A Literature Review on Collaborative-filtering and Content-based recommendation approaches with Future Perspectives in Music Recommendation Systems

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Abstract

In recent years, the online digital music brands have simply gone far and beyond. And therefore, the need of managing and sorting through the gigantic amount of music data leads to the study and development of some automation system to help users experience the true beauty of music on their fingertips via various devices like mobile phones and iPods. Though music information retrieval (MIR) techniques are developed and evolved effectively in last ten years, the development of music recommender systems is still at an early stage.

Recommendations can be classified as *personalized or non-personalized*. In non-personalized type, selection of the items for a user is based on how often an item has been visited in the past by other users. However, in the personalized type, the basic objective is to provide the best items to the users based on their taste and preferences. Although, in many domains recommender systems gained significant improvements and provide better services for users, they still require further research to enhance the accuracy of recommendations in many aspects. In fact, the current developments in recommender systems are far from the ideal model of the recommender system. Two popular algorithms: **content-based model (CBM)** and **collaborative filtering (CF)** implement the aforementioned recommendation ideas respectively.

This paper reviews state of art in recommender systems algorithms and techniques that are researched upon already, which is necessary to identify the gaps and improvement areas. Along with that, we provide possible solutions to overcome the shortcomings of existing recommender systems.

Keywords: Collaborative-filtering, Content-based recommendation system, Context-awareness recommendation, Cold-start problem

Introduction

With the boom of World Wide Web(2.0) in the past decades, internet has become the major source of retrieving multimedia information such as video, books, and music etc. Information recommendation has become an important research area since the first papers on collaborative filtering published in the 1990s*[1]*. Extensive work has been done in both industry and academia on developing new approaches on recommendation systems over the last decades. Recently, the interests have been increased due to the abundance of practical applications such as recommendation system of books, CDs, and other products at Amazon.com, flipkart.com, and movies by Movie Lens, YTS and so on.

Music recommendation is also an area where this recommendation system is required. As the World Wide Web becomes the source and distribution channels of diverse digital music, a large amount of music is accessible to people. In this situation, music recommendation gets required for each person since it becomes a difficult and time-consuming job to search and change the music whenever he wants to. There is already a commercial product like iTunes by Apple Computer even though they have used simple rules described by the users [3]. Previously, H. Chen and A. Chen*[2]* presented the music recommendation system for website, and Kuo and Shan(2002)*[3]* proposed a personalized music filtering system considering user preference. These studies considered the user preference fixed in their recommendation models. However, a *user's preference on music changes according to the context and mood of the user*. It varies so dynamically that the recommendation system should consider this information.

In this paper, we classify comprehensive review of literatures on recommender systems that were published in academic, to obtain insight on recommender systems. This paper is organized as follows:

1). The research methodologies that we have adopted to come up with the following review is described.

2). State of art in recommendation systems are explored.

3). Conclusions are presented and the limitations and implications of this study are discussed with the proposal of a new model based on users' motivation.

Survey Methodologies

The main motivation of this study is to get acquainted with the works already been done in this area of research by examining the literatures published till now, relevant to our project and to provide ourselves with the new insightful dimension that can be added in the existing recommender models to enhance it to the next level.

We have done a broad exploration on Google Scholar for music recommendation models related papers. We selected articles that provide the overview of **CFM** and **CBM** recommendation system. We also emphasized upon considering researches taking into account intrinsic, extrinsic, and contextual aspects of the users. For instance, personality and emotional state of the listeners (intrinsic) *[4]* as well as their activity (extrinsic) *[5]* are known to influence musical tastes and needs. So are users' contextual factors including weather conditions, social surrounding, or places of interest *[6]*. Also the composition and annotation of a music playlist or a listening session reveal information about which songs go well together or are suited for a certain occasion. Therefore, researchers and developers of MRS should consider incorporating techniques to predict users' mood and surroundings for the algorithm to predict the best recommendation at a point of time.

Common(Basic) Approaches:

Yading Song, Simon Dixon, and Marcus Pearce*[19]* present a vast overview of **MRS** techniques. The two common approaches are Collaborative-filtering(**CFM**) and Content-based filtering(**CBM**). Xiaoyuan Su*[7]* provides an in-depth analysis on **CFM**. Also, correspondence should be addressed to Michael J. Pazzani and Daniel Billsus*[8]* for we drew resources for **CBM** in our review.

1] Collaborative-filtering

Collaborative systems generate recommendations by comparing ratings of items between different users. Collaborative systems do not attempt to model the actual item being recommended; they only analyze users' responses to those items. 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. Last.fm is an example of a prominent collaborative system.

Defining gaps or challenges

A) Cold start problem- One of the major problems of recommender systems in general, and music recommender systems in particular is the cold start problem, i.e., when a new user registers to the system or a new item is added to the catalog and the system does not have sufficient data associated with these items/users. In such a case, the system cannot properly recommend existing items to a new user (new user problem) or recommend a new item to the existing users (new item problem. Another subproblem of cold start is the sparsity problem which refers to the fact that the number of given ratings is much lower than the number of possible ratings, which is particularly likely when the number of users and items is large. The inverse of the ratio between given and possible ratings is called sparsity. High sparsity translates into low rating coverage, since most users tend to rate only a tiny fraction of items. The effect is that recommendations often become unreliable.

2] Content-based approach

Instead of comparing user ratings, content-based systems construct models of the items being recommended and compare them to the preference model of the current user. The user's preference model doesn't necessarily contain any information about specific songs that the user does or does not like. Instead, it records the user's response to each of the components in the item model. For instance, the item model may include the gender of the vocalist. If the user consistently has a positive response to songs with female vocals, the user preference model will likely indicate a positive bias towards female vocals.

Defining gaps or challenges

B)The major problem with content-based filtering is that it relies on the correctness of the item model. The system is thus limited by what it understands about the music. Regardless of how much user input is collected, the system is unable to overcome limitations in the item models. Schedl(2018) describes this problem as the "glass-ceiling effect" of music recommendation*[9].*

For example, the item model may not take into account important differences between otherwise similar songs. The system may not know the difference between a hard rock song with melodic lyrics and a hard rock song with screamed lyrics. It might then repeatedly recommend songs with screamed lyrics to users who only like melodic hard rock.

Applied and Proposed techniques:

1] Context-awareness(situation based recommendation)

Context-awareness is to use information about the circumstances that the application is running in, to provide relevant information and services to the user. The term 'context-aware' was introduced by Schilit and Theimer *[10]*. They defined 'context' through giving a number of examples of context-location, identities of nearby people and objects, and changes to those objects.

Defining problem or challenges-

In order for future applications to become intelligent ubiquitous applications that are capable of context-awareness, *one of the main challenges* is the capability of recognizing the user's context. In other words, the applications should be capable of grasping the user's intention. For example, John is now in the department store. By a context-awareness system, such factors as person, place and time are collected and accordingly the products that are judged as appropriate for him, e.g., men's suits and neckties, will be recommended to him. However, these recommended products are useless for his situation because he came to the department store to buy a birthday present for his girl friend. This useless recommendation occurs because the context is judged using the superficial factors only. If he came here to buy a present for his girl friend, the products for women should be recommended. Therefore, by analyzing his past buying patterns and the kinds of shops he has been browsing today, we need to find out his intention. The research area related to this example is called 'context reasoning'. Context reasoning is defined as "deducing new and relevant information to the use of application(s) and user(s) from the various sources of context data"

2] Psychologically inspired music recommendation

Using human emotion state with recommendation engines may increase recommendation engines performance. Shin et al.*[11]*, presented an automatic stress-relieving music recommendation system. System used wireless and portable finger-type PPG sensor. Nirjon et al.*[12]*, proposed a context-aware, biosensor – based, music recommender system for mobile phones. Liu et al.*[13]*, presented a music recommendation system which is aware of user heartbeat and preference. Yoon et al.*[14]* implemented personalized music recommendation system using selected features, context information and listening history.

Biosensors can monitor physiological attributes of the human body that are controlled directly by autonomous nervous system. These sensors can collect signals including skin conductance, blood volume, temperature, heart rate.

Defining problems or challeneges-

All these mentioned references stressing upon implementing *human emotion and psychological awareness techniques* with recommendation engines have drawbacks of one over the other. For instance, *[11]* proposed a wireless finger-type PPG sensor to be used with the engines which clearly an additional hardware requirement for a user just to stream a bit of a music. So, the first primary goals of recommendation system i.e., to make the recommendation system as effortless for the user as the pull shot of RG Sharma. Same is the case with*[12],* the app requires various sensors to be present in the users' smartphone.

For *[14]*, again, context-awareness algorithms are not as efficient as it is required(explained in detail in Context-Awareness section of Applied and Proposed techniques).

In *[13]*, Liu proposed the methodology by including *the metadata information retrieval* about the songs. Though it is fast and accurate, the drawbacks are obvious. First of all, the user has to know about the editorial information for a particular music item. Secondly, it is also time consuming to maintain the increasing metadata. Moreover, the recommendation results is relatively poor, since it can only recommend music based on editorial metadata and none of the users' information has been considered.

3] Active learning

Active learning is the process of giving recommendations that will help the system to learn as much as possible. This technique helps to quickly overcome data sparsity.

For example, suppose a user has given a positive response to many songs from artist A but has never heard a song from artist B. A new, unheard song from artist A would likely receive a positive response, but a response to a song from artist B would tell the system more about the user's preferences.

Defining problem or challenges-

Active learning techniques also suffer from a number of issues. First of all, the typical active learning techniques propose to a user to rate the items that the system has predicted to be interesting for them, i.e., the items with highest predicted ratings. This indeed is a default strategy in recommender systems for eliciting ratings since users tend to rate what has been recommended to them. Even when users browse the item catalog, they are more likely to rate items which they like or are interested in, rather than those items that they dislike or are indifferent to. Indeed, it has been shown that doing so creates a strong bias in the collected rating data as the database gets populated disproportionately with high ratings. This in turn may substantially influence the prediction algorithm and decrease the recommendation accuracy [63]

4] Listening History

[15] demonstrates how deeper inferences about music preferences can be made by partitioning the listening histories into sessions. These sessions can indicate the similarities between songs in the user's collection. Songs are more likely to be similar if the user listens to them in succession. *[16]* demonstrates that temporal aspects from the history can also improve recommendation. They present a model that examines which songs the user listens to based on different temporal factors like time of day and day of week. *[17]* shows that temporal context can be combined with session-based collaborative filtering for further improvement. Finally, *[18]* uses listening histories to differentiate between the user's short-term and long-term preferences.

Defining problems or challenges-

Again, the problem of cold start arises as we tend to monitor playing sessions and history of the user, since there's not enough data for a newly registered user.

5] Hybrid Model

Content-based model(CBM) is like a car with high acceleration but low top speed. It can give effective recommendations quickly because it doesn't need a lot of users, but the effectiveness of those recommendations won't improve after the system does gain many users. Collaborative-filtering model(CFM) is the opposite; it has high top speed but low acceleration. As such, the two approaches can be combined into a hybrid system that draws on the strengths of each*[19]*. Collaborative and content-based filtering can be combined in many ways. One method is to use collaborative filtering as the default system while content-based filtering is used when the collaborative system lacks sufficient data about a particular item. Methods like these help to mitigate the inherent challenges of each approach, such as data sparsity. Experimental studies show that hybrid systems outperform systems that rely on only one recommendation approach*[20, 21]*.

Defining problem and challenges-

Although, this hybrid model overcomes the individual shortcomings of both CBM and CFM, the problem of lack of user-related context awareness is still there. The users' activity information, emotional context, social context, cultural context all matter when it comes to recommending something to the user.

Suggested method to fill the gaps

A new music player application could at first use content-based filtering and *active learning* to explore the user's music collection. Instead of forcing the user to create playlists or otherwise select which songs to play, the app would choose automatically the next track to play. This setup is known as *next-track recommendation*. The user's skipping behavior would be recorded and used to construct a *complete listening history*. Since skipping behavior includes both songs the user listens to and songs the user skips, the history would include songs that the user didn't want to listen to at a certain time (i.e. failed recommendations). The skipping behavior also gives a user-centric way to evaluate the system's performance. After the app gains enough users, it could gradually *switch over to a collaborative approach* in order to recommend new songs. These recommendations could be streamed to the music player to minimize human effort, and feedback would still be collected through *skipping behavior*. This would be a hybrid system in two different ways: the system combines collaborative and content-based filtering, and it combines streaming playback with local playback.

Related Systems:

NextOne *player* is a more recent system that also uses a content-based model combined with skipping behavior*[22]*. It uses the listening history to calculate a "freshness" value for each song. This allows the player to give more weight to songs that haven't been played recently. Although the app uses the listening history, it doesn't do any session based analysis. It also doesn't incorporate active learning or collaborative filtering; however, the authors of papers that we have explored till now, do recommend collaborative filtering as a subject for future work.

Future Research:

As of now, we have planned to work on Cold-start problem, however, analyzing user behavior and implementing context-awareness model for APC problem is our next target in the future.

1. To provide context based recommendations.

2. To provide Automatic playlist continuation

Conclusions:

We have presented a literature Review of the *state of the art* in music recommendation with a focus on collaborative and content-based filtering. I have found that a hybrid recommender system built on user skipping behavior could be a useful next step in recommendation system design. This system has the potential to provide users with a music experience that seamlessly integrates local playback with streaming playback for effective recommendations while requiring minimal human effort.

References:

[1] Resnick et al., 1994; Shardanand and Maes, 1995

[2] https://dl.acm.org/doi/10.1145/502585.502625

[3] Kuo, F.F. and Shan, M.K. (2002). A Personalized Music Filtering System Based on Melody Style Classification. In Proceedings of IEEE international Conference on Data Mining, pp. 649–652.

[4] .

Ferwerda B, Schedl M, Tkalˇciˇc M (2015) Personality & emotional states: understanding users music listening needs. In: Extended proceedings of the 23rd international conference on user modeling, adaptation and personalization (UMAP), Dublin, Ireland

[5] .

Gillhofer M, Schedl M (2015) Iron maiden while jogging, debussy for dinner? An analysis of music listening behavior in context. In: Proceedings of the 21st international conference on multimedia modeling (MMM), Sydney, Australia

[6] Adomavicius G, Mobasher B, Ricci F, Tuzhilin A (2011) Contextaware recommender systems. AI Mag 32:67–80

[7] http://downloads.hindawi.com/archive/2009/421425.pdf

[8] http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.130.8327&rep=rep1&type=pdf

[9] .

M. Schedl, E. Gmez, J. Urbano, and Now Publishers, Music information retrieval: recent developments and applications. 2014, OCLC: 905837683, isbn: 978-1-60198-807-2. [Online]. Available: http : / / dx . doi . org / 10 . 1561 / 1500000042 (visited on 04/04/2017).

[10] Schilit, B., Theimer, M.: Disseminating Active Map Information to Mobile Hosts. IEEE Network, Vol. 8. (1994) pp. 22-32

[11] .

I.-h. Shin, J. Cha, G. W. Cheon, C. Lee, S. Y. Lee, H.-J. Yoon, and H. C. Kim, “Automatic stress-relieving music recommendation system based on photoplethysmography-derived heart rate variability analysis,” in IEEE Int. Conf. on Eng. in Med. and Bio. Soc. IEEE, 2014, pp. 6402–6405

[12] .

S. Nirjon, R. F. Dickerson, Q. Li, P. Asare, J. A. Stankovic, D. Hong, B. Zhang, X. Jiang, G. Shen, and F. Zhao, “Musicalheart: A hearty way of listening to music,” in Proc. of ACM Conf. on Emb. Netw. Sens. Sys. ACM, 2012, pp. 43–56

[13] .

H. Liu, J. Hu, and M. Rauterberg, “Music playlist recommendation based on user heartbeat and music preference,” in Int. Conf. on Comp. Tech. and Dev., vol. 1. IEEE, 2009, pp. 545–549.

[14] .

K. Yoon, J. Lee, and M. U. Kim, “Music recommendation system using emotion triggering low-level features,” IEEE Trans. Consum. Electron, vol. 58, no. 2, pp. 612–618, May 2012

[15] .

S. E. Park, S. Lee, and S.-g. Lee, “Session-based collaborative filtering for predicting the next song,” in Computers, Networks, Systems and Industrial Engineering (CNSI), 2011 First ACIS/JNU

International Conference on, IEEE, 2011, pp. 353–358. [Online]. Available: http://ieeexplore.ieee.org / abstract / document / 5954341/(visited on 03/28/2017).

[16].

C. H. Park and M. Kahng, "Temporal dynamics in music listening behavior: A case study of online music service," IEEE, Aug. 2010, pp. 573– 578, isbn: 978-1-4244-8198-9. doi: 10. 1109/ICIS.2010.142. [Online]. Available: http : / / ieeexplore . ieee . org / document / 5591002/ (visited on 03/05/2017).

[17].

R. Dias and M. J. Fonseca, "Improving music recommendation in session based collaborative filtering by using temporal context," IEEE, Nov. 2013, pp. 783–788, isbn: 978-1-4799-2972- 6 978-1-4799-2971-9. doi: 10 . 1109 / ICTAI . 2013 . 120. [Online]. Available: http : / / ieeexplore .ieee.org / document / 6735331/ (visited on 03/08/2017).

[18].

I. Kamehkhosh, D. Jannach, and L. Lerche, "Personalized next-track music recommendation with multidimensional long-term preference signals," [Online]. Available: http : //ceur-ws.org/Vol-1618/IFUP_paper_ 3.pdf (visited on 03/08/2017).

[19] .

Y. Song, S. Dixon, and M. Pearce, "A survey of music recommendation systems and future perspectives," in 9th International Symposium on Computer Music Modeling and Retrieval, 2012. [Online]. Available: https : / / www.researchgate.net/profile/Yading_Song / publication / 277714802 _ A _Survey_of_Music_Recommendation_Systems_and_Future_Perspectives/ links / 5571726608aef8e8dc633517.pdf (visited on 03/05/2017).

[20].

Bo Shao, M. Ogihara, Dingding Wang, and Tao Li, "Music recommendation based on acoustic features and user access patterns," IEEE Transactions on Audio, Speech, and Language Processing, vol. 17, no. 8, pp. 1602–1611, Nov. 2009, issn: 1558-7916. doi: 10.1109/ TASL . 2009 . 2020893. [Online]. Available: http : / / ieeexplore.ieee.org / document / 5230332/ (visited on 03/13/2017).

[21].

M. Schedl, "Ameliorating music recommendation: Integrating music content, music context, and user context for improved music retrieval and recommendation," in Proceedings of International

Conference on Advances in Mobile Computing & Multimedia, ACM, 2013, p. 3. [Online]. Available: http : / / dl . acm . org / citation . cfm ? id = 2536856 (visited on 03/05/2017).

[22].

Y. Hu and M. Ogihara, “NextOne player: A music recommendation system based on user behavior.,” in ISMIR, 2011, pp. 103–108. [Online]. Available: http : / / www . academia.edu/download/38297540/PS1-11.pdf

(visited on 03/05/2017).