Survey on Playlist Generation Techniques

Sneha Antony, Jayarajan J N

Abstract— **Music is everywhere around us. It is quite difficult to spot a person walking on the streets without his headphone on or to spot a coffee shop without music. We listen to a variety of music on the same day from place to place. It is undeniable that music is everywhere in our lives. Music has been in existence for atleast 12,000 years and it has now evolved to become a fundamental constituent of our lives. It brings us joy, soothes our soul, connects people and certain type of music creates its own listeners community. Due to the digitization of music and the availability of a large collection of songs online, it might be difficult for users to select their favourite song. To address this issue a variety of playlist generation techniques has been developed. In this paper we propose a study on the different playlist generation techniques.**

Index Terms—**music, playlist generation, recommendation systems.**

I. Introduction

All people in the world, including the most isolated tribal groups, have a form of music. A culture's music is influenced by numerous aspects of that culture, including social and economic organization, experience, climate, and access to technology. The emotions and ideas that music expresses, the situations in which music is played and listened to, and the attitudes toward music players and composers all vary between regions and periods.

Never before in the history of humanity have so many different kinds of music been so easily available to so many people. The development of the electronic media in the latter part of the 20th Century revolutionized access to and use of music in our everyday lives. We can turn on the radio, play a CD or tape, or listen to music on video or TV with very little effort. This has not always been the case. Prior to these developments, music was only accessible for most people if they made it themselves or attended particular religious or social events. The effects of these changes have been dramatic. It is now possible for us to use music to manipulate personal moods, arousal and feelings, and create environments which may manipulate the ways that other people feel and behave. Individuals can use music as an aid to relaxation, to overcome powerful emotions, to generate the right mood for going to a party, to stimulate concentration, in short, to promote their well-being. It has become a tool to be used to enhance our self-presentation and promote our development .

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Internet technology and the digitalization of music have led to the availability of a large collection of songs online. With this huge collection available and with the taste of music varying from person to person, it becomes a difficult task for the user to select the required songs. Various playlist generation techniques have been developed in which playlists are lists of sequentially ordered tracks, represent a possible solution to this issue and help users to explore the huge collection of songs available.

In this work, we review existing playlist approaches and discuss the different methods for evaluating the quality of the generated playlists. The paper is organised as follows: section.I contains the introduction, section.II deals with the different playlist generation techniques and elaborates on each. Section.III contains a conclusion for the discussion.

II. Playlist Generation Techniques

In the last few years, a number of approaches for the automated generation of playlists have been proposed in the literature. The different approaches are as follows.

A. Local search based Approach

In [1] [21], a local search based approach is used for generating playlists. The key feature of local search is that it searches the solution space by iteratively stepping from one solution to a neighbouring solution, and comparing their quality. Neighbouring solutions to a given solution is usually obtained by making small alterations like replacements, insertions, deletions and swaps of songs to the given solution. The cost function used for search is given by the total weighted penalty of the playlist, which is denoted by *f(p)*. The disadvantage of this technique is that the solution gets stuck in local optimum.

B. Simulated Annealing

In [22], an adapted simulated annealing technique is used. It provides a way to escape from local optima without a need for restarting. In contrast to local search algorithms, simulated annealing replaces the deterministic criterion by a stochastic criterion. A control variable t is included and the acceptance probability which gives the chance of accepting a neighbouring solution p' to a given solution p is given by:

$$P_r(p' \mid p) = \begin{cases} 1 & \text{if } f(p') \le f(p) \\ \exp\left(\dfrac{f(p)-f(p')}{t}\right) & \text{otherwise} \end{cases}$$

For each value of t, solution sequences are generated and evaluated. After this the control variable is lowered by a

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decrement function. This leads to decreasing the chances of accepting a deteriorated solution as the algorithm progresses.

C. Constraint based Approach

In [11] [13], the authors propose a constraint-based approach to music selection. The constraints are grouped in three categories: user preference, constraints on the coherence of the sequence, and constraints on the exploitation of the catalogue. Then, the user-specified constraints are solved by the constraint satisfaction programming.

In [16], three constraint types are used: unary constraints, binary constraints, and global constraints. Simulated annealing procedure is used to resolve the playlist generation problem and to find an optimal playlist with minimal penalty. In [6], three constraint types are defined: parameter-specified constraints, derived constraints, and user-defined constraints.

Derived constraints are the constraints that are derived from user behaviour. User defined constraints are the constraints explicitly specified by the user. Parameter specified constraints are the explicit constraint specification by an user with the help of pluggins. Then genetic algorithm is used to solve the playlist generation problem by attempting to optimize the number of matched constraints.

D. Similarity based Approach

In [8] [12] [19] [24], a similarity based approach is used for solving the playlist generation problem. Given a seed song or a set of seed songs, the system creates a playlist in which songs similar to the seed songs are generated.

In [17] [18], the playlist generation problem is mapped to the travelling salesman problem. Here, a playlist containing all tracks stored in the music player is generated such that in average, consecutive pieces are maximally similar. This is achieved by applying a Travelling Salesman algorithm to the pieces, using timbral similarities as the distances. The generated playlist is linear and circular, thus the whole collection can easily be browsed with only one input wheel. When a chosen track finishes playing, the player advances to the consecutive tracks in the playlist, generally playing tracks similar to the chosen track.

In [15], the authors present a playlist creating approach which is based on user skipping behaviour. If the user skips the current song, similar songs are removed from the list. If the user accepts the current song, those songs similar to the song are added to the playlist.

In [9], an automatic playlist generation using start and end songs is used. For the playlist to be generated automatically, the user should select the start and end songs. The songs in between is generated automatically such that it forms a smooth transition. The songs at the beginning will sound similar to the start song, songs at the end similar to the end song and songs in the middle similar to both the start and end songs. This approach is based only on audio analysis and does not require any kind of meta data.

There are mainly three issues that come up in similarity based approaches. The first one is the fact that music similarity is not consistent between different humans/ cultures/regions etc. For example, most pieces of folk music from the island of Crete would sound very similar to all people whereas to people from Crete they sound completely unique. The second issue is that similarity is not a one dimensional quantity. So judging the similarity of two songs cannot be done based on a single fact. The third issue is whether similarity can be context independent. Billie Holiday is very different from Ella Fitzgerald in a context of female jazz singer however might be perceived as very similar in a general context of female singers including Britney Spears and Anni DiFranco.

E. Markov chain Approach

In [5], an attempt is made to recommend tracks that represent a smooth transition with the previous track. This corresponds to the Markov property and leads to a first-order Markov model in which states can correspond to track Ids or any other representation of the tracks. Given a history *h* of a playlist and a candidate track *t*, the probability of *t* in such a model thus only depends on *ti* , the last element of *h*.

$$P_{markov}(t \mid h) = p(t \mid t_i)$$

Two approaches used for implementing markov model of playlist generation are: Metric embedding and Graph based method.

E.1. Metric Embedding

In [4], a machine learning algorithm, Markov Embedding (LME), for generating such playlists is presented. Unlike matrix factorization methods for collaborative filtering, the algorithm does not require songs to be described by features a priori, but it learns a representation from example playlists. The problem is formulated as a regularized maximum-likelihood embedding of Markov chains in Euclidian space. Playlists are treated as Markov chains in some latent space, and the algorithm learns to represent each song as one (or multiple) points in this space. Training data for the algorithm consists of existing playlists, which are widely available on the web.

E.2. Graph based Method

In [23], a novel algorithm for automatic playlist generation based on paths in Minimum Spanning Trees (MSTs) of music networks is used. The relationship between music genres and expression of emotions is incorporated by capturing the presence of temporal rhythmic patterns. Edge weights are used in the searching process which maximizes the similarity between sub-sequent songs.

The disadvantage of these models based on markov approach is that, the assumption on which they are based are too strong. The user's choice of next track to listen to may or may not depend on the previous track heard. The markov approach is not flexible in the sense that it holds the assumption to be true all the time. Though similarity between songs do have importance, in practice, the rules users use to generate the playlist can be different and may at times contradict the assumptions used in the markov approach.

F. Network flow Approach

In [10] [14], the authors use the network flow approach to solve the playlist generation problem. In this system, a song is represented as a node and constraints as edges with cost and weight. The aim of this system is to find a path with minimal cost connecting a source node and a sink node in the network (i.e, the first and last song in the playlist). This system consists of two constraints: absolute and coherence constraints. Absolute constraints are the maximum and the minimum percentage of each attribute; they are represented by weights associated with edges in the network flow model. The coherence constraints enforce certain correlations between successive songs in the sequence such that they are similar. The coherence constraints are represented by costs associated with edges in the network flow model. After setting up the corresponding network model, the problem of finding path will be transformed into an integer linear program and solved by the technique of branch and bound. However, in the worst case, the time complexity will be in exponential time.

G. Content based Approach

In [20] generating playlists by content based approach is used. By incorporating additional information into the recommendation process, like information on name of artist, composer name, genre, year of production, mood etc, the performance of similarity based approaches and pattern based approaches can be improved. In this case, each song can be represented as a vector of attributes. The constraints provided by the user or derived by the system will depend on the values of the attributes. It is hypothesized that the use of artist names is particularly promising as this type of data is objective, easy to obtain and to process.

H. Popularity based Approach

Popularity based techniques are elaborated in [2] [3]. Popularity based approach can be of two types. In case of Same artists - greatest hits, it specifies a baseline algorithm that recommends the most popular songs of the artists appearing in the users listening history. The second approach is that of Collocated artists - greatest hits, in which the previous scheme is used for playlist generation along with an extension to it. It works by the assumption that different artists that are included in playlists by the users are not too different from each other. Tracks are recommended based on the frequency of the collocation of artists.

III. CONCLUSION

Various kinds of promising music services have been proposed to deal with large music collections. This paper proposes a classification of existing approaches for playlist generation and discusses the advantages and disadvantages of these techniques. Based on this discussion, we propose that to overcome the limitation of a particular approach, one or two approaches can be combined so that a more efficient playlist can be generated.

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