As per UGC guidelines an electronic bar code is provided to seure your paper

International Journal for Modern Trends in Science and Technology, 8(01): 205-209, 2022

ISSN: 2455-3778 online
DOI: https://doi.org/10.46501/IJMTST0801034
Available online at: http://www.ijmtst.com/vol8issue01.html

Music Recommendation System

Roshan Kumar | Sachin | Kavita Saxena

Department Of Computer Science , Maharaja Agresane Institue of Technology, New Delhi
*Corresponding Author Mail Id: rkrockstar9990@gmail.com

To Cite this Article
Roshan Kumar, Sachin and Kavita Saxena. Music Recommendation System. *International Journal for Modern Trends in Science and Technology* 2022, *8* pp. 205-209. https://doi.org/10.46501/IJMTST0801034

Article Info
Received: 09 December 2021; Accepted: 06 January 2022; Published: 12 January 2022.

ABSTRACT

Fast improvement of cell phones and web has made feasible for us to access diffe providing rent music assets openly. The number of songs accessible surpasses the listening limit of songs capacity of single person. Individuals in some cases feel hard to look over large number of melodies. Music is a integral part of our life. We pay attention to music regularly according as we would prefer and mood.With the headway and expansion in volume of computerized content, the decision for individuals tolisten to different sort of music has additionally expanded significantly. Hence, the need of delivering the most fit music to the audience members has been an intriguing field of examination incomputer science. One of the significant measures to convey the best music to audience members couldbe his/her character characteristic. In this venture, we intend to find the effect of character traitson the collective filtering (client to client) which is one of the most famous recommendationengines utilized today. In order to request to decide the character of an individual, web-based media like Facebook can be a utilization ful stage where individuals express their perspectives on various issues, share their viewpoints andthoughts. Such articulations of musings and feelings can be utilized to concentrate on the individual ality attributes of the individual and subsequently utilize this data to attempt to improve existing client touser cooperative filtering strategies for music proposal. characteristics of theusers can be contemplated as far as standard Big Five Personality Traits defined as Opennessto experience, Conscientiousness, Extraversion, Agreeableness, and Neuroticism [2].Withthis project, we had the option to discover that character of the client can be one of the crucialfactor, in the suggestion of the music.

1.INTRODUCTION

Fast improvement of cell phones and web has made feasible for us to access diffe providing rent music assets openly. The number of songs accessible surpasses the listening limit of songs capacity of single person. Individuals in some cases feel hard to look over large number of melodies. Moreover,music service providers need a productive method for manage songs and help their users to discover music by providing a efficient music recommendation algorithm. Music recommendation system is a software which provides a efficient way to manage songs and help users to select those songs which they like most to listen. Since organising and processing of such a large dataset is time consuming and highly memory inefficient. We used validation set of our main data. It contains 10,000,000 triplets of 10000 users. From this big data ser we focus on features that seem to be most relevant in recognizing. Right now, there are numerous music web-based features, similar to Pandora, Spotify, and so forth which are chipping away at building high-accuracy business music proposal sys-tems. These organizations produce income by assisting their clients with finding applicable music and charging them for the nature of their suggestion administration. Consequently, there is a solid flourishing business sector for great music recommenda-tion frameworks. Music recommender system is a system which gains

from the users past listening history and suggests them songs which they might likely want to hear in future. We have executed different calculations to attempt to build a viable recommender system We first and foremost im-plemented fame based model which was very simple and instinctive. Cooperative separating calculations which foresee (sifting) taste of a client by gathering inclinations and tastes from numerous different clients (teaming up) is additionally executed. We have additionally done examinations on content based models, in light of inactive elements and metadata. Music listening services own enormous music catalogs, to give a wide open use. These equivalent services deal with the copyright issues for every country. They adjust the melodic inventory concurring the duplicate and propagation freedoms of the melodic name related to every collection. The vast majority of these music services are paid, some give free admittance to the music list, however no proliferation privileges. There is a wide assortment of these frameworks and new choices are continually arising progressively improved. Some are straightforward players giving playlist usefulness (spotify.com), others go with the player with a suggestion arrangement of comparative specialists (www.spotify.com), additionally there are mind boggling cooperative services in which many individuals leave remarks on melodies (www.pandora.com, www.lastfm.com) and get the opportunity of collaborate with one another as in the recently arising informal organization.

2. Related Work

Dmitry Bogdanov et al. [1] talked about a recommendation wherein the work process of the execution of the systemcan be separated into information gathering, sound examination, music proposal, and inclination perception. The client indicates his/her record name on Last.fm and additionally SoundCloud administrations from which the favored tracks ought to be recovered. Canoris 8 API has been utilized to acquire semantic portrayals. Canoris is a web administration created by the UPFs Music Technology Group 9 for the investigation and combination of sound and music. To create suggestions, an in-house music assortment of 50,000 music extracts, covering a wide scope of melodic sorts was utilized. This assortment was dissected through the Canoris API to recover similar semantic depictions as utilized for the inclination set. Utilizing this, a bunch of melodies near the clients inclination set is made and introduced to the client.

Ms. Nishigandha Karbhari et al. [2] presents a model to position proposals System dependent on signs of understudy. It utilizes 3 methodologies; community proposal approach, content suggestion approach and half and half suggestion approach. They present a technique to think about the different requirements with fluctuating degree of ability. Sorting understudies dependent on their qualifications from that point, it finds best answers for create proposals for position dependent on the imprints and different elements remembered for the profile of the understudy. Utilizing these delicate processing methods, the understudy can be alluded to the work profile which isn't utilized as reference for the situation in any case.

Kunhui Lin et al. [3] proposed the utilization of further developed user- based collaborative filtering algorithm to manage the clients long haul inclinations. Then, at that point, as indicated by the client tag-music connections, getting the music that related with the client through proposal calculation dependent on bipartite diagram is finished. For music customized proposal, the generally utilized techniques incorporate substance based suggestion innovation, the cooperative sifting suggestion innovation and crossover proposal innovation, where half breed is the mix of the two. The substance put together is with respect to producing playlist dependent on the clients most loved music while the community situated in where every music accompanies a tag, consequently prescribing comparative label music to the client. There is utilization of k-means bunching calculation to group clients to fill user music network, observing client of comparative music taste. The further developed proposal calculation dependent on bipartite diagram chiefly utilizes data of client label two-dimensional relationship and tag-music two dimensional relationship. Subsequent to testing it was observed that further developed customized music suggestion framework was most exact rather than client based community oriented model or proposal dependent on bipartite chart.

In their paper, Miao Jiang et al. [4] propose a further developed algorithm dependent on profound neural network on comparability between various tunes. The proposed strategy makes it conceivable to make proposals in an enormous framework to make correlations by understanding the substance of melodies. This paper proposes a model dependent on intermittent neural organization to anticipate clients next most conceivable tune by likeness. They directed tests and assessments dependent on Million Song Dataset and show how it beats the conventional techniques. It gathered the verses for an aggregate of 34412 melodies, and sound examples for 4240 tunes, bringing about a verses dataset comprising of 28,000 sets, and a sound dataset comprising of 1000 sets. Cross approvals was led for both to part the datasets into preparing and testing sets. The proposed model in the paper depends on a Long-momentary memory-based design. The inspiration driving utilizing a LSTM-based design originates from the way that sound is intrinsically consecutive in nature and the likeness between two melodies (especially between their sound signs) should in at minimum some way be dictated by the similitudes between their groupings over the time.

3. ALGORITHMS

We have implemented four different algorithms to build an efficient recommendation system.

3.1 Popularity basedModel

It is the most basic and simple algorithm. We find the popularity of each song by looking into the training set and calculating the number of users who had listened to thissong.Songsarethensortedinthedescendingorderof their popularity. For each user, we recommend top most popular songs except those already in his profile. This method involves no personalization and some songs may never be listened infuture.

3.2 Collaborative basedModel

Collaborative filtering involves collecting information from many users and then making predictions based on some similarity measures between users and between items. This can be classified into user-based and item-

3.3 SVDModel

Listening histories are influenced by a set of factors spe-Locality of scoring function is also necessary to empha- size items that are more similar. We have used exponential function to determinelocality.

fects the overall scoring between two items. The similar things are emphasized more while less similar ones con- tribution drop down to zero.

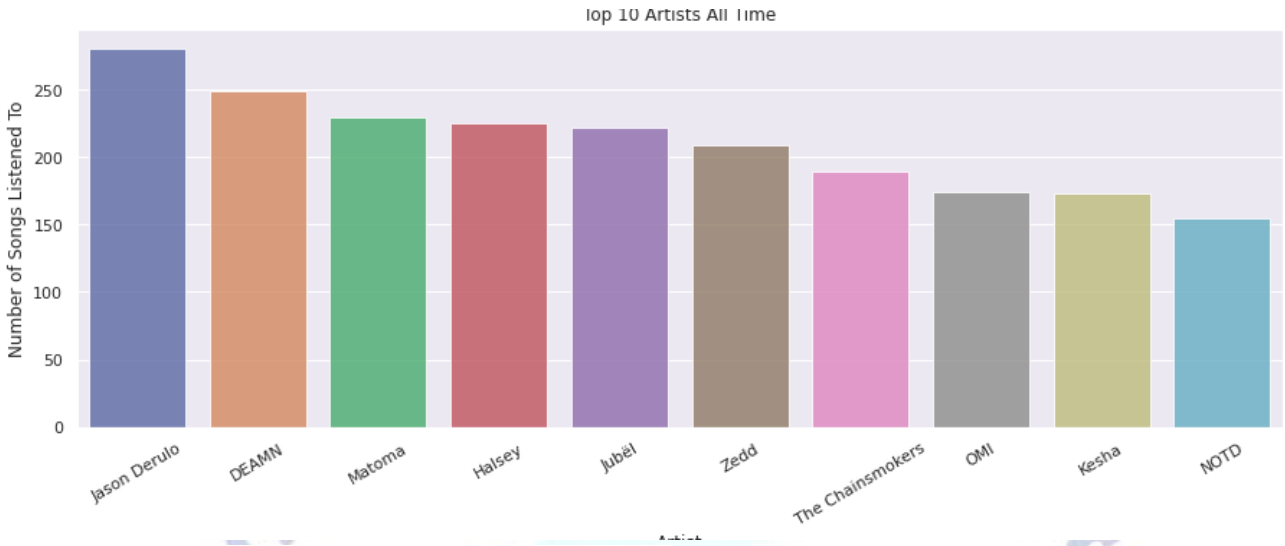
After computing user-based and item-based lists, we used stochastic aggregation to combine them. This is done by randomly choosing one of them according to their probability distribution and then recommending top scored items from them. When the song history of auser is too small to utilize the user-based recommenda- tion algorithm, we can offer recommendations based on song similarity, which yields better results whennumber

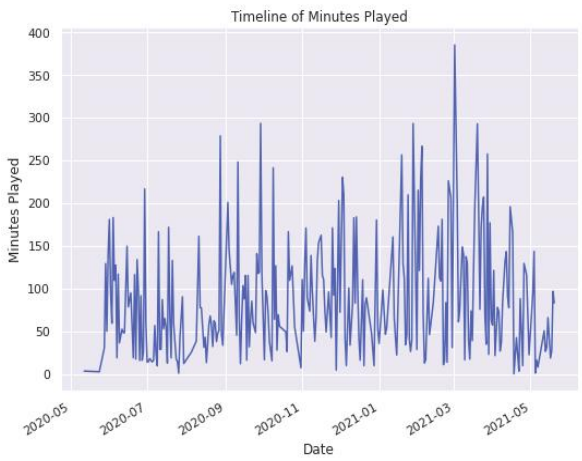
3.4 KNNModel

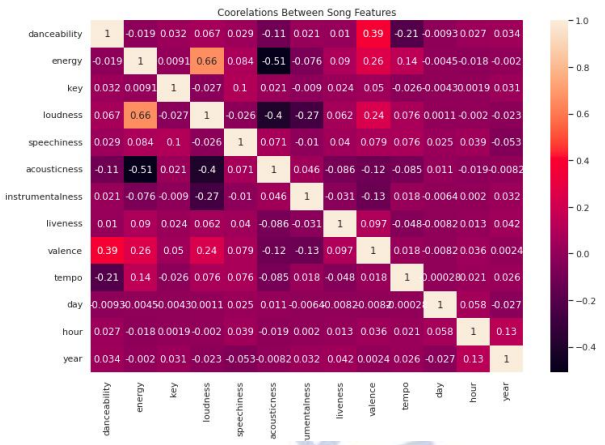
In this method, we utilize the available metadata. We create a space of songs according to their features from metadata and find out neighborhood of each song. We choose some of the available features (e.g loudness,genre,mode , etc) which we found most relevant to distinguish a song from others. After creating the feature space, to recommend songs to the users, we look at each users profile and suggest songs which are neighbors to the songs present in his listening history. We have taken top 50 neighbors of each song. This model is quite personal- ized and uses metadata. But since, we had 280GB file of metadata which takes huge amount of time in processing, we extracted features of only 3GB (10,000 songs), which is less than 2 % of total number. Due to this, we had fea- tures of only small number of songs, which gives us very smallprecision.

4 RESULTS

We got best outcomes for memory based shared fil-tering calculation. Our SVD based inactive element model gives preferred outcomes over prominence based model. It falls behind community separating calculation on the grounds that the mama trix was too scanty which forestalled objective capacities to unite to worldwide ideal. Our KNN model didn't function admirably and performs more awful than even the notoriety model. The purpose for this that we have the highlights of just 10,000 melodies, which is under 3 % of the entire dataset so just a portion of these 10,000 tunes could be rec-ommended. The tremendous absence of data prompts the awful exhibition of this strategy.







5. CONCLUSION

This is a task of our Artificial Intelligence course. We observe it is excellent as we got an opportunity to rehearse speculations that we have learnt in the course, to do some implemen-tation and to attempt to improve comprehension of a truly computerized reasoning issue. tem. There are many different approaches to thisproblem and we get to know some algorithms in detail and espe-cially the four models that weve explained in the paper. Bymanipulatingthedataset,changingthelearningsetand testing set, changing some parameters of the problemand analyzing the result, we earn a lot practicing skills. We've faced a lot of problem in dealing with this huge dataset, howto explore it in a better way and we alsohad difficul-ties in some programming details. However, with lot of efforts, we have overcame all ofthese.As far as exploration, we actually have a great deal to do to make our examinations a superior one. Music Recommender System is a wide, open and muddled subject that we can take a few drives and do significantly more tests in future.We additionally got to understand that building a recommender sys-tem is anything but a minor assignment. The way that its enormous scope dataset makes it troublesome in numerous viewpoints. Right off the bat, suggesting 500 right tunes out of 380 million for various clients is anything but a simple errand to get a high accuracy. That is the reason we didnt improve than 10 %. Indeed, even the Kag-gle victor has just got 17 %. Also, the metadata incorporates colossal data and while investigating it, it is dif-ficult to separate applicable highlights for tune. Thirdly, techni-cally talking, handling such an immense dataset is memory and CPU escalated. This multitude of troubles because of the information and to the actual framework make it seriously testing and furthermore more appealing. We trust that we will get different freedoms in the future to work in the space of man-made brainpower. We are sure that we can make a superior showing.

6. FUTURE WORK

Many different adaptions,tests and experiments have been left for the future due to lack of time (i.2 the experiments with real data are usually very time

consuminig, requiring even days to finish a single run). Future work concerns deeper analysis of particular mechanisms, new proposals to try different methods, or simply curiosity.

7. ACKNOWLEDGEMENTS

We would like to acknowledge the efforts of Mrs. Kavita Saxena as without her constant support and guidance this project would not have been possible.

REFERENCES

[1] D. Bogdanov; M. Haro; F. Fuhrmann ; A. Xambo ; E. Gomez ; P. Herrera, A content-based system for music recommendation and visualization of user preferences working on semantic notions, 9th International Workshop on Content-Based Multimedia Indexing (CBMI), 2011.

[2] ash Jagda , Mihir Jethwa , Jatin Metar , Amruta SankheEngineering College Recommendation and Prediction of Cut-offs

[3] TY - BOOK ,AU - Wang, Jingjin , AU - Lin, Kunhui , AU - Li, Jia , PY - 2013/04/01 , SP - 1473 , EP - 1476 , SN - 978-1-4673-4464-7 , T1 - A collaborative filtering recommendation algorithm based on user clustering and Slope One scheme , DO - 10.1109/ICCSE.2013.6554158

[4] Miao Jiang, Ziyi Yang, Chen Zhao, What to play next? A RNN-based music recommendation system, 51st Asilomar Conference on Signals, Systems, and Computers, 2017.