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A Hybrid Music Recommendation Model Based on Personalized Measurement and Game Theory

WU Yun[1,2], LIN Jian[1,2], and MA Yanlong[1]

(1. *The State Key Laboratory of Public Big Data, Guizhou University, Guiyang 550025, China*)

(2. *College of Computer Science and Technology, Guizhou University, Guiyang 550025, China*)

Abstract — Music recommendation algorithms, from the perspective of real-time, can be classified into two categories: offline recommendation algorithms and online recommendation algorithms. To improve music recommendation accuracy, especially for the new music (users have no historic listening records on it), and real-time recommendation ability, and solve the interest drift problem simultaneously, we propose a hybrid music recommendation model based on personalized measurement and game theory. This model can be separated into two parts: an offline recommendation part (OFFLRP) and an online recommendation part (ONLRP). In the offline part, we emphasize users personalization. We introduce two metrics named user pursue-novelty degree (UPND) and music popularity (MP) to improve the traditional items-based collaborative filtering algorithm. In the online part, we try to solve the interest drift problem, which is a thorny problem in the offline part. We propose a novel online recommendation algorithm based on game theory. Experiments verify that the hybrid music recommendation model has higher new music recommendation accuracy, decent dynamical personalized recommendation ability, and real-time recommendation capability, and can substantially mitigate the problem of interest drift.

Key words — Music recommendation, Personalization, Game theory, Interest drift, Hybrid music recommendation model.

I. Introduction

In this digital era, the Internet has become the prominent essential of life. People are using various platforms on the Internet to entertain their different needs and activities such as shopping, watching videos, education, communication, following their favorite celebrities, generating new trends, business, entrepreneurship and many more activities. These all activities are not only producing huge data but also demanding a structured approach to access the information that is fast, reliable and relevant. Data overload results in the increasing demands of personalized. Recommender systems (RSs) can conduct recommendations effectively by analysis of user behavior logs. Traditional RSs present a very high similar recommendation among various users, and ignore their personalized completely [1], [2]. Therefore, it is highly necessary to strengthen RSs' personalized recommendation ability.

In the past decades, a multitude of recommendation algorithms has been developed [3], [4]. However, there are still large amounts of challenges and dilemmas existed in RSs, such as unsatisfying recommendation accuracy, and real-time recommendation problems. Up to now, collaborative filtering is one of the most widely used recommendation technologies in recommendation systems research. Collaborative filtering is the technology that focuses on the relationships between users and between items to make a prediction. The goal of the recommender system is to compute a scoring function that aggregates the result of computing similarities between users and between items. An increasing amount of digital music is being published daily. Music streaming services often ingest all available music, but this poses a challenge: how to recommend new and interested songs for users. Li *et al.* [5] developed a portrait model of music users, and combined the clustering algorithm to analyze the similarity of a large amount of data. Combined with the clustering algorithm, several groups of users are obtained. Then, for each user group, different recommendation lists are obtained. Shen *et al.* [6] proposed a PEIA model which employs hierarchical attention under deep framework to learn the correla-

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tions among user personality, user emotion and music. Mogale *et al.* [7] use a self-similarity matrix developed in R to visualize repetitive patterns in text-extracted lyrics and generate a visual pattern of a song, which is then compared with patterns of many other songs available on the platform, especially those that have not been played before. The comparison is then made and if the similarity index of the comparison is higher than 70%, then the song is recommended to the user. Elbir *et al.* [8] aim to classify and recommend songs using acoustic features, extracted by digital signal processing methods and convolutional neural networks. Yu *et al.* [9] designed a new model for music recommendation systems combining BRNN, GRU and several attention mechanisms. Experiments show that the simple neighbor-based approach can still achieve very competitive performance on MPD data by choosing appropriate similarity functions and properly considering list-song similarity. Jin *et al.* [10] believe that music is good or bad depending on environmental characteristics, and constructs a context-aware music recommender, to study the four aspects of controlling context characteristics in terms of perceived quality, diversity, validity and cognitive load in music recommendation system influences. Wu *et al.* [11] proposed a novel user similarity computation method based on ratio and proposes a new ratio-based collaborative filtering method (RACF). Then, get the similarity between users or between items by comparing the attribute values directly and obtain a better prediction. However, this method merely considers the similarity between users, and does not consider the underlying relationships between items. Sun *et al.* [12] proposed a personalized music recommendation model based on convolutional neural network (CNN), which divides music into different types according to the audio signal beat of the music, and outputs the output of CNN with the history of all users. The log files are combined to recommend music to the user. These methods, however, fail to consider the variable sensitive degrees of individuals toward new items and the fluctuations of items popularity corresponding to time. This paper thereby proposes the concepts of user pursue-novelty degree (UPND) and music popularity (MP) in which UPND is regarded as a metric to measure users interest change and MP is viewed as a metric to evaluate the items popular degree. Thus, OFFLRP algorithm integrated UPND with MP has been proposed to further improve the accuracy and obtain better performance in RSs.

Chen *et al.* [13] proposed a method to detect user interest drift in the context of Douban movie reviews. Users' reviews and the frequency with which users watch certain types of movies are used to determine the extent of user interest drift. A hierarchical user interest classification tree (named HC-tree) and a time window table were designed to maintain interests and their weights in a multi-granularity manner. Xu *et al.* [14] proposed a dual model, including a truster model (Truster SVD) and a trustee model (Trustee SVD), and a two-way trust recommendation in an AI IoT system named TT-SVD. This model integrates trust and rating information more comprehensively and thus is able to solve the cold start and data sparsity problems. Jiang *et al.* [15] proposed a scratch adaptive user interest drift recommendation framework (SRFA-UID) in order to provide the required resources for users. First, a user interest drift model is designed, which employs a temporal decay factor and weights of operational behaviors to track the dynamic interest of users. Then, based on users' current and historical interests, their combined user similarity is calculated. Mao *et al.* [16] presented the singing song recommendation technique for the online social singing community. They focus on satisfying user's performance needs for singing. However, it ignores the connections between items. Vagliano *et al.* [17] describes a new recommendation algorithm based on structured data published on the Web (linked data). The algorithm exploits existing relationships between resources by dynamically analyzing both the categories to which they belong to and their explicit references to other resources. A user study conducted to evaluate the algorithm showed that their algorithm provides more novel recommendations than other state-of-the-art algorithms and keeps a satisfying prediction accuracy. Although these literatures listed above have improved the recommendation accuracy and performance at a certain degree, especially on the datasets with very high sparsity, few of them has tackled the interest drift problem. Hence, we propose ONLRP to deal with this tricky problem to further improve recommendation performance.

Therefore, based on the current RS research progress, we proposed a hybrid music recommendation model (HMRM). As shown in Fig.1, we divide it into two parts: the offline recommendation part (OFFLRP) and the online recommendation part (ONLRP). First, personalized features based on user pursuit (UPND) and music popularity (MP) are introduced in OFFLRP to enhance the personalized features of offline computed recommendations, and the relationship between users and items is used to improve the accuracy of recommendations, especially for new music recommendations. Then, in ONLRP, using the gap between two offline computations, we treat the interaction between users and the system as a game relationship (the specific game steps are visible in Section IV) to implement online recommendation computation to maintain the accuracy of recommendations and solve the interest drift problem, which leads to better real-time performance of HMRM.

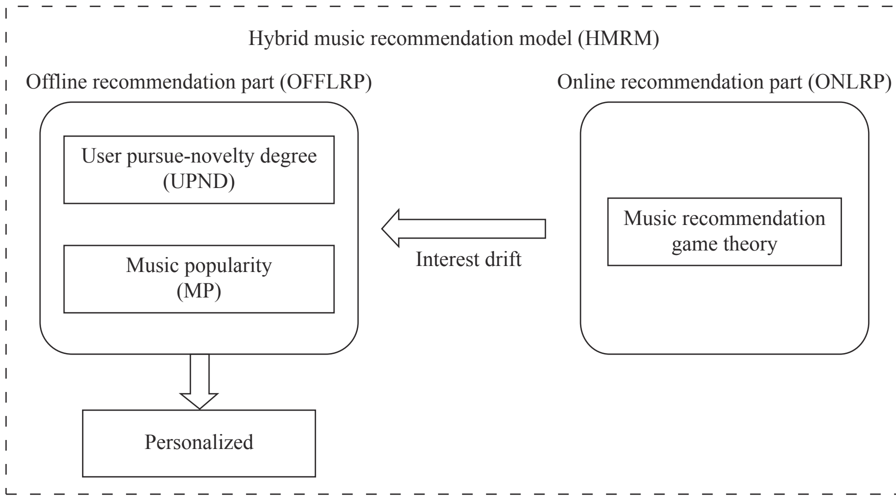

Fig. 1. The framework of HMRM.

II. Relevant Concepts and Prerequisite Constraints

1. Personalized measurement

The collaborative filtering (CF) based recommendation is the most well-known approach, and is widely utilized in products, services and travel recommendations [18]. The personalized measure is a measuring method of users interests and hobbies, which is of vital significance in a personalized recommendation. We put forward UPND and MP to improve the personalized measure accuracy, thus further improve the personalized recommendation accuracy.

Items-based collaborative filtering algorithm is put forward by Amazon engineers [19], [20]. Unlike traditional method that matches items to users behaviors, items-based collaborative filtering algorithm builds up a huge item-to-item similarity table. Through the table, it can extract a series of similar items that are similar to users current purchases and then recommend the highest correlation or best sell items to users [21], [22]. The more purchases users created, the more accuracy the recommendation will be. Items-based collaborative filtering algorithm utilizes the following formula to conduct personalized recommendation [23], [24]:

$$P_{uj} = \sum_{i \in N(u) \cap S(j,K)} W_{ji} \tag{1}$$

where P_{uj} denotes the preference degree of user u to item j; $N(u)$ denotes the purchases collection of user u; $S(j, K)$ denotes the highest similar collection (K items) to item j; W_{ji} denotes the similarity degree of item j and item i. By computing P_{uj}, it is possible to determine the user preference for each item, and further conduct Top$N$ recommendation.

2. Game-theoretical thought

Game theory was proven by John Von Neumann, and its relevant theories are one of the main subjects of current economics [25]. Game theory is about equilibrium: equilibrium means balanced. With regard to an online recommendation, this article uses game theory to address the interest drift of users. We treat the users' usage of recommendation systems as a game between the users and the system. We treat what the users do base on their own interest as users strategy and the recommendations based on users strategy as the strategies of the system. Specifically, we treat the music that users listen to in the online music recommendation system as users strategies and the dynamic recommendation based on users online subscription as the strategies of the system. Payoffs of both sides are reflected in terms of the acceptance rate of the recommendations. In other words, the more accurate the recommendation is, the higher the payoff.

3. Conditions for HMRM

The algorithms this paper addresses is composed of two parts, offline recommendation and online recommendation and they can used in the following circumstances:

1) Users action logs have their time stamps.

2) Users have repetitive actions, such as one user listens to the same piece of music multiple times or the same user purchases the same product repetitively.

3) Products vary in how new they are, such as the different distribution dates of music and whether the music has been listened or not.

In the experiment in this paper, we adopt the public musical dataset of Last.FM and the subscription log meets the above conditions. In the paper, new music refers to the music never heard of by the user.

4. Brief introduction to HMRM

The conventional recommendation algorithms can be divided into offline and online types based on their timely nature. This work is built on the recommendation system of offline+online. It is a hybrid music recommendation model which is constituted by offline recommendation part (OFFLRP) and online recommendation part (ONLRP).

The key contributions and innovations of this paper are three-fold:

1) The OFFLRP makes innovation in stressing personalization, introducing the metric of follow degree describing how much users follow the new music, and thus putting forward the collaborating filtering algorithms, effectively improving the accuracy of recommendations, especially for new music.

2) The ONLRP makes innovation by introducing the game-theoretical algorithms of learning through games, substantially mitigating the problem of interest drift. The online recommendation algorithm combines the recommendation results of the offline recommendation algorithm with the online recommendation in the process of system-user interaction, which effectively alleviates the interest drift problem in the offline recommendation and improves the real-time performance of the recommendation algorithm.

3) We conduct experiments on the public music dataset of Last.FM. We prove that the music popularity and user catch-up proposed in the offline recommendation part can effectively improve the recommendation accuracy, and the introduction of game theory in the online recommendation part can greatly alleviate the problem of interest drift.

III. Offline Recommendation Part of HMRM

To highlight personalized, we analyze traditional items-based collaborative filtering algorithm and propose a novel offline recommendation algorithm based on UPND and MP. We first define UPND and MP respectively, then put forward the improved offline recommendation model, and compare its performance with a traditional method.

1. UPND and MP based OFFLRP algorithm

User pursue-novelty degree Different users have different attitudes toward new and hottest music: some have a sincere preference for new and hottest music, while others have a particular love on old and conventional music. We utilize the Last.FM dataset, take the first 100-day data, and randomly select user 553 (user id) and user 820 (user id) and their new and hottest music listening net increase trend, as shown in Fig.2.

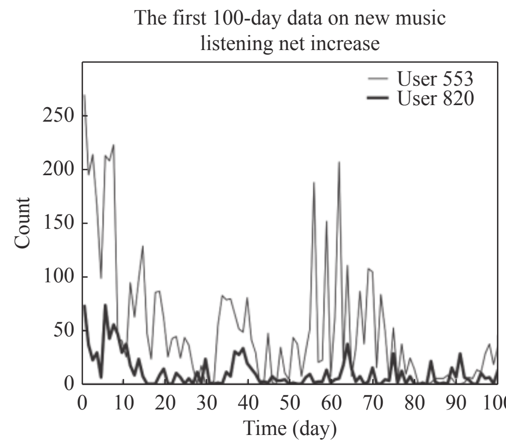

Fig. 2. The first 100-day data on new music listening net increase.

From Fig.2, it is highly obvious that different users have different new music listening net increase values at the same time point. In other words, different users have different attitudes and changeable degree toward new music. According to the pattern we found, we define the user pursue-novel degree (UPND) as follows:

$$M_u = (A_u, K_u) \tag{2}$$

where M_u denotes user model; A_u denotes the average amount of songs a user listening daily, it reflects users overall preference degree of new music; K_u denotes the slop after linear regression on new music listening net increase statistic, it reflect the change trend of the new music preference.

Music popularity The popularity of different music is different. Some music might catch attention since they are launched; while others might be popular in a small group. Simultaneously, the popular duration various among music. Some music might have been popular from the start to the end and finally, become classic music; while others might bring about a boom in a short time but fade quickly. We randomly select music 350421 (song id) and music 415226 (song id), and count their daily listening frequency in first 100-days, and its statistic can be shown in Fig.3.

From Fig.3, it is highly obvious that different songs have different listening frequently at the same time point. That's to say, the popularity varies in different songs. And the popular durations also vary in different songs. According to the pattern we found, we define the music popularity (MP) as follow:

$$M_m = (A_m, K_m) \tag{3}$$

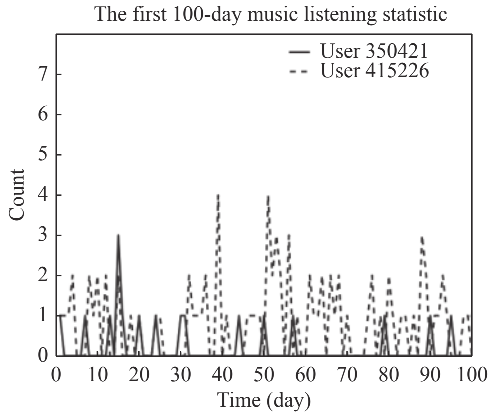

Fig. 3. The first 100-day music listening statistic.

where M_m denotes music model; A_m denotes the daily average listening frequency of a song, it reflects this song popularity; K_m denotes the slop after linear regression on statistic of songs listening frequency, it reflects the change trend of music popularity.

Offline recommendation After defining the UPND and MP, we further propose an improved offline recommendation algorithm formula. It can be described as follows:

$$P_{um} = \left(\sum_{i\in N_{(u)}\cap S(m,M)} W_{mi}\right) \cdot e^{-t[bK_u+(1-b)A_u-a]} \cdot \Big[cK_m + (1-c)A_m\Big] \tag{4}$$

where, P_{um} denotes the preference degree of user u to song m; $N(u)$ denotes the songs listening collection of user u; $S(m, M)$ denotes the highest similar collection (M songs) to song m; W_{mi} denotes the similarity of song m and song i; A_u denotes the daily average of user listening to new music; K_u denotes the slop after linear regression on new music listening net increase statistic; A_m denotes daily average listening frequency of a song; K_m denotes the slop after linear regression on statistic of songs listening frequency; t denotes the flag that whether user u has historical listening records to song m; $t = 1$ means user u has historical listening records to song m; $t = -1$ means user u has no historical listening records to song m; a denotes the recommendation weight coefficient used for adjustment between users music listening historic records and new music, and $a \in [0, 600)$; b denotes UDPN computation coefficient, which is used to adjust the mean and trend dominate relationship and $b \in [0, 1]$; c denotes MP computation coefficient, which is used to adjust the mean and trend dominate relationship and $c \in [0, 1]$.

2. Analysis of OFFLR

Analyzing formula (4), it is obvious that the improved offline recommendation model is an exponential model which integrates UPND and MP into traditional items-based collaborative filtering algorithm. Then, it can dynamically adjust the recommendation result by UPND and MP. Before moving on to model details, Fig.4 demonstrates the detail exponential information.

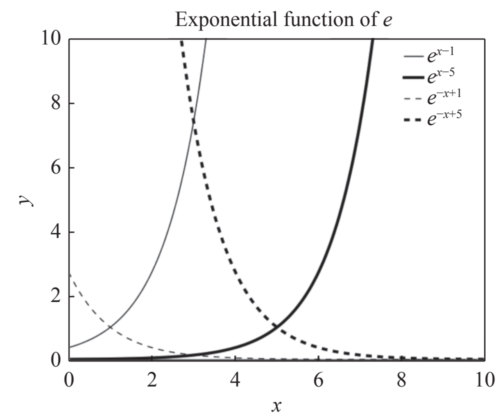

Fig. 4. The exponential function of e.

From Fig.4, it can be seen that 1) For $y = e^{x-k}$ in the range of $x \in [0, +\infty)$, k is inversely proportion to when is fixed; 2) For $y = e^{-x+k}$, in the range of $x \in [0, +\infty)$, k is positively proportion to y when x is fixed.

In formula (4), $e^{-t[bK_u+(1-b)A_u-a]}$ is an exponential function of UPND. $t = -1$ implies that user u has no historical listening records to song m; while $t = 1$ means user u has historical listening records to song m. We have already analyzed the effects of the multiplication of offline similarity matrix and music popularity. Then, we will further import UPND to set up a much appropriate recommendation model. When $t = -1$, uses have no historic listening records to a song, then a is inversely proportion to $e^{-t[bK_u+(1-b)Au-a]}$; while $t = 1$, uses have historic listening records to a song, then a is positive proportion to $e^{-t[bK_u+(1-b)A_u-a]}$.

Similarity, in a particular dataset, each user has a fixed UPND, namely a fixed x. Then the adjustment of a will change user preference degree on old music (the music users have historic listening on) and new music (the music users have no historic listening on). When a is less than UPND, users preference degree on new music will increase and the preference on old music will decrease on the contrary; while when a is larger than UPND, the result will be verse, namely the preference will present an increase trend on old music and decrease trend on new music.

In conclusion, $\left(\sum_{i\in N(u)\cap S(m,M)} W_{mi}\right)$ denotes the order of preference degree of a specific user u to a specific song m. $[cK_m + (1-c)A_m]$ will affect this order by importing music popularity. $e^{-t[bK_u+(1-b)A_u-a]}$ will further affect this order by comparing the numerical value of with that of UPND and adjusting the weight ratio between old music and new music. Therefore, this method on one hand considers the importance of music popularity; on the other hands, it treats old music and new music to user differently.

Due to the import of UPND and MP, the improved offline recommendation model will have a better performance than traditional items-based collaborative filtering algorithm. The details comparisons on them will be elaborated in Section III.3.

3. Performance comparisons analysis

Using formula (4), we assume $M \in \{5, 10, 20, 40, 80\}$, $a \in \{0.01, 0.1, 1, 9, 81\}$, $b \in \{0.01, 0.05, 0.1, 0.2, 0.5, 0.8\}$, $c \in \{0.01, 0.05, 0.1, 0.2, 0.5, 0.8\}$. Run the program and we list partial results in Table 1 for saving space.

Table 1. Algorithm performance comparisons

Order number	M	a	b	c	RecA*	NMRecA*	Coverage	Popularity
1	80	–	–	–	0.40349	0	0.01216	1.84233
2	40	–	–	–	0.39767	0.00208	0.01149	1.94454
3	20	–	–	–	0.39419	0.00313	0.01012	2.07212
4	10	–	–	–	0.39302	0.00833	0.0091	2.16374
5	80	81	0.5	0.5	0.47093	0	0.00835	2.1298
6	80	0.01	0.05	0.01	0.14884	0.13333	0.00285	2.69841
7	80	9	0.5	0.5	0.35465	0.06563	0.00647	2.32523
8	80	1	0.5	0.5	0.13953	0.12396	0.00303	2.70692
9	40	81	0.5	0.5	0.44535	0	0.00821	2.16615
10	20	81	0.5	0.5	0.4314	0	0.00796	2.24868

Table 1 lists the most representative results among all the parameters combination. Especially, the order number 1, 2, 3, and 4 are rows that present the results produced by using traditional items-based collaborative filtering algorithm. By simply comparing these results, the order number 5 has the highest recommendation accuracy, which represents almost 7% of performance improvement when compared with the traditional items-based collaborative filtering algorithm with the identical parameters M. The order number 6 has the highest recommendation accuracy for new music, which represents 16 times better performance than the traditional items-based collaborative filtering algorithm with the identical parameters.

There is one thing that must be emphasized. In the process of recommendation accuracy computation, we consider users historic listening records. While in the process of recommendation accuracy of new music computation, we ignore users historic listening records. Be more exact, as for new music recommendation, the 100 recommendation songs produced by the improved offline recommendation model includes 13 songs that users have no historic listening records on them but will definitely listen in near future. While, at this point, the traditional items-based collaborative filtering algorithm has an average hit ratio of 8 songs in 1000 recommendation songs.

From Table 1, it is obvious that M, b, c have little affections on recommendation performance, while has obvious and direct affection on recommendation performance. Fig.5 exhibits the affections of a (in this case, we assume $M = 10$, $b = 0.5$, $c = 0.5$).

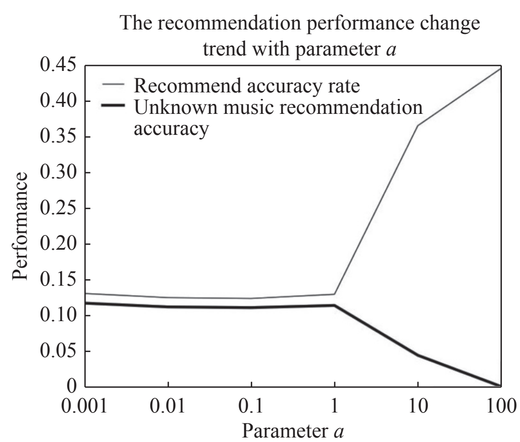

Fig. 5. The recommendation performance change trend with parameter a.

From Fig.5, when $a < 1$, the recommendation accuracy and new music recommendation accuracy almost stay stable. When $a > 1$, as a increases, the recommendation accuracy increases dramatically, while the new music recommendation will decrease gradually and finally reach 0.

In conclusion, by adjusting the factor of a, the offline recommendation model proposed in this paper can flexibly and dynamically adjust the recommendation accuracy and new music recommendation accuracy, and it improves the accuracy and flexibility, and is more likely to meet the needs of practice products.

IV. Online Recommendation Part of HMRM

Even the offline part of the hybrid music recommendation can dynamically adjust the recommendation accuracy and new music recommendation accuracy, but it requires huge and tense time computation, and more worse, it cannot conduct real-time online music recommendation, which means the recommendations produced by the offline part of the hybrid music recommendation based on the 100 days historic listening records work for the next 100 days. The recommendations produced by the offline part of the hybrid music recommendation have to be updated regularly to ensure the recommendation accuracy for a particular user. If the update interval is too small, its computation is extremely cost; while if the update interval is too long, then the interest drift occurs during the update interval. There should be a tradeoff between the huge computation cost and interest drift. Therefore, we further propose an online recommendation method based on game theory, which can better conduct real-time recommendation and eliminate interest drift problem.

1. Interest drift

In the long process of users listening to music, the interest drift problem will occur, as shown Fig.6.

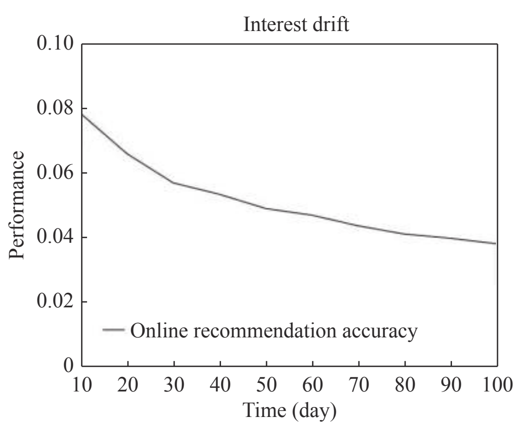

Fig. 6. An illustration of interest drift problem.

Interest drift requires the regular update of offline recommendation to ensure the recommendation accuracy for a specific user. However, how long should the update interval be in terms of computation cost and interest drift. This is the motivation that we further propose the online recommendation part.

2. Traditional solutions to interest drift

Time window model theory It focuses on the items which users show tense interests in the last period of time and assumes that users current preferences can be accurately reflected by their recent past behaviors. However, it is extremely difficult to define "the recent past time" and predict the drift occurrence ratio.

Forgetfulness model theory [26] According to the relevant discipline of psychology, people's interests in a certain thing will weaken as the time increasing and the weaken speed is gradually slowing down. Finally, the accumulation of interests during this weakening process will become very stable. However, this model emphasizes the rational forgetfulness instead of extracting new interests, therefore, it presents a "slow beat" on the interest drift problem.

Long-short term model theory [27] The long-short term model maintains two models simultaneously: one model is used to dig out users' long-term interests; the other model is used to dig out users' short-term interests at the same time. Undoubtedly, long-short term model theory can alleviate the interest drift problem effectively. But maintaining two models at the same time is time-consuming and will bring about a huge computational cost.

Drift detection theory [28] It abandons the specific model to adapt to the interest drift, instead, it sets an error threshold. When the error is over than the error threshold, then it will be defined as the occurrence of interest drift and adjust the parameters correspondent. However, how to determine an appropriate the error threshold is another new problem and challenge.

3. Music recommendation game theory

Even though there are a variety of solutions to interest drift problem, but each of them exists inherent drawbacks. In this part, we propose a novel solution to the interest drift problem. Consider users visiting system as a game between users and system. In this game, users make operations according to their own preferences, which can be regarded as users strategy. Similarity, system will adjust itself corresponding, which can be regarded as systems strategy.

Based on the ideas above, as shown in Fig.7, we further regard users historical listening records in the personalized music recommendation system as users strategy, and regard systems dynamically recommendations corresponding to users historical listening records as systems strategy. Their revenues can be qualitatively reflected by recommendation accuracy. The higher the recommendation accuracy, the higher the revenues will be.

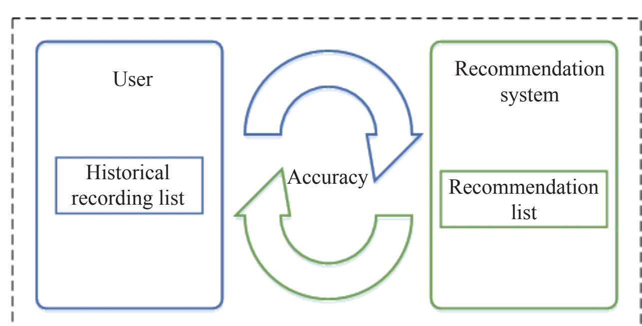

Fig. 7. Music recommendation game.

Personalized music recommender system under the assumption of rational person can be regarded as dynamical game of incomplete information. Recommender system cannot learn and understand users preference completely, and there is interest drift existed in users preference. In addition, users behaviors come first, and then form the personalized music recommender system. This process repeats and repeats and finally form a dynamical game. The uncertainty of this process is highly strong. Hence, it is very difficult to analyze it by mathematical tools. At the same time, there is imbalanced objects in recommendation system and it is rigorous, even impossible, for a user to be a rational person. Therefore, the music recommendation game theory proposed in this paper is inspired by the idea of dynamical game of incomplete information, a combination of idea of dynamical adaptive, and an effective model formed in the game learning. Any leaning process of it includes maintaining new knowledge and abandoning outdate knowledge, therefore it can ensure a higher learning efficiency.

4. ONLRP algorithm and performance analysis

The online recommendation algorithm based on game theory can be described as follows.

– Step 1: Utilize the 100 days offline data and obtain the 100 days offline recommendation candidate set as the input data of online recommendation, and form the initial online recommendation list T; Initiate the count of songs in T as zero; Build up a users offline recommendation reflection dictionary C; Select the parameters combination with the highest offline recommendation accuracy.

– Step 2: Count the daily listening records of users and constitute a list L; For each song in L, if the song has already existed in T, then go to step 3; otherwise go to step 4. Repeat step 2 until all songs are processed.

– Step 3: Update the count of this particular song in T with an adding of days D, then go to step 2 to check the next song in T.

– Step 4: Generate a random number R, which is in the range of $R \in [0, X]$; if the length of R is longer than L, then go to step 2 to check the next song in T; otherwise go to step 5.

– Step 5: Remove this current song in List L; Extract users having the relationship with this current song in C; Add songs which have relationship with the extracted users into (which are not included in T) and update count of each song by $D+1$; then go to step 6.

– Step 6: Clean L, eliminate songs whose count is less than D completely; eliminate songs whose count is in the range of $[D, D+2]$ with a certain probability P; then go to step 2 and check the next song.

In these steps, the parameter X and probability P are dynamical adjustment factors. The parameter X determines the degree of users listening records amount. The more listening records amount, the larger the T will be. Meanwhile, the probability P can reduce the size of T effectively, eliminating the irrelevant or low-relevant songs and ensure higher recommendation accuracy.

Under this context, X denotes the management of maintaining new knowledge, P denotes the management of abandoning outdate knowledge. When users become positive active, resulting in longer length of L, if the recommendation accuracy is very low in this case, the recommender system will take a new strategy in which the “maintaining new knowledge” will be raised (X will decrease) or “abandoning outdate knowledge” will be declined (P will decrease). On the other hand, the contrary is the case. Furthermore, when the recommendation accuracy is high, then the recommender system will maintain the current strategy, which means it will not change the values of X and P. By dynamical adjusting X and P, further achieve the goal of “maintain new knowledge” and “abandon outdate knowledge”, and present an effective solution to interest drift.

In order to conduct the validation of the ONLRP, we have to utilize the results produced in the OFFLRP, which is literally demonstrated in the ONLRP algorithm. In this context, we adopt the public musical dataset of Last.FM and we set the OFFLRP parameters M, a, b and c as before (the exhaustive illustrations can refer to Section III.2 (Analysis of OFFLRP) and Section III.3 (Performance comparisons analysis)). Then, we take the offline recommendation results of the OFFLRP as the input data of ONLRP. In this case, we compare the performances of traditional online recommendation algorithm which has the interest drift problem and the ONLRP algorithm on 100 days respectively. The detailed performance comparisons are shown in Fig.8.

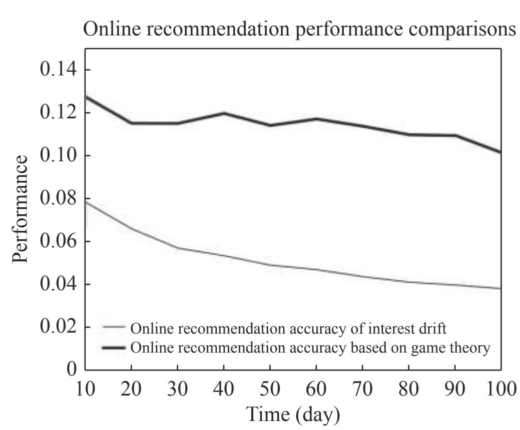

Fig. 8. Online recommendation performance comparisons.

From Fig.8, there is no obvious decline in the curve of online recommendation algorithm based on game theory when compared with that of online recommendation algorithm with interest drift. Therefore, the online recommendation algorithm based on game theory can effectively alleviate the interest drift problem and further improve the recommendation performance.

V. Conclusions

The main contribution of this paper is proposing a hybrid music recommendation model by leveraging personalized measurement and game theory. This hybrid music recommendation model can be partitioned into two parts: offline recommendation part (OFFLRP) and online recommendation part (ONLRP).

OFFLRP improves the traditional items-based collaborative filtering algorithm by importing the UPND and MP. First, define the UPND by analyzing users overall preference for new music and users preference change trend for new music; define the MP by analyzing the overall popularity of music and the music popularity change trend. Then, utilize the natural constant exponential function to integrate the UPND and MP into the traditional items-based collaborative filtering algorithm, and finally form the improved offline recommendation model.

ONLRP proposes a novel online recommendation algorithm by importing game theory. Moreover, this method can be treated as an effective solution to the interest drift problem. The online recommendation model maintains an online recommendation candidate list of which the original data stemming from the results of offline recommendation model.

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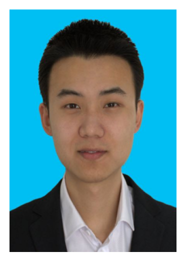
WU Yun was born in 1973. He received the Ph.D. degree from Guizhou University, Guizhou, China, in 2009. Now he is an Associate Professor, a Senior Member of CCF, the Director of the Institute of Computer Simulation of Guizhou University, an Evaluation Expert of Guizhou University, and the Academic Leader of the Big Data Technology and Internet Application. His research interests include game theory, recommender system, big data and its application.
(Email: wuyun_v@126.com)

LIN Jian (corresponding author) was born in 1994. He is an M.S. student in the College of Computer Science and Technology, Guizhou University. His current research interests include recommender system and data mining.
(Email: gs.linj19@gzu.edu.cn)



MA Yanlong was born in 1991. He received the M.S. degree in the College of Computer Science and Technology, Guizhou University, China, in 2016. His research interests include distributed computing and recommender system.