A Survey of Music Recommendation Systems with a Proposed Music Recommendation System

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Abstract With the advent of digital music and music-streaming platforms, the amount of music available for selection is now greater than ever. Sorting through all this music is impossible for anyone. Music recommendation systems reduce human effort by automatically recommending music based on genre, artist, instrument, and user reviews. Although music recommendation systems are widely used commercially, there does not exist any perfect recommendation system that can provide best music recommendation to the user with the minimal user effort. In this paper, we reviewed the various recommendation systems that are currently in use including content-based, collaborative, emotion-based, and other techniques. We have also explored the strengths and weaknesses of each recommendation technique and at the end, we have provided an overview of a music recommendation system that may solve many of the challenges that existing recommendation systems face through an improved hybrid recommendation system.

Keywords Recommendation system · Metadata · Collaborative filtering · Content-based filtering

1 Introduction

The access to large amounts of music online has made it increasingly difficult to properly enjoy so much content. Music recommendation systems help users to find songs that they may like. Music recommendation systems aim to provide real-time recommendations of both new and old songs to the users. Music-streaming platforms like Spotify and Apple Music use recommendation systems heavily.

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Music is an integral part of human life. People responds to music better than any other form of media, so recommending songs properly and efficiently has become important. The challenge of music recommendation systems is that human beings are unpredictable, and they may like one music today but may like an entirely different music tomorrow. It is impossible to identify users real-time reactions [1]. All recommender systems, at their basic form, rely on user behavior by recording activities of users who interact with a service or system, or by simply asking users for their preference [2].

Popular recommendation models that are currently in use are content-based filtering, context-based filtering, and metadata-based model. We are also seeing music being recommended based on mood, emotions, and social media interactions of the user. In this paper, we first explained popular music recommendation models that are in use and their challenges, and in the later part of the paper, we proposed a recommendation model that aims to overcome some of the challenges that current recommendation models face.

2 Methodology

We first searched online about various music recommendation systems and how they use user data to recommend songs. Then, we studied articles that provided us with different music recommendation systems. We studied the methods they described in the articles for writing this paper. We focused on the existing recommendation systems and their shortcomings and studied articles that can help us to give an idea of a recommendation system that can solve many of the shortcomings of the existing recommendation systems.

3 Music Recommendation Techniques

Commercially, the music-streaming sites like Spotify, Apple Music, and Pandora use different recommendation techniques to recommend music to its users. Broadly speaking, they use hybrid recommendation model or a recommendation model that is a combination of one or more recommendation technique.

3.1 Collaborative Filtering

Collaborative filtering is a method of generating automatic responses or predictions about the interests of a user by collecting preferences or taste information from many users. This filtering technique uses user ratings for its recommendation. Collaborative systems are built on the assumption that users who rate items similarly in the past will continue to rate them similarly in the future [3].

This filtering technique uses *k*-nearest neighbor algorithm to provide recommendations. Ratings can be divided into two categories—explicit or implicit. Examples of explicit ratings are one-to-five-star rating systems that e-commerce sites use. These ratings are explicitly provided by the users. Implicit ratings can be obtained by interpreting user behavior. Play counts can be used for implicit rating. A song which is being played multiple times will automatically get higher implicit rating.

The biggest drawback of this system is that at early stages it provides poor recommendation. Especially, for items with very few ratings, recommendations performed in a fashion as outlined are not very reliable [4]. This is known as the cold-start problem. When a new user enters the system, the system cannot give effective recommendation as the user has not rated anything yet, so the system does not know what to recommend. Human effort is another challenge for this system. The more effort it will take to generate a recommendation, the less the users will be willing to rate.

3.2 Content-Based Filtering

In content-based filtering technique, songs are recommended based on the comparison done by the system between the content of the items and a user profile.

Several issues must be considered when implementing a content-based filtering system. First, terms can either be assigned automatically or manually. When terms are assigned automatically, a method must be chosen that can extract these terms from items. Second, the terms must be represented such that both the user profile and the items can be compared in a meaningful way. Third, a learning algorithm must be chosen that is able to learn the user profile based on seen items and can make recommendations based on this user profile.

The content of each item is represented as a set of descriptors or terms, typically the words that occur in a document. Acoustic features of the song like loudness, tempo, rhythm, and timbre are analyzed to recommend songs. Most common methods to compute similarity are: K-means clustering [5] and expectation-maximization with Monte Carlo sampling. This technique solves the cold-start problem as it can recommend songs based on very few data.

The major drawback of content-based model is that it relies on the correctness of the item model [6]. It also faces glass-ceiling effect. Another major drawback is that this technique fails to differentiate important differences between otherwise similar songs.

3.3 Metadata-Based Filtering

Metadata-based filtering uses metadata of a song like artist name, genre, and album name. This system uses metadata to recommend songs to the users. It is the most basic and traditional form of filtering technique.

The recommendation results are relatively poor, since it can only recommend music based on editorial metadata, and none of the user's information has been considered [6].

3.4 Emotion-Based Filtering

Music and human emotions are closely connected, so the recommendation model that considers human emotions is emotion-based filtering. Both in commercial and academic sectors, huge research is ongoing about music and its impact on human emotions.

Different acoustic features of the song are used to determine emotions that a song may trigger. Research has also shown that user's mood also plays a key role in selecting the songs [7]. Music-streaming sites create playlists based on human emotions and moods to better suit an emotion that a listener might feel. Recommendation system based on emotion can provide highest satisfaction to the listeners.

The biggest advantage of emotion-based filtering model is also its biggest disadvantage as this model requires huge data collection, huge number of datasets require a lot of human effort [8]. Another drawback is that one song may create different feelings to different persons, and this results in ambiguity of the datasets.

3.5 Context-Based Model

Context-based model uses public perception of a song in its recommendation. It uses social media sites like Facebook, twitter, and reddit and video platforms like YouTube to gather information about public perception of a song and recommend them accordingly to the listeners. It uses users' listening history to gather information about the user and recommends similar songs based on the engagement the songs are seeing in the social media sites. This model can behave efficiently with small amount of data. Platforms like Apple Music and Spotify use top charts or similar methods, where songs that are listened most by its entire user-base in reflected as well as the songs that see most social media engagements are recommended on that list. Context-based model can create a For You section for the user based on users listening history and social media engagement of different songs. Another method of context-based model uses location of the user to recommend songs. Listeners of the same region may tend to like similar songs and through this method the system recommends songs.

Research has suggested that this model performs well due to the collection of social information [7]. Context-based model can recommend better than other recommendation models with few data as it uses social media sites to gather the songs that are currently popular around the globe.

4 Commercially Used Models

Commercially, a combination of these models along with several other parameters is used in recommendation systems.

4.1 Hybrid System

A hybrid model recommendation system uses a combination of previously mentioned recommendation models. It can recommend songs far more efficiently than a system that uses only a single recommendation technique.

An example of a hybrid system is a system that combines content and collaborative techniques. These models can mitigate the shortcomings of each recommendation models.

4.2 Listening History

Users' listening history is another important parameter that the music platforms use to recommend songs. A user is most likely to listen to similar songs and maybe even the same song, so in the commercial sector, listening history plays a critical role in recommendation models.

Different techniques are available to extract the information from the users' listening history, and one such approach is breaking down the entire listening history in sessions [9]. This can provide information on the songs that the user listens in succession. Breaking down the histories also gives an idea to the recommendation model about the difference between the user's short-term and long-term preference [10].

4.3 User-Centric Experience

Not a single person's music preference is identical to another person, but traditionally music recommendation models measured performance of new systems through comparing new datasets to existing datasets [11]. So, the modern music-streaming sites are using recommendation techniques that create a user-specific experience by understanding the music-listening habits of the users.

5 Proposed Model

Commercial recommendation models use a variation of hybrid recommendation systems. When a user first signs up with their email address, recommendation system works by asking the user to input some artists that he/she may like than with this user selection and location data the songs are recommended to the user. Then over time, as the user listens to more and more songs, the recommendation system uses the user's listening history to recommend songs.

We propose a slightly different recommendation model. We propose a recommendation model where initially during the sign-up process the system will ask the user for information like age, gender, location, and then music preference like which language of music user likes, what genre they prefer, and then the artists the user likes. Using this data, the system will initially be recommended songs in the following way to solve cold-start problem. System will categorize the user by their age groups. For example, if the user falls under 18–35 age demographic, chances are that the user will like to listen to currently popular songs. So, the system will initially offer currently popular songs by analyzing music charts like Billboard or equivalent charts and using social media sites. Through these combinations of metadata filtering, context-based model, and content-based model, the system will solve the cold-start problem. Then over time, as the system learns about the listening habits and listening patterns and creates an emotion-based model of the user than accordingly, the system will try to recommend a user-specific experience.

Several issues remain with this type of recommendation system. Firstly, human beings are unpredictable. A person in one age demographic may prefer a song that the system thinks the person will not like; so, this recommendation model cannot account for the unpredictability factor.

6 Conclusion

Through the course of working on this paper, we studied different music recommendation systems and their shortcomings and came to realize that there does not exist any perfect recommendation technique. Several issues remain in each recommendation model. Even, the hybrid recommendation technique that we proposed will not be accurate in predicting songs correctly all the time. One thing we came to realize is that creating a personalized experience for the user though difficult is the best way to recommend songs. User-centric models are far more effective in predicting accurately than other models. In the future, we hope for a hybrid recommendation model that will be more accurate than existing models with minimum human effort.

References

1. J. Lee, et al., Music recommendation system based on genre distance and user preference classification. J. Theor. Appl. Inf. Technol. **96**(5) (2018)
2. M. Millecamp, et al., Controlling spotify recommendations: effects of personal characteristics on music recommender user interfaces, in *Proceedings of the 26th Conference on User Modeling, Adaptation and Personalization, ACM* (2018)
3. J. O'Bryant, *A Survey of Music Recommendation and Possible Improvements*. (2017)
4. P. Knees, S. Markus, A survey of music similarity and recommendation from music context data. ACM Trans. Multimedia Comput. Commun. Appl. (TOMM) **10**(1), 2 (2013)
5. S. Ferretti, Clustering of musical pieces through complex networks: an Assessment over Guitar Solos, in *IEEE MultiMedia* (2018)
6. Y Song, D. Simon, P. Marcus, A survey of music recommendation systems and future perspectives, in *9th International Symposium on Computer Music Modeling and Retrieval*, vol 4 (2012)
7. P. Deshmukh, K. Geetanjali, *A Survey of Music Recommendation System* (2018)
8. J. Skowronek, M.F. McKinney, S. Van De Par, Ground truth for automatic music mood classification, in *ISMIR* (2006)
9. S.E. Park, S. Lee, S. Lee, Session-based collaborative filtering for predicting the next song, in *2011 First ACIS/JNU International Conference on Computers, Networks, Systems and Industrial Engineering (CNSI)*, IEEE (2011)
10. I. Kamehkhosh, D. Jannach, L. Lerche, Personalized next-track music recommendation with multi-dimensional long-term preference signals, in *UMAP (Extended Proceedings)* (2016)
11. M. Schedl, A. Flexer, J. Urbano, The neglected user in music information retrieval research. J. Intell. Inf. Syst. **41**(3), 523–539 (2013)