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Research Article

AI-Based Music Recommendation Algorithm under Heterogeneous Network Platform

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Music service is one of the diversified network services offered by people in the Internet era. Various music websites provide many tracks to meet people's music needs. Hundreds of millions of music of various genres at home and abroad, and there is a severe problem of information asymmetry between users and music. As a branch of the information filtering system, the recommendation system can predict users' preferences, increase flow, and drive consumption. A personalized music recommendation system can effectively provide people with a list of favorite tracks. Recently, many researchers have paid attention to heterogeneous networks because of their rich semantics information. Research has confirmed that rich relationship information in heterogeneous networks can improve the recommendation effect. Therefore, under the platform of a heterogeneous network, this paper divides the digraph set of track characteristics into several clusters with maximum heterogeneity, which makes the digraph of track characteristics in each cluster isomorphic to the maximum extent. When matching similarity, only searching in the cluster with the highest similarity to the target user can match a sufficient amount of applicable tracks, thus improving the efficiency of music recommendations to users. Experimental results show that the proposed algorithm has a high recall, precision, and F1 and can recommend personalized track lists to users to meet their music needs.

1. Introduction

Recently, the rapid advancements of mobile network technology have resulted in quick advancements of digital multimedia technology. Young people, especially students, have emerged as the primary consumers, and digital music has emerged as one of their preferred forms of consumer material [1, 2]. When users want specific music, they can easily search for it by entering information like title or artist, but when they do not have a clear query, that is, when they want the music system to give them music that meets their preferences without a clear goal, personalized music recommendation can be a better solution [3, 4].

The massive and huge music data generated in the music library undoubtedly exceeds the basic needs and bearing capacity of users, which leads to user information fatigue. In the face of the massive music data of the music library, ordinary music users often cannot quickly find the tracks that meet their preferences, and many personalized requirements for the music library recommended by others cannot be met [5–7]. Users cannot grasp or master a significant quantity of product information, or users have no specific aim in a certain sector but simply a broad desire, which is now an important problem to be handled [8]. The purpose of personalized music recommendation is to help users quickly screen out the music they are interested in from the vast music library. At present, most large-scale music portal websites have vast music libraries with a wide range of genres and styles of music, with new music being uploaded at a rapid rate every month. To begin with, the music library has hundreds of millions of tracks. Users will never have enough time to listen to all of the tunes before selecting their favorite. Second, music services are nonimmersive, and users can complete other things while listening to music. Music is only used as a background sound, which leads to vague demands of users, such as "recommend one or several nice tracks to me." The future market of music recommendation is very broad, which fully meets the needs of users and can be accepted by users [9].

With the rise of music service, music recommendation technology related to music service also has a lot of research achievements [10–13]. Many music stations now offer not only basic music services but also the ability to push personalized playlists to users, notably Pandora and Last.fm. However, due to the uniqueness and sensibility of music itself, the contemporary suggestion results are lacking in personalized features and have a low coverage rate. People are more attracted to utilize mobile terminals for amusement and communication, thanks to the rapid growth of mobile terminal communication. A social network-based recommendation system has a clear business potential [14]. People are generally ready to share things with their friends on social networks, which include a large quantity of user information. Taking advantage of this link can boost the success rate of recommendations. At present, some mature social music platforms in China mainly use the data generated by users when they use the platform for social behaviors to calculate the similarities between users, thus predicting their interests and hobbies. On the social music platform, users can express their opinions on track messages and comments, from which we can extract the social tags that users place on track. The contents of these tags may include artists, music styles, music genres, users' current situations, feelings, moods, backgrounds, etc. These tags provide much information about the attributes of the track, as well as information about the scene when the user listens to the track, the user's immediate mood, ongoing activities or geographical location, etc., which are all helpful in our judgment.

Among many proposed recommendation algorithms, collaborative filtering algorithm is widely used, which uses the user's historical rating to recommend items that may be of interest to the user. However, due to the large number of items, users are often only able to rate a small number of items, resulting in data sparsity problems [15]. In addition, for a new user, due to the lack of rating information, it is difficult to make appropriate recommendations, so the recommendation system often faces the problem of cold start. To solve the problem of data sparsity and cold start, researchers have proposed many different algorithms. They have found that they can improve recommendations by exploiting relationships between users or items [16]. Since people with similar interests tend to like the same items, items with similar characteristics are more likely to be liked by the same users, while heterogeneous network contains rich relationship information, which can be used to improve the recommendation effect [17–19].

The main contributions of this paper are summarized as follows:

(1) Tag sequence-related attributes are mapped to a heterogeneous network.

(2) The digraph sets of track features are divided into several maximal isomorphic clusters so that each cluster's digraph of track feature is maximal isomorphic. In contrast, the digraph of track features in the different clusters differs. When matching similarity, sufficient applicable tracks can be matched only by querying in the cluster with the highest similarity with the target user, thus improving the efficiency of track recommendation for users.

The rest of this paper is organized as follows. In Section 2, we review the related works. The directed tag-based collaborative filtering algorithm in heterogeneous network is presented in Section 3. Experimental results are presented in Section 4. Section 5 concludes this paper.

2. Related Works

People's lives have created a demand for recommendation systems, and people want to consult other people's ideas while making judgments because of their highly socialized character. How to provide consumers with accurate and useful suggestions can help solve the problem of information overload while also benefiting the industry. Researchers have proposed a content-based recommendation algorithm and a collaborative filtering recommendation algorithm. These two recommendation algorithms, as well as their several modified variations, are now the most popular and widely utilized. Content-based recommendation is based on the user's historical behavior record to find the same as the item or has a certain context to recommend, requiring content information or expert annotation. The algorithm based on collaborative filtering has social characteristics and mainly recommends music matching users' interests and hobbies according to their interests, behavior records, and collection history. In [20], a new content-based recommendation method based on Gauss mixture model was proposed to improve the accuracy and sensitivity of probabilistic recommendation problems. In [21], a content-based recommendation algorithm based on convolution neural networks was proposed. To solve the cold start problem, in [22], the authors presented a rating forecasting framework, allowing the system to predict user ratings for unscripted music pieces, resulting in good recommendations. Currently, few recommendation systems consider users' interests and preferences at the same time. Considering each user's interaction, in [23], the authors proposed a user model and captured the user's interest. The traditional collaborative filtering recommendation algorithm has high computational complexity in calculating user similarity, leading to low recommendation efficiency. Therefore, in [24], the authors introduced the quantum computing theory to prepare the user score vector into a quantum state and calculate the similarity score in parallel. In [25], a hybrid web service recommendation method combining collaborative filtering and text content based on deep learning was proposed (HWSR-DL). In [26], a novel algorithm combining collaborative filtering and support vector machine was proposed to classify goods with positive feedback and negative feedback (CF-SVM). In [27], the authors proposed a new collaborative filtering method, which introduced information entropy and double clustering into collaborative filtering and extracted local dense rating module to deal with the problems of data sparsity and low computational efficiency of traditional recommendation algorithms (IE-DC-CF).

In heterogeneous network platform, there are different types of links between nodes, which represent different kinds of relations and contain rich semantic information. How to calculate the similarity between nodes is an important problem in the process of extracting the relation information of heterogeneous networks [28–30]. With the rapid development of artificial intelligence machine learning in recent years, many new technologies have emerged. Researchers use various algorithms' characteristics to improve recommendation system performance. One is to guarantee the quality of recommendation results by data preprocessing. Some studies from quality evaluation and other aspects believe that the future recommendation system will become more perfect and mature.

3. Directed Tag-Based Collaborative Filtering Algorithm in Heterogeneous Network

Music tags might provide information about the track's information. Tags are primarily classified in tag-based music recommendation by the information relevance between tags [31]. However, because tags are separate from one another and disseminated in a distinct manner, we cannot know what users are thinking when they tag or classify music, and we cannot know their cognitive order of tags directly. To address this issue, we can make the tag directed to improve the situation. We may vectorize the time and times of users' activity data in music tagging to express the link between users, music, tags, and cognitive order and increase music recommendation accuracy.

Music stations offer services that allow users to comment on and rate music, thus keywords in user evaluations may be turned into music tags, and users can also choose from a list of optional tags for music tagging. The first few tags of a track are frequently named based on the artist's description, topic, and emotion, as well as the album's genre. When users play music, according to their perceptions of the music, they choose corresponding tags or, through the music, create their own tags to complete tagging. Users may have completely different feelings after repeatedly listening to the same song, and there may be many tags with significant differences. Each tagging of users will be recorded, and repeated tagging and comments will increase the weight.

The music tags issued by the music station are usually consecutive, and the more sophisticated the tags are, the more they match the track's features. This paper's data comes from the Million Song Dataset (MSD), which is an integration platform of music resources. It collected the data of seven well-known authoritative foreign music communities, sorted out and analyzed the data, and provided researchers with offline datasets and analysis results obtained by various algorithms. The offline dataset given by Last.fm [32] is mostly used for the optimization method data in this subsection. The offline dataset given by Last.fm is separated into a training set and a test set, with the training set accounting for 80% of the dataset and the test set accounting for 20%. This website is useful for comparison and discussion of subsequent studies since it gives tags and commonalities of track level. Figure 1 depicts the information for a specific piece of music on Last.fm.

There will be albums with various themes and playlists with various categories for artists. Each piece of music can be tagged by many people in the case of music. These tags may be similar or dissimilar, resulting in the music appearing in various playlists based on the tags. We may obtain the tag sequence for an artist's album as well as the tag sequence for music that has been tagged by various users. It should be noted that, in the playlist, users' cognition can be reflected in the sequence of tags. The more music can highlight the theme of the playlist, the more its tag and position should be placed in the front of the playlist. In the Last.fm dataset, track tags of users and artists are recorded, so the data is extremely large, with more than 200000 titles. The top 20 tags and their popularity are shown as Table 1.

Every user will have behaviors when listening to the tracks, such as playing, playing next, liking, looping, downloading, forwarding, and commenting, and the process time of the above behaviors will be recorded, which will make users become closely connected with tags. Tag information represents users' opinions on music, through which users are more likely to be interested in music, and in case of vague queries, we can use the tag of music to determine if the music is what they want.

We associate users with tag sequences according to certain rules and embody the relationship in terms of equations. U_i is the current i th user number. Assuming there are a total of x tags, the tag sequence is represented by $t_1, t_2, \ldots, t_x$, the tag sequence of the associated user is represented by a_{Ti}, the x th tag of the i th user tag is represented by $t_{i,x}$, and the associated user forms the following record as shown in

$$a_{Ti} = U_i, t_{i,1}, \ldots, t_{i,x}, \tag{1}$$

gSTU is used to represent the tag sequence after the user is associated, so when we obtain the different track and tag sequences that the user collects and tags; we can get the set of m tag sequences of the user, as shown in

$$a\mathrm{STU}_i = \left\{a_{Ti}^1, a_{Ti}^2, \ldots, a_{Ti}^i\right\}. \tag{2}$$

We use equation (3) to identify the sorted tags in Table 1.

$$a_{\mathrm{Tra}_j} = \mathrm{Track}_j, t_{i,1}, \ldots, t_{i,x}. \tag{3}$$

The above equation represents the sequence in which a certain track j is noted in a tracklist, and the x th label marked by this track is recorded as $a\_\mathrm{Tra}_j^n$. In addition, a piece of track may have multiple tags at the same time, and the track may appear in different track lists. Therefore, this tag sequence is recorded, as shown in

$$a\mathrm{STT}_j = \left\{a_{\mathrm{Tra}_j^1}, a_{\mathrm{Tra}_j^2}, \ldots, a_{\mathrm{Tra}_j^n}\right\}, \tag{4}$$

where $a_{\mathrm{Tra}_j^i}$ represents the i th tagging that track j has appeared in n tracklist tagging sequences.

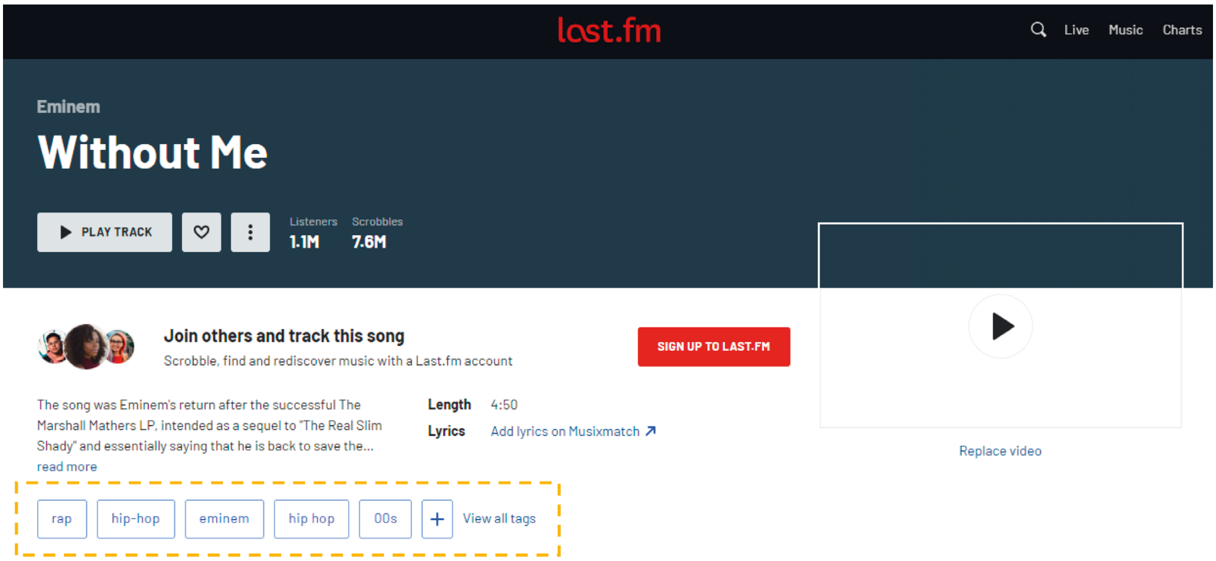

Figure 1: A track information from Last.fm.

Table 1: Parts tags and popularities.

Tag	Popularity
Hip-hop	101072
Rap	69159
Pop	55777
West coast	48175
Kendrick lamar	46720
Conscious hip hop	42564
Compton	39951
Jazz rap	31598
Trap	33618
West coast hip hop	31234
California	30433
Rnb	30125
Baby keem	29124
American	27810

For a heterogeneous network G, we assign a_{T_i}, $a\mathrm{STU}_i$, a_{Tra_k}, and $a\mathrm{STT}_j$ to G, that is, $G = (a_{T_i}, a\mathrm{STU}_i, a_{\mathrm{Tra}_k}, a_{\mathrm{Tra}_k})$. a_{T_i} corresponds to the vertex of G in the directed graph of heterogeneous information network, $a\mathrm{STU}_i$ corresponds to the edge of G, a_Tra_k corresponds to the vertex type of G, and $a\mathrm{STT}_j$ corresponds to the edge type of G.

The feature digraph of heterogeneous network is established by associating users with tags and track with tags [33]. Clustering was established for the digraph of track feature in heterogeneous network, and the track clustering was completed by using the clustering algorithm to obtain the central digraph of each cluster. The isomorphism degree of the cluster center digraph and user feature digraph in heterogeneous network is calculated, and then the isomorphism degree of the track feature digraph and user feature digraph in the cluster center digraph meeting the threshold value in heterogeneous network is calculated in turn to obtain the final result.

Through the above steps, we obtain the user's interest feature digraph, complete the clustering division of the track feature digraph, and obtain the feature digraph of its cluster center. The user's digraph of interest features is matched with the digraph of cluster center feature one by one, and the clusters whose isomorphism reaches the threshold are selected. Then the user's digraph of interest features is matched with the digraph of track feature in the cluster one by one, and the results are sorted.

When the total amount of track is small, the recommendation result of a single cluster may not be able to meet the needs of users. Therefore, when matching in this case, the critical value of isomorphism is taken as the definition, and the clusters with isomorphism higher than the critical value are stored in a new cluster. It is assumed that the critical value of isomorphism is γ, and the higher the critical value is, the higher the requirement for isomorphism is. Here, according to the average number of tags in the dataset, the isomorphism critical value is set at four to make track recommendation. When TopN is recommended, users will switch according to the scene and mood when playing tracks [34]. They will switch quickly if they are unsatisfied with the tracks when listening. If five or six tracks recommended in a row cannot satisfy users, they may even give up the recommendation and choose again. Considering that most users who listen to music using the recommendation list need a piece of background music or music that fits their mood in their spare time, the length len of the recommendation list is set to 25.

Our ultimate goal is to create a TopN list of music recommendation for U_i, that is, to calculate whether the isomorphism of the digraph of track feature and the digraph of user interest feature in the track cluster meets the recommendation requirements. If so, it is merged into a collection. Therefore, we need to create an adjacent clustering set $C_{\mathrm{neighbour}} = \{C_{n1}, C_{n2}, \ldots, C_{nN}\}$, where N represents the total number of clustering clusters. We store the set of the closest neighbors of the target digraph in this clustering set, then calculate the clustering center CC_i of the digraph of track features in heterogeneous networks, and calculate the value of the isomorphism degree θ. Here, we compare the value of the isomorphism θ with the isomorphism threshold $\gamma = 4$ we set earlier. If $\theta > \gamma$, indicating that the isomorphism meets the recommended requirements, put the cluster of CC_i into $C_{\text{neighbour}}$; otherwise skip and judge the next cluster.

Put digraphs of track features in heterogeneous information network into recommendation list RecList[len] in descending order. Repeat this step until all the digraphs of track features in the cluster are judged and put into the recommendation list, and a complete recommendation list is obtained, in which clusters of the corresponding order are placed. By using the one-to-one relationship between digraph and track, we can get a track list created for users, which is defined as TrackRecList. Each digraph of track feature has its unique corresponding track, which is put into TrackRecList in order. We can get the final complete track recommendation list, which can be output as a result, so that users can get the final recommendation result. Due to the extensive data in this database, when analyzing the isomorphism degree of the digraph of user interest in the cluster center, we only need to query and match it with the clustering where the digraph with the highest similarity is located. Then we can make the music recommendation more efficiently.

The collaborative filtering algorithm based on user, track, tag, and tag sequence is the core of personalized music recommendation based on heterogeneous network designed in this paper, and its detailed process is shown in Figure 2.

4. Experimental Results and Performance Analysis

4.1. Dataset. There are 943347 matched tracks in the Last.fm dataset, with 505216 tracks having at least one tag, 584897 tracks having at least one comparable track, 522366 unique tags, and 8598630 track-tag pairs. We obtained 952067 tracks matching artists from the Last.fm dataset, stored them in the database for statistics, and then obtained the number of tags. Similarly, we counted the total number of tagged tracks, the number of users, the number of active users, the number of active tags, and the number of tracks with at least one tag. The specific statistics are shown in Table 2.

In Table 2, users who have tagged track for at least five times are defined as active users, and tags that have tagged track for at least five times are defined as active tags. Tagged track is track that has been tagged at least once. Based on the above data, the collaborative filtering algorithm model based on directed tags is used to carry out quantitative analysis of the model and construct a complete model. After our first step of screening, the tag noise has been reduced as far as possible. We have recorded the track tags and their corresponding occurrence frequency from the dataset to make recommendations.

We randomly selected 1000 users from the Last.fm dataset who were highly active users (with more than 10 tagging behaviors) and 1000 users from the normal active users (with 5–10 tagging times) as experimental objects. Users with low activity levels are not considered, because any recommendation system must be based on user data, and without user behavior data, it is impossible to provide users with accurate and satisfactory track recommendation services. Two groups of data extracted are used for the experiment, namely, High-Active User Dataset (HAUD) and Normal-Active User Dataset (NAUD). The specific data is shown in Table 3.

Using the playing time and tagging time recorded in the database, the first 80% users in the dataset were taken as the training set, and the rest were taken as the test set. Although the weight of each user is different, leading to differences in individual recommendation results, such an experiment is more appropriate to a real recommendation system on the whole, and the results are closer to real data.

In addition to the above algorithm reference, we set the length of the recommendation list to 5, 10, 15, 20, 25, 30, and 35, respectively, to consider the accuracy of the algorithm. The reason for this is that a short recommendations list is not persuasive, while a long recommendations list can lead to impatience, disgust, and poor results. We need to select the most appropriate length of track recommendation list through experiments. After setting up the control group, a fair standard is needed to evaluate the excellence of each algorithm. Generally, accuracy or recall is used for consideration, which is based on recommendation results, order, and actual item correlation value. Since the evaluation of these two metrics is not comprehensive, F1 score is introduced as a comprehensive evaluation standard for the experiment.

It is assumed that reco is the resource set with length n obtained from the recommended result, and real is the real resource set of the user. count_i is used to record whether the i th resource of reco is in real. If count_i is in the real, the value is 1; otherwise it is 0. To verify the performance of the proposed algorithm, three algorithms such as HWSR-DL [25], CF-SVM [26], and IE-DC-CF [27] are used as baselines.

4.2. Results and Analysis. In the experiment, considering that it is meaningless and has some side effects when recommending track lists to users, here we take {5, 10, 15, 20, 25, 30, 35} as seven values to test the list length of recommended tracks and then test the datasets HAUD and NAUD separately. Subsequently, DTCF-HN is used to represent directed tag-based collaborative filtering algorithm proposed in this paper. We compare the recall, accuracy, and F1 of each algorithm in two different test sets HAUD and NAUD with different n values.

As can be seen from Figure 3, with the increasing of recommendation list length, recall of all algorithms shows an increasing trend. The recall performance of all algorithms in HAUD dataset is superior to that in NAUD dataset, indicating that sufficient user behavior data information can make the algorithm perform better. Comparing the results of the two datasets, it can be seen that the recall of the DTCF-HN algorithm decreases a lot in the NAUD dataset, and the stability of the algorithm is slightly worse than that of the IE-DC-CF algorithm with a higher degree of data dependence, but it still has advantages over the other two algorithms. This

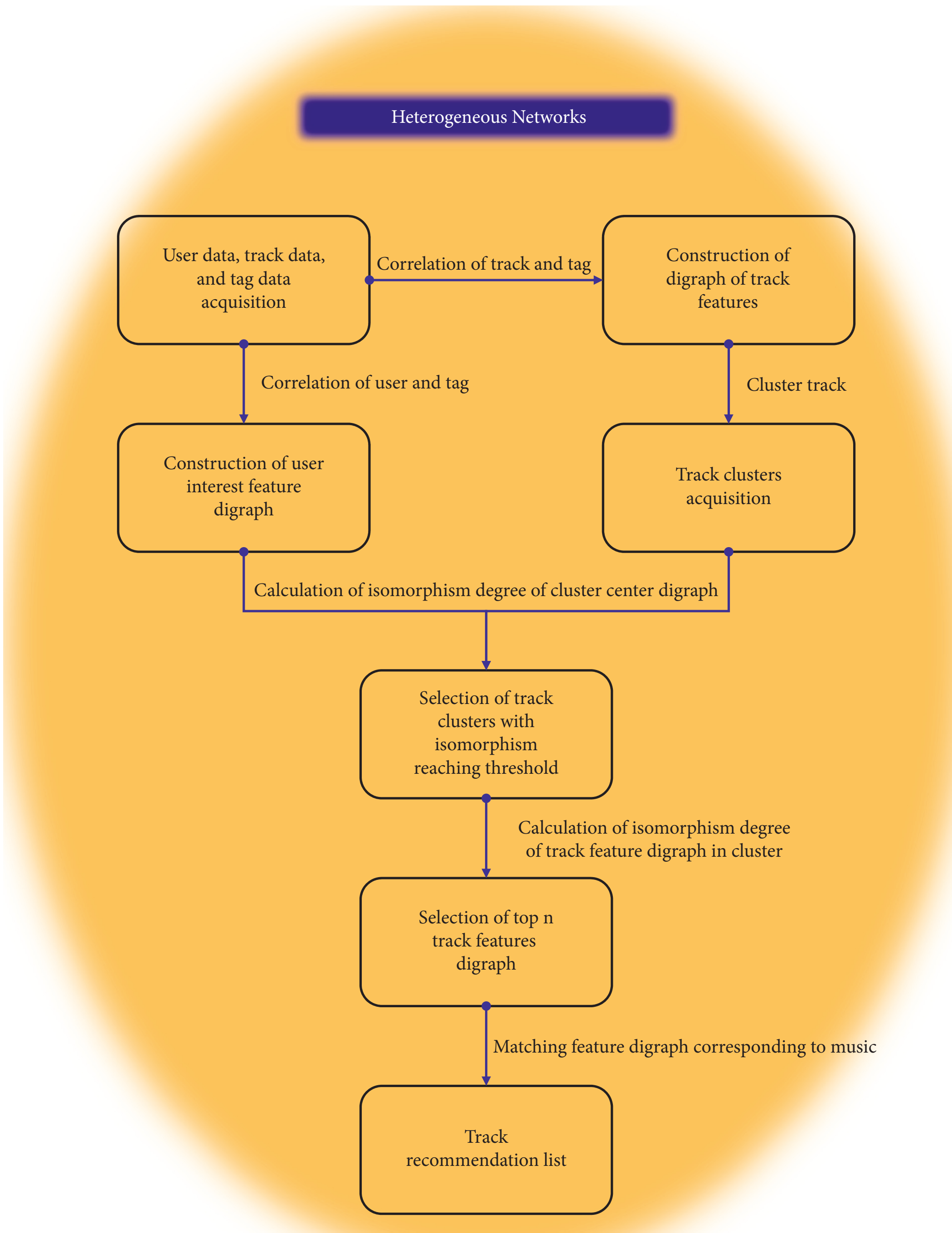

Figure 2: Music recommendation algorithm based on artificial intelligence under heterogeneous networks platform.

Table 2: Data statistics from Last.fm.

Number of users	Number of active users	Number of tags	Number of active tags	Number of tracks with tags
1573950	1157451	532648	128456	502635

Table 3: Information of HAUD and NAUD.

Dataset	Number of users	Number of tracks	Number of tags	Tagging times
HAUD	1000	20987	1982	15129
NAUD	1000	16534	1374	7651

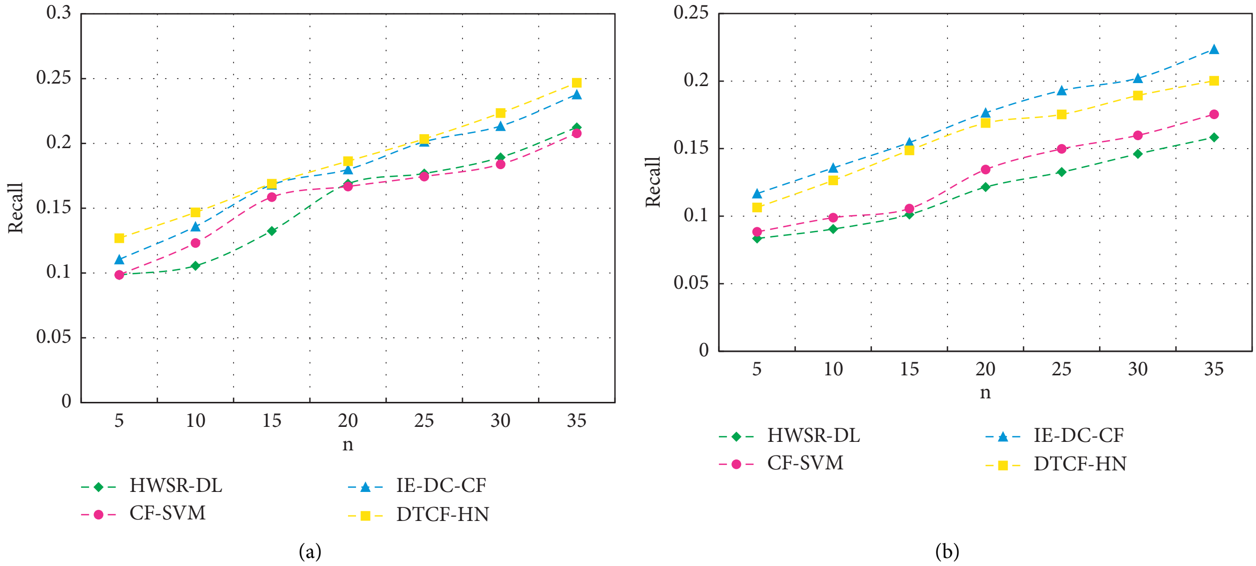

Figure 3: Recall of four algorithms in different datasets. (a) HAUD. (b) NAUD.

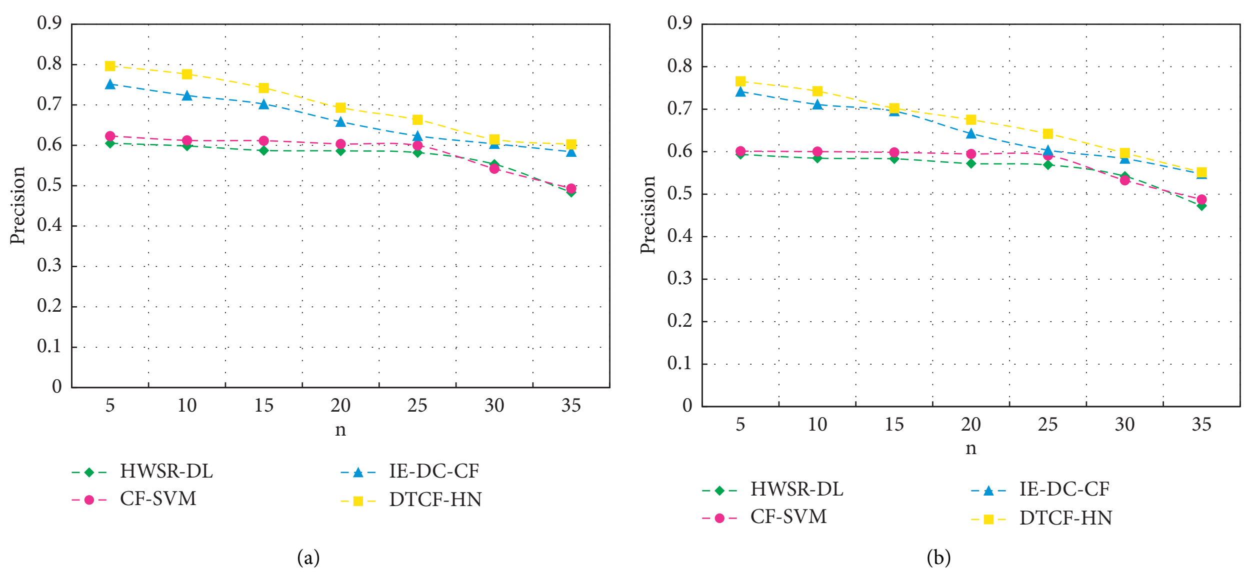

Figure 4: Precision of four algorithms in different datasets. (a) HAUD. (b) NAUD.

shows that DTCF-HN algorithm performs well and proves the hypothesis that tags have certain sequentiality.

As can be seen from Figure 4, with the increasing of the length of the recommendation list, the precision of the four algorithms shows a decreasing trend. HWSR-DL and CF-SVM algorithms show a relatively stable performance in the first recommendation list length of 5–25, and the precision begins to decline when n is greater than 25. The accuracy of DTCF-HN algorithm shows an accelerating trend in the process of decreasing, and the overall precision is good, indicating that the track with the sequence in the front can satisfy users more and proving that the track recommendation results provided by the algorithm have a relatively clear sequence. The performance of each algorithm on HAUD dataset is better than that on NAUD. DTCF-HN algorithm has the most obvious performance gap in the two datasets, indicating its stronger dependence on data. The main reason is that this algorithm focuses on mining the horizontal relationship between tag data, and the number of tagging behaviors has a significant impact on algorithm performance. In the NAUD dataset, the performance of DTCF-HN algorithm is slightly worse than that of IE-DC-CF algorithm, but it still has certain advantages compared with the other two algorithms, indicating that DTCF-HN algorithm performs well in accuracy.

As indicated in Figure 5, F1 of each algorithm shows a trend of increasing first and then decreasing. Compared with the datasets of HAUD and NAUD, the reduction of data volume leads to an increase in the recommended list length n required to reach the peak value of F1, which means that the

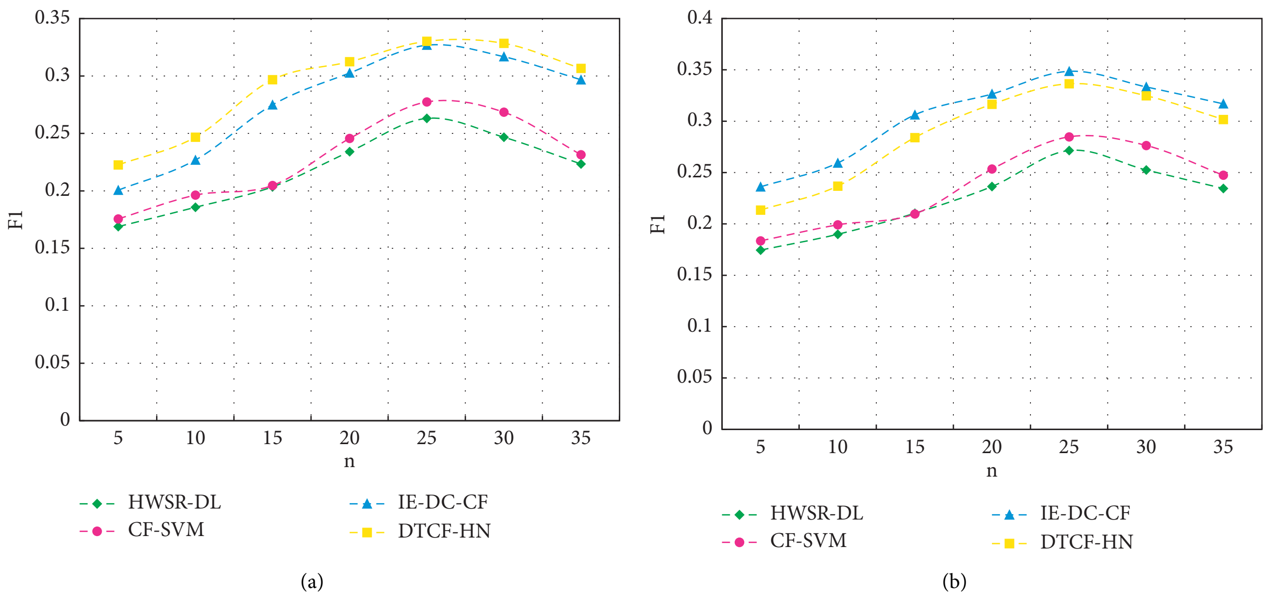

Figure 5: F1 of four algorithms in different datasets. (a) HAUD. (b) NAUD.

accuracy will decrease and the corresponding performance will decrease. In the experimental results, the performance of DTCF-HN and IE-DC-CF algorithm is significantly better than that of the other two algorithms. In the HAUD dataset, the performance of DTCF-HN is better than that of IE-DC-CF algorithm, but it is the opposite in NAUD. This is because DTCF-HN considers the sequential relationship between tag data and is more dependent on the amount of data. According to the above experimental results, except for the IE-DC-CF algorithm, compared with the other two algorithms, DTCF-HN has apparent advantages in performance and can provide users with more satisfactory recommendation results, which verifies the hypothesis that there is a specific sequence between tags and also indicates that DTCF-HN algorithm has good performance.

5. Conclusion

The rapid development of mobile terminals has made digital music mainstream, and major Internet companies have also increased their investment in the music field. Huge demand brings enormous traffic, so how to provide users with their favorite music in the massive music database has become the focus of competition among significant Internet music businesses. Therefore, music recommendation algorithm based on personalization has been developed for decades. There are countless outstanding researchers to provide music recommendation services by combining advanced mathematical statistics ideas with computers with high-speed processing power. Mainstream recommendation algorithms have advantages and disadvantages, and combining them will improve the recommendation effect. In the case that open datasets are relatively easy to obtain, the cost of a collaborative filtering algorithm is lower than that of the content-based algorithm, and it has a better effect on cluster recommendation. In this paper, the music feature digraph is clustered and divided, so there is an apparent distinction between the clusters. At the same time, it ensures that each cluster's music is isomorphic with the cluster center feature digraph to the greatest extent. When recommending track lists, it only needs to match the user feature digraph with the track in the cluster with the highest fitness. Experimental results show that the proposed algorithm has a high recall, precision, and F1 and can recommend personalized track lists to users to meet their music needs.

Through the analysis of the experimental results, it is proved that the algorithm has good performance, but there are still some shortcomings. We can further improve the performance through the following aspects.

(1) The algorithm proposed in this paper relies on user data and track data. If there is a problem with data sparsity, the recommendation result cannot meet the expectation. In the future, the content-based music recommendation can be integrated into the content-based music recommendation according to the semantics of lyrics, that is, using the hybrid model.

(2) The amount of data has a significant impact on the performance of the algorithm. Music recommendations that meet the requirements cannot be provided for users with few annotation behaviors. In future research, we can conduct in-depth longitudinal research on tags, such as mining emotional indicators and implicit semantic information in tags, to further improve the performance and stability of the algorithm.

(3) Construct more advanced computing frameworks, such as Spark, a distributed memory framework, and MapReduce, a framework in Hadoop, to increase the batch processing capacity of files. For tasks such as Last.fm, which have a large amount of data and require intensive computing, the use of distributed

frameworks can reduce time costs and improve iteration efficiency.

Data Availability

The data used to support the findings of this study are available upon the reasonable request.

Conflicts of Interest

The author declares that he has no conflicts of interest in this article.

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