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RECOMMENDATION SYSTEM FOR MUSIC BASED ON CONTENT AND POPULARITY RATINGS

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***Abstract*-Digital music is more accessible than ever before, thanks to commercial music streaming services accessible through mobile devices. Organizing all of this digital music takes a long time and causes information overload. As a result, creating a music recommender system that can automatically scan your music library and recommend the appropriate songs to your consumers is quite beneficial. Music providers can employ a music recommender system to anticipate and deliver relevant songs to users based on the qualities of previously listened music. Because the availability of digital music is so vast today compared to the past period, sorting all of it takes a long time and produces information fatigue.**

Be it buying a kindle book, selecting music on Netflix, or studying an essay on Medium, recommender systems have shaped our online choices. They are, though, still in the early stages of development and far from ideal. We explore Music recommender systems in particular, as well as numerous types of recommendation strategies and the issues they encounter, in this study. We also attempt to critically evaluate some work on music recommendation systems and explore various research articles that have aided in the resolution of numerous issues that these systems have faced. Despite these advancements, recommender systems must still be developed to a greater level in order to be more successful in giving correct suggestions on a wide range of topics.

The paper discusses how to create a music recommendation system, as well as different methodologies, alternative ways that might be employed, and future developments.

***Keywords*-Recommendation, Ratings, Popularity, Users**

I. INTRODUCTION

In the digital era, music is one of the most popular forms of entertainment. Music is a work of human creation that uses melodies, harmony, and rhythm to communicate thoughts and emotions in the form of sounds. Pop, rock, rap, blues, and folk tunes are examples of diverse music genres. In the digital age, listening to music is simple because smartphones can play music both offline and online. Because the availability of digital music is so vast today compared to the previous period, sorting all of it takes a long time and produces information fatigue. As a result, developing a music recommendation system that can automatically search the music collection and select tracks that are appropriate is quite useful.

Music fans now have access to tons of millions of songs via streaming services like as Spotify, Jio Saavn, and itunes. Recommender systems are generally highly good in suggesting songs that meet their customers' preferences by filtering this plethora of music items, hence limiting option overloading.

Recommendation systems are one of the most successful and widely used machine learning techniques in the commercial world. A recommendation is a content proposal to users, meaning that if the user wanted to check out some new material, this suggestion would be well matched to their interests, with content relating to a variety of topics such as music, news, literature, music, and so forth. When a person attempts out the suggested material and likes it as the recommender intended, the suggestion is said to be excellent. As a result, a recommendation system is meant to give information to users that is tailored to their specific requirements based on criteria such as their favourite content, personal background, and so on.

Collaborative filtering and content based filtering are the two most common types of such systems. Content is presented through collaborative filtering algorithms based

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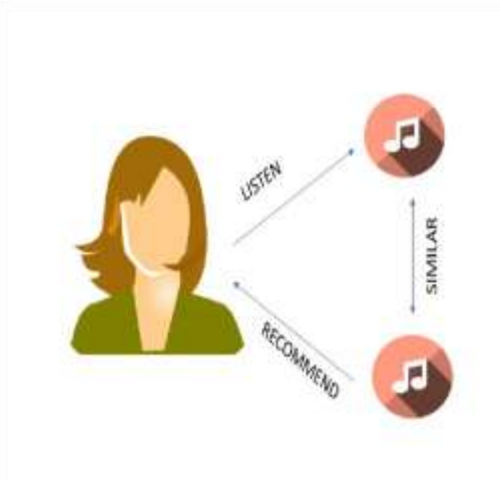
on comparable users who are also using the system. If two users have comparable tastes in material, the algorithm will recommend their favourite to the other person while avoiding anything they dislike[4]. Comparable content is the subject of content-based filtering, which focuses on the particular user's likes and locating similar fresh content to that of the user's past. Content-based techniques use item property similarity to calculate similarity, whereas collaborative methods use interactions to estimate commonality.



Recommendation System

II. LITERATURE SURVEY

We studied a research paper [1] in which it is discussed that according to users behavior like genre,time pattern the recommendation system will recommend the songs. The approach will be effective when we evaluate the results. Further, in local device we can merge recommendation of music and server data to decrease the issue for tough start and suggest new songs.

In another paper [2], we viewed that a system is presented that filters information related to music from RSS based on user profile. This system can understand users in two ways psychological variable and behavioral factor. Users inquiries can be filtered and contextualized. Using news filtering like album,interviews,artists can inprove the system in dynamic way. This method can open many application and usage. The evaluation is planned to be done by comparing the recommendation system with collaborative recommendation system.

Another paper [3], we viewed that a music recommendation system is presented that combines context data and usage. The evaluation is done online on a commercial website for users. Music web site End-to-end services are provided and took into account the growth of the recommenders, as well as their abilities like evaluation setup, as well as deployment and maintenance. Users were separated into three categories based on their behavior that tells how they are responding to the recommendations. Adaptation over time is a topic that will be addressed in future research.

In another paper [4], it is discussed that deep learning can also be used in the area of recommendation system. Various research work is discussed mainly in three types of recommendation system i.e. content based, collaborative based and hybrid systems. And we found that deep learning has shown a great improvement in collaborating filtering than the art matrix factorization approach.

We studied another paper [5] in which a Hindi lyric dataset is created and used a variety of methods to clean the unstructured data. An algorithm for unsupervised stemming was used to reduce the n-grams. These methods can also be used in IR systems to clean unstructured data. This research will facilitate the development of recommendations specifically in hindi songs.

Another paper[6], we viewed that a basic metadata-based model and two music recommendation approach-collaborative filtering and content based are explained. They both achieve great success there are drawbacks too like human efforts and popularity bias. Hybrid model incorporates the advantages of both methods so it would outperform a single model. By using content based and collaborative based, the quality of recommendation system improves largely as due to subjective nature of music , human centered approach can create issues.

In next paper [7], it is discussed that a model is created which recommend songs based on the emotion facial reaction detected. Music has a power to heal anyone's stress or any kins of emotion. There is a wide scope in development of emotion based music recommendation system. This system will detect the emotion and play the song accordingly.

Another paper [8], it is discussed that a system is proposed for music recommendation, characterized by a voice assisting agent that uses speech recognition, synthesized voice and facial expression generation. Speech is recognized using a speech recognition system called Julius, the preset parameters synthesize the facial expressions that depend on each vowel. We used MMD Agent to create the agent, it allowed us to produce the voice of the agent by the built-in speech synthesis function setting. We added a new function that changes the facial expression of the agent in accordance to the responses of the users to music recommended. The effectiveness of the proposed system was verified.

In this paper [9], we saw various type of recommendation techniques and its type are briefly described with the discussion the feedback techniques for recommender system. for efficient recommendation systems in future,other attributes and techniques can be developed and evaluated Fir example combining recommendation systems with machine learning (ML) and natural language processing (NLP), can be used which will consider various aspects. Using ML, we can train the system to provide best recommendations based on its past experiences. This will result in a recommendation system with its own intelligence to predict the best interest of the user to provide recommendations with high accuracy.

This article [10] explores the inequality fostered by streaming platforms by a small-scale network analysis case study. Unequal distribution patterns of music consumption and discovery did not disappear with the advent of the digital space but rather reappeared and reformulated in the digital cultural industries (Hesmondhalgh, 2019). In the realm of digital music, bands operating from a central geo graphical location still have way more opportunities to distribute and communicate their work (Verboord and Noord, 2016). By the recommendation practices (Prey, 2018), controlled by platforms acting as the new gatekeepers (Aguiar and Waldfogel, 2018), practicing their newfound "algotorial power" (Bonini and Gandini, 2019), algorithmic bias and inequality (Bauer, 2019; Goldschmitt and Seaver, 2019) foster unequal music consumption and discovery patterns in the streaming ecosystem. Therefore , it can be seen that the way bands are represented in the recommendation system—the connection with other band-significantly overlaps with their offline connections. Those bands signed with international labels have more level 3 connections and are more likely to be recommended based on genre similarity. However, bands published by Hungarian labels or are self-published tend to have level 1 connections and tend to be paired with other artists by Spotify's recommendation system according to their country of origin. Also, the stronger the international connections are, the more genre-based are the recommendations. Thus, on the basis of sample, the primary determinant of outward and reciprocal connections in the recommendation system is label connections. This way, the streaming platform replicates and reproduces local industry patterns, as it represents and reproduces the bands' geographical (dis)advantage at the same time. algorithms are not the only ones to blame for reproducing inequalities in the music industry. Due to "black box" problem, we have scarce information on how the ratio of algorithmic and human curatorial decisions is distributed on the platform and exactly which decision- making mechanism is dedicated to human or automated agents (as described in detail by Bonini and Gandini, 2019). However, most likely , the decisions of related artists tabs are outcomes of automatized mechanisms mainly because of the sheer amount. large numbers of artists' connections cannot be managed by human agents. Still, this process might include a certain amount of direct human intervention too. Besides ultimately, human listeners signal and share their decisions via the interface while interacting with algorithms. By unearthing such invisible patterns, we aimed to understand better how the sociotechnical system of music recommendation works and reproduces existing music industry inequalities in the streaming ecosystem.

In this paper [11],the discussion on the user based collaborative filtering method for music recommendation system was done. without the user feedback explicitly this system takes user interest into consideration . our system is evaluated on benchmark dataset. by taking the time at whish user listens a particular item This work can be extended for recommendations.

Another paper [12] , we viewed that according to a study the total amount of time spent on deciding which movie to watch among huge number of choices, that time could be utilized in watching at least half of the movie. Hence every week an average customer would save an hour, doing something more productive. The user interface is designed to promote user interaction . Due to the simple andcompact UI, future changes can be made in the front end with ease.

Next paper[13], we saw that by the use of content-based filtering We have illustrated the modelling of a movie recommendation system. Implementation of the KNN algorithm along with the principle of cosine similarity gives more accuracy and lesser complexity than other matrices. Recommendations systems have become essential for a relevant and reliable source of information in the world of internet. Simple ones consider a few, while the more complex ones make use of more parameters to filter the results to make it more user friendly. To built stronger system the inclusion of advanced deep learning and other filtering techniques like collaborative filtering and hybrid filtering are used.it will not only make it more efficient to use but also increase the business value even further in the development phase.

We studied another paper [14], it is discussed that isn order to achieve more accuracy than collaborative filtering methods; for the first time the maximal clique method has been used for social network analysis in a movie recommendation system and the output of this method is very effective. This experiment and output showed that the k-clique method, which is very effective in social networks, was more effective than maximal clique method. Therefore, this paper also proposed an improved and more efficient k-cliques method. Finally, after several experimentation; in terms of the mean absolute percentage error used to calculate, shown in Fig. 5, which is the mean value calculated, the best method was found when $k = 11$ and rated at least 200 movies with five movies recommended to the user.For performance evaluation, we evaluated the collaborative filtering method using a k nearest neighbor, maximal clique method, k-clique method and improved k-clique methods. The results showed that the precision of movie recommendation system was improved by kclique method in comparison to other methods. Until now, it takes a long time to calculate the k-clique methods. In future studies, will shorten this time. And data mining method with the improved k-clique method will increase the accuracy and effectiveness of the movie recommendation system.

Another paper[15], we saw that the experimentation is done using twenty artists. In the future, fir better playlist we will try to add a greater number of artists and languages for better recommendations. For comparison and better results the system can be tried with other machine learning models.our motive was to give the users their preference and satisfaction of their choices of songs among millions of options which they want to listen to. For future applications, an emotional detector system that will recommend the songs by recognizing our facial emotion can be developed.

In paper [16] it is discussed that the system is currently under development as a mobile application on the iOS platform on iPhone models 5S and newer running iOS 85 . The plan is to have about 20-25 participants use the application for a week and answer the following research questions: “What information shown on the user interface would make the music recommendations transparent for users?”, “Which modality (mood-basedcontext or activity-based-context) influences the user more?”, “Is the content-based re-ranking for song relevancy necessary for recommendations?”. Future work in this topic includes a number of challenges such as removing the hard-coding of contextual tags and making the tag generation process dynamic. Other alternatives may include playlist titles and tracks within the recommendations. Our design concept and motivations for this system however remain the same—to expand the musical horizons of users while making the music discovery process less tedious and more serendipitous.

In another paper [17],the following are the conclusions based on experiment results. First,to increase the quality the music recommender system should consider the music genre information. Second, CRNNs that considers both the frequency features and time sequence patterns has overall better performance. It indicates the effectiveness of its hybrid structure to extract the music features. Thus, it can suggest to improve the accuracy of the recommendation system features like tempo gram for capturing local tempo at a certain time can be added.

Next paper [18], it is discussed that recommendation systems frequently dictate the music we listen toon Spotify and the videos we watch on YouTube. Research continues to advance the sophistication and precision of these systems. In our paper, we describe one such recommendation system, T-RECSYS, that takes input of both content-based and collaborative filtering that learns user music preferences to create song recommendations, in similarity with Spotify, Pandora, and iTunes. By development in algorithm, we sought to overcome recurring problems in existing algorithms, such as the lack of real-time updates and multiple variable input types. This result in achieving high recommendation precision and readily extensible to different market services such as Amazon or Netflix.

We studied another paper[19],it is discussed that by personalized music recommendation, the user’s context information is classified and modeled, and the traditional content-based recommendation technology is used to aggregate user preference context for recommendation; then, but it cannot recommend new points of interest for users and further through multiple linear regression we can combine context information, introduce the concept of popularity, calculate the popularity prediction, and use it for further screening the client recommended resource collection; finally, to integrate the environment context information, use the naive Bayes to classify the environment context, calculate the recommendation probability of media resources, to select Top-k resources, select the appropriate display format for the user’s device context information, and finally, present to users. (e algorithm is simulated by simulation tools, and the simulation results of MRAPP algorithm and CB algorithm shows that MRAPP has good performance in terms of recommendation accuracy and user satisfaction. Class methods have the advantages of good real time performance and strong scalability. (e experimental showed that this algorithm has better prediction performance and scalability than the traditional Pearson collaborative filtering, based on singular value decomposition collaborative filtering and Kmeans based collaborative filtering.

Another paper [20], we saw that music Recommendation System is used to recommend songs based on factors like lyrics similarity, audio features, metadata of songs using Arificial Neural Network (ANN) and KNN Regression algorithm. The system allows users to create playlists, and stream it whenever they are logged in. Recommendations are also made based on the same artist. The system contains 2215 songs which can be played along with instantaneous recommendations for each song which is being played.

III. MUSIC RECOMMENDATION

The developer's main goal is to create a Music Recommendation System that provides users with music recommendations

Music is one of the most popular types of entertainment in the digital age. Music is a work of art in which melody, harmony, and rhythm are used to convey thoughts and feelings through sound. Pop, rock, jazz, blues, and folk music are just a few examples of many musical genres. Listening to music is simple in the digital era since smartphones can play music both offline and online. Because there is so much digital music available today compared to in the past, sifting it all takes a long time and causes information fatigue.

As a consequence, creating an automated music recommendation that can browse the music library and choose songs that are acceptable for the user is rather simple.

A.Types of Recommendation System

a. **Content based Recommender System**

It is primarily defined as a continuation and extension of information filtering research. Objects in the system are primarily associated by their features. Based on the qualities contained in the things the user has rated, a content-based recommender creates a profile of the new user's interests. It's essentially a keyword-based recommender system, with keywords used to characterise the objects. Thus, in a content-based recommender system, the algorithms utilised are such that it offers consumers similar goods that the user has previously liked or is now investigating. It's mostly classified as a result of and extension of information filtering research. The objects in this system are primarily characterised by their associated features. Based on the attributes contained in things the user has rated, a content-based recommender creates a profile of the new user's interests. It's essentially keyword-based recommender system in which keywords are used to describe products. Thus, the algorithms utilised in a content-based recommender system are such that it promotes users similar products that the user has liked in the past or is presently looking at.

b. Collaborative Recommender System These are the most widely researched, deployed and mature technologies available on the market. The collaborative recommendation system aggregates ratings or recommendations of the subjects, realizes what users have in common based on their ratings, and generates new recommendations based on comparisons between users. The greatest strength of collaborative techniques is that they are completely independent of any machine-readable representations of the proposed objects, and they work well for complex objects where variation Changes in taste are responsible for most of the variation in preferences. Collaborative filtering is based on the assumption that people who have agreed in the past will agree in the future and that they will like items similar to those they have liked in the past.

IV. DATASET

There are two files in the Million Songs Dataset: triplet file and metadata file. User id, song id, and listen time are all stored in the triplet file. Song id, title, release, year, and artist name are all included in the metadata file. The Million Songs Dataset is a collection of songs from multiple websites, together with user ratings after listening to each song.

	A	B	C
1	user_id	song_id	listen_count
2	b80344d0(	SOAKIMP1	1
3	b80344d0(	SOBBMDR	2
4	b80344d0(	SOBXHDL1	1
5	b80344d0(	SOBYHAJ1	1
6	b80344d0(	SODACBL1	1
7	b80344d0(	SODDNQT	5
8	b80344d0(	SODXRTY1	1
9	b80344d0(	SOFGUAY1	1
10	b80344d0(	SOFRQTD1	1
11	b80344d0(	SOHQWYZ	1
12	b80344d0(	SOIYTOA1	1
13	b80344d0(	SOIZAZL12	5
14	b80344d0(	SOJNNUA	1
15	b80344d0(	SOJPFQG1	1
16	b80344d0(	SOKRIMP1	5
17	b80344d0(	SOLLGNU1	1
18	b80344d0(	SOMGIYR1	6
19	b80344d0(	SOMLMKI	1
20	b80344d0(	SOMSQJY1	1
21	b80344d0(	SONSAEZ1	1
22	b80344d0(	SOOKGRB	1
23	b80344d0(	SOPCVQE1	1
24	b80344d0(	SOQIVUD1	1
25	b80344d0(	SOQJLDY1	1

triplets_file

Triplet file

	A	B	C	D	E
1	song_id	title	release	artist_nam	year
2	SOQMMH	Silent Nigl	Monster B	Faster Pus	2003
3	SOVFVAK	Tanssi vaa	Karkuteill	Karkkiautc	1995
4	SOGTUKN	No One Cc	Butter	Hudson M	2006
5	SOBNYVR	Si Vos Qu	De Culo	Yerba Brav	2003
6	SOHSBXH	Tangle Of .	Rene Abla	Der Mystic	0
7	SOZVAPQ	Symphony	Berwald: S	David Mor	0
8	SOQVRHI1	We Have (	Strictly Th	Sasha / Tu	0
9	SOEYRFT1	2 Da Beat	Da Bomb	Kris Kross	1993
10	SOPMIYT1	Goodbye	Danny Boy	Joseph Loc	0
11	SOJCFMH	Mama_ m	March to	The Sun H	0
12	SOYGNWI	L'antarctic	Des cobra	3 Gars Su'	2007
13	SOLJTLX12	El hijo del	32 Grande	Jorge Negr	1997
14	SOQOESG	Cold Beer	Internatio	Danny Dia	0
15	SOMPVQB	Pilots	The Loyal	Tiger Lou	2005
16	SOGPCJI1	N Gana	Afropea 3	Waldemar	0
17	SOSDCFG1	6	Lena 20 Ã	Lena Phili	1998
18	SOBARPM	(Looking F	Cover Girl	Shawn Col	1994
19	SOKOVRQ	Ethos of C	Descend I	Dying Fet	2009
20	SOIMMJI1	Rock-N-Ru	I'm Only A	Emery	2007
21	SOVMBTP	La bola est	La bola est	Los Ronal	0
22	SOOUESZ1	I Made It (	Let's Celel	Rev. Timot	0
23	SOAGMGC	Debussy :	Debussy :	Pierre-Lau	0
24	SOGFWVT	Nervous	Let No On	Nicolette	1996
25	SOKLPMH	In The Jou	In The Jou	Martin Sex	2001
26	SOEPAIN1	Fuckin Eth	CrazeÃ« N	Craze	0

song_data

Metadata file

B.Libraries Used

a.Pandas

This is a Python-based software suite for data analysis and manipulation. It mainly consists of numeric tables and data structures and methods for processing time series. This is free software under the BSD 3 times license.

- DataFrame object with built-in indexing for data manipulation.
- Read and write data between in-memory data structures and multiple file formats using tools.
- Align data and handle missing data in uniform way.
- The data set can be reshaped and rotated.
- Label-based large dataset slicing, smart indexing, and subsets
- Inserting and deleting columns in data structures.

b.Recommenders

This package contains features that simplify common tasks related to the development and evaluation of recommender systems.

By default, we recommend that you do not install all the dependencies used in the code and sample notebooks in this repository. Instead, you need a minimal set of dependencies to execute the proposed package functions (except Spark, GPU, and Jupyter functions). Users can also specify the

required dependencies during the installation (or later when upgrading the Pip installation). The following groups are provided:
Example: Jupyter related dependencies needed to run the sample notebook gpu: Dependencies on activation of GPU features (PyTorch and TensorFlow)

Spark: Used in datasets Dependencies on activation of Apache Spark features
Analysis, evaluation, and some algorithms xlearn: xLearn package (some platforms) This requires cmake installation)

C.Data Pre-Processing

Data cleaning is the initial stage in data pre-processing. The majority of the data we work with today is unclean, necessitating a significant degree of data cleaning. Some have missing numbers, while others include trash data. Our system would not produce valid results if these missing variables and discrepancies were not correctly addressed.

a. Data Cleaning
Filling in missing numbers, smoothing or deleting noisy data and outliers, and resolving discrepancies are all part of this work.

b. Data Integration
We'll merge the metadata file with the triplets file after reading the metadata file. There will be duplicate columns every time two or more datasets are combined. With song id, we remove duplicates from two datasets.

Combination of data

c. Data Transformation To improve the quality and predictive power of our models, new features from existing variables are often created. We can create some interaction (e.g., multiply or divide) between each pair of variables hoping to find an interesting new feature.

By integrating the artist's name with the song title, we've developed a new function. We'll take a look at a portion of this dataset (the first 10,000 songs). We subsequently combine the song and artist name into a single column, which is summed by the total number of iterations a song has been listened to by all visitors. Data transformation helps us to compress our data and further make it easier to interpret.

Creating new feature

d. Partitioning the data into training and testing

After that, we separated our dataset into training and test data to develop a music recommender. Scikit-train test split learn library's function is used. It's vital to remember that anytime we design a machine learning model, we always want to partition our divided into training and testing datasets before we train our model.

train_data,test_data=train_test_split(so
ng_df,test_size=0.20, random_state=0)

We decide on a testing size of 20% at random. As a prototyping tool, we employed a popularity-based recommender class to train our model. We establish a popularity-based recommender class instance and populate it with our training data.

D.Algorithms Implemented

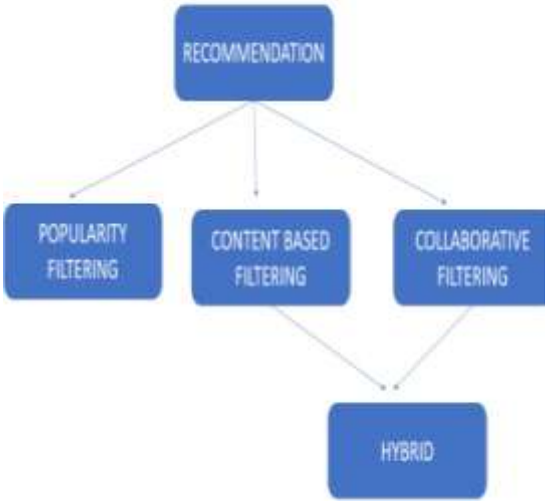
i. Popularity Filtering The popularity model is a fundamental model which is based on a user's rating and popularity of a product. It's a onesize-fits-all algorithm.The popularity model suggests goods to the user based on available data. It may propose to the user the objects that are most frequently used by the subscriber.

The following code accomplishes the desired goal: Create a recommender that accepts a user id as input and returns a collection of that user's suggested songs based on their popularity.

pm=Recommenders.popularity_recommender_py()
pm.create(train_data, 'user_id', 'song'user_id=users[5]
pm.recommend(user_id)

ii. Collaborative Filtering
The next phase of this project is to use the item similarity based collaborative filtering model to develop a machine learning tailored music recommender system. Remember

that there are two sorts of recommender systems: content-based and collaborative-based.



Recommendation

a. **Content based Filtering**

Content-based Filtering is a Machine Learning approach that makes choices based on the feature similarity. This strategy is frequently employed in recommender systems, which are algorithms that promote or recommend the product to people based on information gathered about them. A content-based method estimates what a user would enjoy based on previous preferences. A collaborative based system predicts what a certain user like based on the preferences of other user interests. The hybrid technique is used by most organisations, such as Netflix and Hulu, to make recommendations based on the integration of what a user likes in the past as well as what other similar users prefer.

b. Collaborative Filtering The two major ways to collaborative filtering are user-item filtering and item-item filtering.

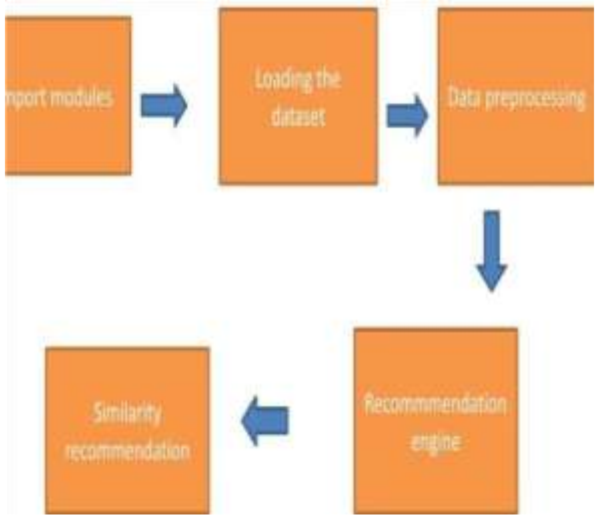
The item-item filtering method entails creating a co-occurrence matrix based on a user's favourite music. We're looking for a solution to the issue of how many times a visitor who has been exposed to one song will also listen to another set of music. To make things even easier, depending from what you've loved in the before, we can predict what other comparable songs you'll enjoy based on what other users have liked. Let us just put this into practise using our program. We begin by creating an edition of similaritybased recommender class and populating it with our dataset.

The generate top recommendations feature in the recommender system's code base computed a weighted average of the scores in the cooccurence matrix for all user songs. Because it's impossible to forecast whether such a user would appreciate a given song, or just a million others, this co-occurence matrix will likely to be sparse. The possibilities are endless. We will be able to anticipate a user's favourite music list using our model.

E.Other Approaches

When you try to choose a song to listen on your streaming platform of choice, it could be depending on who else is in the room, whether you're going to go for a long run, or whether you've just had a rough day. One of several major drawbacks of both content-based and collaborative filtering methods is that none takes the listener's "background" into consideration. Context can allude to a lot of things in this case, including the emotion of the listener, the time of day, and the climate outdoors.

V. WORKFLOW



Direction of workflow

VI. FUTURE DIRECTIONS

The music industry's market pattern has evolved away from commodity sales and toward subscriptions and streaming in recent years. Thanks to the changes financial model in the music world, digital is now more readily available than in previous eras. As a consequence, the value of a music recommendation system for music distributors cannot be emphasised. It can predict what songs its consumers would enjoy and afterwards promote them; as a consequence, music providers may increase user satisfaction and offer more diverse music. Create a music recommendation system that can predict a user's musical tastes over a timeframe.

The goal isn't to get to understand the user; rather, it's to guess what he would like right immediately. Examine the many music streaming services available at the moment in search of a comprehensive and freely accessible music collection as well as free streaming services. Build a workable system good enough to take use of free web services in order to give the customer with a totally free platform that allows them to find new music.

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