A Survey Paper on Music Recommendation System

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Abstract- *A recommender system aims to provide users with personalized online product or service recommendations to handle the increasing online information overload problem and improve customer relationship management. Given the huge amount and heterogeneity of online musical contents, it is nontrivial for users to obtain music that meets their preferences. In general, people have different music tastes and preferences in different contexts. Thus, a good music recommender system should be personalized and context-aware, in which users' preference can be learned from historical behaviours of music selection and consumption. Even with all the music content available on the web and commercial music streaming services, Discovering new music remains a time consuming and taxing activity for the average user. To date, many music recommendation systems begin to take into account various contextual information of users, including time, location, activity, weather and emotion. Especially, since music is an emotion-loaded type of content often described by emotions, there exists a direct association between users' emotion and their preferred music. For example, we all listen to different music in a sad mood compared to when being happy. However, emotional state of the user is an example of a secondary context, since it cannot be measured directly, but needs to be derived from other types of contextual in-formation. Content-based recommendation systems predict users' preferences in terms of the music content. Collaborative filtering systems predict users' ratings based on the preferences of the friends of the targeting user. In this study, we proposed a hybrid approach to provide personalized music recommendations. This is achieved by using the traditional approaches i.e. Collaborative filtering systems and Content-based recommendation systems with deep content-based music recommendation***.***

Keywords- Music, user based, item based, Content-based recommendation, Collaborative filtering, Deep Content-based.

I. INTRODUCTION

Recommender systems can be defined as programs which attempts to recommend the most suitable *items* to particular *users* by predicting a user's interest in an item based on related information about the items, the users and the interactions between items and users. The aim of developing recommender systems is

To reduce information overload by retrieving the most relevant information and services from a huge amount of data, thereby providing personalized services. The most important feature of a recommender system is its ability to "guess" a user's preferences and interests by analysing the behaviour of this user and/or the behaviour of other users to generate personalized recommendations.

Nowadays, Internet has become the lead source for everyone for getting information about anything. The web is the place where billions to millions information sources are available as per user need. As there is huge amount of data available over web, the problem of information overloading appears. Because of Information overload the mining results can take more time to search the required information or even can provide wrong prediction as scarcity of data. To overcome information overloading problem, information filtering systems are required.

Recommendation is subsystem of information filtering. This system filters required information from large number of available information over web and provides suggestion as per user preference. Many of search engines such as Google etc. have partially solved the information overload problem but there is a lack of posterization and personalization. So, recommendation is the personalized way of predicting items as per user need from users past history. The recommendation system helps users forgetting required information within a very less time and saves time.

Although many researches made great efforts on music recommendation system, most of them only rely on user behaviours: the combination of user-based song rating scores and relevance of songs/items to each other. This is called collaborative filtering approach. [5] Collaborative filtering (CF) is used by researchers to discover the relations between users and items. It can be model-based or memory-based. Model-based recommender system uses machine learning techniques to represent user preferences by a set of rating scores. [5] Memory-based recommender system finds an active user's nearest neighbours using a massive number of explicit user votes. Then it aggregates the neighbour's ratings to predict the active user's ratings of relevant items. Another approach is to recommend music based on available metadata: [5] information such as the album, artist, and year of release is usually known. However, this approach is not always useful to recommend songs by artists that the user is known to enjoy, because it [5] disregards the fact that the repertoire of an artist is rarely homogenous: listeners may enjoy particular songs more than others.

Generally, CF-based recommendation system outperforms content-based recommendation system in predicting rating scores. However, collaborative filtering is applicable only when usage data is available. Besides, CF-based recommendation system suffers from the cold start problem. For example, it cannot recommend new songs that have not been rated, [4,5] and it cannot provide recommendation to new users who have not rated any songs. Additionally, songs that are only of interest to a niche audience are more difficult to recommend because usage data is scarce. Especially in music recommendation, they comprise the majority of the song, because the user's rated patterns follow a power law. However, content-based recommendation system is not affected by these issues.

Thus, many researchers have developed hybrid recommendation systems, combining both collaborative filtering [5] and content-based algorithms to make more accurate prediction. The experiment results of Wang's and Yoshii's experiments showed that hybrid methods outperform individual approaches. However, limitations existed that many of them only take into consideration attributes of items (e.g. singer, genre, etc.), which have a gap with high level music concepts, rather than acoustic features.

Besides, in music recommendation domain, context information is useful in predict user preferences. For example, when users are searching music, the location, the time, and their mood would affect their preferences.[5] And the changes of counter information make it impossible for recommendation system to make correct predictions every time. To solve these problems, some researches showed that similarity of audio signals can be a bridge between a song and its' high-level tags such as genre, mood, and instrumentation.

- In this paper, we designed a hybrid music recommendation system that considered the user personalities and audio features of song. In order to solve the sparsity of preference ratings[5] problem and cold start problem, we proposed the use of content based model which will analyses the audio features of the songs using neural network. After processing neural network gives out an understanding of the songs, including characteristics of particular song like estimated time signature, key, mode, tempo and loudness.

Our experiments show that the proposed music recommendation system outperforms the collaborative filtering approach in predicting user rates

II. BACKGROUND

Machine learning algorithms used for recommendation are classified into two categories

- Content based
- Collaborative filtering methods

Although modern recommenders combine both approaches. Content based methods are based on similarity of item attributes and collaborative methods calculate similarity from interactions.

1) Content – Based Recommendation System

Content based recommendation system provides prediction based on user or item information and past interests of user. Content-based filtering method examines users' past interests for particular item. Upon examines the user interests, the system provides recommendation for the items that have highly similar kind of features related to user interest or items accessed in past.

Content-based (CB) recommendation techniques recommend articles or commodities that are similar to items previously preferred by a specific user. The basic principles of CB recommender systems are:

- To analyze the description of the items preferred by a particular user to determine the principal common attributes (preferences) that can be used to distinguish these items.[1] These preferences are stored in a user profile.
- To compare each item's attributes with the user profile so that only items that have a high degree of similarity with the user profile will be recommended.[1]

In CB recommender systems, two techniques have been used to generate recommendations. One technique generates recommendations heuristically using traditional information retrieval methods [1], such as co- sine similarity measure. The other technique generates recommendations using statistical learning and machine learning methods, largely building models that are capable of learning users' interests from the historical data (training data) of users. [2,6]

2) Collaborative Recommendation System

This technique analyses a large amount of data collected from users' responses to an item as rating in past and recommends items to user. Here, analysing item content is not necessary and information is shared between two users so that model can provide surprising recommendation which user may pretend to be interested. The base of this method depends on relationship between user and items. An anti feedback matrix is generated where each element representing a specific rating on a specific item.

Collaborative filtering (CF)-based recommendation techniques help people to make choices based on the opinions of other people who share similar interests.[1]The CF technique can be divided into two types:-

- User-Base CF approach: - In the user-based CF approach, a user will receive recommendations of items liked by similar users.
- Item-Based CF approach: - In the item-based CF approach, a user will receive recommendations of items that are similar to those they have loved in the past.[1]

Similarity between users or items can be calculated by Pearson correlation-based similarity, constrained Pearson correlation (CPC)-based similarity, cosine-based similarity, or adjusted cosine based measures. When calculating the similarity between items using the above measures, only users who have rated both items are considered. This can influence the similarity accuracy when items which have received a very small number of ratings express a high level of similarity with other items. [7] To improve similarity accuracy, an enhanced item-based CF approach was presented by combining the adjusted cosine approach with Jaccard metric as a weighting scheme. [1] To compute the similarity between users, the Jaccard metric was used as a weighting scheme with the CPC to obtain a weighted CPC measure. To deal with the disadvantage of the single-rating based approach, multi criteria collaborative filtering was developed.

3) Knowledge-based recommendation techniques

Knowledge-based (KB) recommendation offers items to users based on knowledge about the users, items and/or their relationships. Usually, KB recommendations retain a functional knowledge base that describes how a particular item meets a specific user's need, which can be performed based on inferences about the relationship between a user's need and a possible recommendation. Case-based reasoning is a common expression of KB recommendation technique in which case-based recommender systems represent items as cases and generate the recommendations by retrieving the most similar cases to the user's[1] query or profile. Ontology, as a formal knowledge representation method, represents the domain concepts and the relationships between those concepts. It has been used to express domain knowledge in recommender systems. The semantic similarity between items can be calculated based on the domain ontology.[8]

The semantic gap in music

Latent factor vectors form a compact description of the different facets of users' tastes, and the corresponding characteristics of the items. To demonstrate this, we computed latent factors for a small set of usage data, and listed some artists whose songs have very positive and very negative values for each factor in Table 1. This representation is quite versatile and can be used for other applications besides recommendation, as we will show later. Since usage data is scarce for many songs, it is often impossible to reliably estimate these factor vectors. [9] Therefore it would be useful to be able to predict them from music audio content.

	Artists with positive values	Artists with negative values
1	Justin Bieber, Alicia Keys, Maroon 5, John Mayer, Michael Buble'	The Kills, Interpol, Man Man, Beirut, the bird and the bee
2	Bonobo, Flying Lotus, Cut Copy, Chromeo, Boys Noize	Shinedown, Rise Against, Avenged Sevenfold, Nickelback, Flyleaf
3	Phoenix, Crystal Castles, Muse, Röyksopp, Paramore	Traveling Wilburys, Cat Stevens, Creedence Clearwater Revival, Van Halen, The Police

There is a large semantic gap between the characteristics of a song that affect user preference, and the corresponding audio signal. [9] Extracting high-level properties such as genre, mood, instrumentation and lyrical themes from audio signals requires powerful models that are capable of capturing the complex hierarchical structure of music. Additionally, some properties are impossible to obtain from audio signals alone, such as the popularity of the artist, their reputation [9] and and their location.

Researchers in the domain of music information retrieval (MIR) concern [9] themselves with extracting these high-level properties from music. They have grown to rely on a particular set of engineered audio features, such as mel-frequency cepstral coefficients (MFCCs), which are used as input to simple classifiers or regressors, such as SVMs and linear regression. Recently this traditional approach has been challenged by some authors who have applied deep neural networks to MIR problems.[9]

Table 1: Artists whose tracks have very positive and very negative values for three latent factors. The factors seem to discriminate between different styles, such as indie rock, electronic music and classic rock. [9]

- **Deep content-based music recommendation**

Deep content-based music recommendation is used to solve cold start problem using Convolutional Neural Networks.**convolutional neural network** (**CNN**, or **ConvNet**) is a class of deep, feed-forward artificial neural networks, most commonly applied to analyzing visual imagery's use a variation of multilayer perceptrons designed to require minimal preprocessing. They are also known as **shift invariant** or **space invariant artificial neural networks** (**SIANN**), based on their shared-weights architecture and translation invariance characteristics.
The audio frames go through these convolutional layers, and after passing through the last one, you can see a "global temporal pooling" layer, which pools across the entire time axis, effectively computing statistics of the learned features across the time of the song. After processing, the neural network spits out an understanding of the song, including characteristics like estimated time signature, key, mode, tempo, and loudness.

III. RELATED WORK

A content-based personalized music filtering system learns the user's preferences by mining the melody patterns from the music objects in the user's access history. Using these melody patterns, a melody preference classifier is then constructed fetch user. An incoming music object will be recommended to the user if it is classified into the preferred class. In this system, only the pitch information is considered for feature extraction. Ignoring other information, e.g., duration and loudness, provided in the music objects limits the system to deal with other kinds of user preferences. Ringo is a pioneer collaborative music recommendation system. In Ringo, each user is requested to make ratings for some music objects. These ratings constitute the personal profile. For collaborative recommendation, only the ratings of the users whose profiles are similar to the target user are considered. A music object will be recommended based on the weighted average of the ratings considered.

Gaana uses collaborative and content based filtering systems. Gaana app analyzes the content of its entire application and recommends features based on the user's preferences or interests. If the app suggests the items and preferences which the user has already used in the past it leads to overspecialization. Collaborative filtering (CF) systems compute correlations between users; they predict song / album ratings for the current user, based on the song/ album ratings provided by other users, who have preferences for the songs which are highly correlated to the current user.

Spotify is a digital music service that gives you access to millions of songs. Spotify provides access to over 30 million songs, with more music being added every day. As of June2016, Spotify has 100 million monthly active users, and as of September 2016, it has 40 million paying subscribers. It uses Content-based filtering algorithm for Spotify Radio services and Collaborative filtering Algorithm to discover weekly playlist using Implicit Matrix Factorization method.
Pandora utilizes a classification system that is the heart of their service. Pandora recommends by matching up the user's artist and song [10] likes with other songs that are similar. The greatest challenge for Pandora is classifying songs in their database and building their musical taxonomy. To accomplish this, Pandora employs a team of trained musicians who perform a manual classification on each song before adding it to their database. [10] The musicians spend their workdays listening to a collection of songs and tagging each according to approximately 400 musical attributes. Once songs are properly classified in the database Pandora compares the description of musical tastes of a station selected by an individual user with the classification of the songs in the music database. This comparison returns a collection of songs that drive the playlist. The key to Pandora's method of recommending music from its database [10] is to utilize an efficient and effective proximity measure algorithm to determine the neighbourhood of music to play on a station.

IV. PROPOSED METHODOLOGY

In this paper, there are three methods are used

1) Collaborative Approach.
2)Natural Language Processing (NLP)
3) Deep content-based music recommendation.

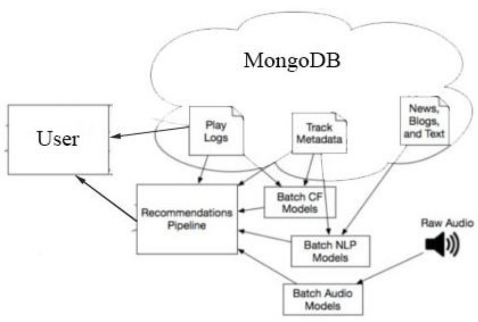

Figure 1 Proposed Methodology

- Collaborative Approach:-

In this model similaritybetween users or items is measured: they recommend items consumed by other users with similar preferences, or similar items to the ones that the user has already consumed.

- Natural Language Processing (NLP):-

The source data for these models are regular *words*: track metadata, news articles, blogs, and other text around the internet.Each artist and song had thousands of top terms that changed on daily basis. The NLP model uses these terms and weights to create a vector representation that can be used to determine if two pieces of music are similar and then recommend the user accordingly.

- Deep content-based music recommendation:-

Convolutional neural networks are the same technology used in facial recognition software. Audio data is used instead of pixels.After processing, the neural network gives out an understanding of the song, including characteristics like estimated time signature, key, mode, tempo and loudness.

Music Feature Attribute Information

1) **Dancibility** - 0.000000 to 1.000000 - Combination of Rhythm, Beat & Overall Regularity. 0.0 Least danceable and near to 1.0 most danceable.
2) **Energy** - 0.000000 to 1.000000 - Fast, loud, noisy track represents measure of intensity and activity.
3) **Loudness** – -60 to +60 – Represents quality of sound and correlates to physical amplitude.
4) **Speechiness** - 0.000000 to 1.000000 - Detects presence of Spoken Words.
5) **Acousticness** - 0.000000 to 1.000000 – Detects whether the track is acoustic or not.
6) **Instrumentalness** - 0.000000 to 1.000000 – Detects whether track contains no vocal.
7) **Liveness** – 0.000000 to 1.00000 – Detects presence of audience.
8) **Valence** – 0.000000 to 1.000000 – High Valence relates to happy and Low valence relates to sad tracks.
9) **Tempo** – 0.000 to 0.250 – Speed of average beat duration.

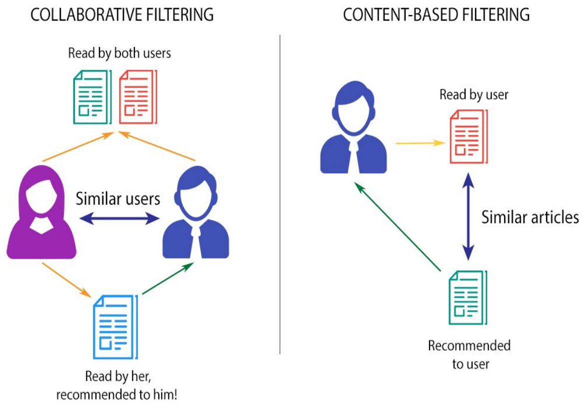

Figure 2 Collaborative and content based filtering

V. CONCLUSION

The classic recommendation approach, such as Collaborative Filtering still play a dominant role in music recommendation. But it doesn’t solve the cold start problem. Natural language processing helps to find popular songs and relations between artists. A hybrid model using deep content-based music recommendation is necessary for efficient recommendation. A hybrid music recommender system will rank musical pieces by comprehensively considering collaborative and content-based data, i.e., rating scores derived from users and acoustic features derived from audio signals.

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