



e-ISSN: 2319-8753 | p-ISSN: 2347-6710

IJIRSET

International Journal of Innovative Research in
SCIENCE | ENGINEERING | TECHNOLOGY



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

Volume 11, Issue 5, May 2022

ISSN INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA

Impact Factor: 8.118

A Survey of Music Recommendation Systems and Future Perspectives

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ABSTRACT: Coupled with the rapid expansion of digital music formats, Managing and searching songs has become important. Although the music Information retrieval (MIR) techniques have been successfully performed in the past ten years, the development of music recommendation systems is still ongoing very early stage. Therefore, this paper reviews the general framework and Latest methods in recommending music. Two common algorithms: Collaborative Filter (CF) and Content-Based Model (CBM) Found to perform well. Because of the relatively bad experience in research Long-tailed songs and strong emotional meanings in music two User-centric approaches: the context-based model and the emotion-based model, Increased attention has been paid. In this paper, there are three main components in a music recommend-er—user modelling, object profiling, and matching Algorithms are discussed. Six recommendation models and four possible User experience issues are explained. However, subjective music the recommendation system has not been fully investigated. To this end, we Proposing a stimulus-based model using experimental human studies Behavior, physical education, music psychology.

I. INTRODUCTION

With the explosion of the network in the past decades, the Internet has become the pioneer A source for retrieving multimedia information such as video, books, music, etc. People considered music an important aspect of their lives and they Listening to music, an activity they do frequently. Previous research also has He noted that participants listened to more music than anyone else Activities [57] (i.e., watching TV, reading books, watching movies). Therefore, music, as a powerful approach to communication and self-expression, He has resumed a wealth of research.

*Yarding is supported by the China Scholarship Council. We would like to thank Geraint A. Wiggins for his advice.

However, the problem now is to organize and manage millions of music Titles produced by the community [51]. MIR technologies are developed to solve them Problems such as genre classification [42, 75], artist identification [46], and in text recognition [49]. Since 2005, an annual evaluation has taken place called Music Information Retrieval Evaluation Exchange (MIREX1.1) To facilitate Development of MIR algorithms.

In addition, the music recommendation tool helps users to filter and discover songs according to their tastes. A good music recommendation system should be able to Automatically detect preferences and create playlists accordingly. at the same time, the development of recommend-er systems provides a great opportunity in the industry to bring together users who are interested in music. more important, it raises challenges for us to better understand and model users' preferences Music [76].

Currently, based on users' listening behavior and historical ratings, the collaborative discursive filtering algorithm has been found to perform well [9]. combined with Using the content-based model, the user can get the list of similar songs by low-level audio features like tempo or pitch or high-level features like genre, instrument etc. [7].

Some music discovery sites like Last.fm² all music³ and Pandora⁴ and Shazam⁵ has actually successfully used both of these approaches. Currently, these sites provide a unique platform for rich retrieval and useful in shaping user studies.

Music is subjective and universal. It can not only convey feelings, but also It can modify the mood of the listener [23]. Tastes in music differ from person to person Therefore, the previous methods cannot always meet the needs of users Need. An emotion-based model and a context-based model have been proposed [18, 34]. The first recommends music based on the mood that allows the user to determine their expected emotions on a two-dimensional valence-excitation interface [22]. The latter collects other contextual information such as comments and music Review or social tags to

create a playlist. Although hybrid music is recommended That would outperform traditional models, the evolution is still in very early stage [88]. Due to recent studies in psychology and signal processing, Machine learning and musicology, there is a lot of room for expansion in the future.

This paper, therefore, reviews the general music recommendation framework of User profile, element modeling, and user profile of the corresponding element are a series of modern methods. Section 2 gives a brief introduction to the components in music Recommendation systems in section 3, the latest recommendation techniques are explained. At the end of this paper, we conclude and propose a new file Motivational model of users.

¹ http://www.music-ir.org/mirex/wiki/MIREX_HOME

² <http://www.last.fm/>

³ <http://www.allmusic.com/>

⁴ <http://www.pandora.com>

⁵ <http://www.shazam.com/>

1 Components in Music Recommender System

In general, a music recommendation system consists of three main components - users, Elements and user element matching algorithms. Defining a User Profile (see Section 2.1) brings out the variance in the Users' profile. This move aims to distinguish their music Tastes using basic information. Element profiling (see Section 2.2) on the contrary, describes three different types of metadata - editorial, cultural, and audio, which are used in different recommendation approaches. In section 2.3, we explained the query in music suggestion systems and matching algorithms shown in section 3.

1.1 User Modelling

A successful music filter needs to meet different user requirements. However, obtaining user information is costly in terms of financial and human labor costs [74]. For user-oriented design, a lot of effort should be put into user studies are being investigated.

User modeling, as one of the key elements, it makes the difference in the private file. For example, the difference in geographical area or age, their music Preferences may be different. It is interesting that other factors such as sex and life Styles and interests can also determine their music choices.

Recent research has revealed that intelligence, personality and users Preference in music is related [57]. According to Renfrew and Gosling [26, 58] who investigated the relationship between music preference and Big-Five Inventory (BFI: openness, conscientiousness, extraversion, agreeableness, and neuroticism), their studies showed that a highly extroverted person tends to Choose active music, with greater preference for rhythmic and Active music was associated with greater extraversion and conformity. User Modeling, therefore, is essential in predicting their music taste. it has been Divided into two parts: User Profile Modeling and User Experience Modeling.

Step One - User Profile Modeling Selma [14] suggested that the user The profile can be categorized into three areas: demographic, geographic, and psycho-Cho graphic (shown in Table 1). Based on persistence, psychological data has It is further divided into stable features which are essential in making a long time Prediction of term and fluid attributes that can change on an hour-to-hour basis [24].

Data type	Example
Demographic	Age, marital status, gender etc.
Geographic	Location, city, country etc.
Psychographic	<i>Stable:</i> interests, lifestyle, personality etc. <i>Fluid:</i> mood, attitude, opinions etc.

Table 1. User profile classification

Step two - Modeling the user's listening experience based on the level of musical expertise, their expectations in music vary accordingly. Gene Ning's [32] analyzed the different types of listeners aged 16-45. He classified listeners into four groups: loyal, enthusiastic, casual, and non-listener (see Table 2).

Type	Percentage	Features
Savants	7	Everything in life seems to be tied up with music. Their musical knowledge is very extensive.
Enthusiasts	21	Music is a key part of life but is also balanced by other interests.
Casuals	32	Music plays a welcome role, but other things are far more important.
Indifferents	40	They would not lose much sleep if music ceased to exist, they are a predominant type of listeners of the whole population.

Table 2. Use listening experience categorisation

This information gives us a good example that their expertise should be taken into account when designing user-oriented recommendation systems. For example, based on their expectations, we need to think about how much music is discovered and filtered in a long tail, which is interesting and unknown music but hidden in the tail of the popular curve [3]. Other user information including the access pattern, the listening behavior is also useful for user modeling and dynamic optimization [50]. User information can be explored either by preliminary scanning or observing their long-tailed musical behavior.

1.2 Item Profiling.

The second component of recommender systems is the music component. It identifies a variety of information used in MIR. In 2005 Patchett [53] classified music metadata into three categories: editorial (EM) metadata, and cultural metadata (CM) and audio metadata (AM).

- **Editorial metadata:** metadata obtained by a single expert or a group of experts. This is literally obtained by the editor, and can also be seen as information provided by them. For example, cover name, author, title or type and so on.
- **Cultural metadata:** metadata obtained from a group analysis. Text information, usually from the Internet or other public sources. This is information results from the analysis of emerging patterns, groups, or communities from the source documentation. For example, the similarities between the elements of music.
- **Audio metadata:** metadata obtained from the analysis of the audio signal. This must be without any reference to textual or descriptive information. For example, beat, tempo, pitch, instrument, mood, etc.

Editorial metadata is mostly used to retrieve metadata information (see Section 3.1), cultural metadata has been used to a large extent in the existing context information retrieval (see Section 3.5). However, most of the music recommendations the systems use audio metadata to discover music named Retrieval of information on the basis of content (see Section 3.3).

1.3 Query Type

Assuming that users already know the information about the music, the fastest way to search for music is via key editorial information such as Nickname, singer's name, lyrics, etc. However, this is not always the case knowing them. In the past ten years, advanced and more flexible music information retrieval system called "Query by Hum/Singing System (QBSH)" [25]. Allows user to find songs either by hum or singing.

However, it still requires a lot of human efforts. In recommender systems, the most convenient way is to use listening records or stub music as a query to discover their musical preferences.

II. STATE-OF-ART APPROACHES IN MUSIC RECOMMENDATION

The perfect music recommendation system should be able to recommend automatically music intended for human listeners [36, 52]. Different from books or movies, the length of the piece is much shorter, and the times you listen. Usually the songs are favorites more than once.

Existing recommendation systems such as Amazon and eBay have gained an advantage Success. Can recommend complementary goods, the buyer can compare Products (new item/old item) and negotiation with vendors [69]. However, the music the filter not only gives products at a reasonable price, but also suggests They have personal music.

So far, there are many music discovery sites like Last.fm, All music, Pandora and Audiobaba6, Mog7, Music very 8, Spotify9, and Apple “Genius” have amassed millions of users, and the development has been explosive [10, 11]. In this section we present the most common methods, retrieval of metadata information (see Section 3.1), Collaborative filtering (see Section 3.2), content-based information retrieval (see Section 3.3), Emotion-based model (see Section 3.4), Context-based information recall (see section 3.5) and hybrid models (see section 3.6). at the end of each approach, described its limitations.

2.1 Metadata Information Retrieval (Demographic-based Model)

As the primary method, it is the easiest way to search for music. Retrieval of metadata information uses text metadata (editing information) provided by creators, such as song title, artist name, and lyrics for Searching for targeted songs [20].

⁶ <http://audiobaba.com/>

⁷ <http://www.mog.com/>

⁸ <http://www.musicoverly.com/>

⁹ <http://www.spotify.com/>

Limitation Despite its speed and accuracy, the flaws are obvious. first of All, the user must know the editorial information of a particular music purpose. Second, it also takes a long time to maintain the incremental metadata. Furthermore, recommendations results are relatively poor, as they can only recommend music based on editorial metadata and none of the users' information It has been considered.

2.2 Collaborative Filtering

To recommend items by choosing other similar users, collaborative filtering A technique has been proposed [28]. As one of the most successful methods in Recommendation systems, it is assumed that if user X and Y rate n number of items similarly or have similar behavior, they will evaluate or act on other items similarly [59].

Rather than calculating similarity between items, a set of “closest neighbors” users for each user whose previous ratings with the strongest correlation were have found. Therefore, scores for invisible items are predicted based on a set of scores known from nearest neighbors [65]. Cooperative Filtering is divided into three subcategories: memory-based, model-based, and hybrid cooperative liquidation [63, 68].

Memory-based collaborative filtering is memory-based collaborative filtering for item prediction based on complete sets of previous evaluations. Each user is grouped with people with similar interests, so that it is a new element Produced by finding the nearest neighbor using a huge number of express Users' votes [9].

Model-based collaborative filtering as opposed to memory-based filtering, Model-based CF uses machine learning and data mining algorithms that reduce the system to train and model user preferences. It represents the user preference through a set of rating scores and builds a special prediction model [2]. Based on the well-known model, the system makes predictions for the test and the real-world Data.

Hybrid Collaborative Filter Hybrid CF model to make prediction by combining different CF models. It has been shown that the hybrid CF model outperforms any single method [83].

Restrictions due to subjectivity in music, the assumption that users' Similar behaviors with similar tastes have not been extensively studied. Although the collaborative filter proposal works well, the main issues such as a cold start, popularity bias is inevitable [27].

-**Popularity bias** in general, popular music can get more ratings. Music In the long tail, it is rarely possible to get any. As a result, collaborative filtering Mainly recommend folk music to listeners. Although serving popular items is reliable, it is still risky, since the user rarely gets happy Surprised.

-**Cold start** It is also known as data scattering problems. at an early stage, few reviews are provided. As a result of the lack of these classifications, prediction results the poor.

-**Human effort** A perfect recommendation system shouldn't contain much Human efforts, because users are not always willing to evaluate. Categories It may also grow towards those making the assessment, but it may not be representative. Because of this absence of even distributed evaluations, it can give us an error Positive or negative results.

2.3 Content/Audio/Signal-based Music Information Retrieval

The content-based approach is different from the collaborative filtering approach Prediction by song-track analysis [2, 41]. It is rooted in treble re-information and information-filtering [13] that recommends a similar song for those that the user listened to in the past instead of listening to them Rated "Like" [4, 43]. Much attention has been paid to extracting and comparing vocal features in finding similar perceptive pathways [8, 45]. The most representative to date are timbre and percussion [7, 10, 11].

Based on the extracted features, the distance between songs is measured [43]. Three typical similarity measurements are listed below [44].

- **K stands for aggregation with Earth-Mover's distance:** It calculates the general distance between Gaussian Mix Models (GMM) by combining the individual distance between Gaussian components [62].

-**Expectation maximization with Monte Carlo sampling:** This confirmatory measurement uses vectors taken directly from the GMMs of the two songs to be compared. Sampling is performed computationally by generating local numbers [51].

-**Average feature vectors with Euclidean distance:** computes low-order statistics such as mean and variance across segments [16].

Query by Humming (QBSH) Buzzing and singing is the natural way to do it expresses songs [31]. In the early 1990s, based on a content-based model, the query by the proposed hum system [25, 80]. Early inquiry by hum systems They were using the melodic contour which was seen as the most recognizable Features in songs.

It follows three steps: creating a song database, and copying files Query users' melodic information and pattern matching algorithms that Used to get the closest results from groups [1]. In the past few years, Except for melody, better performance was also achieved by inclusion with Lyrics and main voice reinforcement [19, 77].

Limitations To some extent, the content-based model solves problems with column-specific laboratory filtering. For example, by measuring the similarity of acoustic features Between songs, the system can recommend music using distance measurements. Therefore, no human classification is needed. However, the method based on its similarity It has not been fully investigated in terms of listener preference. None of the search Prove that similar behavior leads to choosing the same music.

Since the content-based model is largely based on audio features, the number of the features selected need further consideration. Moreover, other user information and non-voice information should be included for future modification and increase.

2.4 Emotion-based Model

Music acts as a tool for self-expression, always with emotion. Rich in content Expressionism [86], traditional approaches to musical information retrieval It is no longer sufficient. Musical passion has attracted a lot of research and it has succeeded It became the main direction of music discovery and recommendation [34]. A commercial web service called "Music very" uses a basic emotion model (2D Valence - arousal) found by psychologists. Allows users to set their expected location Perceived feelings in a two-dimensional space: valence (whether positive or negative) and arousal (How exciting or soothing.)



Similar to the content-based model, emotion perception is associated with Different patterns of audio signals [6, 35, 48, 61]. Various perceptual traits Such as energy, rhythm, temporal, spectral, harmony have been widely used in recognizing feelings [84].

Limitations

- **Data collection** in order to accurately model the system, a large amount of A data set is needed. However, finding the reliable truth is expensive and it requires a lot of human efforts [67]. Instead of human annotations [73], Social tags [36, 74], and annotation games like Major Miner [47] and Tag a Tune [37], lyrics or music review are used to collect data.

- **Ambiguity and detail** are difficult to define and describe the emotion itself. The same emotional feeling that different people feel may be different an emotional expression (i.e., fun, happy) and no relationship is perfect between emotional terms and emotions [64, 85]. Some research was based on Basic classification (sad, happy, angry, etc.), but it cannot describe richness from our human perception. The MIREX rating rated your passion as 5 temperament groups [29] (see Table 3). Russell [60] found a peripheral model Which emotional concepts lie in a circle in the following order: pleasure (0 degrees), agitation (45 degrees), agitation (90 degrees), distress (135 degrees), resentment (180 degrees), depression (225 degrees), drowsiness (270 degrees), relaxation (315 degrees). It can represent the structure of emotional experience and now it is more noticeable 2D Emotional valence and arousal model. The emotion classification problem has been solved, because each point on the level represents an effect term.

Cluster 1	Passionate, rousing, confident, boisterous, rowdy
Cluster 2	Rollicking, cheerful, fun, sweet, amiable/good natured
Cluster 3	Literate, poignant, wistful, bittersweet, autumnal, brooding
Cluster 4	Humorous, silly, campy, quirky, whimsical, witty, wry
Cluster 5	Aggressive, fiery, tense/anxious, intense, volatile, visceral

Table 3. MIREX five mood categories

2.5 Context-based Information Retrieval

Instead of using audio features in the content-based model and ratings in laboratory filtering, the context-based information retrieval model uses the audience Opinion for discovering and recommending music [18]. Along with the development of social networks like Facebook 10 And Youtube11 and Twitter 12, these sites Provide us with rich human knowledge such as comments, music review, tags and Friendship networks [36].

Therefore, context-based information retrieval uses web/document mining Techniques to filter important information to support problems like the artist Similarity, gender classification, emotion detection [82], semantic space [39, 40] Some researchers have suggested that the use of social information led to the performance of the content-based model [70, 81].

However, the same collaborative filtering problems, popular music can Always get more general opinions than those in the long tail [21]. in the end rich the music gets richer reviews, which again leads to the fame bias problem.

2.6 Hybrid Model Information Retrieval

Hybrid form aims to combine two or more forms to increase the totality of each form. Burke [9] mentioned several ways to build a hybrid model such as Weighted, Switch, Hybrid, Feature Set, and Cascading. There is no doubt That a suitable hybrid model will outperform a single method, because it is capable of it Combine the advantages of both methods while inheriting disadvantages No [65, 87, 88].

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¹⁰ <https://www.facebook.com/>



¹¹ <http://www.youtube.com/>

¹² <https://twitter.com/>

Dynamic Evolution As users gather in recommender systems, it must be able to adapt to new data such as the user's listening and listening history Behavior to further customize their musical taste [30]. This procedure is called has evolved. It addresses the problem that when the new and new user comes elements in the system, it can develop itself dynamically and automatically [65].

Create playlist Another problem is playlist sequencing [38]. Most Recommendation systems are not flexible, because the playlist is arranged according to Similarity distance between seed songs. Although the songs that are most similar are in order, the subject and mood can be significantly altered between them. This may lead to dissatisfaction and interruption of songs.

Research indicates that a playlist should have a main theme (mood, event, activity) evolve over time [17]. Instead of random shuffling, human jump the behavior can be considered for dynamic playlist creation [15, 54]. For exam, assuming users hate the song when skipping it, the system Therefore, it removes songs similar to the skipped song [55, 56, 78].

UI design Bad UI design can't affect system accuracy, it affects ratings and listening experience. Clear The design always gives the user a better understanding of the system. Furthermore it, Comprehensive system control and less human effort required to operate It must be taken into account during the design.

Rating There is no common objective rating in the music recommendation systems [72]. Most assessment techniques are based on a personal system A test that allows users to rank systems according to a playlist generated by different approaches [5, 79]. However, it is very expensive in terms of financial costs and human work. Another important factor is that the evaluation in different Regions (i.e, different background, age, and language) may give different results. Hence, appropriate evaluation criteria are necessary and highly recommended.

III. CONCLUSION AND FUTURE WORK

In this paper, we explain a basic metadata-based model and two popular recommending approaches using the mu sic method: collaborative filtering and content-based modeling. Although they are a huge success, their drawbacks are like popularity Bias and human effort are obvious. Moreover, the use of the hybrid model It is superior to a single model because it incorporates the advantages of both methods. Its complexity has not yet been fully studied.

Because of the subjective nature of music and the issues that exist before Methods, two human-centered approaches are proposed. By looking at the emotion social information, emotion-based model, and largely context-based model Improve the quality of the recommendation. However, this research is still at a level early stage.

As we can see from the evolution of music recommendations over the past years, results tend to be more personalized and subjective. Just looking at the music itself and the ratings of humans is no longer enough. A large amount from work in recent years in musical cognition, psychology, neuroscience, and sports that studies the relationship between music and influence of human behavior. David Huron also mentioned that music has sex and looks like drugs adjectives. There is no doubt that music has always been an important component of our group life, and now we have greater access to it.

Research in psychology has indicated that music not only improves mood, increases activation, visual and audio visuals, but also summons associated elements Movies or music videos relieve stress [33]. Moreover, experimental trials in sports have indicated the main benefits of listening to music Which include extending work output, improving performance, letting go of unpleasant feelings, etc. [71]. For example, athletes prefer up-tempo, Music is traditional, intense, rebellious, lively and rhythmic rather than re Reflective and complex music [66]. This is an important fact that psychologists have found Users' preference in music is related to their personality. Also, worth noting This fast, upbeat music produces a stimulating effect while being slow while being soft Music produces calming effects [12]. All this highlights that the music redirector is not only a tool for relaxation, but also serves as an effective tool for meeting Our needs under different contexts. To our knowledge, there is little existing research on these experimental results.

Designing a custom music recommendation tool is complex, and it is difficult to accurately understand and meet the needs of users. A survey among athletes has shown that practitioners in both sports and exercise environments tend to choose music in a somewhat random manner in a way without full consideration of their motivational properties. So, the future music suggestion should be able to lead users to choose reasonably Music. In the end, we hope that with this study we can build the bridge Among isolated research in all other disciplines.

Acknowledgments: Thanks, and appreciation. Yarding is supported by the China Scholarship Council. We would like to thank Geraint A. Wiggins, Steven Hargreaves, and Emmanuel Bennetto's for their advice.

IV. CONCLUSION

In this paper, we explain a basic metadata-based model and two popular approaches to music recommendation: the collaborative filtering and the content-based model. Although they are a huge success, their drawbacks are like popularity Bias and human effort are obvious. Moreover, the use of the hybrid model It is superior to a single model because it incorporates the advantages of both methods. Its complexity has not yet been fully studied. Because of the subjective nature of music and the issues that exist before Methods, two human-cantered approaches have been proposed. By looking at the emotion

Social information, emotion-based model, and largely context-based model Improve the quality of the recommendation. However, this research is still at a level early stage. As we can see from the evolution of music recommendations over the past years, results tend to be more personalized and subjective. Just looking at the music itself and the ratings of humans is no longer enough. A large amount from work in recent years in musical cognition, psychology, neuroscience, and sport that studies the relationship between music and influence of human behavior. David Huron also mentioned that music has sex and looks like drugs adjectives. There is no doubt that music has always been an important component of our group life, and now we have greater access to it.

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As discussed above, future research direction will mainly focus on the music recommendation systems in use. A survey among athletes has shown that practitioners in both sports and exercise environments tend to choose music in a somewhat random manner in a way without full consideration of their motivational properties. So, the future music suggestion should be able to lead users to choose reasonably a musician. In the end, we hope that with this study we can build the bridge Among isolated research in all other disciplines.

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