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Research on Digital Display Technology for Traditional Music Culture

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Abstract The outdated methods of storage and preservation currently in use pose a significant risk of traditional music cultural resources being lost, necessitating an effective form of resource information protection. This paper explores the integration of traditional music culture with the digital age, taking into account the unique characteristics of traditional music. For data processing, a Bayesian classifier is employed to categorize traditional music data types. Based on this, a semantic proactive service workflow centered on “resource collection-resource analysis and organization-resource publication” is designed, leading to the development of a proactive service architecture. Subsequently, using an information grid model, user needs and resource content are grid-modeled to comprehensively establish a semantic model for traditional music culture. A collaborative filtering recommendation algorithm is introduced, improving the Apriori algorithm to address its issues of data sparsity and cold start problems, thereby enhancing the accuracy of recommendation results. Combining the traditional music culture semantic model with the improved recommendation algorithm, a preliminary digital display system for traditional music culture was established, tested, and evaluated for performance. The designed system model demonstrated significantly superior recommendation accuracy (HR@10 > 0.5, NDCG@10 > 0.5) and average recommendation error (0.75) compared to similar models across various experimental environments.

Index Terms traditional music, Bayesian classifier, semantic model, improved Apriori algorithm

I. Introduction

In today's era of global digitalisation, traditional music faces numerous challenges and opportunities [1], [2]. On the one hand, with the acceleration of the pace of life and the diversification of entertainment options, the audience for traditional music is gradually shrinking, and its inheritance and development are encountering bottlenecks [3], [4]. On the other hand, the rapid development of digital technology has provided unprecedented possibilities for the protection, dissemination and innovation of traditional music [5], [6].

Traditional music is a treasure of a nation's cultural heritage, embodying rich historical memories, ethnic emotions, and aesthetic values [7], [8]. From ancient folk ballads to elegant court music, from melodious ethnic instrumental music to unique opera vocal styles, each form of traditional music possesses its own unique charm [9], [10]. However, these precious musical heritage are now facing the risk of being lost [11]. Many traditional music pieces have gradually been forgotten due to their age and the difficulties in passing them down [12]. The emergence of digital technology has brought new hope for the protection and transmission of traditional music [13]. Through digital means, traditional music can be recorded, stored, and disseminated, ensuring its permanent preservation [14], [15]. Additionally, digital technology can break the temporal and spatial constraints of traditional music dissemination, allowing more people to learn about and appreciate these outstanding cultural heritages [16], [17]. For example, through internet platforms, traditional music can quickly spread worldwide, attracting audiences of different ages and regions [18], [19]. Digitalisation has made music culture more diverse, enabling people to access and share musical works more conveniently, and music production has become more efficient [20]-[22].

This paper first explains the classification method for traditional music data guided by Bayesian theory and proposes a Bayesian classifier. Combining the user characteristics of traditional music culture, it explains the semantic active service process and system framework, and then establishes a semantic model for traditional music culture. Next, it introduces the collaborative filtering recommendation algorithm, analyzes the improved method of the Apriori algorithm and the steps for generating association rules, and provides recommendation algorithm support for the proposed semantic model. Furthermore, the proposed semantic model and recommendation algorithm are utilized to establish a traditional music digital display system for testing. A user needs and satisfaction survey questionnaire is compiled, and statistical analysis is conducted on users' basic information. The study then explores the correlation between users' willingness to use the system and their age and identity. Finally, through comparative experiments, the recommendation accuracy and average error of the proposed model and algorithm are evaluated, and a correction test for user comprehensive similarity is conducted.

II. Semantic Model of Traditional Music Culture

II. A. Classification of Traditional Music Data

To facilitate the digital preservation of traditional music data, the music data is categorized. Bayesian theory is a crucial theorem in probability theory, combining prior knowledge about the classification of data samples with new knowledge obtained from new samples. This paper introduces it into the classification model, using probabilistic statistical knowledge to integrate and classify traditional music data. Assume that the set of training samples and their corresponding classifications is denoted as T. Given a category $c \in C$, the sample data set contains n attributes $A_1, A_2, A_3, \cdots, A_n$, and the test sample $x = (a_1, a_2, \cdots, a_n) \in X$. Directly calculating $P(x|c)$ using the known sample set with multiple attributes would consume a significant amount of computational time. To achieve an effective estimate, the Naive Bayes classifier generally assumes that different attributes are mutually independent. For a specific category, if the attributes are independent, then equation (1) applies:

$$P(x|c) = \prod_{k=1}^{n} p(a_k|c) = P(a_1|c)P(a_2|c)\cdots P(a_n|c) \tag{1}$$

According to Bayes' formula, we can derive equation (2):

$$P(c|x) = \frac{P(x|c)}{P(x)} = \frac{P(a_1|c)P(a_2|c)\cdots P(a_n|c)P(c)}{P(x)} \tag{2}$$

The above formula indicates that all classifications $P(x)$ are the same, so the Bayesian classifier can be expressed by formula (3):

$$NB(x) = \arg\max_c P(c)\prod_{k=1}^{n} P(a_k|c), x = (a_1, a_2, \cdots, a_n) \tag{3}$$

Formula (3) is the Bayesian model, which is a simple and effective classification model that outperforms classifiers such as decision trees and neural networks.

The Bayesian classification principle uses the number of statistical samples to obtain the prior probability of any sample data, then calculates the posterior probability of this sample belonging to a certain class through the Bayesian model, and finally determines the class with the highest posterior probability as the data sample class.

Assuming that tuples are divided into m categories: $c_1, c_2, \cdots, c_i, \cdots, c_m$, to classify test data into m categories, the following classification model can be constructed, with equation (4) derived from equation (3):

$$\begin{aligned} B(x) &= \arg\max_c \frac{N(c)}{N}\prod_{k=1}^{n}\frac{N(c,a_k)}{N(c)} \\ &= \arg\max_c \frac{\prod_{k=1}^{n} N(c,a_k)}{N(c)^{n-1}}, x = (a_1, a_2, \cdots, a_n) \end{aligned} \tag{4}$$

In Formula (4), $N(c)$ denotes the number of sample points in class c, and $N(c, a_k)$ denotes the number of times the attribute value a_k appears in class c.

From formula (4), it can be seen that in the process of classifying traditional music sample data, it is only necessary to calculate $N(c)$ and $N(c, a_k)$, which to some extent reduces the computational load. Based on the above classification of traditional music data, this provides a basis for digital music storage.

II. B. Active service system for semantics

Semantic active services are an information resource service system based on Web service technology. Their purpose is to utilize information resources and electronic media on the Web to provide users with free, consistent, concise, and efficient access to the information resources they require. For network information resources, due to the consistent interests of users, the information resources of interest can be continuously, proactively, and instantly distributed to users, thereby providing personalized on-demand services tailored to user needs. Additionally, the intelligent semantic understanding provided by the Semantic Web enables dynamic changes in semantic computations executed on the Web, allowing on-demand services to be implemented based on application requirements and the semantic content of information resources, thereby exhibiting flexible and effective organizational and management characteristics. For example, the collection of thematic information on the Semantic Web is primarily based on the distribution of thematic information. If a page is related to a theme, the probability that the hyperlinks pointing to the content of the page belong to that theme is significantly higher than that of a random page, indicating an association between information resources.

According to analysis, the composition of the semantic active service framework system includes five functional components: information resource collection, information resource analysis and organization, information resource publication, service mining, and user terminal environment. The service workflow is shown in Figure 1.

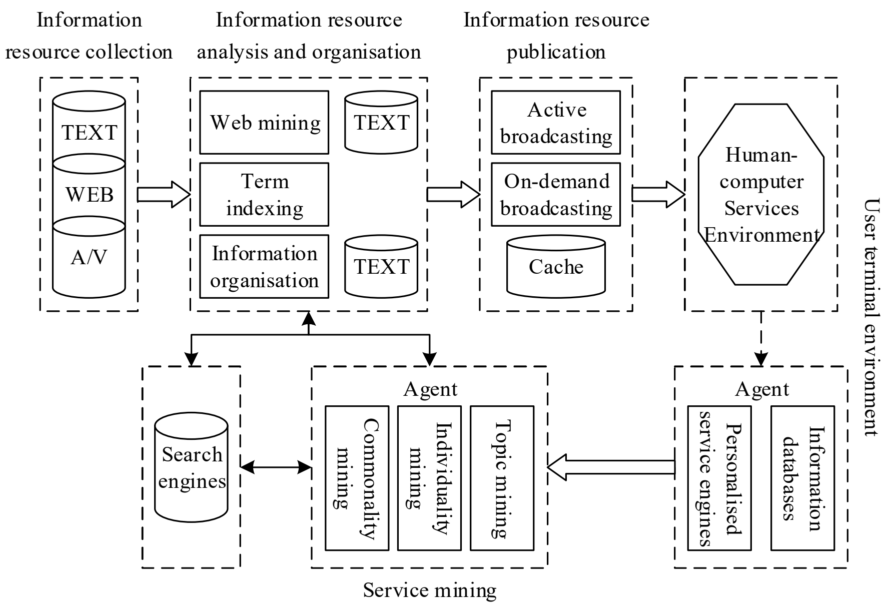


Figure 1: Proactive service workflow

In a semantic active service system, both the front end and the terminal require support from information resource search. A network without information search is inefficient. Search engines achieve operations such as locating information webpages, establishing relevant indexes, querying keyword-related information, and pre-fetching results through three subsystems: webpage collection, preprocessing, and querying.

Semantic active services leverage existing network technology standards, combined with service and data mining technologies, to decompose networks and services into a series of basic agent components. Based on users' specific needs, these components automatically connect with relevant devices on the network to form a customized, personalized active service framework system. Its architectural structure is shown in Figure 2.

Among these, the system platform is the foundation of the semantic active service framework system. It uses mining technology to discover relevant information resources from massive amounts of network information resources, and provides intelligent, active, on-demand services through active agent components called ActiveAgents. Finally, it interacts with users through the application layer computing environment to provide personalized and common services.

II. C.Semantic Information Model

In this study, a grid model of information is used to construct a semantic information model for ethnic folk cultural resources. Since RDF uses schema to encapsulate resource information in a data structure of {subject, predicate, object}, after research and analysis, user needs and resource content can be modeled using a grid structure to form a spatial data structure of {user, need, resource}. The shared model analysis is shown in Figure 3.

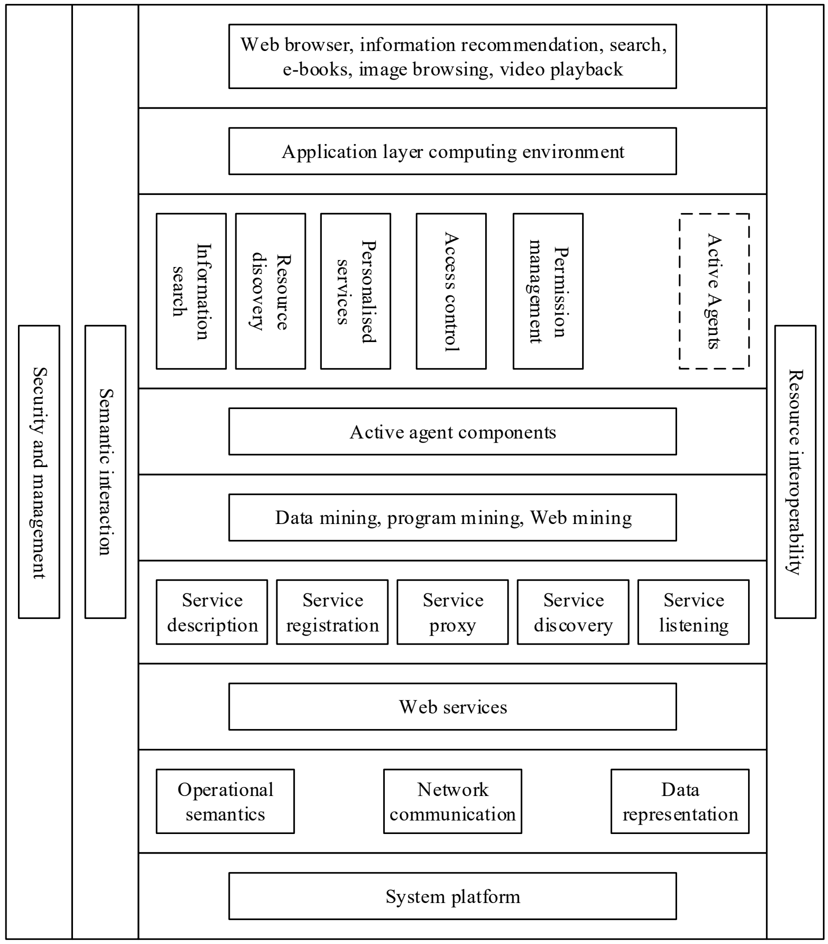


Figure 2: Proactive service architecture

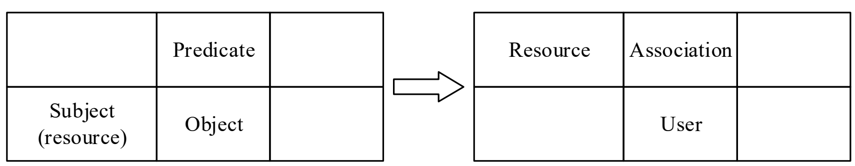


Figure 3: Analysis of Semantic Service Sharing Model

The grid model is a service sharing model for semantic information developed based on the semanticization of resource information. It is a geometric diagram formed by a set of parallel lines intersecting at right angles. This model can be used to express the potential supply and demand relationships inherent in semantic information.

The semantic grid model is shown in Figure 4. Horizontal lines represent information resources, vertical lines represent users, and the intersection of horizontal and vertical lines forms a rectangular grid pattern. The intersection points indicate the corresponding users' demand for the corresponding resource information. The grid model connects user resources and information resources within an information system, forming an interconnected network system. User resources and information resources are connected on-demand within the network, forming complex relationship links. The richer the information resources, the more horizontal lines there are; the broader the demand for resource information, the more vertical lines there are. Nodes represent the on-demand connections between resources and users. The ultimate goal is to ensure that any resource serves multiple users, and any user receives parallel services from multiple resources.

Assumption: □ represents brocade, △ represents bamboo houses, and the others represent silver jewelry, tie-dyeing, wooden huts, etc. It can be seen that three users need to obtain information about brocade, four users need to obtain information about bamboo houses, and one user needs to obtain information about both brocade and bamboo houses simultaneously.

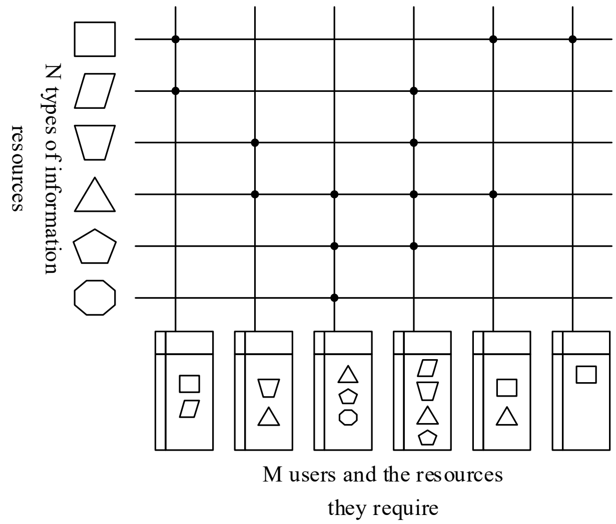


Figure 4: Semantic raster model

Based on the semantic resource information grid model, we can obtain the relationship matrix $A=(a_{ij})$ for row i and column j. When the value is 1, it indicates that user i has a demand for information j. When the value is 0, it indicates that there is no demand.

The application of resource information on the Semantic Web is not merely about file exchange and information browsing; it aims to connect all individuals and organizations into a virtual social entity. The grid model's key feature is its mature integration, presenting users with a visually intuitive system image filtered based on resources and needs, rather than an overwhelming array of complex information resources. The characteristics of this model form the foundation for the implementation of a semantic-based ethnic and folk cultural resource repository, enabling effective semantic information modeling and the provision of proactive service sharing applications.

III. Improvements based on association rule recommendation technology

This paper selects the collaborative filtering recommendation algorithm, which is the most widely used and whose recommended content is not constrained by the type of recommended resources, as the recommendation algorithm for the digital display system. In this section, the Apriori algorithm is improved to optimize the mining of association rules. Association rule mining is performed in two stages: the first stage mines frequent item sets, and the second stage mines association rules.

III. A. Use frequent items to find frequent item sets

The Apriori algorithm process is as follows: first, find the frequent 1-item sets, denoted as L_1, use L_1 to find the frequent 2-item sets L_2, and use L_2 to find L_3, and so on, until no frequent $k-$item sets can be found. The algorithm consists of two steps: joining and pruning.

Union step: Find L_k by generating a set of candidate k-items C_k through self-connection using L_{k-1}. $l[i][j]$ denotes the j th item of l_i. Perform the concatenation of L_{k-1} and L_{k-1}, where the elements of L_{k-1} are concatenable if their first $(k-2)$ terms are the same, i.e., $(l_1[1]=l_2[1])\wedge(l_1[2]=l_2[2])\wedge\cdots\wedge(l_1[k-2]=l_2[k-2])\wedge(l_1[k-1]<l_2[k-1])$. The condition $(l_1[k-1]<l_2[k-1])$ ensures that no duplicates are produced. The resultant item set generated by connecting l_1 and l_2 is $l_1[1]l_1[2]\cdots l_1[k-1]l_2[k-1]$.

The algorithm complexity is given by equation (5):

$$L_1'*L_1'+L_2'*L_2'+L_{k-1}'*L_{k-1}'+L_k'*L_k' \tag{5}$$

In the formula, L_k' denotes the number of frequent items containing the item k.

Due to formula (6):

$$L_1'\le C_n^1, L_2'\le C_n^2,\ldots,L_k'\le C_n^k\,(k\le n) \tag{6}$$

Therefore, the result of equation (5) is at most no greater than equation (7):

$$C_n^1 * C_n^1 + C_n^2 * C_n^2 + C_n^{n-1} * C_n^{n-1} + C_n^n * C_n^n = C_{2n}^n - 1 \tag{7}$$

Therefore, the algorithmic complexity of the connection step is $O(C_{2n}^n)$.

Pruning step: C_k is a superset of L_k, and its members may or may not be frequent, but all frequent k-item sets are contained in C_k. Scan all transactions to determine the count of each candidate in C_k. If the count is not less than the minimum support count, it is considered frequent. To compress C_k, we apply the Apriori property: any non-empty subset of a frequent item set must also be frequent. Conversely, if a candidate non-empty subset is not frequent, then the candidate is definitely not frequent and can be removed from C_k.

The process of generating the set of candidate 3-item sets C_3: From the join step, we first have equation (8):

$$C3 = \{\{I1, I2, I3\}, \{I1, I2, I5\}, \{I1, I3, I5\}, \{I2, I3, I4\}, \{I2, I3, I5\}, \{I2, I4, I5\}\} \tag{8}$$

Among them, C3 is generated by connecting L2 with itself.

According to the Apriori property, all subsets of frequent item sets must also be frequent, so we can determine that there are four candidate sets: $\{\{I1, I3, I5\}, \{I2, I3, I4\}, \{I2, I3, I5\}, \{I2, I4, I5\}\}$ cannot be frequent because they contain subsets that are not part of the frequent set, so they are removed from C3.

It is not difficult to see that the computational complexity of the join step is the same as that of the entire Apriori algorithm, i.e., $O(C_{2n}^n)$. Algorithms of this complexity will exhibit extremely low running speeds in practical applications. To address this issue, extensive research and verification have been conducted on the join step, leading to the proposal of an improved algorithm:

First, identify the set of frequent 1-item sets L_1. Then, perform self-joining between the frequent 1-item sets L_1 and L_1 to find the set of frequent 2-item sets L_2; join L_2 with L_1 to find L_3, and so on, until no frequent $k-$ item sets can be found. When finding frequent $(k-1)-$ itemsets from frequent $k-$ itemsets, the determination is made by identifying a non-empty subset of frequent 1-itemsets added to each frequent $(k-1)-$ itemset. The algorithm begins to differ when generating candidate frequent 3-itemsets.

The classic Apriori algorithm requires $6+5+4+3+2+1=21$ join scans to generate candidate frequent 3-item sets, while the improved algorithm requires $5+4+3+2+1=15$ join scans. The improved algorithm performs fewer joins than the classic algorithm, and when there are a large number of resource item sets, the number of frequent $k-$ item sets can be significantly larger than frequent 1-item sets. However, the efficiency improvement achieved by the improved algorithm is more pronounced. Comparing the results of candidate frequent 3-item sets and frequent 3-item sets generated by the classic Apriori algorithm and the improved algorithm, we utilize the Apriori property: any non-empty subset of a frequent item set must also be frequent. Conversely, if a candidate non-empty subset is not frequent, then the candidate is definitely not frequent and can be removed from C_k. Ultimately, the results obtained by the two algorithms are consistent. The improved algorithm flow is shown in Figure 5.

The complexity of the improved algorithm is given by equation (9):

$$L_1' * L_1' + L_2' * L_1' + L_{k-1}' * L_1' + L_k' * L_1' \tag{9}$$

In the formula, L_k' denotes the number of frequent items containing the term k.

Similarly, we obtain formula (10):

$$(C_n^1 + C_n^2 + C_n^{n-1} + C_n^n) * C_n^1 = (2^n - 1)n \tag{10}$$

Therefore, the complexity of the improved algorithm is $O(n2^n)$.

III. B. Generating association rules from frequent item sets

The steps for generating association rules are as follows:

(1) Generate all non-empty proper subsets of each frequent item set l.

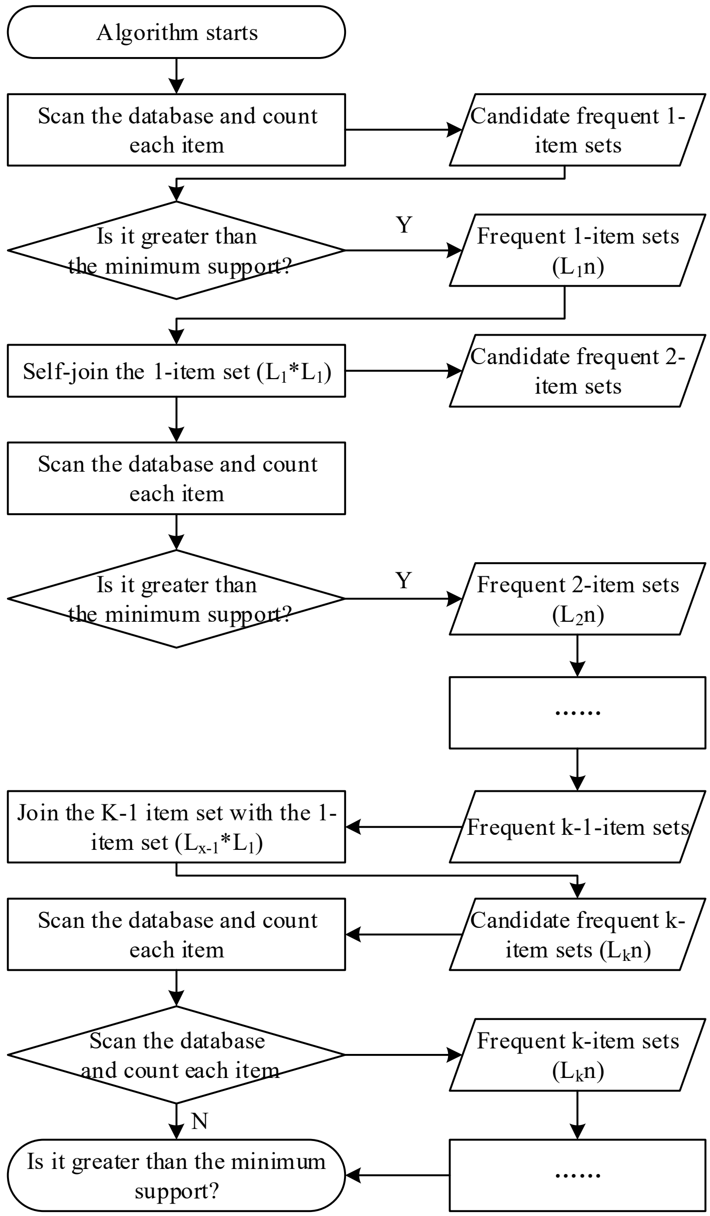


Figure 5: The improved process of the Apriori algorithm

(2) For each non-empty proper subset s, if the ratio of the support of set l to the support of set s is greater than the minimum confidence level, then output the association rule $s \Rightarrow (l-s)$ for set s with respect to l. Based on extensive data and program runs, it has been found that adding an accuracy judgment factor to the algorithm can increase the accuracy of the generated association rules.

The steps for generating association rules are as follows:

(1) Generate all non-empty proper subsets of each frequent k-item set L_k.

(2) For each non-empty proper subset s, if equation (11):

$$\frac{Sup(l)}{Sup(s)} \geq \min\_conf \tag{11}$$

And equation (12):

$$Acc(s \Rightarrow (l-s)) \geq \min\_accuracy \tag{12}$$

Only when both Equations (11) and (12) hold simultaneously is the association rule $s \Rightarrow (l-s)$ output.

In the equation, $Sup(l)$ denotes the support of set l, $Sup(s)$ denotes the support of set s, $\min\_conf$ denotes the minimum confidence, $Acc(s \Rightarrow (l-s))$ denotes the accuracy of association rule $s \Rightarrow (l-s)$, and $\min\_accuracy$ denotes the minimum accuracy.

IV. User Analysis of Digital Display Systems

Based on the semantic model and recommendation algorithm mentioned above, this paper establishes a preliminary digital display system for traditional music culture and randomly selects 2,000 users for a pilot program. In combination with the characteristics of the system, a questionnaire is designed to survey user needs and satisfaction with the digital display system. The questionnaire consists of three main parts: the basic information of the respondents, their user experience, and their willingness to use the system. The “basic information” module includes the respondents' gender, age, identity, and educational background, while the “usage experience” module consists of the following six questions:

(1) Are you satisfied with the search functionality of the digital display system for traditional music culture?

(2) Do you think the information resources of the digital display system for traditional music culture are sufficient?

(3) Do you think the interactive interface design of the digital display system for traditional music culture is user-friendly?

(4) Are you satisfied with the user support services of the digital display system for traditional music culture?

(5) Do you find the user interface of the digital display system for traditional music culture aesthetically pleasing?

(6) Are you satisfied with your overall experience using the digital display system for traditional music culture?

The “usage intent” module includes the following question: Have you ever used or are you interested in using the cultural resource database within the digital display system?

IV. A. Basic Information

A total of 2,000 questionnaires were distributed for this survey. After excluding 116 invalid questionnaires, 1,884 valid questionnaires were returned, resulting in a response rate of 94.20%. The basic demographic information of the respondents is presented in Table 1, where the mean represents the central tendency of the data, and the standard deviation indicates the variability. It can be observed that the number of female respondents (916) is closely matched by the number of male respondents (968). In terms of age, the majority of respondents were aged 18–29, accounting for 48.99% of the total. In terms of occupation, the majority were students (30.47%) and corporate employees (23.41%), with relatively even distribution among teachers, government employees, freelancers, retirees, and other groups. In terms of education level, the majority were college graduates (42.94%).

Table 1: The basic information of the respondents

Item	Option	Frequency	Proportion	Mean	SD
Gender	Female	916	48.62%	4.460	0.544
	Male	968	51.38%		
Age	under 18	146	7.75%	5.283	1.07
	18~29	923	48.99%		
	30~39	219	11.62%		
	40~49	263	13.96%		
	Over 50	333	17.68%		
Identity	Student	574	30.47%	5.369	1.968
	Teachers and researchers	124	6.58%		
	Government staff members	152	8.07%		
	Enterprise staff	441	23.41%		
	Liberal professions	175	9.29%		
	The emeritus and retired	418	22.19%		
	Else	205	10.88%		
Education background	Below undergraduate	532	28.24%	5.135	0.815
	Undergraduate	809	42.94%		
	Postgraduate	457	24.26%		
	Above postgraduate	86	4.56%		
Total		1884	100.00%		

IV. B. Reliability and validity testing

The reliability test results for the "User Experience" module are shown in Table 2. The Cronbach's α coefficient for this questionnaire is 0.938. The correlations between the deleted items and the overall questionnaire after deletion are all greater than 0.850, and the Cronbach's α coefficients after deletion are all lower than the Cronbach's α coefficient of the questionnaire, indicating that the item settings are reasonable and no further deletions are necessary. The CITC values for the analysis items are all greater than 0.700, proving that the analysis items are well correlated. The reliability of the questionnaire is very good, and the structure and content can continue to be analyzed.

Table 2: The reliability test results of the variable

Module	Item	The total correlation of the correction items (CITC)	The coefficient of α that has been deleted	Cronbach's α coefficient
User experience	(1)	0.879	0.894	0.938
	(2)	0.747	0.911	
	(3)	0.673	0.922	
	(4)	0.842	0.897	
	(5)	0.716	0.917	
	(6)	0.783	0.907	
Usage intention		0.805	0.887	

IV. C. Analysis of user intention survey results

IV. C. 1) User willingness to use and age correlation

The results of the cross-analysis of users' willingness to use a digital display system for traditional music culture, categorized by age, are shown in Table 3. In this table, (U1) indicates those who have used or are willing to use the system, while (U2) indicates those who have not used or are unwilling to use the system. It can be observed that the age groups with the highest willingness to use the system are those under 18 years old and those aged 18–29, both exceeding 81.00%. The 30–39 age group has a usage intention rate of 41.55%, the 40–49 age group has a usage intention rate of 30.04%, and the 50+ age group has a usage intention rate of 11.41%. This indicates that the willingness to use digital display system information resources decreases with age, with younger individuals being more inclined to use such resources.

Table 3: Cross-analysis of user usage intention and age

Item	Option	U1		U2	
		Number of people	Proportion (%)	Number of people	Proportion (%)
Age	under 18	119	81.51	27	18.49
	18~29	754	81.69	169	18.31
	30~39	91	41.55	128	58.45
	40~49	79	30.04	184	69.96
	Over 50	38	11.41	295	88.59

IV. C. 2) User willingness to use and identity relevance

The results of the cross-analysis of users' willingness to use a digital display system for traditional music culture and their identities are shown in Table 4. The groups with the highest willingness to use the digital display information system resources are mainly students and government employees, accounting for 82.93% and 91.45%, respectively. Due to their needs for learning, research, and work, both groups exhibit a high willingness to use the system. This indicates that the willingness to use the information resources of the digital display system for traditional music culture is closely related to users' daily lives, work, and learning needs.

Table 4: Cross-analysis of user usage intention and identity

Item	Option	U1		U2	
		Number of people	Propor-Tion (%)	Number of people	Propor-Tion (%)
Identity	Student	476	82.93	98	17.07
	Teachers and researchers	61	49.19	63	50.81

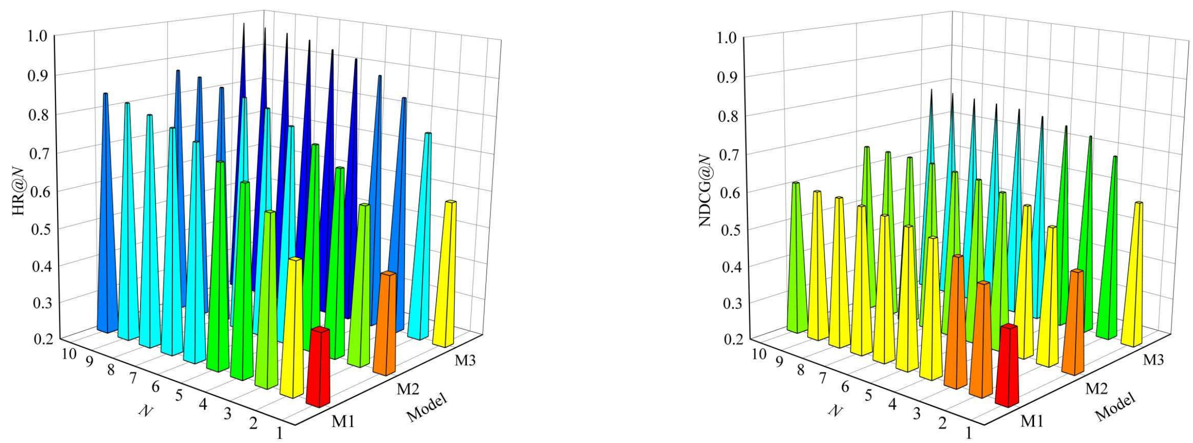
	Government staff members	139	91.45	13	8.55
	Enterprise staff	217	49.21	224	50.79
	Liberal professions	143	81.71	32	18.29
	The emeritus and retired	96	22.97	322	77.03
	Else	99	48.29	106	51.71

V. Performance evaluation and correction of digital display systems

Select (M1) KGMT and (M2) DMF as comparison models, and conduct experiments on recommendation accuracy, average error, and user comprehensive similarity correction tests with (M3) the model in this paper in this section.

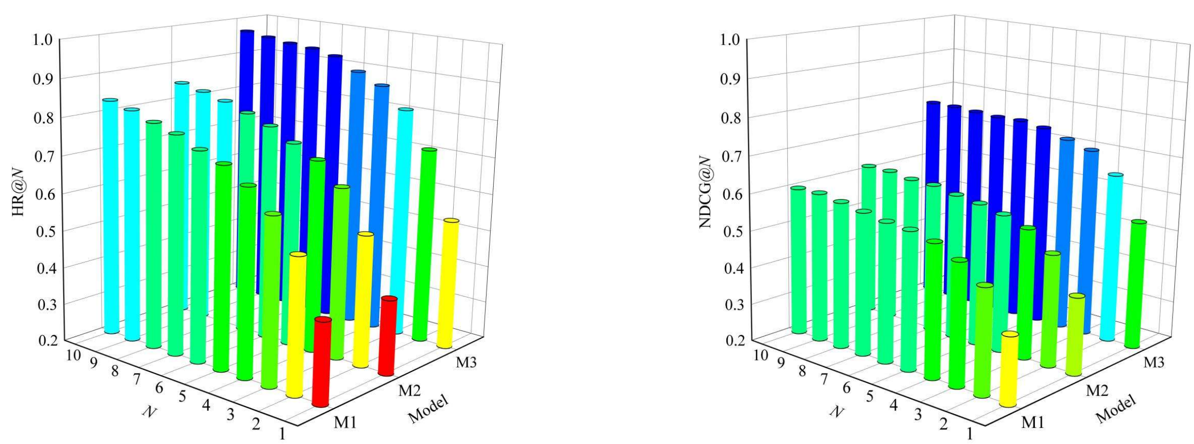
V. A. Recommendation Accuracy

The National Music Culture Cloud dataset was selected as the experimental dataset, with HR@N and NDCG@N as evaluation metrics. HR@N is calculated using the ratio of users who were matched to the total number of users, measuring the model's recall capability. NDCG@N considers the ranking of items of interest to users in the list, measuring the model's ranking capability. By having the model predict the Top-N recommendation list for each user, the recommendation results for the video domain using the three models on the experimental dataset are shown in Figure 6, for the music domain in Figure 7, and for the culture domain in Figure 8.



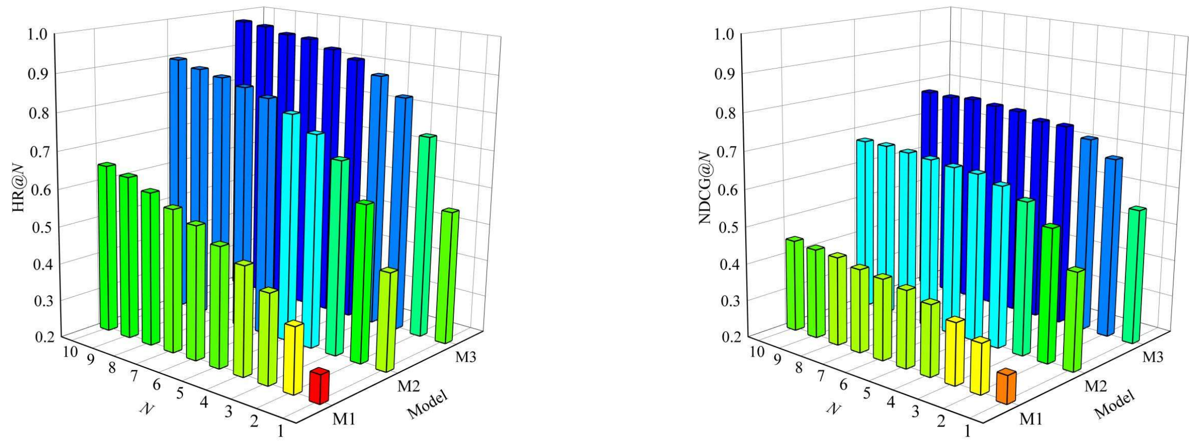
(a) HR@10 (b) NDCG@10

Figure 6: The video domain recommendation results of the three models



(a) HR@10 (b) NDCG@10

Figure 7: The music domain recommendation results of the three models



(a) HR@10 (b) NDCG@10

Figure 8: The cultural domain recommendation results of the three models

As shown in Figures 6–8, regardless of whether it is the video domain, music domain, or cultural domain, the system model proposed in this paper (M3) significantly outperforms the other two comparison models. Under recommendation list sizes ranging from 2 to 10, the system model proposed in this paper (M3) achieves scores greater than 0.6 for both HR@10 and NDCG@10, and even achieves a score greater than 0.5 for a recommendation list size of 1. This indicates that the model effectively combines user needs to provide precise recommendations across multiple resource domains.

V. B. Average error

This paper uses the Mean Absolute Error (MAE) to evaluate the performance of the recommendation algorithm, utilizing 300 resources from the Chinese National Traditional Music Cultural Resource Database for performance testing. A random sample of N data points is selected as the test set, with the remaining 300-N data points forming the training set. The number of neighbors K is initially set to 10, with each iteration increasing K by 10. The changes in MAE corresponding to different K values in the experiment are shown in Figure 9. The mean errors of all three models decrease gradually as K increases. Both the system model (M3) and the DMF model (M2) converge when K reaches 20. Among the three models, the system model (M3) exhibits the smallest mean error, stabilizing around 0.75, making it the best-performing model.

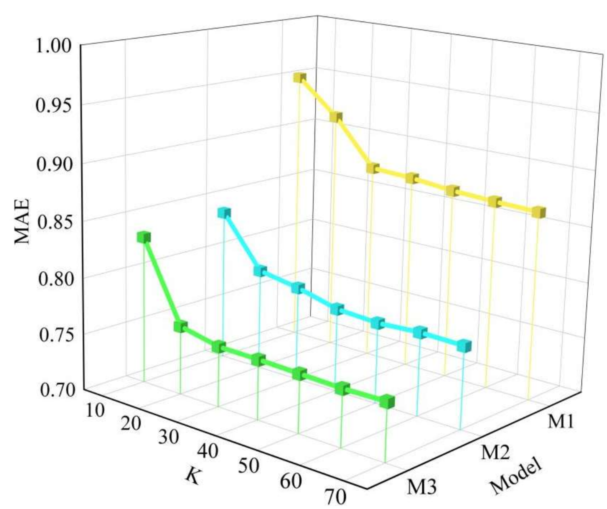


Figure 9: The number of nearest neighbors and the average error

V. C. Adjustment of comprehensive user similarity

Based on the analysis in the previous section, this paper pre-sets the number of nearest neighbors K for the target users to three sets of data: 20, 40, and 60. In this section, we explore the impact of the user comprehensive similarity adjustment parameter α on the model algorithm of this paper. We conduct experiments by incrementally increasing the value of the user comprehensive similarity adjustment parameter α from 0.1 to 0.9 in steps of 0.1. The experimental results for different values of parameter α are shown in Figure 10.

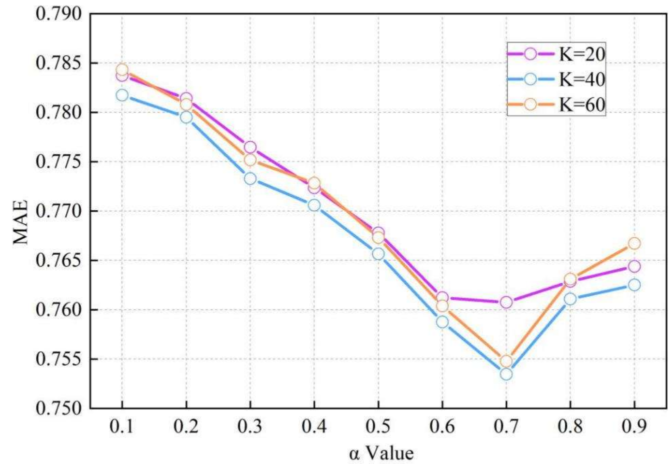


Figure 10: The variation of MAE with α

Under three different numbers of nearest neighbors, the MAE values of the model algorithm in this paper all change with the variation of the α value, first decreasing and then slowly increasing. The MAE values for all three nearest neighbor counts reach their minimum at α = 0.7, and when the nearest neighbor count K is 40, the MAE value is as low as 0.7535. Therefore, when calculating user similarity, with a weight of 0.7 for user ratings and 0.3 for tags, the proposed model algorithm achieves good prediction performance, so the value of α is 0.7.

VI. Conclusion

In the field of digital display technology for traditional music culture, this paper constructs a semantic information model through processes such as data classification and active service work. By improving the Apriori algorithm, a collaborative filtering recommendation algorithm with higher recommendation accuracy is obtained. In comparative experiments with similar models, the proposed model algorithm achieves HR@10 and NDCG@10 metrics both exceeding 0.5 for recommendation results in the video domain, music domain, and cultural domain of traditional music. The average error converges when K is 20, stabilizing around 0.75, with overall performance significantly outperforming models in the same field.

With the support of the proposed model and algorithm, a digital display system for traditional music culture was established and put into experimental use. Currently, users' willingness to use the system decreases with age, with usage intentions exceeding 81.00% among both the under-18 and 18–29 age groups. Additionally, the willingness to use the digital exhibition system is correlated with user identity, primarily concentrated among students with academic or research needs (82.93%) and government employees (91.45%).

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