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Music Recommendation System using Machine Learning Algorithms

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Abstract: Music plays an important role in human lifestyles. Humans prefers to hear to music/songs more often than abig apple other pursuit. With internet technologies, large quantity of music content hold music of several genres has become's easily accessible to millions of user around whole world. Music group since decade and compgrowing of many genres of music is accessible. The major difficulties that customer face is to choose appropriate song/music from such big collection of music. The objective of our project was to recommend songs to customers built exclusively on their listening habits, with no knowledge about the music. Music applications are attempting to improve their recommendation structures in order to offer their customers the quality possible listening experience and keep them on their platform. For better recommendations, view analysis will be perform on the lyrics of song and the use of random-forest algorithm will be use for classified the song lines into various category (happy, sad).
Keywords: Collaborative filtering, applications of machine learning, data science, recommend song, content-based model, Random Forest algorithm.

I. INTRODUCTION

In the present secenario varities of music industries like wynk , amazon, gaana are using ML algorithms for recommendation and the traditional way of selling music has turned to a different online mode . At present the music is present in the cloud and users can access songs directly from the same. Problem occurs due to the variety of songs present in the cloud . So we need to categorise all the music based on different aspects and the main goal is to categorisethe musicaccording to the taste of the user. As user expects consumable return after the investment of time as well as money and we can attract a lot of customers by providing valuable resources of their interests. The recommendation systems that really emerged in the 1990s have developed strongly in recent years, especially with the introduction of Machine Learning and networks. Indeed, on the one hand, the growing use of the current digital environment, characterized by an overabundance of information has allowed us to obtain large user databases. On the other hand, the increase in computing power made it possible to process these data especially thanks to Machine Learning when human capacities were no longer able to carry out an exhaustive analysis of so much information.

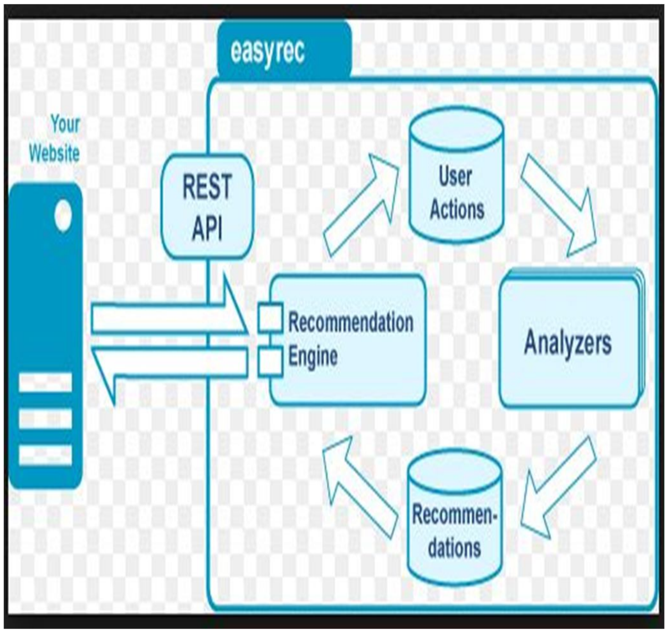
Unlike search engines that receive requests containing precise information from the user about what they want, a recommendation system does not receive a direct request from the user, but must offer them new possibilities by learning their preferences from their past behavior.

E-commerce sites that aim to sell a maximum of items or services (travel, books, ...) to customers must therefore recommend suitable goods quickly. As for sites that offer streaming music and movies, their goal is to keep their users on their platform as long as possible. The common point is that it is necessary to make adequate recommendations. Recent progress in this field is considerable and these recommendations are as beneficial for companies that maximise their profits as they are for customers who are no longer overwhelmed by the number of possibilities. Decision-making is made easier and a good recommendation is therefore a significant time saver.

In 2006, Netflix, which was an online DVD rental service, launched the Netflix Challenge with $1 million to be won. The goal of the contest was to build a recommendation algorithm that could surpass the current one by 10% in tests.

The contest generated a lot of interest, both in the research community and among movie lovers. The prize was won 3 years later and highlighted several methods and research directions to solve this kind of problem. A recommendation system will be defined according to Burke's definition: [2]: it is a system capable of providing personalized recommendations or guiding the user to interesting or useful resources (called items) within a large data space. The aim of this project is to explore the different recommendation approaches, the available datasets, the ways to take into account the user's preferences and the machine learning methods in order to build a suitable recommendation system.

One important part was only dedicated to determine how to evaluate this recommendation system.
The recommendation systems are more and more used in many fields: hotels, travels, products. But the musical field has some particularities to take into account. [3] The first factor to consider is the duration of a music track. As a track is short, it is less critical to make a bad recommendation than it is for a movie or a book, for example. The user can also quickly browse through the music to quickly see if it suits their taste or not.



A second specificity is the number of tracks available, indeed the choice is very wide, it is estimated that at least tens of millions of songs are accessible on the Internet. It is common for repeated recommendations of the same music to be appreciated. While for trips or movies the user is looking for diversity, the user may like to listen to the same music over and over again. Moreover, it is possible that at the first listening the user was not attentive since listening to music is often done in parallel with another activity (sport, work...). Attentive listening requires quality hardware, the proper mood, and exclusive attention time. Moreover, it is quite easy to extract a set of features from one piece of music. Indeed information can be extracted through signal processing, thanks to musical knowledge, thanks to lyrics, or just using user feedback. Old music is as relevant as new music: recent music, as well as music from a few decades ago or classical music can be as enjoyable. It is a matter of correctly understanding the user's tastes. It must also be taken into account that music listening is often passive: the listener doesn't necessarily listen attentively to it: in shops, bars, while working... The last point that distinguishes music from other items that may be recommended is that music is often played in sequence. Indeed, as they are short, they are often chained together in the form of a playlist.

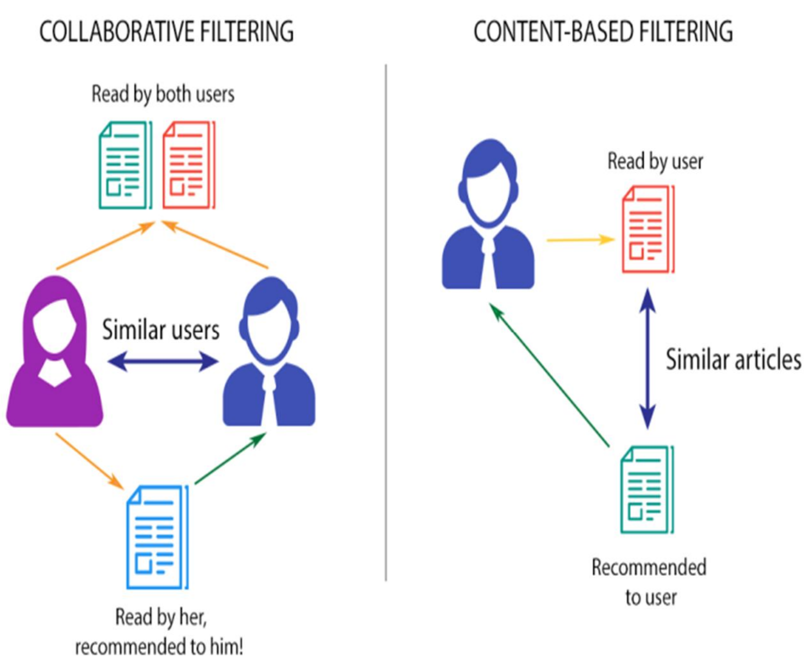
II. LITERATUREREVIEW

The procedures and methods in our recommendation system are used extensively, not only for music, but in different other fields such as news, movie and e-commerce applications. Businessess such as Twitter, Facebook and Linked-In aswell use aforesaid methods to recommend followers /families/ contacts [4]. As of now, we have a huge amount of literature relating to the topic. Perhaps most famously, Netflix confronted opponents to find up an algorithm which would recommend movies to the users on the basis of their viewing history. The winning entry used a combination of different methods, among them, the most successful algorithm was established on Latent Factor Model, that we shall explain in this project. Also other brilliant examplar, Amazon Inc. uses both user-user and item-item correlation for recommending items to its consumers on its portal [6]. We shall try to imitate this approach using co-sine similarity. As said/mentioned by Hu et al. [3], one of the most common approach to collaborative filtering is that of neighborhood models (see below for more explanation). The underlying assumption is that consumers with similar ratings on range of products will have similar-type of ratings on the others (an analogous hypothesis is made for products that share similar ratings for many consumers).

Another set of methods that has shown promise recently relies on low rank matrix factorization, which seeks to uncover the most important factors governing song choices. The exist recommendation system using collaborative filtering algorithms have gain great success's. Netflix open a challenge for better collaborative filtering
algorithm [3], and the winning algorithm that used the latent factor models could make 10.09% improvement over algorithm use by Netflix that time. Amazon use's user-user base and item-item base collaborative filtering [4], which greatly contributes to the success of their business. Recently a newer algorithm that used neural network, neural collaborative filtering (He 2017) [5],
Music recommendated system share some similarity with other commercial recommendated system, but focuses more on providing best and personaliz advice's on music, rather than goods for user to buy. The ideal song recommender system should be able to automatic recommend personaliz music to human listeners. Different from book or movie, the length of a piece of music is much short, and the times that listening their favorite songs are normal more than once, which are the main difficulty we are going to faces in this project. The following section survey more techniques that are use by the recommendation system.

A. Collaborative Approach

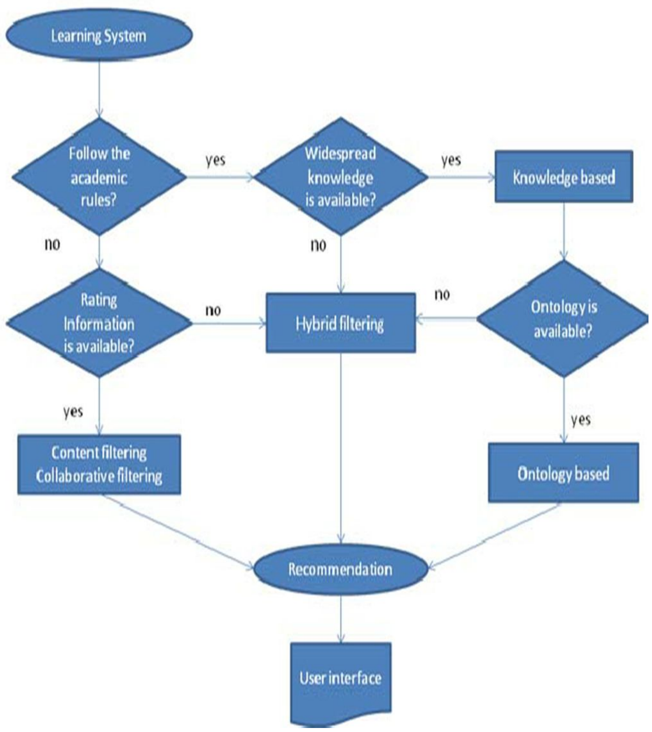
This recommendation method is based on the analysis of both the behavior of the listeners and the behaviour of all others users of the platform. The fundamental assumption here is that the opinions of other users can be used to provide a reasonable prediction of another user's preferences for an item that they have not yet rated: a user is given recommendations based on users with whom they share the same tastes with. Indeed, during years, in order to choose music, restaurants, movies, etc.. We have been asking our friends, family, and colleagues to recommend something they liked. And it is this mechanism that is attempted to be reproduced here. Netflix was a pioneer of this method (based on stars given by other users) but it is now widely used, including for Spotify's Discover Weekly. [8] The first family of collaborative filtering methods is called memory-based approach. The principle is to store all data in a Users/Songs matrix. This can be done thanks to implicit or explicit feedback. In the former, if the item has been listened at least once the value is 1, 0 otherwise. In the latter the value is the number of stars if available, 0 otherwise. There is a second approach called model-based: the goal is to predict the user's rating for missing items using machine learning models. The key advantage of the collaborative approach is that we do not need to analyze and extract features from the raw files, so there is no need to have the audio files, nor to have an in-depth knowledge of music or physics. Moreover, it brings serendipity, it is the effect of surprise that the user can receive by being given a relevant recommendation that they would not have found alone.



B. Content Based Approach

The content-based recommendation consists in the analysis of the content of the items candidates for recommendation. This approach aims to infer the user's preferences in order to recommend items that are similar in content to items they have previously liked.

This method does not need any feedback of the listener; it is only based on sound similarity which is deduced from the features extracted from the previous listened songs. [8] This method is based on the similarities between the different items. To estimate similarities, it is a matter of extracting features to best describe the music. The Machine Learning algorithms then recommend the closest item to those that the user already likes. It is, therefore, necessary to create items profiles based on features extracted from items. Moreover, this method requires user profiles based on both their preferences and their history on the platform. These profiles will be in the following form: a list of weights (which reveals the importance) corresponding to each feature we have selected. The main advantage of this approach is that an unknown music is just as likely to be recommended as a currently popular one, or even a timeless one. This allows new artists with a few "views" to be brought up as well. Moreover, the problem of the cold start and in particular of the new items is thus avoided: when new items are introduced into the system, they can be recommended directly, without requiring integration time as is the case for recommendation systems based on a collaborative filtering approach



C. Context Based Approach

Public opinion is taken for the Content – based approach to recommend the musical and sentimental contents [15]. Public opinions can be obtained through social networking sites such as Facebook, Twitter, Instagram and YouTube etc. in the form of comments, reviews and posts etc. In context-based model the information is obtained by using various document mining techniques. Research has indicated that this model performs well due to the collection of social information based on the approach [16] [17].

D. Hybrid Model

Hybrid model combines two or more of the above-stated models to improve the performance of the music recommendation system. Broke [18] proposed that various methods such as weighted, switching, mixed, feature combination and cascade can be used to develop a hybrid recommendation model.

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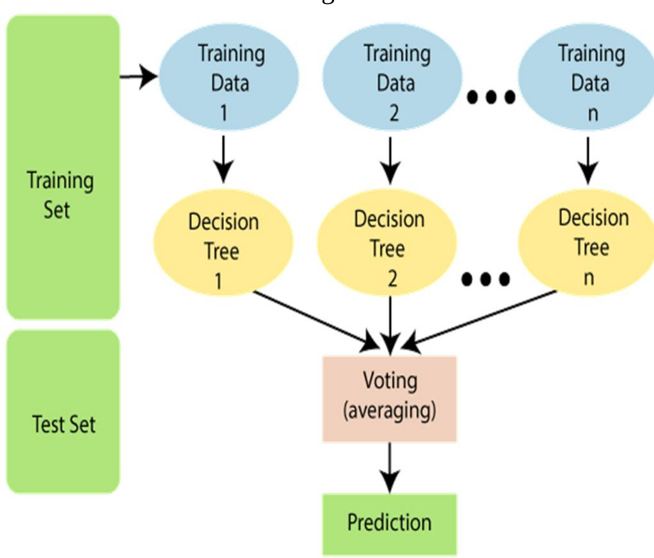
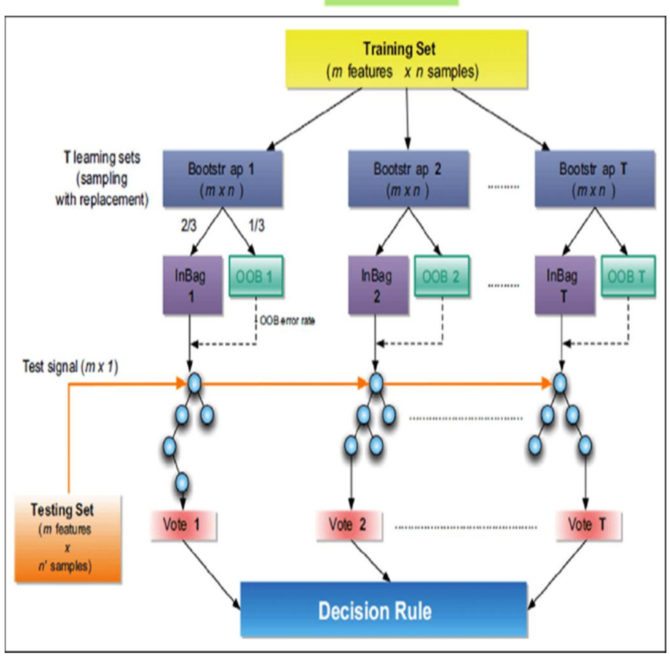
III. METHODOLOGY

The present track advice gadget recommends music based on the pre-categorized song series. The songs are already categorized into one of a kind genres. Our proposed recommendation gadget is random woodland set of rules, random woodland is a non inflexible and effortlessly used and implement gadget –mastering form of set of rules. On this set of rules we will not approach hyper parameter tuning, still we can gain a profitable result and acquire it's most used algorithms as it is straightforward and also it uses both class and regression learning. The random uses the random forest classifier and it allows multiple alternatives and selections.

Random wooded area builds more than one choice timber after which merges them to obtain a more top of the line and correct as well as strong prediction. Its main agenda or unique technique is that it may use both the class and regression. This paper work maximizes gadget mastering systems. This model has almost comparable hyper parameters as a selection tree. It is similar with choice tree. Otherwise it rather than trying to find the most critical function or attribute at the same time as deleting node and searching function amongst a random sets of functions. That is it specializes in the first-rate and top of the line characteristic and now least critical. Random procedures are classified and divided into sets. It results in a huge variety that basically effects in a higher version. Consequently within the random forest set of rules, best the random subsets are considered by using the set of rules for splitting of the records . The songs are categorized based at the lyrics. Evaluation of the lyrics is performed to decide their sentiment value and then they may be labeled into one of a kind genres for this reason.





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A. Random Forest Algorithm Process

Our proposed Random Forest Algorithm works in two-phase way, first way by combining any N decision tree, and second way is to make predictions for each tree created in the first phase.

The Working process of our proposed Algorithm can be explained in the below steps:

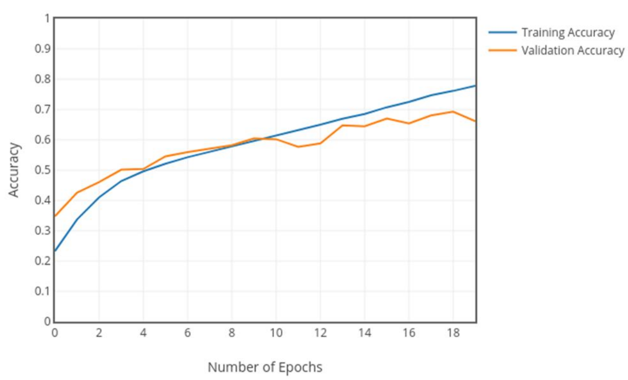
1) *Step 1:* Take any K arbitary data points from the training dataset.
2) *Step 2:* Create the decision trees associated with the selected data points. (Sub-sets).
3) *Step 3:* Select N number of decision trees that we want to build.
4) *Step 4:* Reiterate Steps 1 & 2.
5) *Step 5:* For all new data points, look for the predictions from every decision tree, and then assign the new data points to the group that wins the majority of votes for better outcome/result.

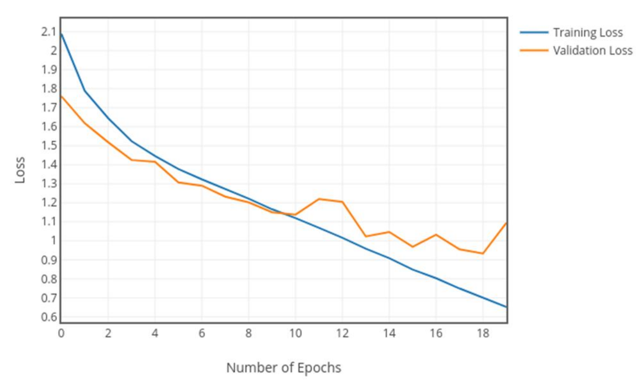
We have used Jupyter-Notebook platform to create a program in Python to show the approach that our paper suggests. This program can also be implemented on the cloud using Google Collab platform which supports all python notebook libraries. Detailed explanations about the modules with pseudo codes for their output graphs and algorithms are given as follows:

IV. IMPLEMENTATION

We have implemented the random forest algorithm on the musical songs using 80 and 20 of the ratio of training set and test set of data.

This graph shows the accuracy of the predictions of music recommended by random forest algorithm. These two graphs shows the accuracy and losses from the data sets.





V. RESULTS

Our code displays out the number of false-positives it identified and links it with the real value. It is used to analyze the accurateness score and accuracy of the algorithm.

The division of data we used in it for quicker testing was 20% of the entire data-set. This whole data-set was also used at the end and all the results are displayed.

The results alongside the classification report for every algorithm is mentioned in our output as follows, the result matched alongside the class-values to check for false positives, results after 20% of the dataset was used.

VI. CONCLUSION & FUTURE WORK

Music recommendation system will reduce human efforts by searching the huge media collection containing many songs and movies of various genres. Recommendations to the user will be provided according to their mood. The mood of the user will be determined by their posts. Hence this system will provide higher user satisfaction in less time and eff orts as they will be automatically provided a recommendation for music and movies based on their mood. The proposed recommendation system works on songs and movies in English language. This system can be further extended to recommend songs and movies in Hindi language or other native languages since the users can better express themselves using their native languages. The emotion category can be further improved to consider more complex emotions as hatred, anxiety, jealousy, excitement, etc.

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