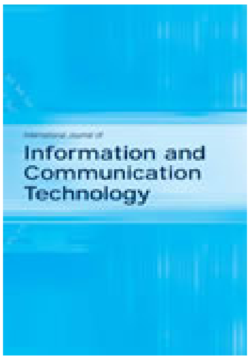

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An ELM-based approach to promoting reading of library books

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An ELM-based approach to promoting reading of library books

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Abstract: Personalised book recommendations have become a major difficulty given the fast growth of digital resources and online libraries. This work presents a hybrid recommender system based on extreme learning machine (ELM) to improve the accuracy and diversity of book recommendations in libraries. Combining content-based filtering and collaborative filtering, the system uses the advantages of both techniques above their respective restrictions. The suggested system effectively handles extensive user behaviour and book information by including ELM, which provides fast training and high generalising capacity. Comparatively to conventional approaches, experimental data reveal that the hybrid model considerably increases suggestion accuracy, diversity, and coverage. Key parameters used in evaluation of the system include precision, recall, variety, and coverage, therefore proving its possible use in library book recommendation systems.

Keywords: extreme learning machine; ELM; hybrid recommender system; library books; personalised book recommendations.

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1 Introduction

Libraries, as a vital venue for knowledge distribution and learning, are always developing and reinventing their service functions and management approaches in line with the fast growth of information technology (Ifijeh and Yusuf, 2020). Given the backdrop of digitisation and intelligence, how best to suggest library books and improve readers' tailored reading experience becomes a crucial question for library information service (Kucirkova and Cremin, 2018). Particularly in cases of a lot of books and complicated readers' wants, how to precisely propose books that satisfy readers' preferences is a difficult problem. Library book recommendation system has also progressively become a research hotspot in the academic and technical domains.

Two basic types of algorithms form the foundation of present library book recommendation systems: content-based filtering (CBF) and collaborative filtering (CF). While CBF depends on the book's attribute information such title, author, category, etc. to suggest content (Thorat et al., 2015), CF forecasts the user's interest in an unaltered book based on the user's history behaviours and ratings information (Herlocker et al., 2004). Each of these two conventional methods has major drawbacks, though; CF is prone to data sparsity and cold-start issues while CBF overlooks user similarities and cannot fairly represent their potential interests. Consequently, a single recommendation system is usually not able to satisfy the varied and particular needs of consumers.

In order to solve these problems, hybrid recommender system came into being (Karga and Satratzemi, 2018). Hybrid Recommender System improves recommendation accuracy and diversity by combining multiple recommendation methods, using the advantages of different algorithms to make up for the shortcomings of a single method (Walek and Fajmon, 2023). In the field of library book recommendation, hybrid recommendation methods have become an effective solution. Especially in recent years, Extreme learning machine (ELM), as an efficient learning algorithm (Wang et al., 2021), has been widely used in recommender systems due to its superior training speed and strong generalisation ability (Ding et al., 2015). ELM greatly simplifies the training process of traditional neural networks and improves the training efficiency of the model by randomly generating the connection weights from the input layer to the hidden layer. Therefore, the hybrid recommender system combined with ELM shows a better application prospect in library book recommendation.

The main innovations include:

1. Combining ELM with hybrid recommendation approach: This study overcomes the restrictions of a single recommendation system by means of ELM. Conventional recommender systems rely just on CF and CBF. ELM's training efficiency and generality help it to rapidly learn and optimise difficult recommendation tasks. It is relevant as this mix increases system training speed and suggestion accuracy.

2. Optimising diversity and personalisation of recommendation results: We describe in this study a hybrid recommender system considering recommendation outcome diversity and customisation requirements. By offering reliable recommendations and broadening users' options, a weighted combination of several recommendation systems increases user satisfaction.

3. ELM-based efficiency and scalability: By minimising computational overhead, ELM lets the recommendation system in this study examine a lot of book and user data faster than conventional neural network training. The system can manage growing user demand and book counts as it is scalable. With this capability, the recommender system gets more adaptable and successful.

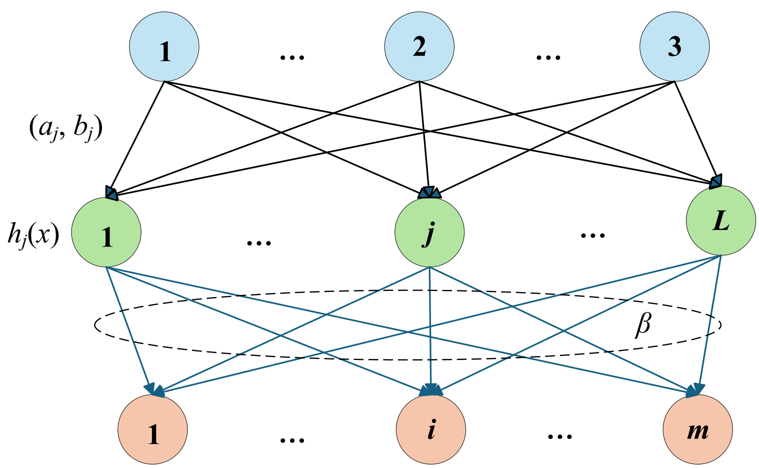
To address the challenges of personalised book recommendations in libraries, this study introduces ELM and hybrid recommender systems as innovative solutions. ELM is a powerful learning algorithm known for its fast training speed and strong generalisation capabilities, making it suitable for processing large-scale user behaviour data. Hybrid recommender systems, on the other hand, combine multiple recommendation techniques to overcome the limitations of single-method approaches. By integrating ELM with a hybrid recommendation strategy, this research aims to enhance the accuracy, diversity, and coverage of book recommendations, thereby improving the overall user experience in library settings.

2 Relevant technologies

2.1 Theory of ELM

ELM is an SLFN single layer feedforward neural network quick learning method (Zhu et al., 2005). ELM is mostly distinguished by the random generation at initialisation of the weights and biases of the hidden layers, which remain constant. It does not take part in the training process; least squares calculates just the output layer weights. See Figure 1, ELM shows notable benefits in training speed because to its non-iterative and non-tuning characteristic.

Figure 1 ELM's network structure (see online version for colours)



In a typical SLFN, given a training dataset $\{(x_i, t_i)\}_{i=1}^{N}$, where $x_i \in \mathbb{R}^n$ denotes the input vector and $t_i \in \mathbb{R}^n$ denotes the target output. the output of the SLFN can be expressed as:

$$f(x) = \sum_{j=1}^{L} \beta_j h_j(x) \tag{1}$$

where L is the hidden layer's node count; $h_j(x)$ is the output of the j-th hidden layer node; β_j is the weight of the hidden layer towards the output layer.

An activation function can help ELM to depict the output of a hidden layer node:

$$h_j(x) = g\left(a_j \cdot x + b_j\right) \tag{2}$$

where $g(\cdot)$ is the activation function (e.g., Sigmoid or ReLU, etc.; a_j and b_j are the input weight and bias of the j-th hidden node, respectively. ELM's secret is to randomly create these hidden-layer parameters a_j and b_j and not change them during training, hence improving the computational efficiency and simplifying the network's topology.

The ELM creates a hidden layer output matrix H of the following type to help to compute the outputs of every training sample:

$$H = \begin{bmatrix} h_1(x_1) & h_2(x_1) & \dots & h_L(x_1) \\ h_1(x_2) & h_2(x_2) & \dots & h_L(x_2) \\ \vdots & \vdots & \ddots & \vdots \\ h_1(x_N) & h_2(x_N) & \dots & h_L(x_N) \end{bmatrix}_{N \times L} \tag{3}$$

The activation output of all samples through the hidden layer is described by this matrix H; the ELM output can be expressed as a matrix form $H\beta = T$, where T is the target output matrix and β is the weight vector from the hidden layer to the output layer (Liu et al., 2019).

The ELM minimising the error function defines the weight vector β of the output layer, therefore obtaining the optimal output.

$$\min_{\beta} \|H\beta - T\|^2 \tag{4}$$

We can immediately find the ideal β by least squares approach:

$$\beta = H^{\dagger}T \tag{5}$$

in which $H^{\dagger}$ is H's generalised inverse matrix. By means of it, the weights of the output layer can be rapidly solved without iteration, therefore avoiding the tiresome training process.

The generalised inverse matrix is computed in connection between the number of nodes L in the hidden layer and the number of samples N. Calculated as the generalised inverse matrix L:

$$H^{\dagger} = \left(H^T H\right)^{-1} H^T \tag{6}$$

The generalised inverse matrix therefore is given by N:

$$H^{\dagger} = H^T \left(HH^T\right)^{-1} \tag{7}$$

Especially appropriate for large-scale data scenarios requiring fast reaction and little computational overhead, this direct method bypasses the iterative parameter setting in the conventional backpropagation algorithm and considerably increases the training efficiency.

ELM's effective training speed and simple parameter tuning approach clearly benefits huge data and real-time application scenarios (Frances-Villora et al., 2018). ELM's fast learning capacity is appropriate for processing large-scale reader behaviour data and can efficiently cope with the challenges of great data scale and different aspects for the purposes of book reading promotion in libraries. ELM's good generalisation capacity helps to capture readers' possible interest patterns and optimise the suggestion strategy, so supporting tailored and accurate reading promotion services. This also enables the promotion model to get strong prediction performance.

The integration of ELM into library book reading promotion methods is pivotal for enhancing the efficiency and accuracy of book recommendations. ELM's rapid training capability and robust generalisation make it an ideal solution for handling the vast and complex datasets typical of library environments. By incorporating ELM, the recommendation system can quickly adapt to new user behaviours and book additions, ensuring that the recommendations remain relevant and diverse. This approach not only streamlines the recommendation process but also significantly improves the user experience by providing tailored book suggestions that align with individual preferences.

2.2 Hybrid recommender system

Combining several recommendation algorithms, hybrid recommender systems help to compensate for the limitations of a single approach and raise recommendation accuracy (Kaššák et al., 2016). Common recommendation approaches in personalised recommendation situations are CF and CBF.

Based on the interaction between users and objects, CF is a recommendation system By computing user similarity, user-based collaborative filtering forecasts user ratings for unobserved items; the formula is stated as:

$$\hat{r}_{u,i}^{CF} = \frac{\sum_{v \in N_u} \mathrm{sim}(u, v) \cdot r_{v,i}}{\sum_{v \in N_u} |\mathrm{sim}(u, v)|} \tag{8}$$

where sim(u,) is the similarity between user u and v; N_u is the set of users comparable to user u, $r_{v,i}$ is the rating of item i by user v.

Conversely, CBF bases recommendations on the characteristics of the products and the prior preferences of the user. The recommender system's rating prediction formula assuming x_i is the feature vector of item i and y_u is the interest vector of user u is:

$$\hat{r}_{u,i}^{\mathrm{CBF}} = y_u \cdot x_i^T \tag{9}$$

Both strategies have restrictions, though. Whereas content-based suggestions may produce too homogeneous and lack diversity, collaborative filtering is prone to cold-start and scant data difficulties. Hybrid recommender systems were developed to help tackle these issues; see Figure 2.

Combining the benefits of several recommendation techniques helps hybrid recommender systems go beyond the constraints of one method. Typical hybrid techniques include on weighted summation, cascading and hybrid selection.

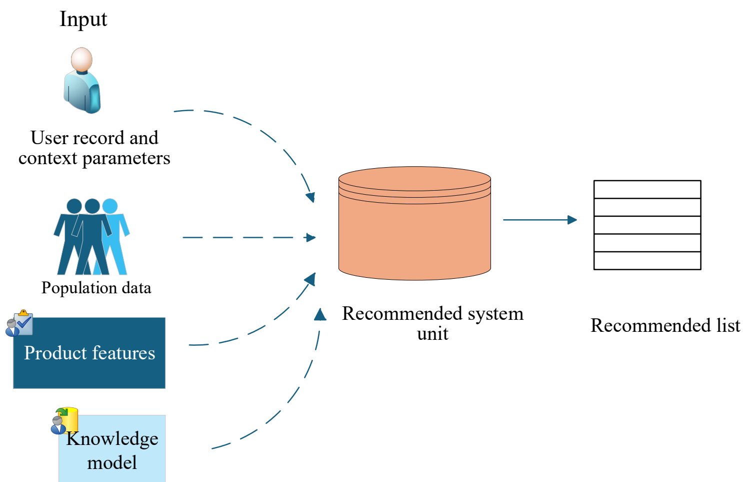
The weighted summing approach weights and aggregates the outcomes of several recommendation strategies to generate a final recommendation score (Kong et al., 2019):

$$\hat{r}_{u,i} = \alpha \cdot \hat{r}_{u,i}^{\mathrm{CF}} + (1-\alpha) \cdot \hat{r}_{u,i}^{\mathrm{CBF}} \tag{10}$$

where α is a weighting factor that controls the proportion of fusion between the two.

First producing candidate items using one approach, the cascade technique then optimises the candidate items using another approach. For instance, some prospective products can be screened by content-based recommendation initially, and then these items can be rated via collaborative filtering to ultimately produce recommendation results.

Figure 2 Hybrid recommendation system structure (see online version for colours)



Effective overcoming of the cold-start issue and enhancement of the accuracy and diversity of recommendation outcomes are made possible by hybrid recommendation approaches (Panda and Ray, 2022). Further enhancing the fusion effect is the combination of the hybrid recommendation system with ELM model (Li et al., 2020). ELM's training generates the hidden layer output H by use of random weights W and the activation function σ, equation:

$$H = \sigma(WX + b) \tag{11}$$

After that, linear regression determines the weight β of the output layer, thereby producing the final recommendation score:

$$\hat{r}_{u,i} = \beta^T H \tag{12}$$

Effective integration of the outputs of several recommendation approaches and enhancement of the general prediction accuracy of the system depend on ELM's quick training and strong nonlinear modelling capacity.

3 Design of a personalised book recommendation system for libraries based on ELM

Based on ELM model, this recommender system combines CBF and CF approaches to hybrid recommendation strategy increase recommendation accuracy and diversity. Data collecting and preprocessing, feature extraction, ELM model training and optimisation, hybrid recommendation strategy, recommendation result generation and assessment module makes up the system's general framework.

3.1 Data collection and pre-processing

The whole recommendation system starts with data collecting and preparation (Cho et al., 2002). First of all, the system must gather book content – e.g., titles, authors, labels, categories, etc., – as well as user past behaviour – e.g., borrowing records, rating records, etc.). Following this, the gathered data is denoised, cleaned, either normalised or otherwise for next model development. The formula is as follows:

$$X_{norm} = \frac{X - \mu}{\sigma} \tag{13}$$

where X is the original data; μ is the mean; σ is the standard deviation; X_{norm} is the data in normal form.

3.2 Feature extraction

Mostly transforming user behaviour data and book content data into features fit for ELM model processing is the feature extraction module (Cambria et al., 2015). Usually for CF techniques, the feature matrix is based on user-item interaction behaviour, such rating or borrowing history. The features for CBF come from the metadata of the book (e.g., categories, labels, writers, etc.).

Assuming book b_i's content feature vector is $f_i = (f_{i1}, f_{i2}, \ldots, f_m)$ and user u_j's behavioural feature vector is $h_j = (h_{j1}, h_{j2}, \ldots, h_{jn})$, one may write:

$$X = [f_1, f_2, \ldots f_N] \tag{14}$$

where N is the book count; X is a matrix with all the book content elements. Likewise, one may represent the user feature matrix H as:

$$H = [h_1, h_2, \ldots h_M] \tag{15}$$

where H is the user behaviour data matrix; M is the user count.

3.3 EML model training and optimisation

Learning the mapping link between input features and target outputs helps ELM to produce effective recommendation outcomes. Under ELM's training, least squares solves the output layer weights while the input layer weights of the model are randomly produced.

One may represent the ELM model's output by means of the following equation:

$$Y = H \cdot W_{out} \tag{16}$$

where W_{out} is the output weight matrix; H is the input data matrix comprising user and object characteristics; Y is the projected ELM model output.

Often employed are regularisation techniques to prevent overfitting and enhance the generalisation of the model. Typical regularisation terms used are:

$$L_{reg} = \lambda \|W_{out}\|^2 \tag{17}$$

where λ is a regularisation parameter to control the size of the weights.

3.4 Hybrid recommendation strategy

The blended recommendation comes out to be Y_{CF} assuming the CF advice produces Y_{CF} and Y_{CBF} assuming the CBF recommendation produces Y_{CBF}.

$$Y_{mixed} = w_{CF} \cdot Y_{CF} + w_{CBF} \cdot Y_{CBF} \tag{18}$$

where w_{CF} and w_{CBF} respectively satisfy the requirements and represent the weights of content-based recommendation results and collaborative filtering correspondingly:

$$w_{CF} + w_{CBF} = 1 \tag{19}$$

Either cross-valuation or experimental optimisation of the weights w_{CF} and w_{CBF} will help to increase the system's recommendation efficacy.

3.5 Recommendation result generation

The hybrid recommendation strategy's estimated final ratings help to create the user's suggested book list (Burke, 2002). The technology will specifically arrange the results based on user rating forecast and suggest the best rated books to her. By adding some diversity measures, one can modify the variety of the recommendation results and prevent over-concentration on a given category of books.

The recommendation list R_j for every user u_j can be written as follows equation:

$$R_j = Top\text{-}k(Y_{mixed}) \tag{20}$$

where Y_{mixed} is the weighted mixed recommendation score; Top-k is the procedure of choosing among them the top k recommended books.

3.6 Evaluation and feedback

Four often used metrics for recommender system evaluation are selected in order to assess the effectiveness of the proposed ELM-based hybrid recommender system: root mean square error (RMSE), mean absolute error (MAE), diversity and originality.

The discrepancy between the expected and actual ratings of a recommender system is expressed in RMSE (Silveira et al., 2019). It shows the general accuracy of the recommender system; reduced RMSE values point to improved predicted performance.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(r_i - \hat{r}_i\right)^2} \tag{21}$$

where r_i is the actual rating; $\hat{r}_i$ is the expected rating; N is the book count.

Calculating the mean absolute difference between projected and actual scores, MAE is another measure of accuracy. Like RMSE, a smaller MAE suggests improved predicting ability.

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|r_i - \hat{r}_i\right| \tag{22}$$

Diversity quantifies the variation among suggested products (Brown et al., 2005). High diversity in library book recommendations guarantees avoid homogeneity of recommendation results and promotes user happiness. Calculating the similarity between suggested books and averaging them with the formula helps one assess the variety of recommendations:

$$Diversity = 1 - \frac{1}{N(N-1)} \sum_{i \neq j} \mathrm{sim}(i, j) \tag{23}$$

where sim(i, j) is the recommended book i's and j's similarity. High diversity of a recommender system will expose the user to many book categories, therefore raising their interest in reading.

Novelty measures the products advised to the user's originality. A recommender system should give consumers a specific percentage of fresh books to inspire discovery. In library book recommendations, novelty is particularly crucial since it helps readers come across fresh reading materials. The popularity of a book allows one to determine novelty using the formula:

$$Novelty = \frac{1}{N} \sum_{i=1}^{N} \log\left(1 + \frac{1}{f(i)}\right) \tag{24}$$

Higher frequency items indicate lower novelty; $f(i)$ is the frequency of recurrence of item i in the dataset. High novelty systems suggest books that the user would find interesting even though they are seldom borrowed.

4 Experimental results and analyses

4.1 Data sets

Real user borrowing history and book metadata abound in the dataset utilised in this research from a sizable library. The dataset's information spans several angles, including users' borrowing past, book classification and metadata, and user ratings. Table 1 shows the particular dataset organisation and information.

The dataset comprises 10,000 books and 50,000 users; while metadata including book categories and authors supports content-based recommendations, user behavioural data (ratings and number of times borrowed) is used for collaborative filtering recommendations. Combining CF and CBF techniques lets the recommender system generate unique and varied book recommendations.

4.2 Ablation experiments

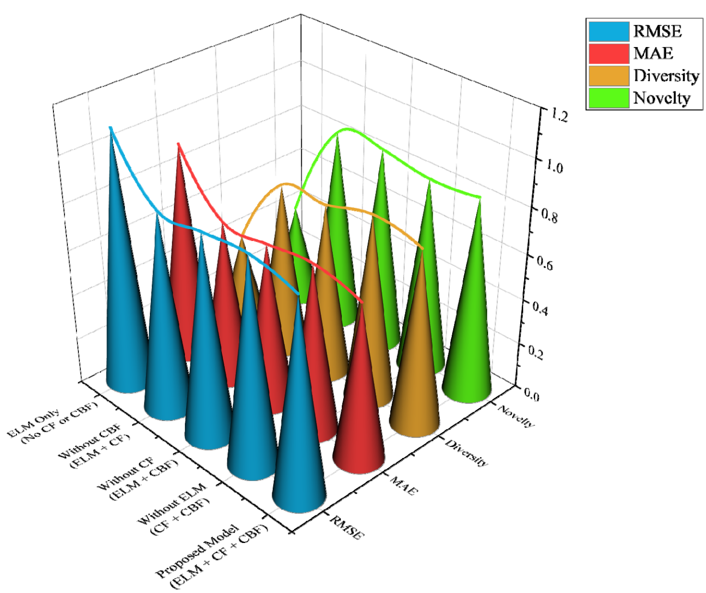
The ablation experiment aims to assess, by eliminating various system components (e.g., CF, CBF, ELM, etc.), their effects on the recommender system performance. With data comprising user ratings, borrowing history, and information including the book's genre and author, our dataset consists of 50,000 users and 10,000 volumes offers the required basis for collaborative filtering and content-based recommendations.

Table 1 Dataset statistical information

Field	*Description*
UserID	A unique identifier for each user, used to link their borrowing history and ratings.
BookID	A unique identifier for each book, used to link the book's detailed information.
Title	The title of the book.
Category	The category of the book, such as 'Literature', 'Technology', 'History', etc.
Author	The author(s) of the book.
BorrowCount	The number of times a book has been borrowed, reflecting its popularity.
Rating	The user's rating of the book, typically ranging from 1 to 5, representing their level of preference.
BorrowDate	The date the user borrowed the book, providing temporal information for the book's borrowing history.
Tags	Tags assigned to the book by users or the system, such as "Sci-Fi," "Classic," etc., to help enhance content-based recommendations.

First we create a whole model with all components in the experimental design, where ELM, CF, and CBF-based cooperation generates book recommendations. We next eliminate each element in turn and examine the model's performance upon removal. When removing collaborative filtering, the system uses only content-based recommendation and ELM; when removing content-based recommendation, the system uses collaborative filtering and ELM; and when removing ELM, the system uses only collaborative filtering and content-based recommendation. Furthermore, we analyse the impact of ELM when it runs by itself by comparing the models employing simply ELM. Figure 3 shows the experimentally obtained results.

Figure 3 Results of ablation experiments (see online version for colours)

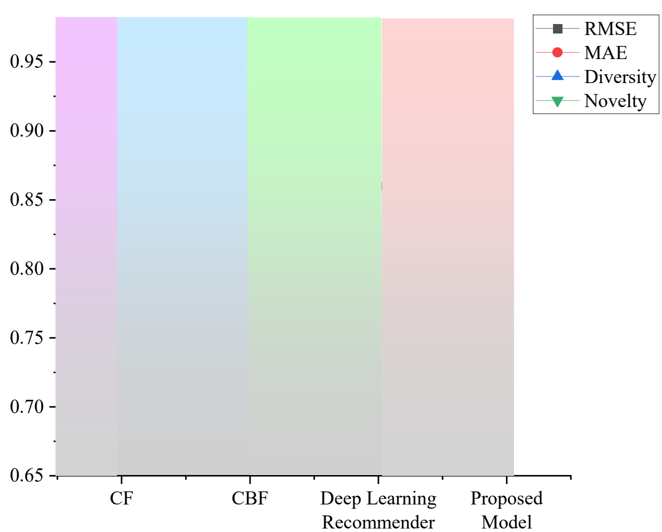


With regard to required accuracy (RMSE: 0.845, MAE: 0.675), variety (0.763), and novelty (0.852), the testing results revealed that the Proposed Model (ELM + CF + CBF) performed best. Eliminating ELM produced a little decline in accuracy (RMSE: 0.894, MAE: 0.725) but a gain in diversity (0.802) and novelty (0.835). Accuracy and diversity and originality altered when deleting content-based suggestions or collaborative filtering, implying that these two methods have complimentary functions in raising recommendation quality. Using just ELM drastically reduced the accuracy and diversity of recommendations, suggesting that ELM is less successful employed alone. A hybrid recommender system's components taken together are complimentary and absolutely essential.

4.3 Comparative experiments

We run comparative studies with many typical recommendation algorithms to assess the benefits of ELM's hybrid recommender system in terms of accuracy, efficacy, and diversity. These comprise deep learning recommendation systems, CBF, and CF. While content-based recommendation matches the metadata of objects (e.g., category of books, authors, etc.), collaborative filtering approaches produce recommendations by computing similarities between users and depend just on previous interaction data between users. Deep learning recommendation systems automatically learn possible user and item features from data by means of neural network models.

Figure 4 Results of comparative experiments (see online version for colours)



Using the same dataset as the ablation studies, our tests include rating data for 10,000 books and 50,000 consumers together with borrowing histories. Deep learning methods are trained using neural network architectures such as multilayer perceptron machines (MLPs), and a hybrid recommendation system based on ELM combines collaborative filtering and content-based recommendation by optimising the ELM model. Every method was trained separately; collaborative filtering calculates similarity based on the user-item interaction matrix, content-based recommendation calculates similarity using item metadata (e.g., categories and labels), deep learning methods are trained using neural network architectures. Figures 4 illustrate the experimental outcomes.

The results clearly reveal that in all evaluation criteria the ELM-based hybrid recommender system displays more important benefits. Particularly, the values of RMSE and MAE are 0.845 and 0.675 respectively, which are much lower than those of collaborative filtering (0.912, 0.855) and content-based recommendation (0.880, 0.725), so indicating that the present model has a considerable increase in the accuracy of recommendation. The ELM-based hybrid recommender system shows that it can give consumers more varied book recommendations since on the variety metric it scores 0.763, higher than the other techniques. Further enhancing the innovativeness of the recommender system is the present model's 0.852 novelty score, which is much higher than that of previous techniques and indicates that it can suggest more books that users have not encountered.

In terms of accuracy, diversity, and novelty, the hybrid recommendation system based on ELM beats content-based recommendation and deep learning recommendation approaches generally as well as conventional collaborative filtering. This demonstrates particularly great benefits in terms of suggestion accuracy and originality since ELM may efficiently raise the general performance of recommender systems by integrating content-based recommendation and collaborative filtering.

5 Conclusions

In this work, we offer a library book recommendation system based on ELM and hybrid recommendation algorithms, which combines CF and CBF approaches thereby improving the accuracy and diversity of tailored recommendations. First confirmed in the experiments, the effect of each recommendation strategy on the system performance is first ablation experiments; the results show that the hybrid recommendation method considerably increases the quality and accuracy of recommendations over the single collaborative filtering and content-based recommendation methods. Furthermore verified are the benefits of the suggested approach in terms of accuracy and novelty by means of comparative studies with conventional recommendation systems.

Still, there are certain restrictions even if the suggested recommender system shows good performance in trials. On the one hand, especially in the cold-start phase, data sparsity presents a significant difficulty for recommender systems. Lack of enough historical data causes the suggestion results to be poor when the system encounters new users or books. In these situations, the accuracy and diversity of recommendations are nevertheless influenced even if hybrid recommendation strategies mix CF and CBF. Furthermore, content-based recommendation systems depend on book metadata – e.g., categories, authors, publication dates, etc., – which does not properly reflect the intricate relationships between books and hence may not fairly represent users' possible preferences for particular books.

On the other hand, while handling big-scale data ELM models might have some computational restrictions. ELM has high efficiency and good generalisation ability during the training process; however, when facing a lot of user and book data, the computation time and memory consumption during the training process will considerably increase, which may affect the performance of the system especially in resource-limited environments. Concurrently, the weighting and fusing techniques of current hybrid recommendation systems could not yet be ideal and might not fully exploit the benefits of separate recommendation algorithms, therefore influencing the outcome of recommendations.

To address the above limitations, future research can be improved and extended in the following ways.

1. Solving the data sparsity problem can boost recommender system performance: Future studies could include user behaviour data (browsing logs, click records, social network information, etc.) to improve the user profile and lower the cold-start issue. Suggestion accuracy and distinctiveness are enhanced outside of data sources by expert and social book recommendations.

2. Future ELM variants can be more efficient: Combining distributed computing architectures – e.g., Hadoop, Spark, etc., – will boost system responsiveness and scalability while expediting huge data processing and model training. As hardware technology develops, GPU acceleration could become indispensable for raising ELM training efficiency.

3. Future recommender systems should dynamically update user profiles and models: Long-term user behavioural data enables more intelligent models to dynamically change the suggestion method, therefore enabling the system to react to user interests. The recommender system with reinforcement learning can dynamically change its recommending strategies.

4. Future study should additionally optimise hybrid recommendation methods: Experiment with different recommendations including fusion, intelligent weighing, graph neural networks, and deep learning-based collaborative filtering. An adaptive weighing mechanism modifies the fusion method depending on the advantages of several recommendation systems to raise suggestion accuracy.

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