Research Article

Personalized Intelligent Recommendation Algorithm Design for Book Services Based on Deep Learning

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Machine learning is one of the important branches of artificial intelligence, which provides new technical means for analyzing users, understanding users, and gaining insight into users. The framework of the personalized intelligent service model for libraries based on user portraits is proposed, and intelligent technologies such as machine learning are applied to analyze and mine users’ big data, build user portraits, associate users and resources with user portraits, and provide personalized intelligent services for users. The study gives a case study of book recommendation by firstly extracting users’ personalized interests, then applying the plain Bayesian algorithm to discover users’ current personalized potential demands for books, and finally providing users with personalized intelligent book recommendation services that match their interests and mainly meet their potential demands.

1. Introduction

Personalized recommendation is one of the important contents of personalized services in university libraries, and an accurate and in-depth understanding of users is a prerequisite for personalized recommendation. The application of “Internet+,” social networks, and other technologies in libraries has provided multiple sources of data for user analysis, and scholars focus on how to tap into users’ preferences and interests and meet them through recommendation services. In [1], based on library borrowing records, book reading correlations were mined, book category correlation linking relationships was used, and the expression of user personalization patterns to provide personalized book recommendation services for users in terms of both long-term and short-term interests was proposed. The contextual information of library users for collaborative filtering recommendation oriented to big data was integrated [2]. Batmaz et al. [3] provided personalized recommendation service for users based on their social behavior by analyzing the social closeness among users, resource usage, and recent preference factors of users. Khan et al. [4] proposed a reading recommendation method based on social network analysis to discover users’ diverse interests and then provided thematically diverse reading recommendation services. Sengupta et al. [5] applied SOM neural network to cluster and optimize users’ web access behavior, identify users’ interest points, and then provide topic recommendation, book recommendation, and expert recommendation.

Library personalized recommendation services have received a lot of attention and have achieved many results, but still face challenges. With the development of libraries and the increasing variety and complexity of documents, materials, and contents, the problems of “information overload,” “information disorientation,” and “emotion deficit” of personalized recommendation services are still serious. User interest is the explicit expression of emotion, while user demand is the potential implicit emotional need. In reality, the resources recommended to meet users’ explicit interests often do not meet users’ potential needs. For example, a computer science student who checked out the book “Data Structures” shows that he is obviously interested in “data structures,” but if he is recommended such books and literature, he may not need it [6]. He may feel that one copy of Data Structures is enough and he does not need more than a book on algorithmic analysis and design. Yin et al. [7] pointed out that libraries depend on users to exist,
and users’ needs are the basis for the existence and development of libraries. For libraries to retain users and grow their user base, it is not enough to focus on users’ explicit interests, but more important to capture users’ potential needs. Analyzing the current research, the personalization of recommendation is mainly reflected in meeting users’ explicit preferences and interests, but there is a lack of in-depth exploration on how to meet users’ potential needs. In order to realize user-centered recommendation service, it is necessary to study how to meet users’ deep potential needs instead of just explicit interests, so as to finally provide personalized recommendation service with high user satisfaction [8].

2. User Profiling and Personalized Smart Services for Libraries

User profiling is a big data processing method for personalized services in the big data environment [9–12]. Through the mining and refining of massive user data, we can obtain a full picture of users, profile them from different dimensions such as background, characteristics, personality, behavior, and scenario, and connect their needs with services. Wang et al. [13] proposed the model of recommending library resources from single-user and multiuser perspectives, understanding users’ preferences and potential needs based on the outlined user profiles and precisely pushing resource information that meets users’ needs. Li et al. [14] designed a personalized and accurate library knowledge discovery service model based on user profiles, which can effectively improve the library knowledge service experience. Cao et al. [15] used the gesture behavior of users in the mobile reading system to improve the library knowledge service experience.

Smart libraries are the future development model of libraries, and their most significant feature is smart services [16]. According to [17], smart libraries are characterized by ubiquitous place, virtualized space, intelligent means, knowledgeable content, and satisfactory experience.

Wisdom service has the characteristics of efficiency, personalization, and diversification, and personalized service is the core of library wisdom service [18]. The personalized wisdom service is user-centered and user-driven, with the characteristics of contextuality, knowledge, initiative, and real-time, reflecting humanistic sentiment and humanistic wisdom.

User portraits provide powerful tools for insight and analysis of users, and the introduction of user portraits in the personalized service system of libraries can make personalized services more “intelligent” and guarantee the level of intelligent services of libraries.

3. Machine Learning Advantages

Currently, all industries in China are promoting the application of artificial intelligence technology. Through modern information technologies such as artificial intelligence, big data, and the Internet of Things, disruptive reconfiguration and revolutionary transformation of the industry are implemented. Artificial intelligence is much applied in libraries, which has sublimated libraries into a new form of intelligent libraries, and library services are moving towards intelligent services that are adapted to the times [19]. In the context of intelligent services, libraries need to improve the intelligence of traditional recommendation services. Personalized intelligent recommendation service is a further development of traditional personalized service, making full use of intelligent technology, which can not only discover users’ explicit interests but also dig deeper into users’ deeper needs, realize upgraded personalized recommendation service, take the initiative to recommend users the resources they need, meet users’ personalized needs comprehensively and deeply, and improve the utilization rate of resources. Lalitha and Sreeja [20] argued that machine learning-related tools and algorithms can help libraries analyze user behavior data, business processing data, etc., so as to provide more intelligent information services to users. Lin et al. [21] pointed out that personalized recommendation service is one of the important applications of machine learning in the field of library intelligence, and the application of machine learning technology can identify and analyze users’ retrieval, reading, browsing, and other records, then determine the potential information needs and interest preferences of users, and finally provide resources that meet the needs of users.

4. Personalized Intelligent Recommendation Service Solution Based on Machine Learning

This paper designs a personalized intelligent recommendation service solution for libraries based on machine learning, as shown in Figure 1. The solution consists of three parts: library user data collection and cleaning, personalized interest extraction and demand discovery, and personalized intelligent recommendation. Among them, machine learning is mainly used for personalized demand discovery.

4.1. User Data Collection and Cleaning. In the stage of data collection and cleaning, the user data of university libraries are comprehensively collected. In addition to the basic information of users, borrowing records, website behaviors (clicking, browsing, downloading, collecting, etc.), the application of modern information technology in university libraries such as “Internet+,” Internet of Things, and social networks generates various new types of user data [21]. The social data are generated by the social platform of microblog, the teaching system and research system of the university can provide the learning data and research data of teachers and students, and the intelligent terminals such as mobile library, eye-tracking device, and physiological monitor can provide the perceptual data about the user’s situation, physiology, and status. The cleaning, normalization, and integration of heterogeneous user data from multiple sources can lay the foundation for further analysis of user data and personalized interest extraction and demand discovery from them.
4.2. Personalized Interest Extraction and Demand Discovery

4.2.1. Personalized Interest Extraction. Personalized explicit interest is the explicit expression of user’s emotion, while personalized potential demand is the implicit expression of user’s emotion. In the stage of personalized interest extraction and demand discovery, we first obtain the explicit expression of users’ emotion through traditional methods and techniques such as keyword extraction, collaborative filtering, and statistical analysis, extract users’ personalized explicit interest, then carry out implicit emotion mining through machine learning technology to overcome the difficulty of users’ emotion deficiency in library resource recommendation service, and discover users’ personalized potential demand [22].

4.2.2. Machine Learning-Based Personalized Demand Discovery. The personalized demand discovery of library users mainly consists of three parts: current demand mining, demand trend prediction, and demand feature identification. ① Current demand mining: current demand mining aims to discover users’ needs in the current short period of time, such as the current needs of a month or a week, or even the needs in a study or a research scenario. ② Demand trend prediction: users’ demand for resources is often coherent in time and content, and demand trend prediction aims to predict users’ demand in a future period based on their current interests and needs. ③ Demand feature identification: demand feature identification aims to discover the unique needs of an individual user or a group of users. For example, a teacher teaching a data structure course will need a variety of textbooks and teaching reference books for this course, and a team researching library services will especially need books, papers, and other literature on librarianship, library management, patron work, and other related directions.

Machine learning methods such as supervised learning, unsupervised learning, active learning, and semisupervised learning are used to discover individualized needs. Machine learning focuses on algorithms that generate models from data on a computer, i.e., learning algorithms, where empirical data, i.e., training data, are provided to learning algorithms, which can then generate models based on this data, and the models can give judgments and predictions.
when faced with new situations. The user data used for machine learning can be divided into two categories: labeled and unlabeled. Training data with known labels or results are labeled data, and vice versa are unlabeled data. According to whether the training data have labeled information or not, machine learning tasks are broadly classified into two categories: supervised learning and unsupervised learning, which are used to learn from labeled data and unlabeled data, respectively. There are also active learning and semi-supervised learning, which are used to learn from a mixture of labeled and unlabeled data [23]. Various types of machine learning algorithms are applied to perform distribution exploration, relationship exploration, feature exploration, anomaly exploration, speculative exploration, and trend exploration in massive user data to discover the potential personalized needs of university library users in learning, research, and teaching.

(1) Application of supervised learning and unsupervised learning in demand discovery: in supervised learning, the input training data has known labels or results, and the training dataset is trained to build a model, and the model is continuously improved by receiving feedback predictions, and learning stops when the model reaches the desired accuracy on the training data; in unsupervised learning, the training data are not labeled with known results, and the model is generated by exploring the structure present in the data which that may be extracting general rules, reducing redundancy through mathematical processes, or organizing the data through similarity tests [14].

From the perspective of service targets, the target of personalized intelligent recommendation service in university libraries can be an individual user, such as a student or a teacher, or a specific group of users, such as a research team. Unsupervised learning is suitable for identifying special user groups among many users and analyzing their needs. Supervised learning is more advantageous in discovering individual user needs, such as predicting users’ ratings or sentiments about resources and overcoming users’ sentiment deficits. Table 1 lists the commonly used supervised and unsupervised learning algorithms and their applications in personalized demand discovery.

(2) Active learning and semi-supervised learning in requirement discovery: supervised learning requires all training data to have labeled information, while, in reality, many data in libraries are incompletely labeled. For example, when recommending literature to users through a recommendation system, users are asked to mark the desired literature to get feedback on the recommendation results, but not all users are willing to take the time to provide the markers, and those who are willing to do so are often in the minority. It is clearly impractical to organize a large amount of manpower to tag the data [11].

With semi-supervised learning and active learning, large amounts of unlabeled data can also be used for library users’ current demand mining, demand feature identification, demand trend analysis, etc.

4.3. Personalized Intelligent Recommendations. Among many machine learning algorithms, the Naive Bayes Algorithm (NBA) is a simple, effective, and widely used supervised learning algorithm [15]. It is based on probability theory and has the advantages of a solid mathematical foundation, stable classification efficiency, and low sensitivity to missing data. A plain Bayesian classifier trained on recent borrowing record data can predict users’ implicit sentiment towards books and thus discover their current book demand.

The idea and process of naive Bayesian algorithm are as follows [11]. Assuming that sample a of class tag set \( C = \{c_i\} (i = 1, 2, \ldots, n) \) has m attributes \( \{a_j\} (i = 1, 2, \ldots, m) \), the naive Bayesian classifier adopts the “attribute conditional independence hypothesis” to calculate the class conditional probability \( P(c_i|a) \) according to

\[
P(c_i|a) = \frac{P(c_i)P(a|c_i)}{P(a)} = \frac{P(c_i)}{P(a)} \prod_{j=1}^{m} P(a_j|c_i).
\]

(1)

The category marker that maximizes \( P(c_i|a) \) is chosen as the classification of sample a. Since \( P(a) \) is the same for each category, the Bayesian decision criterion is given as

\[
h(a) = \arg \max_{c_i \in C} \prod_{j=1}^{m} P(a_j|c_i).
\]

(2)

The process of training a plain Bayesian classifier is to estimate class prior probabilities based on the training dataset \( P(c_i) \) and to estimate conditional probabilities for each attribute \( P(a_j|c_i) \).

A plain Bayesian algorithm is applied to predict the implicit sentiment of target user U1 on unrated books b5-b8 based on the user-sentiment matrix shown in Figure 2, i.e., to discriminate the implicit sentiment category. The sentiments are classified into “positive” and “negative” categories, and the set of category labels \( C = \{C_1 = \text{positive}, C_2 = \text{negative}\} \). The attribute \( a_j \) (j = 1, 2, . . . , 8) indicates the sentiment towards book \( b_j \). For example, if user U5 has “negative” sentiment towards book \( b_1 \), then the attribute value of user U5 in sample a1 is “negative.” The implicit sentiment of the target user U1 on books b5-b8 is “positive,” “positive,” “positive,” “negative,” and “negative” by the plain Bayesian algorithm. “U1 has positive implicit sentiment towards books b5, b6, and b7,” which means U1 has potential demand for these three books.

5. Application Cases

This paper takes “book recommendation service” as an example and proposes a personalized intelligent recommendation service for university libraries with the application of machine learning.

5.1. User Book Service Information. User U1 is the target user, i.e., the target of the recommended service. Users U2–U5 have
some of the same borrowed books as the target user U1 in the recent month. The book borrowing records of users U2–U5 are analyzed to discover the current needs of target user U1. The users’ ratings of books are shown in Figure 3, and since target user U1 did not borrow books b5-b8, the ratings of b5-b8 are indicated by “?”. If the user’s rating of the book is greater than or equal to 3, the user’s emotion for the book is classified as “positive,” otherwise it is classified as “negative.”

The personalized intelligent book recommendation service takes into account the explicit interests and potential needs of users, first extracting the explicit interests of target users and making recommendations based on them, then applying machine learning algorithms to explore the implicit emotions of target users towards book resources, overcoming the lack of emotions, discovering the current potential needs of users and making recommendations based on them, and finally providing books that match the interests of target users and mainly meet their potential needs.

5.2. Personalized Interest Extraction. As seen in Figure 3, the target user U1 expresses dominant sentiment towards books b1-b4. U1’s sentiment towards books b1, b2, and b3 is positive, indicating that he has dominant interest in these three books, while U1’s sentiment towards book b4 is negative, indicating his lack of interest in book b4, as shown in Table 2.

Table 1: Commonly used supervised and unsupervised learning algorithms and their applications in personalized demand discovery.

| Algorithm classification | Algorithm name | Main application |
|--------------------------|----------------|------------------|
| Supervised learning      | Regression     | Linear regression, logistic regression, polynomial regression, ordinary least squares regression, and multiple adaptive regression (MARS) |
|                          | Decision tree  | ID3, C4.5, random forest, classification, and regression tree (CART) |
|                          | Bayesian learning | Naive Bayes, Bayesian network, and EM algorithm |
|                          | Supervised artificial neural network | BP neural network and radial basis function neural network |
|                          | Support vector machine (SVM) | SVM two-class classification and SVM multiclass classification |
|                          | Rule learning | Pruning optimization and first-order rule learning |
| Unsupervised learning    | Clustering     | K-means clustering, hierarchical clustering, and density-based clustering |
|                          | Unsupervised artificial neural network | SOM network, deep neural network (DNN), deep belief network (DBN), and convolutional neural network (CNN) |
|                          | Probability diagram | Hidden Markov model (HMM) and Markov random field (MRF) topic model |
|                          | Dimensionality reduction | Discriminant analysis, principal component analysis (PCA), and multidimensional scaling analysis (MDS) |

Figure 2: Different recommendation effects.
5.3. Personalized Intelligent Book Recommendation Results.

From Table 2, it can be seen that the target users have personalized interest in books b1, b2, and b3. Three books similar to books b1, b2, and b3 are obtained using collaborative filtering based on books, including “New Data Structure Case Study,” “Data Structure in Detail with Exercises (C Language Edition),” and “Discrete Mathematics and Its Applications,” which are used as interest-based recommendation results. The target users have personalized needs for books b5, b6, and b7. First, the three books b5, b6, and b7 for which the target user U1 has potential demand, i.e., The Python Algorithm Book You Can Read Too, Mastering Data Science Algorithms, and Machine Learning: An Algorithmic Perspective, are added to the recommendation section based on personalized demand in Figure 2. Secondly, three algorithm and machine learning books similar to books b5, b6, and b7, namely, “Python Algorithm Guide,” “Algorithm Design and Analysis for Data Mining,” and “Machine Learning Case Study,” were obtained through collaborative filtering and were also added to the recommendation section based on personalized needs.

The recommendation list shown in Figure 2 not only takes into account the user’s personalized explicit interests but also provides insight into the user’s implicit emotions about the book and recommends books that meet their current personalized potential needs, thus gaining high satisfaction from the target users.

As shown in Figure 4, user profiling can facilitate the optimization of library resources and services. Taking personalized reading customization as an example, the library client can obtain the user’s background, reading experience, reading goals, and behavior based on the user profile and actively customize the content for the user, displaying different reading resources for different users to meet the user’s personalized reading needs. For example, if the target user is a second-year university student, whose user profile is labeled “sophomore,” “computer major,” and “travel,” then we can customize travel reading content for him. Users’ interests and needs change over time, and user profiles are updated accordingly. The content of personalized reading should also be adjusted and updated according to the new user profiles to meet the dynamic changes of users’ interests and needs. For example, if the target user enters the third year, the user profile label is updated to “junior year,”

| Personalized interests and needs | Books | b1 | b2 | b3 | b4 | b5 | b6 | b7 | b8 |
|---------------------------------|-------|----|----|----|----|----|----|----|----|
| Personalized interest           | ✓     | ✓  | ✓  |    |    |    |    |    |    |
| Personalized demand             | —     | —  | —  | —  | ✓  | ✓  | ✓  | —  | —  |

Table 2: Personalized interests and needs of target users.

Figure 3: User-book rating matrix.

Figure 4: Different user recommendation effects.
“computer science major,” and “preparing for graduate school,” and the system can automatically customize and deliver computer science major reading resources for him.

6. Conclusions

This paper discusses the application of machine learning technology to build personalized intelligent recommendation service for libraries and proposes a scheme of personalized intelligent recommendation service based on machine learning, which discovers personalized explicit interests from user data by traditional statistical analysis, collaborative filtering, keyword extraction, etc., and provides users with personalized current demand mining, demand feature identification, and demand trend analysis by machine learning methods. We provide users with intelligent recommendation services that match their interests and meet their potential needs.

Data Availability

The experimental data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest regarding this work.

References

[1] M. Andronie, G. Lăzăroiu, M. Iatagan, C. Ută, R. Stefănescu, and M. Cocosatu, “Artificial intelligence-based decision-making algorithms, Internet of Things sensing networks, and deep learning-assisted smart process management in cyber-physical production systems,” *Electronics*, vol. 10, no. 20, p. 2497, 2021.

[2] J. Wu and Q. Feng, “Recommendation system design for college network education based on deep learning and fuzzy uncertainty,” *Journal of Intelligent & Fuzzy Systems*, vol. 38, no. 6, pp. 7083–7094, 2020.

[3] Z. Batmaz, A. Yurekli, A. Bilge, and C. Kaleli, “A review on deep learning for recommender systems: challenges and remedies,” *Artificial Intelligence Review*, vol. 52, no. 1, pp. 1–37, 2019.

[4] A. Khan, A. Sohail, U. Zahoora, and A. S. Qureshi, “A survey of the recent architectures of deep convolutional neural networks,” *Artificial Intelligence Review*, vol. 53, no. 8, pp. 5455–5516, 2020.

[5] S. Sengupta, S. Basak, P. Saikia et al., “A review of deep learning with special emphasis on architectures, applications and recent trends,” *Knowledge-Based Systems*, vol. 194, Article ID 105596, 2020.

[6] F. García-Sánchez, R. Colomo-Palacios, and R. Valencia-García, “A social-semantic recommender system for advertisements,” *Information Processing & Management*, vol. 57, no. 2, Article ID 102153, 2020.

[7] Y. Yin, Z. Cao, Y. Xu, H. Gao, R. Li, and Z. Mai, “QoS prediction for service recommendation with features learning in mobile edge computing environment,” *IEEE Transactions on Cognitive Communications and Networking*, vol. 6, no. 4, pp. 1136–1145, 2020.

[8] A. Da’u and N. Salim, “Recommendation system based on deep learning methods: a systematic review and new directions,” *Artificial Intelligence Review*, vol. 53, no. 4, pp. 2709–2748, 2020.

[9] B. Shao, X. Li, and G. Bian, “A survey of research hotspots and Frontier trends of recommendation systems from the perspective of knowledge graph,” *Expert Systems with Applications*, vol. 165, Article ID 113764, 2021.

[10] Y. K. Ng and U. Jung, “Personalized book recommendation based on a deep learning model and metadata,” in *Proceedings of the International Conference on Web Information Systems Engineering*, pp. 162–178, Springer, Cham, Switzerland, 2020 January.

[11] J. Saha, C. Chowdhury, and S. Biswas, “Review of machine learning and deep learning based recommender systems for health informatics,” in *Deep Learning Techniques for Biomedical and Health Informatics*, pp. 101–126, Springer, Cham, Switzerland, 2020.

[12] T. B. Lalitha and P. S. Sreeja, “Recommendation system based on machine learning and deep learning in varied perspectives: a systematic review,” in *Proceedings of the Information and Communication Technology for Competitive Strategies (ICTCS 2020)*, pp. 419–432, Jaipur, Rajasthan, December 2021.

[13] L. Wang, C. Zhang, and Q. Chen, “A communication strategy of proactive nodes based on loop theorem in wireless sensor networks,” in *Proceedings of the 2018 Ninth International Conference on Intelligent Control and Information Processing (ICICIP)*, pp. 160–167, IEEE, Wangzhou, China, November 2018.

[14] H. Li, D. Zeng, L. Chen, Q. Chen, M. Wang, and C. Zhang, “Immune multipath reliable transmission with fault tolerance in wireless sensor networks,” in *Proceedings of the International Conference on Bio-Inspired Computing: Theories and Applications*, pp. 513–517, Springer, Singapore, January 2016.

[15] C. H. Cao, Y. N. Tang, D. Y. Huang, G. WeiMin, and Z. Chunjing, “IIBE: an improved identity-based encryption algorithm for wsn security,” *Security and Communication Networks*, vol. 2021, Article ID 8527068, 8 pages, 2021.

[16] X. Tao, C. Zhang, and Y. Xu, “Collaborative parameter update based on average variance reduction of historical gradients,” *Journal of Electronics and Information Technology*, vol. 43, no. 4, pp. 956–964, 2021.

[17] J. Wei, J. He, K. Chen, Y. Zhou, and Z. Tang, “Collaborative filtering and deep learning based recommendation system for cold start items,” *Expert Systems with Applications*, vol. 69, pp. 29–39, 2017.

[18] J. Lin, G. Sun, J. Shen et al., “Deep-cross-attention recommendation model for knowledge sharing micro learning service,” *Lecture Notes in Computer Science*, vol. 105596, 2020.

[19] S. Zhang, L. Yao, A. Sun, and Y. Tay, “Deep learning based recommender system: a survey and new perspectives,” *ACM Computing Surveys (CSUR)*, vol. 52, no. 1, pp. 1–38, 2019.

[20] T. B. Lalitha and P. S. Sreeja, “Recommendation system based on machine learning and deep learning in varied perspectives: a systematic,” in *Proceedings of the Information and Communication Technology for Competitive Strategies (ICTCS 2020)*, Jaipur, Rajasthan, December 2020.

[21] S. Lin, Z. Zhou, Z. Zhang, X. Chen, and J. Zhang, “Edge intelligence in the making: optimization, deep learning, and applications,” *Synthesis Lectures on Learning, Networks, and Algorithms*, vol. 1, no. 2, pp. 1–233, 2020.
[22] X. Chen and H. Deng, “Research on personalized recommendation methods for online video learning resources,” *Applied Sciences*, vol. 11, no. 2, p. 804, 2021.

[23] C.-M. Chen, “An intelligent mobile location-aware book recommendation system that enhances problem-based learning in libraries,” *Interactive Learning Environments*, vol. 21, no. 5, pp. 469–495, 2013.