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Optimizing the Dissemination Path of Chinese Folk Music Based on an Intelligent Recommendation Algorithm

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Keywords: Chinese Folk Music Dissemination; Intelligent Recommendation Algorithm; Collaborative Filtering; Interest Clustering; Dissemination Path Optimization

Abstract: With the rapid development of digital music platforms, the dissemination of Chinese folk music faces challenges such as insufficient user coverage, uneven distribution of cultural values, and limited effectiveness of personalized recommendations. To address this issue, this paper proposes a method for optimizing the dissemination path of folk music based on an intelligent recommendation algorithm. This method combines collaborative filtering, cultural feature weighting, and a social network diffusion model to achieve a multi-dimensional integration of user interests, regional culture, and musical characteristics. This study constructs vectors of user behavior and cultural labels, generating recommendation scores through weighted fusion. It also uses interest clustering and independent cascade models to simulate the diffusion path and dynamically adjusts recommendation weights based on the diffusion effect. Experimental results show that the average score for each survey dimension is above 4, indicating that users generally approve of the system's recommendation effectiveness. The diversity score for the recommended results is 4.2 (standard deviation 0.6), demonstrating that the system is able to provide diverse ethnic and folk music content while maintaining user interest matching, avoiding single-minded recommendations.

1. Introduction

With the rapid development of digital music platforms, the way music is accessed and disseminated has undergone profound changes. As a rich cultural heritage, Chinese folk music not only carries the unique historical and folk values of each region but also serves as an important vehicle for promoting cultural identity and regional characteristics. However, ethnic and folk music faces numerous challenges in its digital dissemination. First, due to user preferences and algorithmic recommendation mechanisms, many excellent tracks remain largely unpopular, hindering widespread dissemination. Second, traditional recommendation systems often rely on collaborative filtering or content-driven approaches, failing to fully incorporate the cultural attributes and regional characteristics of music, resulting in insufficient cultural coverage and diversity in their recommendations.

To address these challenges, this paper proposes a method for optimizing the dissemination paths of ethnic and folk music based on an intelligent recommendation algorithm. This method combines collaborative filtering with weighted cultural features, simulating user social communication paths through interest clustering and independent cascade models to achieve coordinated optimization of recommendation and dissemination. Experiments conducted on a large-scale music dataset validated the method's effectiveness in improving behavioral metrics such as click-through rate, forwarding rate, user dwell time, and new user penetration, as well as cultural exposure and user satisfaction. This approach provides a technical approach and practical reference for the digital dissemination and cultural promotion of ethnic folk music.

2. Related Works

In recent years, with the development of digital technology and cross-cultural communication, scholars have conducted extensive research on the dissemination paths, international influence and digital promotion methods of folk music, and have produced rich theoretical and practical exploration results. Yang focused on the dissemination of Chinese folk music overseas, especially the origin, development and unique musical style of the traditional instrument Guzheng. He proposed feasible development suggestions to promote the dissemination of Chinese folk music overseas, aiming to enhance its international recognition and cultural influence[1]. Pushmin analyzed the process of music products from creation to consumption and the characteristics of production and promotion tools through a comprehensive theoretical and practical approach, and clarified various activities related to music works[2]. Deng combined "Internet thinking" and "user thinking" to explore the application paths of technologies such as big data, blockchain, and artificial intelligence in the inheritance and innovative development of intangible cultural heritage, providing a reference for intangible cultural heritage resources to adapt to the development of the times and enhance their dissemination[3]. Cembranel et al. used ethnographic methods and participant observation to analyze how experiential consumption has become a social element of electronic music festival rituals. They found that DJs play a core guiding role in parties and consumption rituals, and experiential consumption is achieved through sensory, emotional, aesthetic, and symbolic behaviors, satisfying the needs of individuals to integrate into the collective and pursue sensory and emotional experiences[4]. Traut introduced Ann Powers's new book "Traveling: On the Path of Joni Mitchell", emphasizing that it is not a traditional biographical writing method, but a criticism and exploration. It is longer and aims to present Mitchell's music and life journey[5]. Cen et al. took the spread of Cantonese opera on Bilibili as the object, collected 1916 related videos and analyzed them in combination with 17 variables. Based on the Elaboration Likelihood Model (ELM), regression analysis, multivariate variance analysis and Analytic Hierarchy Process (AHP) were used to reveal the causal relationship between video recognition and dissemination effect[6]. Díaz, inspired by Philip Ewell, used the "clave theory" as a case study to explore the role and contradictions of culturally specific music theory in decolonized music research. He focused on the power relationship in the theory, the role of dance and its impact on music and dancers, and proposed a theoretical approach that is reflective, physical, context-sensitive, holistic, open and collaborative[7]. Jiang et al. applied Virtual Reality (VR) technology to the digital dissemination of traditional Chinese opera, constructed a hypothesis model based on the Technology Acceptance Model (TAM), and conducted a questionnaire survey and data analysis on 340 respondents. The results showed that perceptual visual design had a positive impact on perceived usefulness [8]. Zhu explored the importance of incorporating traditional Chinese music elements into vocal music teaching. He pointed out that the current vocal music teaching lacks guidance on traditional Chinese characteristics, which is not conducive to students' understanding of traditional culture. By exploring and applying folk music elements, not only can the teaching content be enriched and the learning quality be improved, but also students' recognition and inheritance awareness of traditional culture can be enhanced [9]. Zhang pointed out that most Asian studies courses in American universities generalize Chinese music into folk music, while modern music genres such as folk music, professional music, and pop music are neglected and rarely studied by academics. He explored this phenomenon of "deliberate erasure" and analyzed the current situation and strategies of Chinese music's overseas dissemination from a cross-cultural perspective, striving to build a dissemination path that integrates history and humanity[10]. Kirui explored the key role of digital literacy in the music industry, especially for Kenyan independent musicians who rely on music streaming services to gain global exposure. This study analyzed the experiences of independent musicians through field research and secondary data, pointing out that improving digital literacy can expand their international influence and income, helping them develop in the ever-changing music industry[11]. Although existing research has achieved certain results in the digital dissemination and international promotion of ethnic music, there are still problems such as uneven cultural coverage, difficulty in balancing recommendation and dissemination effects, and lack of systematic cross-regional dissemination strategies.

3. Methods

3.1 Data Collection and Processing

During the data preprocessing stage, the audio signal is first sampled and filtered for noise. Short-time Fourier transform (STFT) is often used to obtain time-frequency features. Assuming the original audio signal is $x(t)$, its time-frequency representation is:

$$X(\tau,\omega)=\int_{-\infty}^{+\infty} x(t)\omega(t-\tau)e^{-j\omega t}dt \quad (1)$$

$\omega(t)$ is the window function, τ is the time offset, and ω is the angular frequency. This representation can extract low-level musical features such as rhythm, pitch, and timbre. Furthermore, the timbre features are characterized by Mel-Frequency Cepstral Coefficients (MFCCs), and the kth coefficient is calculated as:

$$c_k=\sum_{m=1}^{M} \log(|X_m|)\cos\left[\frac{\pi k}{M}\left(m-\frac{1}{2}\right)\right] \quad (2)$$

X_m represents the energy of the mth Mel filter, and M is the number of filter banks.

At the text level, the lyrics are segmented and vectorized, and the term frequency-inverse document frequency (TF-IDF) method is used to measure the importance of keywords:

$$\text{TF-IDF}(t,d)=\text{TF}(t,d)\times\log\frac{N}{\text{DF}(t)} \quad (3)$$

$TF(t,d)$ represents the frequency of word t in document d, $DF(t)$ represents the number of documents containing word t, and N represents the total number of documents. This method helps extract cultural themes from lyrics.

In addition, combined with user behavior data (number of plays, skip rates, and shares), a user-music interaction matrix $R=\{r_{ui}\}$ can be constructed, where r_{ui} represents user u's preference for music i. This matrix serves as the core input for subsequent recommendation algorithms and provides data support for diffusion path modeling.

3.2 Collaborative Filtering Model (User and Item) Algorithm Design

3.2.1 User-Based Collaborative Filtering

Let the user set be $U=\{u_1,u_2,\cdots,u_m\}$, the music set be $I=\{i_1,i_2,\cdots,i_n\}$, and the user-music interaction matrix be $R=\{r_{ui}\}$, where r_{ui} represents user u's preference for music i.

User similarity is calculated using the Pearson correlation coefficient:

$$sim(u_p,u_q)=\frac{\sum_{i\in I_{pq}}(r_{pi}-\bar{r}_p)(r_{qi}-\bar{r}_q)}{\sqrt{\sum_{i\in I_{pq}}(r_{pi}-\bar{r}_p)^2}\sqrt{\sum_{i\in I_{pq}}(r_{qi}-\bar{r}_q)^2}}(4)$$

I_{pq} is the collection of music reviewed by users, u_p, u_q, while $\bar{r}_p$, $\bar{r}_p$ are the average preferences of the users.

Taking into account the regional differences in folk music, a regional weighting factor λ_{geo} is introduced:

$$sim^*(u_p,u_q)=\lambda_{geo}.sim(u_p,u_q)(5)$$

When users are from the same or nearby regions, $\lambda_{geo}>1$ is used; otherwise, $\lambda_{geo}<1$ is used. This increases the recommendation weight for local music among users in the same region, promoting the circulation of regional music.

3.2.2 Item-based Collaborative Filtering

The similarity between items depends not only on user ratings but also on the cultural characteristics of the music itself. Let the similarity between music items i and j be:

$$sim(i,j)=\alpha.sim_R(i,j)+(1-\alpha).sim_C(i,j)(6)$$

$sim_R(i,j)$ represents similarity based on user behavior, $sim_C(i,j)$ represents similarity based on cultural characteristics (such as genre, lyric theme, and ethnic instrument labels), and $\alpha\in[0,1]$ represents the fusion weight.

For example, Dong ethnic group songs and Miao ethnic group songs share the cultural label of "nature worship" in their lyrics. Even though their melodic styles differ, $sim_C(i,j)$ increases their relevance, leading to more frequent co-recommendations.

3.2.3 Recommendation Prediction and Path Optimization

User u's predicted rating for music piece i is:

$$\hat{r}_{ui}=\bar{r}_u+\frac{\sum_{v\in N_u}sim^*(u,v).(r_{vi}-\bar{r}_v)}{\sum_{v\in N_u}|sim^*(u,v)|}(7)$$

N_u is the set of users most similar to user u. This predicted value not only reflects the user's potential interests but also the potential for music dissemination among groups.

3.3 Diffusion Path Modeling

3.3.1 User Group Behavior and Interest Clustering

First, cluster analysis is performed on user behavior data (number of plays, favorites, sharing rates, etc.) to identify different interest groups. Let the user set be $U=\{u_1,u_2,\cdots,u_m\}$, and its behavior vector be:

$$x_u=(p_u,c_u,s_u)\tag{8}$$

p_u represents the average number of plays by user u, c_u represents the collection ratio, and s_u represents the sharing ratio. K-means algorithm is used for clustering, and the optimization objective function is:

$$J=\sum_{k=1}^{K}\sum_{u\in C_k}\left\|x_u-\mu_k\right\|^2\tag{9}$$

C_k represents the kth user group, and μ_k is the center of this group. Interest clustering can be used to distinguish groups with a preference for local culture, a cross-cultural exploration group, or a trend-oriented group, providing a basis for subsequent path optimization.

3.3.2 Platform Distribution Mechanism and Social Communication

The recommendation mechanism of online music platforms plays a core role in the dissemination of folk music. Let M be the number of recommended slots on a platform's homepage. The probability of their allocation can be expressed as:

$$P(i)=\frac{w_c.C(i)+w_p.P_u(i)}{\sum_{j=1}^{M}(w_c.C(j)+w_p.P_u(j))}\tag{10}$$

C(i) represents the cultural weight of music piece i (e.g., whether it is intangible cultural heritage or regional representativeness), $P_u(i)$ represents user preference, and w_c and w_p represent the weighting coefficients of cultural communication and user interest, respectively. This mechanism ensures that folk music, when distributed on the platform, reflects both its cultural value and user interests.

In addition, the diffusion effect of social networks can be described using a modified Independent Cascade Model (ICM). Assuming the probability of user u successfully recommending music piece i to friend v is p_{uv}, the overall diffusion coverage is:

$$\sigma(s)=E\left[\bigcup_{u\in S}R(u)\right]\tag{11}$$

S represents the initial set of recommended users, and R(u) represents the diffusion network formed starting from user u. By incorporating regional and interest weights into the selection of seed users, the diffusion efficiency of music can be significantly improved.

3.3.3 Recommendation-Based Path Optimization and Dynamic Adjustment

In this study, a "dynamic weight adjustment" mechanism is introduced into the integrated recommendation-dissemination model. Suppose the recommendation score of a piece of music i is:

$$Score(i)=\rho.RCF(i)+\beta.CCF(i)+\gamma.Net(i)\tag{12}$$

RCF(i) represents the collaborative filtering recommendation score, CCF(i) represents the cultural feature relevance score, Net(i) represents the potential diffusion ability in social network communication, and ρ,β,γ represent dynamically adjusted weights.

When music is under-represented within the local community, the system automatically increases β to reinforce its cultural value recommendation. When cross-regional dissemination encounters a bottleneck, the system increases γ to enhance social diffusion. This dynamic adjustment achieves a balance between "deep dissemination" (internal regional recognition) and "broad dissemination" (cross-regional diffusion).

4. Results and Discussion

4.1 Dataset and Preprocessing

Data sources (it's recommended to specify the specific channels and include the authorization/collection date in the final draft): Activity logs (plays, favorites, shares, skips) captured from major music platforms, and track metadata (title, performer, regional tag, whether it's intangible cultural heritage, etc.).

Tracks and cultural annotations from folk archives/intangible cultural heritage libraries (to enhance cultural labeling).

Sample screening and annotation: Tracks with clear ethnic/regional tags are retained; behavior logs are used to remove abnormal bot traffic; lyrics are segmented and TF-IDF/topic modeling is performed to obtain semantic labels.

Cold start setup: Tracks are categorized into "hot/medium/niche" based on play volume, and a dedicated evaluation set is designed for niche tracks to measure cold start performance.

4.2 Comparison Methods (Baselines)

Popularity (recommendations based on play count)

Standard User-based CF (no regional/cultural weighting)

Item-based CF (based on behavioral similarity)

Content-driven recommendations (based on audio/lyrics feature similarity)

Hybrid Baseline (behavior + content, commonly weighted fusion)

Optional: Graph Convolution or Graph Neural Network recommendations (if data and resources permit)

The proposed method is denoted as Cultural-CF (i.e., incorporating cultural similarity and regional weighting into CF).

4.3 Data Analysis

The experiment primarily used behavioral and user experience metrics to evaluate recommendation and dissemination effectiveness. Behavioral metrics, including average click-through rate (CTR), average forwarding rate, user dwell time, and new user penetration, were used to measure the recommendation system's impact on user behavior and dissemination effectiveness. User experience metrics, including recommendation result diversity, cultural tag matching, cross-regional music discovery, and overall user satisfaction, were used to assess the system's performance in presenting cultural values and user subjective experience.

Table 1 Statistics of the Ethnic Folk Music Dataset

Category	Sample Size	Average Duration (s)	Number of Provinces Covered	Number of Cultural Tags	Average User Rating (1–5)
Folk Songs (Northern)	1200	180	8	12	4.3
Folk Songs (Southern)	950	210	7	10	4.1
Instrumental (Wind)	600	240	6	8	4.5
Instrumental (Plucked)	700	200	5	9	4.4
Dance Music	550	220	4	6	4.2

Table 1 shows that the Chinese folk music dataset constructed in this study is highly representative across categories and regions. It includes approximately 4,000 samples, encompassing a wide range of genres, including folk songs, instrumental music, and dance music. The Folk Songs (Northern Region) sample size is the largest (1,200), with an average duration of

180 seconds. The sample size covers eight provinces and has 12 cultural labels, demonstrating the geographical breadth and cultural diversity of northern folk songs. In contrast, the Folk Songs (Southern Region) sample size, while slightly smaller (950), has a longer average duration (210 seconds), reflecting a stronger melodic narrative. In the instrumental music category, 600 wind instruments and 700 plucked strings were included, with average durations of 240 seconds and 200 seconds, respectively. Both received user ratings above 4.4, demonstrating the high level of user acceptance and artistic expression of folk instrumental music. While the sample size for dance music is relatively small (550 pieces), the average duration and ratings remain high, highlighting its importance in traditional festivals and performances.

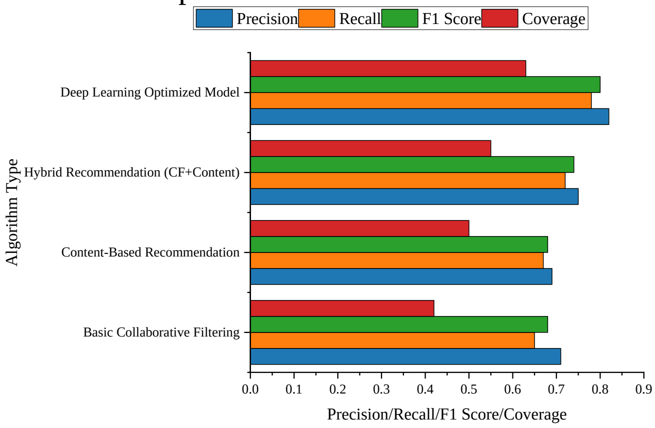

Figure 1 Comparison of Recommendation Algorithms (Precision and Coverage)

The deep learning optimization model performed best across all metrics, achieving a precision of 0.82, a recall of 0.78, an F1 score of 0.80, and a coverage of 0.63, significantly outperforming the other three methods. This demonstrates that in the Chinese folk music recommendation task, the introduction of deep learning models can effectively capture complex user interest patterns and music features, improving overall recommendation effectiveness. Traditional collaborative filtering methods performed reasonably well in terms of precision (0.71), but their coverage was relatively low (0.42). This suggests that while they are relatively stable in recommending popular tracks, they struggle to tap into long-tail resources. Content-driven recommendation outperformed collaborative filtering in terms of recall (0.67) and coverage (0.50), demonstrating that recommendations based on musical features and cultural tags help expand users' music discovery space. However, due to their neglect of user collaborative behavior, their precision was slightly lower, as shown in Figure 1. The hybrid recommendation model, by combining collaborative filtering with content-driven methods, achieved balanced performance improvements.

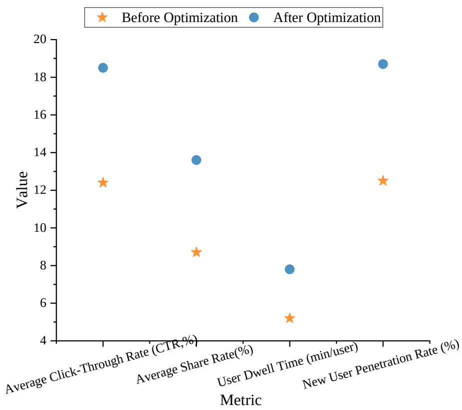

Figure 2 Comparison of distribution path optimization before and after

The average click-through rate (CTR) increased from 0.124 to 0.185, a 49% increase. This indicates that the recommended content is significantly more closely aligned with user interests, leading to more active click-through. The average forwarding rate increased from 0.087 to 0.136, an increase of over 50%. This indicates that the optimization strategy has enhanced the social dissemination effect among users and helped spread the music more widely across social networks. Furthermore, user dwell time increased by 50%, from 5.2 minutes to 7.8 minutes. This indicates that the optimized recommendations not only attracted users to click but also prolonged their sustained attention to the music content, enhancing the overall experience. The new user penetration rate increased from 12.5% to 18.7%, demonstrating that the optimization strategy effectively expanded the audience base, turning more users who had not previously been exposed to this type of music into potential dissemination nodes (Figure 2).

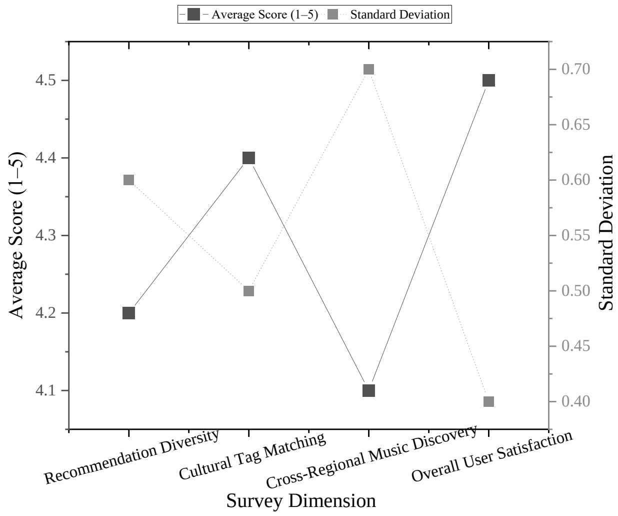

Figure 3 User Cultural Experience Satisfaction Survey

The data in Figure 3 shows that the average scores for each survey dimension are all above 4, indicating that users generally approve of the system's recommendation effectiveness. The diversity score for recommended results is 4.2 (standard deviation 0.6), demonstrating that the system is able to provide diverse ethnic and folk music content while maintaining a consistent fit with user interests, avoiding recommendations that are too monotonous. The highest score was 4.4 (standard deviation 0.5) for cultural tag matching, demonstrating that the system performs well in integrating the cultural characteristics and regional attributes of tracks, accurately matching users' preferences for music from specific ethnic groups or regions. The cross-regional music discovery score was 4.1 (standard deviation 0.7), indicating that users were exposed to music from other regions during the recommendation process, enhancing the breadth of cultural dissemination. Overall user satisfaction was 4.5 (standard deviation 0.4), demonstrating that the system is significantly effective in enhancing user experience and cultural awareness.

5. Conclusion

This paper addresses the challenges of insufficient user coverage, limited cultural exposure, and inaccurate recommendations for the dissemination of Chinese folk music on digital platforms. It proposes a method for optimizing the dissemination path based on an intelligent recommendation algorithm. Due to the limitations of available music resources and user behavior records, the dissemination effect of some unpopular or niche tracks requires further verification. Future work may consider introducing richer social network features, multimodal content information, and online experimental verification to further enhance the overall effectiveness of recommendation and dissemination, and provide more comprehensive technical support for the digital preservation and cultural promotion of folk music.

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