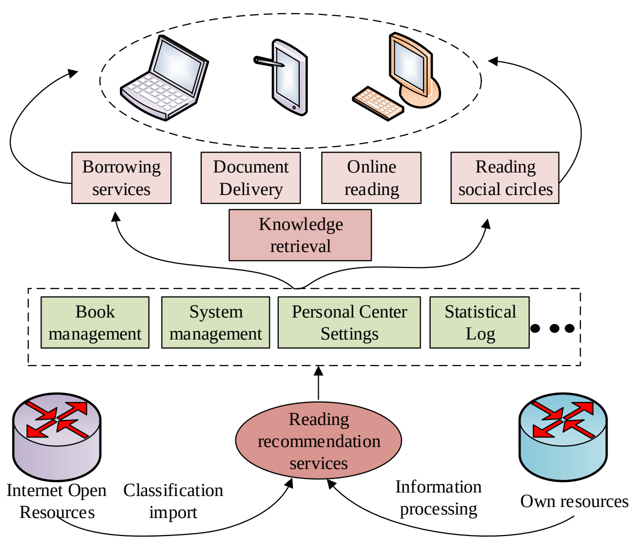



Fig. 1. Digital library system framework.

In the construction of the model, the interest layer of the model is used to obtain information about the borrowing behavior preference of each reader in a short period of time, these contain historical borrowing, historical collection, and historical flipping data, and based on the information to retrieve the suitable candidate set of readers [14]. Define each input as a ternary, the ternary expression is shown in Eq. (1).

$$DH_u = (I_u, O_u, F_u) \tag{1}$$

In Eq. (1), $I_u$ denotes the data set of readers and reading, $O_u$ denotes the social information of readers' reading circle, and $F_u$ denotes the reading data information of readers' candidates, and these contain book names, types, collection areas, etc. The core of the recommendation model construction lies in the implicit from the original data features to the reader representation vector, the reader representation vector is shown in Eq. (2).

$$V_u = f_{user}(I_u, O_u) \tag{2}$$

In Eq. (2), $f_{user}$ denotes the pooling operation, where $V_u$ can also be expressed as shown in Eq. (3).

$$V_u = (\overset{\rightarrow 1}{v_u}, \ldots, \overset{\rightarrow k}{v_u}) \in \mathbb{R}^{dr \times K} \tag{3}$$

In Eq. (3), $V_u$ denotes the representation vector of reader $u$, $K$ is the number of interests, and $dr$ denotes the embedding dimension. The pooling function of candidate book $i$ is shown in Eq. (4).

$$\vec{e}_{\mathrm{i}} = f_{item}(F_i) \tag{4}$$

In Eq. (4), $f_{item}(\cdot)$ denotes Embedding operation. According to the maximum value of the inner product of the candidate household and reader representation vectors as the similarity, the top N candidate books are obtained by sorting as shown in Eq. (5).

$$f_{score}(V_u, \vec{e}_i \, \vec{e}_u) = \max_{1 \le k \le K} \overset{\rightarrow T}{e_{\mathrm{i}}} \, \overset{\rightarrow K}{v_u} \tag{5}$$

In Eq. (5), $T$ denotes the top candidate books. In the actual reading scenario, reader reading information, social information, and relevant features associated with books can be obtained through the system platform, which need to be encoded in order to be recognized by the computer and form high-dimensional sparse features [15]. In order to facilitate the analysis of feature information, embedding technology is used to transform the high-dimensional sparse input into low-dimensional dense features. The processing process using Embedding technique is shown in Fig. 2.

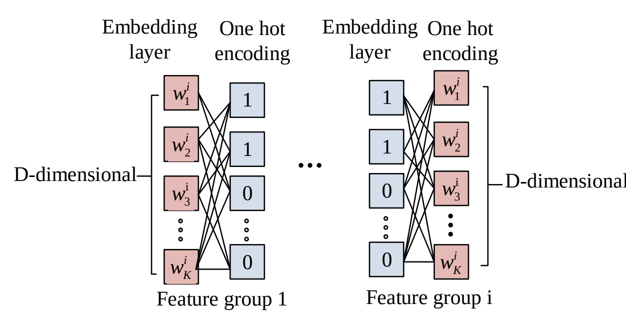



Fig. 2. Embedding technology feature dimension processing process.

The i-th feature group is defined as $W^i = \left[ w_1^i, \ldots, w_j^i, \ldots, w_K^i \right] \in \mathbb{R}^{D \times K_i}$, denoting that it contains the i-th embedding dictionary. $K_i$ denotes the i-th embedding dimension, $D$ denotes the original feature dimension, and $\mathbb{R}^{D\times K_i}$ denotes the embedding dimension vector. Using Embedding technique for table lookup operation, the input feature $x_i$ If it is a one-hot vector, the Embedding of $x_i$ belongs to a single vector $e_i = w_j^i$ , if it is a multi-hot vector, the Embedding of $x_i$ is a list of vectors, which is represented as shown in Eq. (6).

$$\{e_{i1}, e_{i2}, \ldots, e_{ik}\} = w_{i1}^i, w_{i1}^i, \ldots, w_{ik}^i \tag{6}$$

The behavioral sequence of readers is composed of Embedding vectors of items, which contain socially similar reader information, including readers' social crossover features, candidate book information and so on. In reader social similarity analysis, different readers do not have the same vector length when they get the historical behavior sequence through the embedding layer, and the fixed input length of the fully connected layer is needed in the model analysis [16]. For this pooling operation is used to get the fixed length as shown in Eq. (7).

$$e_i = pooling(e_{i_1}, e_{i_2}, \ldots, e_{i_k}) \tag{7}$$

Considering the need for plurality of readers' interests, in order to better tap into the reader's multiple interests, multiple representation vector distributions are utilized to represent the different interests of the readers. In this way, information will be retrieved for each aspect of the reader's items, and dynamic routing in dynamic capsules is used to merge the reader's historical behavior into a cluster and associate it with the recommended books. Define $e_i$ as the initial capsule $i$ , the computational expression from the initial capsule to the lower capsule $j$ is shown in Eq. (8).

$$\hat{e}_{j|i} = W_{ij} e_i \tag{8}$$

In Eq. (8), $W_{ij}$ is the transformation matrix and capsule $j$ will be the weighted sum of the input prediction vector $\hat{e}_{j|i}$ , expressed as shown in Eq. (9).

$$s_j = \sum_i c_{ij} \hat{e}_{j|i} \tag{9}$$

In Eq. (9), $c_{ij}$ is the coupling coefficient, and routing softmax is used for coupling coefficient calculation, as shown in Eq. (10).

$$c_{ij} = \frac{exp(b_{ij})}{\sum_k exp(b_{ik})} \tag{10}$$

In Eq. (10), $b_{ij}$ is the logarithmic prior probability of $i$ coupling with $j$ . Meanwhile, to ensure that the short vector tends to 0 and the long vector tends to 1, the capsule $j$ is processed using a nonlinear compression function as shown in Eq. (11).

$$v_j = squash(s_{ij}) = \frac{|s_j\|^2}{1+\|s_j\|^2} \frac{s_j}{\|s_j\|} \tag{11}$$

In Eq. (11), $s_j$ is the total $j$ input and $v_j$ is the final output capsule, which is obtained by inner product. The readers' embedding interest capsules are obtained through the multivariate interest layer, and each interest capsule indicates different interests of readers. In the actual training, in order to strengthen the effect of reader's interest evaluation on the featured books, a labeled attention layer is designed for improving the matching correlation between readers and books. The labeled attention layer is shown in Fig. 3.

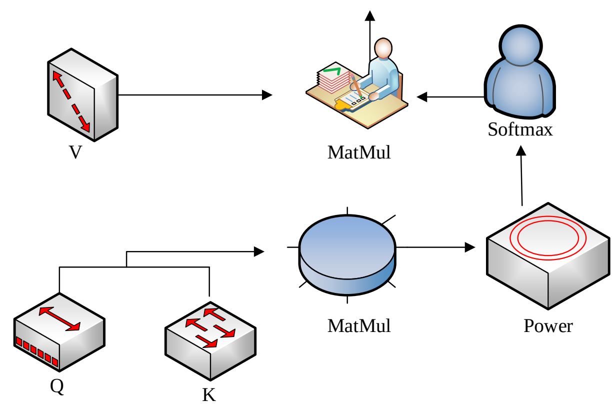



Fig. 3. Structure of label attention layer.

In the labeled attention layer, the candidate book embedding is denoted as query (Q) and the interest capsule is denoted as key (K). Through the attention layer then the reader candidate book output can be obtained as shown in Eq. (12).

$$\overrightarrow{v_u} = Attention(\overrightarrow{e_i}, V_u, V_u) = V_u softmax(pow(V_u^T \overrightarrow{e_i}, p) \tag{12}$$

In Eq. (12), $V_u$ represents the interest capsule matrix output by reader $u$ , $p$ is the attention distribution adjustment parameter.

## B. Modeling Reading Recommendations Based on Long-Term Borrowing Readers

In the construction of library RR systems, it is difficult for traditional recommendation models to obtain current readers' interest items from the historical behavior of LTRs. Especially, it is difficult to obtain the reading interests of current readers when individual readers have long-time borrowing records, some of which are as long as several months. Therefore, a RR technique based on long-term borrowing readers is proposed to address the above problem [17]. This technique focuses on analyzing the borrowing data of LTRs and capturing readers' interests from their recent borrowing behaviors, so as to make effective book recommendations for readers. Firstly, reader $u$ is defined to borrow $L$ books recently as the model input, and the embedding dictionary matrix of books is set to $M \in \mathbb{R}^{|L|\times d}$ and $d$ is the embedding dimension, then the embedding matrix of readers' short-term behaviors is shown in Eq. (13).

$$E = [m_{s1}, m_{s2}, \ldots, m_{sL}] \in \mathbb{R}^{|L| \times d} \tag{13}$$

In Eq. (13), $m_{sL}$ is the embedding matrix of readers' short-term behavior of borrowing L books. The reader's short-term interest representation is reflected by the self-attention model. In the short-term preference representation, since the location relationship cannot be reflected in the attention, the embedding matrix $P = [p_1, p_2, \ldots, p_L] \in \mathbb{R}^{|L| \times d}$ of the learnable location is added to the matrix $E$, and the input matrix $X^{(0)}$ of the attention network is expressed as shown in Eq. (14).

$$X^{(0)} = [x_1^{(0)}, x_2^{(0)}, \ldots, x_L^{(0)}] \in \mathbb{R}^{|L| \times d} \tag{14}$$

In Eq. (14), $x_\ell^{(0)}$ indicates as shown in Eq. (15).

$$x_\ell^{(0)} = m_{s\ell} + p_\ell, \ell \in \{1, 2, \ldots, L\} \tag{15}$$

Next the matrix $X^{(0)}$ needs to be incorporated into multiple stacked self-attention blocks (SABs) and the output of the $b$ th block is shown in Eq. (16).

$$X^{(b)} = SAB^{(b)}(X^{(b-1)}), b \in \{1, 2, \ldots, B\} \tag{16}$$

In the borrowing process, the wearable devices used by readers will record readers' short-term borrowing behavior, which contains a large amount of reader information and is crucial for the prediction of readers' reading interest [18]. At the same time, the book recommendation in addition to the reader characteristics, but also with the recommendation of the scene has an important relationship, such as readers in different bookshelves reading, reading time-consuming is not the same [19]. Therefore, the study adopts self-attention to model the different behavioral sequences of readers, and the model framework is shown in Fig. 4.

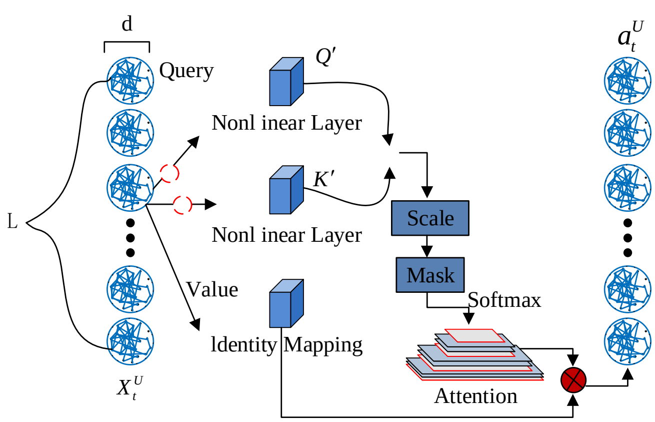



Fig. 4. A reader behavior modeling framework based on self-attention.

In the self-attention model, $Q'$ is the query, $K'$ is the keystroke, and $X_t^U$ is the reader's recently interacted books, the set of which is shown in Eq. (17).

$$X^U = (X_1^U, \ldots, X_t^U)\ t \in [1, 2, 3, \ldots] \tag{17}$$

In Eq. (17), $U$ denotes the set of readership and the set of books is $B$, $X^U \in B$. The study assumes that the reader interacts with books in the short term as $L$ books, and defines $X$ as the embedding set of all books, then the reader interacts with books in the near future at $L$ times as $X_1^U \in \mathbb{R}^{L \times d}$. In self-attention, the query, key, and values are all equal to $X_t^U$, and at the same time, let part of the query and key be linearly transformed, as shown in Eq. (18).

$$\begin{cases} Q' = Relu(X_t^U W_Q) \\ K' = Relu(X_t^U W_Q) \end{cases} \tag{18}$$

In Eq. (18), $W_Q = W_K$, $W_Q$ is the query matrix and $W_K$ is the keying matrix. The attention score mapping matrix is obtained by the above operation as shown in Eq. (19).

$$s_t^U = softmax(\frac{Q' K'^T}{\sqrt{d}}) \tag{19}$$

Finally, the weight output of the self-attention model is obtained, and the weight output is used as the reader interest preference representation as shown in Eq. (20).

$$a_t^u = s_t^U X^U, a_t^u \in \mathbb{R}^{L \times d} \tag{20}$$

In the actual reading process, there is a difference between the impact of long-term and short-term interests on readers. To accurately recommend books to readers, it is also necessary to consider the reader's long-term interest factors. In this regard, the gated cyclic unit structure is used to adjust the weights of readers' long-term and short-term interests through the similarity of readers' long-term and short-term interests, and the gate function is shown in Eq. (21) [20].

$$g = o(ISG(m_{st}, y_r, m_i)) = o([m_{st}, y, m_i] W_G + b_G) \tag{21}$$

In Eq. (21), $ISG(\cdot)$ represents the doorway function, $y_r$ is the long-term interest representation, $m_i$ is the embedding vector of the candidate product, $m_{st}$ is the embedding vector that represents the reader's recent behavior, and $b_G$ and $W_G$ are the adjustment parameters. The final representation of the sequential readers in step $\ell$ is shown in Eq. (22) [21].

$$z_\ell = x_\ell^{(B)} \otimes g + y \otimes (1 - g) \tag{22}$$

In Eq. (22), $\otimes$ is a multiplication-by-sign, and the predicted interaction score of the $i$ th candidate item among the $\ell + 1$th reader is shown in Eq. (23).

$$r_{\ell+1,i} = z_\ell (m_i)^T \tag{23}$$

Through the above study, the entire reading book recommendation for long term readers is then obtained. The entire RR technology route flow is shown in Fig. 5.

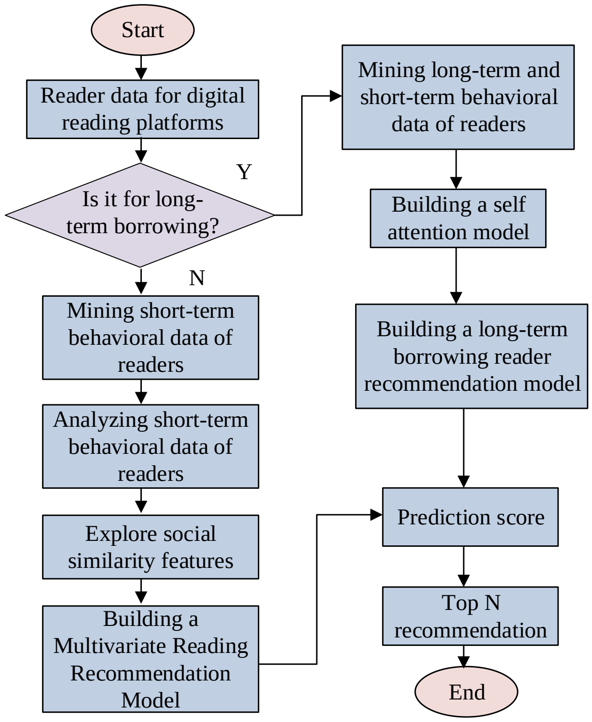



Fig. 5. Digital library reading recommendation technology flowchart.

## IV. Experimental Analysis of the Reading Recommendations Model for Digital Libraries

This part mainly analyzes the recommendation performance of the two models in two different reading scenarios, and examines the recommendation effectiveness of the proposed models by comparing them with similar RR models. The metrics include recommendation accuracy, recall, precision, etc.

### A. *Experimental Analysis of Reading Recommendations Model Based on Multi-Interest Reader*

To analyze the application effect of the proposed RR model, PyTorch is used to build the experimental platform. The records of readers' borrowing information of a university A for the whole year of 2022 are selected, which contains 15683 readers' borrowing information and a total of 698545 borrowing data information, and each reader's information contains at least 8 borrowing information records. The dataset is divided into train and validation, with 70% of the training set and 30% of the validation set. Area under ROC Curve (ROC), Loss, Logloss are selected as evaluation indexes. The relevant parameter settings of the experimental model are shown in Table I.

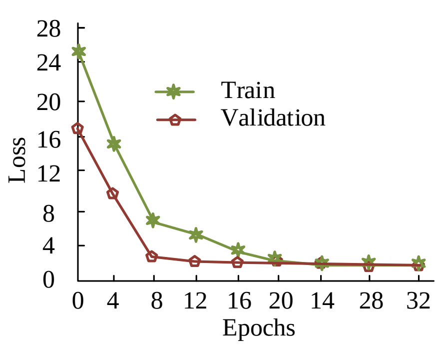
TABLE I. Parameter Settings for Reading Recommendation Model Based on Diverse Interest Readers

| Parameter indicator type | Numerical value |
|---|---|
| Capsule network hidden layer dimensions | [512,256,128,64] |
| Embedding vector dimension | 16 |
| Activation function | RELU |
| Iterations | 100 |
| Optimizer | Adam |
| pow | 2 |
| Attention network hidden vector dimension | 4 |

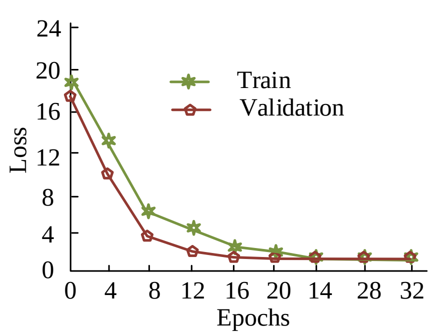
Table I shows the experimental model parameter settings. The hidden layer size of the capsule network is 512256, 128,64. The embedding vector size should not be too large, set to 16. RELU is used as the activation function. The DeepCrossing recommendation model (DeepCrossing) and the convolutional sequence embedded recommendation model (Caser) are introduced as test benchmarks. In model training, optimization is performed by regularization in order to avoid overfitting problem in the model, and the results are shown in Fig. 6.

Fig. 6(a) and Fig. 6(b) show the results of optimization without regularization and with regularization, respectively. The loss under the training set without dropout regularization optimization is 1.23, and the value of the loss under the training set after regularization optimization is 1.03. In addition, comparing the results of the validation set, the training loss under the validation set before dropout regularization optimization is 1.28, and the value of the loss under the training set after regularization optimization is 1.04. Therefore, dropout regularization is used in the experiment to optimization model training. Comparing the RR performance of different models is shown in Fig. 7.

Fig. 7(a) shows the results of model log-loss comparison. Among the three models, the proposed model achieves the fastest convergence and has the smallest log loss of 1.85 compared to the other models, while the log loss of Caser, and DeepCrossing are 5.26 and 7.32, respectively. Meanwhile, comparing the ROC values of the different models, the proposed model has the best performance of 0.83, followed by Caser with 0.795, and the worst one is DeepCrossing at 0.782. Different reading types in the social circle are selected for comparison, as shown in Fig. 8.

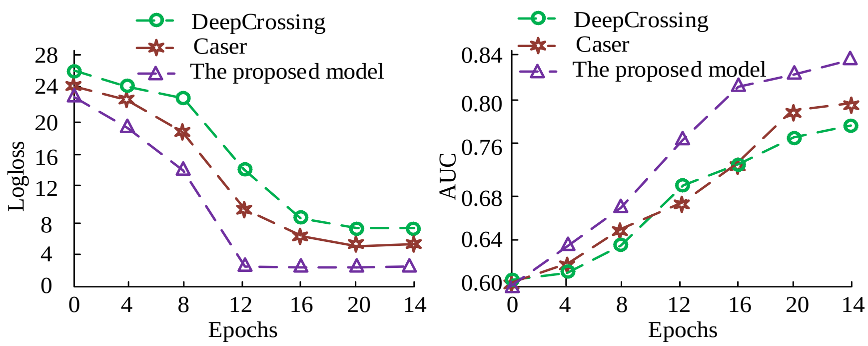



(a) Training without dropout regularization



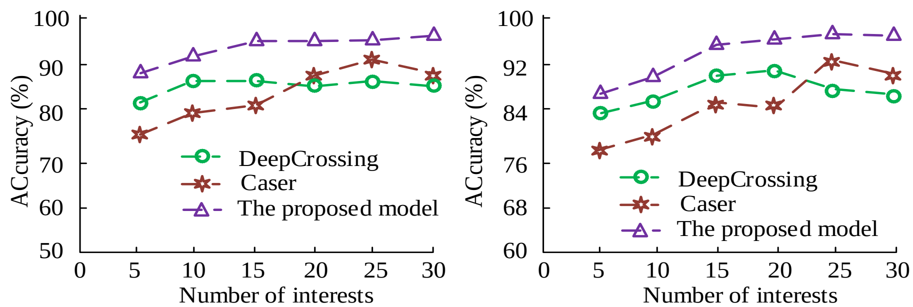

(b) Using dropout regularization training

Fig. 6. Comparison of loss curves using dropout regularization.




(a) Logarithmic loss comparison (b) Comparison of ROC values

Fig. 7. Performance comparison of reading recommendation models.




(a) Liberal Arts Reading (b) Science Reading

Fig. 8. Comparison of recommended effects for different reading types.

Fig. 8(a) and Fig. 8(b) show the recommendation results of two social reading scenarios in Arts and Science, respectively. In the Arts RR, the best recommendation accuracy of the proposed model is 97.65%, which is better than 90.23% and 87.65% of Caser, and DeepCrossing. In science RR, the proposed model has the best recommendation accuracy of 97.24%, which is better than the other two models. The best recommendation accuracy of the two models Caser, and DeepCrossing is 93.24% and 91.68 respectively. This shows that the proposed model has the best recommendation in real scenarios.

### B. *Experimental Analysis of Reading Recommendations Model Based on Long-Term Borrowing Readers*

For long-term borrowing readers, the annual readers' borrowing data of a university A in 2022 is still selected for experimental analysis. Before the experimental analysis, it is necessary to filter 698,545 pieces of borrowing data information, select 1000 readers who have borrowed records for more than 10 times, and take the interaction data of the above readers in the last 3 months as the readers' short-term behavior data. The final short-term data set is 24,365 items and the long-term data set is 56,356 items. The initial parameter settings of the experimental model are shown in Table II.

Table II shows the experimental model parameter settings. The short-term sequence length is set to 10, the embedding vector size is set to 32, and the batch processing size is set to 128. Self-attentive sequential recommendation (SASRec) and factorizing personalized markov chains for next-basket recommendation (FPMC) are introduced as test benchmarks. The recall and precision performance of the three RR models are compared, as shown in Fig. 9.

TABLE II. PARAMETER SETTINGS FOR READING RECOMMENDATION MODEL BASED ON LONG TERM BORROWERS

| Parameter indicator type | Numerical value |
|---|---|
| Short term sequence length | 10 |
| Embedding vector dimension | 32 |
| Iterations | 80 |
| The representation vector dimension of books | 16 |
| BATCH_SIZE | 128 |
| Long term borrowing of interactive data | 26545 |
| Short term borrowing interaction data volume | 13654 |

Fig. 9(a) shows the results of RR model recall comparison, with the increase of the number of recommended books, the recall rate of all three models keeps increasing, the best performance is the proposed model with the best recall rate of 0.198, followed by SASRec with 0.179, and the worst is FPMC with 0.175. In the precision rate comparison, with the increase of the number of recommended books, the precision rate of the three models keep decreasing. The best training performance is the proposed model with the precision rate of 0.062 at 60 recommended books, better than the other models. The best training performance is achieved by the proposed model with an accuracy rate of 0.062 when the number of recommended books is 60, which is better than the other models. Finally, root mean squared error (RMSE) and mean absolute error (MAE) are chosen to compare the training effect of different RR models, as shown in Fig. 10.

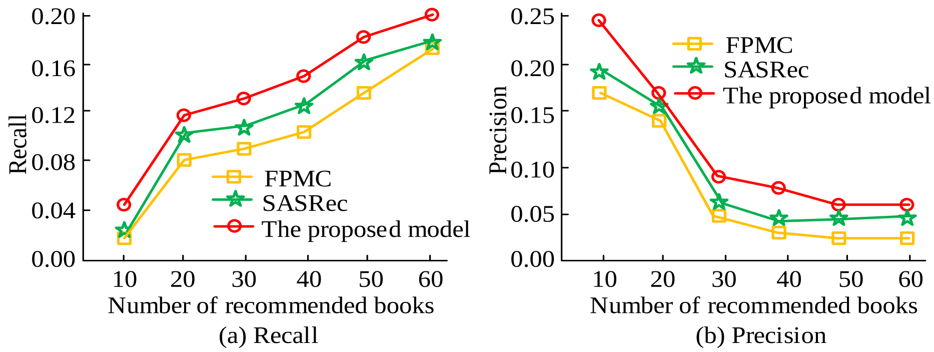



Fig. 9. Comparison of recall and accuracy.

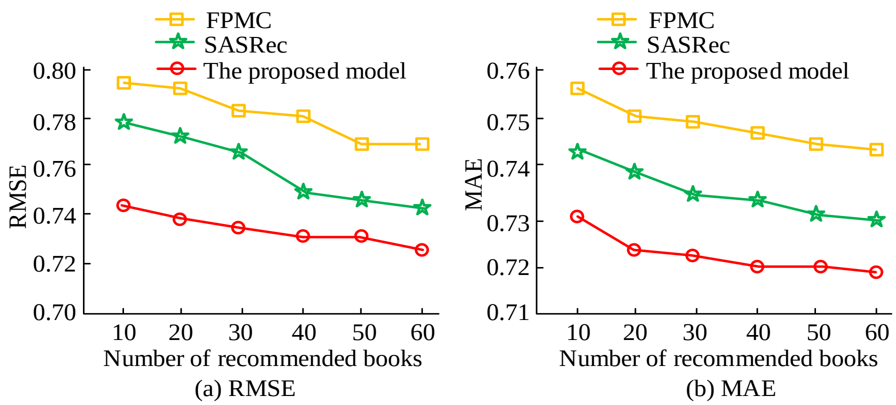



Fig. 10. Comparison results of root mean square error and mean absolute error of the model.

Fig. 10(a) and Fig. 10(b) show the RMSE and MAE training results of the model, respectively. In the RMSE error comparison, the RMSE error of the proposed model decreases gradually as the number of books recommended increases. When the number of recommended books is 60, the RMSE errors of the proposed model, SASRec, and FPMC are 0.731, 0.750, and 0.778, respectively. In the comparison of MAE errors, when the number of recommended books is 60, the proposed model has the smallest MAE error of 0.721, which is better than the other two models. This shows that the proposed model has better RR performance in real scenarios.

## V. Discussion

In recent years, the continuous development of information technology has accelerated the progress of the digital information industry. Moreover, the construction of DL has further strengthened the integration and utilization of resources. At present, recommendation systems are the core of DL construction, including recommendation technologies based on interests, user behavior, and related data. The objective of this study is to furnish users with convenient access to target resources and to enhance their reading experience. Currently, traditional recommendation techniques are mainly based on interest retrieval, which is inferior to fusion of interest and social association data recommendation techniques. In light of the limitations of existing reading recommendation systems in DL, an intelligent recommendation technology is proposed and implemented in the construction of DL, yielding promising results.

The technology proposed by the research considered the reading needs of users in multiple scenarios, such as using interest as the main recommendation technique in regular reading. Similar technologies such as Caser and DeepCrossing were selected for comparison. In the performance loss comparison, Caser and DeepCrossing were 5.26 and 7.32, respectively, while the research model was only 1.85. Comparing with study [5], the loss was 2.58. In addition, in social scenario-based recommendation, the recommendation accuracy of the research model was above 95%, which was better than similar Casers, DeepCrossing and 92.35% in study [5]. It can be concluded that the research model had good application effect in reading recommendations based on multiple interests. For long-term borrowing users, it was not possible to effectively recommend them based on interest data. The research mainly considered users' long-term borrowing data and judged their short-term borrowing interests based on their recent borrowing data. By integrating the above information, reading recommendations for long-term borrowing users could be achieved. In actual training, the recall and accuracy performance of similar models were compared separately. The recall rate of the research model was 0.198, while the SASRec and FPMC of similar models were 0.179 and 0.175, respectively. The research model performed better. In addition, the technology from a study [7] was introduced for comparison, and its recall rate was 0.182. Finally, in the comparison of RMSE recommendation errors, the proposed model, SASRec, and FPMC were 0.731, 0.750, and 0.778, respectively, while the study [7] had a value of 0.745. This indicated that the overall error of the research model was lower and the recommendation effect was significantly better than similar techniques.

Compared to similar technologies, research technology considered user target needs from both short and long-term perspectives. It focused on users' short-term interests and reading behaviors, which could more accurately determine users' potential reading behaviors and needs. This is something that similar technologies do not possess. Moreover, experimental evidence has demonstrated that the research technology considers user needs from multiple perspectives and that its final reading recommendation service is superior to that of similar technologies. Furthermore, this technology has gained recognition from users.

In conclusion, the study has demonstrated through experimentation that the proposed reading recommendation model, based on diverse interest readers and long-term borrowing readers, exhibits high levels of recommendation accuracy, recall rate, precision, and other indicators. Compared with similar technologies, it has better recommendation accuracy and error. Moreover, its application in DL will accelerate the digital development of the book industry and improve the user reading experience.

## VI. Conclusion

Recommendation technology has a wide range of important applications, improving the utilization of massive information by users. To enhance the RR effect of library books, targeted reading models are proposed for two types of reading populations, respectively. For MIR, readers' short-term behavioral preference features and SSF are mainly considered, and the score is calculated by fusing the features to realize content recommendation. For borrowers with long-term goals, their short-term and long-term interests are extracted from the readers' preferences. The scores are then integrated through the self-attention mechanism to provide recommendations for content. In MIRRR, the logarithmic losses of various models were compared and found that the proposed model, Caser, and DeepCrossing had losses of 1.85, 5.26, and 7.32, respectively. Additionally, when compared the accuracy of liberal arts RR, it was found that the proposed model achieved a better recommended accuracy of 97.65% as compared to 90.23% and 87.65% achieved by Caser and DeepCrossing, respectively. In the long-term borrower reader RR experiment, the proposed model achieved the highest recall with a score of 0.198, surpassing SASRec and FPMC, which achieved scores of 0.179 and 0.175, respectively. Moreover, in the precision rate ratio test, the proposed model outperformed Caser and DeepCrossing, exhibiting the best precision rate of 0.062. Finally, the study compared the RMSE and MAE errors of various models, revealing that the proposed model had a more effective recommendation outcome in real book reading scenarios compared to SASRec and FPMC, with RMSE errors of 0.731, 0.750, and 0.778, respectively. However, there are also shortcomings in the research. DL do not consider reader and book context information in their recommendations, including book reviews, book authors, etc. It is imperative that future research endeavors prioritize the development of this capability. At the same time, DL can strengthen the free management and sharing of resources in future construction, and improve the utilization efficiency of resources.

## References

[1] Cui Z, Xu X, Fei X U E, Cao Y. Personalized recommendation system based on collaborative filtering for IoT scenarios IEEE Transactions on Services Computing, 2020, 13(4): 685-695.

[2] Huang Z, Xu X, Zhu H, Zhou MC. An efficient group recommendation model with multiattention-based neural networks IEEE Transactions on Neural Networks and Learning Systems, 2020, 31(11): 4461-4474.

[3] Guo Q, Zhuang F, Qin C, Xie X. A survey on knowledge graph-based recommender systems IEEE Transactions on Knowledge and Data Engineering, 2020, 34(8): 3549-3568.

[4] Liang X, Yin J. Recommendation algorithm for equilibrium of teaching resources in physical education network based on trust relationship. Journal of Internet Technology, 2022, 23(1): 133-141.

[5] Anwar T, Uma V. CD-SPM: Cross-domain book recommendation using sequential pattern mining and rule mining. Journal of King Saud University-Computer and Information Sciences, 2022, 34(3): 793-800.

[6] Swaminathan B, Palani S, Vairavasundaram S, Kotecha K. IoT-driven artificial intelligence technique for fertilizer recommendation model IEEE Consumer Electronics Magazine, 2022, 12(2): 109-117.

[7] Yu K, Guo Z, Shen Y, Wang W. Secure artificial intelligence of things for implicit group recommendations IEEE Internet of Things Journal, 2021, 9(4): 2698-2707.

[8] Anwar K, Siddiqui J, Sohail S S. Machine learning-based book recommender system: a survey and new perspectives International Journal of Intelligent Information and Database Systems, 2020, 13(4): 231-248.

[9] Ko H, Lee S, Park Y. A survey of recommendation systems: recommendation models, techniques, and application fields Electronics, 2022, 11(1): 141-155.

[10] Cong H. Personalized recommendation of film and television culture based on an intelligent classification algorithm Personal and Ubiquitous Computing, 2020, 24(6): 165-176.

[11] Da'u A, Salim N. Recommendation system based on deep learning methods: a systematic review and new directions Artificial Intelligence Review, 2020, 53(4): 2709-2748.

[12] Dong S, Sun J, Mao Z, Wang L. A guideline for homology modeling of the proteins from newly discovered betacoronavirus, 2019 novel coronavirus (2019-nCoV) Journal of medical virology, 2020, 92(9): 1542-1548.

[13] Luo F, Ranzi G, Kong W, Liang W. Personalized residential energy usage recommendation system based on load monitoring and collaborative filtering IEEE transactions on industrial informatics, 2020, 17(2): 1253-1262.

[14] Zhou X, Li Y, Liang W. CNN-RNN based intelligent recommendation for online medical pre-diagnosis support IEEE/ACM Transactions on Computational Biology and Bioinformatics, 2020, 18(3): 912-921.

[15] Yang F, Yao Y. A new regulatory framework for algorithm-powered recommendation services in China Nature Machine Intelligence, 2022, 4(10): 802-803.

[16] Zhou X, Liang W, Kevin I, Wang K. Deep correlation mining based on hierarchical hybrid networks for heterogeneous big data recommendations IEEE Transactions on Computational Social Systems, 2020, 8(1): 171-178.

[17] Manoharan D S, Sathesh A. Patient diet recommendation system using K clique and deep learning classifiers Journal of Artificial Intelligence and Capsule Networks, 2020, 2(2): 121-130.

[18] Chekroud A M, Bondar J, Delgadillo J, Delgadillo J. The promise of machine learning in predicting treatment outcomes in psychiatry World Psychiatry, 2021, 20(2): 154-170.

[19] Erdenebat B, Bud B, Kozsik T. Challenges in service discovery for microservices deployed in a Kubernetes cluster–a case study Infocommunications Journal, 2023, 15(1): 69-75.

[20] Hebbi C, Mamatha H R. Comprehensive dataset building and recognition of isolated handwritten kannada characters using machine learning models//Artificial Intelligence and Applications. 2023, 1(3): 179-190.

[21] Preethi P, Mamatha H R. Region-Based Convolutional Neural Network for Segmenting Text in Epigraphical Images//Artificial Intelligence and Applications. 2023, 1(2): 119-127.