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Construction of Personalized Academic Resource Recommendation Model Based on Association Rule Algorithm under Intelligent Service System of College Library

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Abstract With the rapid development of intelligent service system in university libraries, personalized academic resource recommendation has become a key technology to improve user experience and resource utilization. This paper improves the traditional two-part relationship graph of user thesis and proposes UAMO model. Combined with Page Rank algorithm and sorting model, the importance of academic resources is quantified. Based on Apriori algorithm, an academic resource aggregation model is established to explore the spatial and temporal correlation between user behavior and resource topics. More than 100,000 resource data and 2,864 user behavior records of a university smart library are selected as experimental data to empirically test the effectiveness of the model. The results of association rule mining show that social science academic resources are browsed by college students in December with the highest confidence level of 21.5933%, and engineering and technology academic resources are browsed by college students in October with a slightly higher confidence level than the minimum confidence level of 10.5357%. The MAP value of this paper's model (0.3865) is improved by 25.4% compared with the second best model BERT-TextGNN (0.3082), and the MRR value reaches 0.6927, which verifies the feasibility of the model in the intelligent library services of universities and provides technical support for the dynamic recommendation of resources and optimization of subject services.

Index Terms association rules, UAMO model, Apriori algorithm, smart library, academic resource recommendation

I. Introduction

With the arrival of the era of big data, mobile Internet, artificial intelligence and knowledge economy, the society is in urgent need of digital libraries that can provide personalization, mobility and intelligence, and the library information service model is facing more and more challenges [1]-[4]. In recent years, “smart city”, “smart transportation”, “smart hospital”, “smart campus” and so on have been emerged. The introduction of the concept of “smart library” quickly led to a profound change in the library community, as a new form of future development of libraries, smart libraries are becoming the practice of traditional library transformation and innovative development [5], [6]. Yantian District Library in Shenzhen, featuring “Ocean + Wisdom”, innovatively opens the smart wall, smart bookshelf, smart seat, mobile APP, and provide robot services, building China's first personalized, mobile smart services entity smart library. Intelligent library advocates the core concept of people-oriented, its goal is to strive to promote a higher quality of service libraries, this high-quality service quality, embodied in the user participation in the interactive autonomous service and management as well as a higher degree of intelligence in the personalized service [7]-[10]. And one of the main services in the intelligent services of university libraries is to recommend academic resources for students.

In recent years, the rapid development of society and the rapid changes in science and technology have contributed to the rapid growth in the number of academic resources. Among them, the number of academic papers is increasing by about 6-8% per year, which is equivalent to doubling the number of academic papers every decade or so. As we enter the era of big data, a huge amount of academic resources (papers, books, conference previews, academic news and patents, etc.) appear on the Internet or in online libraries, which satisfies the basic needs of users for academic resources, but also makes it necessary for users to spend a lot of time to obtain academic resources that are really useful to them, which is known as the information overload problem [11]-[14]. One way to solve the information overload problem is personalized recommendation, and personalized recommendation technology is a solution with great value. It is an information service technology that actively recommends academic resources of interest to scholars based on their research characteristics and knowledge needs, etc [15]. Compared with traditional information retrieval, personalized recommendation technology researches the user's characteristic preferences, personalizes and optimizes the recommendation results for different users, and is able to provide different users with personalized academic resources to meet the different academic resource needs of users with different interest preferences, different dynamic concerns, and different scientific research characteristics, etc. [16], [17]. However, in the field of smart library academic resource recommendation, the personalized recommendation technology has poor processing performance for different modalities, the contradiction between privacy and security risks and recommendation efficiency, and the capture defect of unfixed preferences [18].

In this paper, we first propose a user-paper quality graph model to construct a network topology by associating user-papers with the content similarity of papers in the layer. The user demand ranking model is designed by ranking related papers from three dimensions of similarity, quality and topic hotness. The concept of association rules is elaborated, and the resource aggregation model of academic resources is established based on the association rules. The smart library of a university is selected as the core data source platform, and the analysis is carried out focusing on three types of academic resources. Observe the browsing preferences of different groups. Using Apriori algorithm to analyze the correlation between the months of academic resources being browsed and the types of academic resources. Compare the performance of the proposed model with six benchmark models to test the effectiveness of the model.

II. Personalized academic resource recommendation model construction based on association rule algorithm

College library is the school's literature and information resource center, and it is an academic institution serving talent cultivation and scientific research. Under the background of digital transformation of higher education, the intelligent service system of university libraries is committed to realizing the accurate matching of resource supply and user demand by integrating multi-source data and intelligent algorithms. However, the existing recommender system faces two challenges: first, the traditional collaborative filtering and content recommendation model relies on a single attribute sorting, ignoring the comprehensive influence of user behavioral characteristics, resource semantic association and subject heat; second, the resource aggregation process lacks the deep mining of cross-disciplinary relevance and the long-tail distribution of user interest, resulting in serious homogenization of the recommendation results.

In order to solve the above problems, this paper proposes an academic resource recommendation model that integrates network graph model and association rule algorithm, which provides a reference for university smart libraries to improve resource utilization.

II. A. Recommendations for papers that incorporate network graph models and ranking models

II. A. 1) Sorting algorithms

Sorting patterns can be roughly divided into two types, i.e., single-attribute sorting and comprehensive sorting: single-attribute sorting is sorting for a single attribute; comprehensive sorting is weighted sorting according to a certain algorithm.

The sorting pattern of single-attribute sorting is shown in Figure 1.

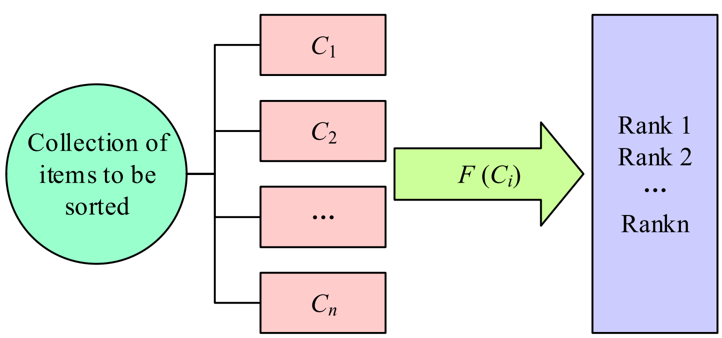

Figure 1: Single attribute sort mode

The sorting pattern for the combined sort is shown in Figure 2.

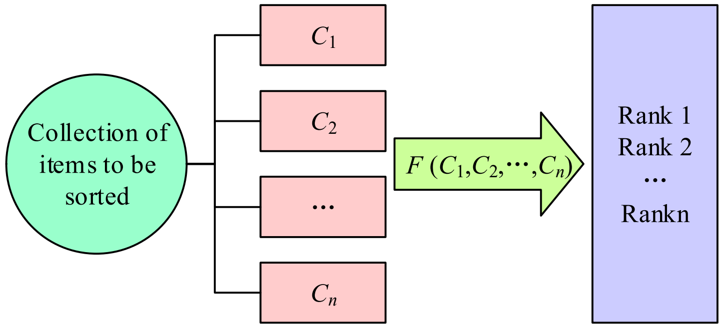

Figure 2: Comprehensive sorting

II. A. 2) User-paper graph model construction

Constructing a User-Athesis Graph Model incorporating the quality of the paper (UAMQ), UAMQ utilizes inter-layer and intra-layer connections to link the various vertices of the user layer and the academic paper layer together.

In this paper, we utilize the reading relation to establish the interlayer connection between the user layer and the academic paper layer.

$$W_{UA}(u_i, A_j) = \begin{cases} 1 & \text{If paper } A_j \text{ is read by user } u_i \\ 0 & \text{If paper } A_j \text{ is not read by user } u_i \end{cases} \tag{1}$$

Intra-layer links are relationships between different vertices in the same layer of the network, and in this paper, we mainly utilize the content similarity relationship between academic papers, without considering the relationship between users.

$$W_{sim}(A_j, A_j) = \begin{cases} Sim(A_i, A_j) & \text{If } A_j \text{ is similar to } A_i \\ 0 & \text{If } A_j \text{ is not similar to } A_i \end{cases} \tag{2}$$

II. A. 3) Sorting papers based on Page Rank algorithm

The Page Rank algorithm is a method used by Google to measure the importance of web pages. This section draws on the Page Rank algorithm to calculate the importance of paper i in a network of paper subgraphs.

$$pr_i(k+1) = (1-\alpha)/N + \alpha \times pr_i(k) \times M_{AA} \tag{3}$$

In Equation (3), N is the total number of papers, $pr_i(k)$ is the Page Rank value of paper i after k iterations, α is the damping coefficient, which is generally taken to be 0.85, and M_{AA} is the initial weight matrix of the paper's subgraph network (content similarity of the paper).

The paper quality formula:

$$Quality(i) = c \times \eta_i \times pr_i^{1-\frac{1}{size(A)}} \tag{4}$$

In Equation (4), $Quality(i)$ is the quality of the paper i, c is the global normalization factor, η_i is the impact factor of the paper i, pr_i is the Page Rank value of the paper i, A is the set of papers, and $size(A)$ is the size of the set of papers.

In this paper, we rank related papers in three dimensions: similarity, quality, and topic popularity, where topic popularity is estimated by the percentage of popular tags among the tags of the papers. The topic popularity formula:

$$Topic(i) = \frac{T_{hot}}{T_i} \tag{5}$$

In Equation (5), $Topic(i)$ is the topic popularity of the paper i, T_{hot} is the number of popular tags owned by the paper, and T_i is the total number of tags in the paper i. The popular tags are obtained by clustering the tags of all papers.

II. B. Association Rule Based Academic Resource Aggregation

II. B. 1) Theory of correlation analysis

Association analysis modeling is a data mining technique, data mining (DM), also known as KDD, is the process of finding hidden and valuable information from a data set. Data mining techniques contain two broad categories: unsupervised learning and supervised learning, and the most important techniques in data mining are clustering and association rule mining. Association rules are used to discover association rules or correlation patterns in a data set. It is mainly used to find the correlation between itemsets in a dataset, i.e., whether the occurrence of one itemset is related to the occurrence of another itemset. Association rules are usually expressed in the form of “If-Then”, where the “If” part is called the antecedent and the “Then” part is called the consequent. In association rules, minimum support and minimum confidence are two important thresholds for filtering out frequent itemsets and association rules with certain importance and association relationships. The association analysis theory contains many criteria, such as support, confidence, relevance, enhancement, frequent itemsets, association rules and so on.

(1) Support degree

The support of an association rule $A \rightarrow B$, $\sup port = P(AB)$, refers to the probability that an event A and an event B occur simultaneously. Support is an important concept in association rule mining and is used to measure the frequency of occurrence of an itemset in a dataset. Support degree indicates the frequency of occurrence of a itemset and is a metric used to filter frequent itemsets in association rule mining. Support can be calculated by the following formula (6):

$$Support(X) = \frac{Transactions\ containing\ X}{Total\ transactions} \tag{6}$$

where (X) is the support of the itemset (X). “Transactions containing (X)” denotes the number of transactions containing the itemset (X). “Total transactions” indicates the total number of transactions in the dataset. The value range of support is $([0,1])$.

(2) Confidence level

Confidence is another important concept in association rule mining, which is used to measure the reliability or accuracy of association rules. Confidence denotes the probability that under the condition that an item set (X) occurs, the item set (Y) also occurs. Confidence can be calculated by the following equation (7):

$$Confidence(X \rightarrow Y) = \frac{Support(X \cup Y)}{Support(X)} \tag{7}$$

where $Confidence(X \rightarrow Y)$ is the confidence level of the association rule $X \rightarrow Y$. $Support(X \cup Y)$ is the number of transactions containing the itemset $X \cup Y$. $Support(X)$ is the number of transactions containing the itemset X. The confidence level takes values in the range $([0,1])$.

(3) Correlation

In data analysis, “correlation” usually refers to the association or interrelationship between two variables. Measures of correlation can help to understand trends, patterns, or dependencies between two variables. The following are some common measures of correlation:

1) Pearson's correlation coefficient

Pearson's correlation coefficient measures the degree of linear relationship between two continuous variables. It takes values in the range $([-1,1])$, where 1 indicates a perfect positive correlation, 0 indicates no linear correlation, and -1 indicates a perfect negative correlation. Equation (8) is given below:

$$Pearson\ correlation\ coefficient = \frac{Cov(X,Y)}{\sigma X \cdot \sigma Y} \tag{8}$$

where $\mathrm{Cov}(X,Y)$ is the covariance of variables X and Y, and σX and σY are the standard deviations of X and Y, respectively.

2) Spearman rank correlation coefficient

Spearman's correlation coefficient is based on the rank of the variable rather than the original value. It is used to measure the monotonic relationship between the ranks of two variables. Like Pearson's correlation coefficient, it takes values in the range of $([-1,1])$, where 1 indicates a perfect positive correlation, 0 indicates no monotonic relationship, and -1 indicates a perfect negative correlation. The calculation of Spearman's correlation coefficient involves rank ordering of the raw data.

3) Coefficient of determination

The coefficient of determination is used to measure how much of the variation in the dependent variable is explained by the independent variable. It takes values in the range $([0,1])$, where 0 means that the model does not explain the variation in the dependent variable and 1 means that the model fully explains the variation in the dependent variable. The coefficient of determination can be obtained by squaring the Pearson correlation coefficient.

(4) Boosting degree

Boosting degree is an important concept in association rule mining, which is used to measure the degree of association between two itemsets. The degree of lift contains the proportion of occurrences of whether a transaction containing one itemset contains another itemset is higher than the benchmark level (i.e., the independence between two itemsets). The formula (9) for calculating the lift degree is as follows:

$$Lift(X \to Y) = \frac{Confidence(X \to Y)}{Support(Y)} \tag{9}$$

where $Lift(X \to Y)$ is the lift of the rule $X \to Y$. $Confidence(X \to Y)$ is the confidence of the rule $X \to Y$. $Support(Y)$ is the support of the itemset Y.

(5) Frequent itemset

A frequent itemset is a collection of items that occur frequently in a dataset. In association rule mining, the concept of frequent itemsets is concerned. Frequent itemset mining is a technique for discovering frequently occurring patterns in a data set and is usually used in areas such as shopping basket analysis, recommender systems, etc.

1) Itemsets

An itemset is a collection of one or more items in a dataset. An item can be any element that can be uniquely identified in a dataset.

2) Frequent itemset

A frequent itemset is a set of items in a dataset that has a high degree of support. Specifically, an item set is said to be a frequent item set if its support exceeds a predefined threshold (support threshold).

3) Minimum support threshold

The Minimum Support Threshold is a value specified in advance by the user to determine which itemsets are considered frequent. Only itemsets with support greater than or equal to the minimum support threshold are considered frequent.

II. B. 2) Construction of Academic Resource Aggregation Model

In association rules, it is usually necessary to mine huge amounts of data in some form and establish certain connections as a collection of rules. This can be measured by the weight value of a vocabulary in an academic resource. While the weight value of the vocabulary is increasing, the frequency of occurrence of the two same vocabulary words appearing in a document can be obtained as:

$$w_{ij} = \frac{t_i \times D_i}{\sqrt{t_j}} \tag{10}$$

where w_{ij} denotes the association frequency of a term in the academic resource collection i and collection j; t_i and t_j denote the number of times the term occurs in the academic resource database i and the database j, respectively; and D_i denotes the support degree of the database for the frequency. Among all the isolated points, it is necessary to find the hidden laws of the association rules, at this time, the result of transaction aggregation can be obtained by connecting the sub-nodes through the support degree and mapping relationship. Distance between two academic resources:

$$X_{AB} = \sqrt{\frac{d_A - d_F}{d_B - d_F}} \tag{11}$$

where X_{AB} denotes the Euclidean distance between resource A and resource B; d_A denotes the virtual node depth of resource A; d_B denotes the virtual node depth of resource B; and d_F denotes the depth of classified node x in the classification. The calculation of similarity between resource A and resource B can be obtained by using them as common ancestors for the construction of the model:

$$\sin\left(A,B\right)=\frac{\sum_{i=1}^{n}(h_{ap}\times h_{bp})}{\sqrt{\sum_{i=1}^{n}h_{ap}^{2}}\times\sqrt{\sum_{i=1}^{n}h_{bp}^{2}}} \tag{12}$$

In the formula, $\sin\left(A,B\right)$ denotes the similarity index between resource A and resource B; h_{ap} and h_{bp} denote the characteristic parameters of two kinds of academic resources, respectively. At this point, the indicator weights between different types of academic resources can be established by means of standardized processing:

$$A_{ij}'=\frac{\left(\frac{a_{ij}-a_{\min}}{a_{\max}-a_{\min}}\right)\times\frac{\alpha_{ij}}{\alpha_{ij}'}}{\left(\frac{a_{\max}-a_{ij}}{a_{\max}-a_{\min}}\right)} \tag{13}$$

where A_{ij}' denotes the indicator weight of an academic resource after normalization; a_{ij} denotes the weight of the academic resource in the indicator; and $a_{\max}$ and $a_{\min}$ denote the maximum and minimum information entropy of the indicator, respectively; α_{ij} denotes the moderating coefficient, and α_{ij}' denotes the predicted value of the moderating coefficient. Based on the parameters of the weights of this indicator, the aggregation function of academic resources under the association rule can be obtained directly:

$$f(x)=-\log\left[\frac{freq(h_{c})}{N_{m}}\right] \tag{14}$$

where $f(x)$ denotes the aggregation function of academic resources; h_c denotes the enigma information of all conceptual branches; and N_m denotes the coefficients of the same conceptual tree on the same semantics. Combining this function, an aggregation model of academic resources can be built.

III. Empirical study of personalized academic resource recommendation model based on association rule algorithm

III. A. Academic Resources and User Data Acquisition and Processing

III. A. 1) Data acquisition

In this paper, a university smart library is selected as the core data source platform, the platform covers social sciences, engineering technology, arts and humanities and other multidisciplinary fields, with a total of more than 100,000 resource data, and the data scale meets the research needs. The specific resource types of the platform are shown in Table 1, and the academic resource types of each discipline are categorized into journal papers, conference literature and dissertations.

The records of 2864 student users are selected, and the data are divided into training set, testing set and experimental set in the ratio of 2:1:1 for model training, method feasibility and effectiveness testing. The behavioral records of some users in the smart library are shown in Table 2, according to the above data and the user browsing content, the method of this paper is used to analyze the behavioral characteristics and recommend personalized resources.

III. A. 2) Data processing

After cleaning the data, the browsing information of undergraduate, master's, doctoral and other student groups was retained for retention, and the browsing record information with missing data was deleted. Unified coding of the data, and standardized data processing of the information of student categories, affiliated faculties and departments, and academic resources categories involved in the experiment. Through the above data processing, 205,739 valid data were retained.

In order to facilitate the observation of the browsing preferences of different groups for different learning resources, this paper plots the alluvial graphs through Origin Pro 2024 to facilitate the overall presentation of students' browsing preferences. Due to the significant differences in students' browsing categories of academic resources, and much of the information is not suitable to be observed by connecting the dots. Therefore, this paper chooses to analyze the browsing data of these students' faculties for academic resources of different disciplines, and the browsing preferences of four categories, namely, social sciences, engineering and technology, arts and humanities, and others, are shown in Figure 3. From the figure, it can be seen that the categories of academic resources browsed account for the largest proportion of social sciences, amounting to 30.13%, followed by engineering technology, arts and humanities, and others.

Table 1: Overview of Online Teaching Cloud Platform Resources

Discipline	Type	Resource data volume/piece
Social science	Journal article	7355
	Conference literature	4858
	Degree thesis	13653
Engineering technology	Journal article	9796
	Conference literature	5965
	Degree thesis	16647
Art and Humanities	Journal article	6484
	Conference literature	3969
	Degree thesis	12647
Other	Journal article	17484
	Conference literature	13536
	Degree thesis	20798

Table 2: User Behavior Records of Cloud Platform (Part)

User serial number	User ID	Consecutive login days/d	Resource interaction times/times	Views/piece	Number of posts/pieces
1	203254	24	187	208	3
2	202482	19	133	87	2
3	207632	22	197	43	5
4	210853	36	38	6	0
5	219744	16	105	197	9
6	210853	35	402	209	15
7	249724	24	184	215	7
8	230753	207	942	724	21
9	229744	74	201	158	4
10	204975	28	328	277	18

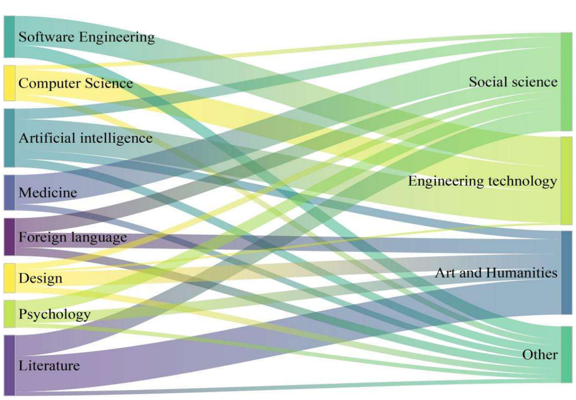

Figure 3: Browsing preferences of the four types of disciplines

III. B. Correlation Analysis Mining Results

Using Apriori algorithm to analyze the association between the month in which academic resources are browsed and the types of academic resources, we can derive the students' interest in different academic resources in different semester phases, which can provide reference for the recommendation of academic resources in different phases of university smart libraries.

Students in colleges and universities experience two semesters in the whole academic year, and the academic resources they need to read in different months of each semester are different, and by mining and analyzing the correlation rules between the types of browsed academic resources and the browsing time, it is possible to explore the browsing rules of the academic resources.

The time of academic resources being browsed is set as the antecedent, and the type of academic resources is set as the consequent, and after several tests, the minimum support degree is finally determined to be 20%, and the minimum confidence degree is 10%. Through the Apriori algorithm, a total of 10 association rules are found, and the results of association rule mining are shown in Table 3, and the academic resources of social sciences, engineering and technology, and arts and humanities are numbered S, E and A. The results of the association rule mining show that the academic resources of social sciences were browsed by college students in December with the highest confidence level of 21.5933%, and the academic resources of engineering and technology were browsed by college students in October with the highest confidence level of 21.5933%. Were viewed by college students in October with slightly higher than the minimum confidence level of 10.5357%.

The Social Sciences category is highly preferred at the beginning and end of each semester, especially at the end of the semester. At the beginning of each semester, some students will systematically prepare for public required courses such as modern history, civics, statistics, etc. At the end of each semester, students need to prepare for the final exams of these courses, so the number of views of related academic resources is also relatively high. The engineering and technology category has been more popular throughout the year with more concentrated browsing. With the rapid development of information technology, college student readers are willing to browse information technology academic resources regardless of the time period. Arts and humanities academic resources are more popular among college student readers at the beginning and middle of the semester, especially in April and October, when students have less pressure and more time after class.

Table 3: Results of Correlation Analysis Mining

Consequent	Preceding paragraph	Support degree(%)	Confidence degree(%)
Academic Resources=S	Month=12	32.7542	21.5933
Academic Resources=E	Month=1	30.5225	20.5374
Academic Resources=S	Month=9	28.5363	18.5397
Academic Resources=A	Month=4	27.4633	17.3893
Academic Resources=E	Month=5	25.4785	16.0832
Academic Resources=S	Month=2	25.0387	15.9375
Academic Resources=E	Month=8	24.6368	14.9375
Academic Resources=A	Month=10	23.9375	14.5972
Academic Resources=S	Month=6	23.6474	13.7488
Academic Resources=E	Month=10	21.5935	10.5357

Through correlation mining analysis, smart libraries can systematically recommend different kinds of academic resources in different months, thus effectively improving the utilization of library resources.

III. C. Model Performance Evaluation

To validate the robustness of the academic resource recommendation model proposed in this paper, the performance of the proposed model is compared with six more popular benchmark methods using the BERT-MLP, TextGCN, CLAVER, HASVRec, BERT-TextCNN, and BERT-TextGNN models.

The performance of the proposed model is verified using Recall@K, MAP, and MRR metrics, and the comparison results of each metric are shown in Table 4, and the corresponding evolutionary trend of Recall@K is shown in Fig. 4, where the horizontal axis represents the type of Recall@K, and the vertical axis is the value of Recall@K. The model in this paper achieves a significant optimal value on Recall@20, and its performance advantage gradually expands as the value of K increases. This trend indicates that the model has a stronger ability to capture relevant items in long sequence recommendation scenarios, and can effectively mine the long-tail distribution characteristics of user interests. The MAP value of this paper's model (0.3865) is 25.4% higher than that of the suboptimal model BERT-TextGNN (0.3082), and the MRR value reaches 0.6927, which indicates that the model not only improves the accuracy of the overall recommendation list, but also optimizes the quality of the sorting of Top-1 recommendation results.

Table 4: Recall@K,MAP,and MRR metrics scoring results

Model	Recall@5	Recall@10	Recall@15	Recall@20	MAP	MRR
BERT-MLP	0.4962	0.5972	0.8474	0.9042	0.2085	0.5108
TextGCN	0.5083	0.4972	0.7929	0.9185	0.2486	0.5255
CLAVER	0.6194	0.5973	0.8056	0.9047	0.2397	0.5174
HASVRec	0.6849	0.7037	0.7583	0.8197	0.2286	0.5829
BERT-TextCNN	0.5976	0.7464	0.8385	0.9025	0.3295	0.6034
BERT-TextGNN	0.6378	0.7783	0.8032	0.9108	0.3082	0.6048
The proposed	0.6974	0.7947	0.9386	0.9802	0.3865	0.6927

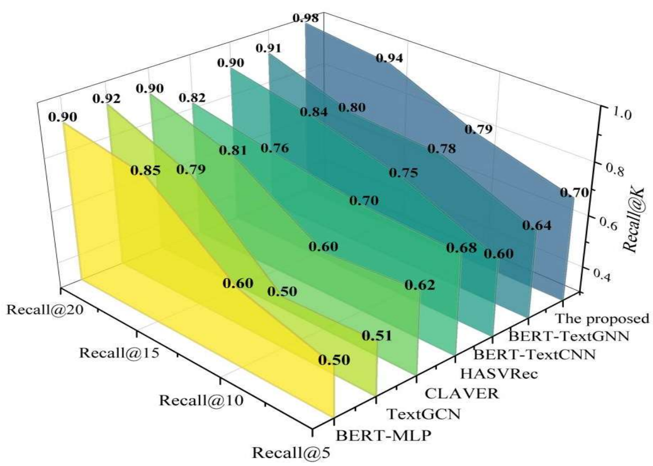

Figure 4: Distribution of performance trends of model Recall@K indicators

IV. Conclusion

In this paper, an academic resource recommendation model integrating network graph model and association rule algorithm is designed and empirically analyzed on a university smart library.

The categories of academic resources browsed by academics in social sciences accounted for the largest proportion of 30.13%, followed by engineering and technology, arts and humanities, and others. The results of association rule mining show that the confidence level of social science academic resources being browsed by college students in December is the highest, reaching 21.5933%, and the confidence level of engineering technology academic resources being browsed by college students in October is slightly higher than the minimum confidence level, which is 10.5357%. By mining and analyzing the association rules between the types of browsed academic resources and the browsing time, the browsing law of academic resources can be explored, which can provide reference for the recommendation of academic resources in different stages of university smart libraries.

The model in this paper achieves a significant optimal value on Recall@20, and its performance advantage gradually expands as the K value increases. The MAP value of the model (0.3865) is improved by 25.4% compared with the suboptimal model BERT-TextGNN (0.3082), and the MRR value reaches 0.6927, which indicates that the model not only improves the accuracy of the overall recommendation list, but also optimizes the quality of the sorting of Top-1 recommendation results. It is verified that the performance of the proposed model is generally better than the current mainstream benchmark model with better recommendation effect.

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