Music Recommendation System Using Content based Analysis of Song meta data

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I. ABSTRACT -

In our project, we decided to experiment, design and implement a song recommendation system. We aim to do this by formulating a similarity distance metric between songs based on three semantic descriptive vectors and validate this against the User's Taste Profile Dataset. We aim to achieve this by performing content based analysis of audio spectral properties. We used the million song dataset which has an extensive collection of audio meta data. We wanted to experiment this approach to eliminate the cold start problem faced in collaborative filtering for music recommendations.

Keywords – Analytics, MapReduce, Hadoop, Hive, Spark, Recommender, Clustering

II. INTRODUCTION

In recent years, the music industry has shifted more and more towards digital distribution through online music stores and streaming services [10]. As a result, automatic music recommendation has become an increasingly relevant problem: it allows listeners to discover new music that matches their tastes, and enables online music stores to target their wares to the right audience [10].

Although recommender systems have been studied extensively, the problem of music recommendation in particular is complicated by the sheer variety of different styles and genres, as well as social and geographic factors that influence listener preferences [10]. The number of different items that can be recommended is very large, especially when recommending individual songs [10]. Broadly, there are two main approaches to recommend items to users: collaborative filtering and content-based filtering.

The goal of this project is to build a recommender system by formulating a similarity distance metric between songs based on three semantic descriptive vectors – "Loudness", "timbre", and "pitch". We also would want to validate this against the User's Taste Profile Dataset.

III. MOTIVATION

With the advent of online services such as Spotify and Pandora, the music industry has shifted away from the traditional distribution model of selling physical copies of music to a cloud-based model that provides music for users to listen to [8]. In this model, value is derived when these services present songs that the customer is interested in; either the customer purchases a subscription, or the customer pays for the song [8]. In both cases, these music services can derive financial gain by improving their recommendations to potential customers of the songs they like. Thus, there is strong financial incentive to implement a good song recommendation system.

We have observed that Collaborative Filtering approach does not provide accurate results when there is no considerable amount of user data available. This becomes a problem for a lot of new artists as their music will not be recommended as much as a popular artist's music would have been recommended. Also when a new user signs up into web sites like Pandora or Spotify, collaborative filtering will not provide accurate results as the user will not have an existing saved playlist.

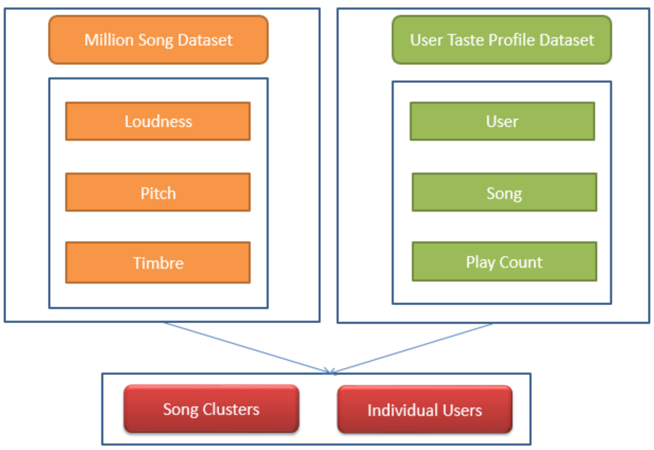
Content based analysis helps in recommending songs based on user's query for a song. We wanted to analyze, if we can recommend an accurate suggestion based on the low level audio features of the queried song. We wanted to experiment if we can eliminate the cold start problem in this way. As the songs on the playlist increase for a particular user, recommendation can be weighed against the low level features of all the songs in the playlist, along with the play count and skip count data, in the long run.

IV. RELATED WORK

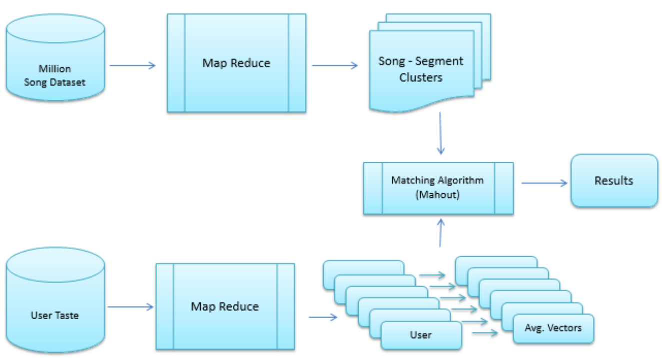
In preparation for this project we researched on a few papers which provide us with an insight on how to go about solving the problem of music recommendation system. The paper Million Song Data Set Recommendation [8] tells us about a novel way to recommend songs that a user might enjoy. They have used KNN and matrix factorization. From this we have concluded that KNN would be effective in clustering the user dataset. The paper learning content similarity for Music Recommendation [6] proposed a method for optimizing content-based similarity by learning from a sample of collaborative filter data. The optimized content-based similarity metric can then be applied to answer queries on novel and unpopular items, while still maintaining high recommendation accuracy [11]. The paper song genre classification [7] revolves around automatic song classification by genre. The paper proved that models like Hidden Markov Model are not particularly effective in creating a recommendation system. Various other papers are particularly useful in the implementation aspect of the project. The scalable hierarchical clustering algorithm [5] paper helps us find out a way to implement the user and song attribute clustering.

V. DESIGN

Music Recommendation System Using Content based Analysis of Song Similarity - Data



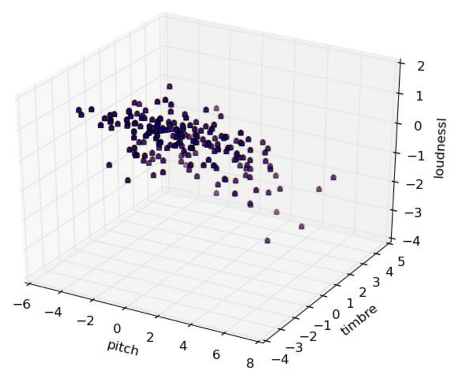
Music Recommendation System Using Content based Analysis of Song Similarity - Architecture



We primarily used two datasets provided by echonest – the Million Song Data Set and the User Taste Profile dataset. The Million Song Dataset is a freely-available collection of audio features and metadata for a million contemporary popular music tracks [12]. The core of the dataset is the feature analysis and metadata for one million songs, provided by The Echo Nest [12]. Taste Profile dataset contains real user - play counts from undisclosed partners, all songs matched to the Million Song Dataset. It has a 48,373,586 user-song –play count triplets.

Audio files can be parameterized into Mel-scaled cepstral coefficients. Similarity measure is a fundamental step in content based audio analysis such as audio classification, audio retrieval and audio scene analysis [9]. In most of current audio analysis systems, similarity measure is based on statistical characteristics of the temporal and spectral features of each frame, and the statistics including mean, and standard deviation or covariance are used to describe the property of an audio clip. These statistical features have proved their effectivity in many previous works[9]

As it is proved from previous research that the spectral features of a song provide a good similarity metric, we have chosen the segment features of a song as primary features of our analytic viz. Loudness, Pitch and Timbre (MFCC like). The following is the 3-D plot of the spectral features of the songs in the Million song dataset.



The User taste profile data set has the triplets of userIds, songIds and play counts. This data is used to suggest recommendations to a user based on the limited playcount history. As User taste profile data set's songIds are matched to the Million song dataset; we designed our algorithm to compute distances of user's song listings to the songs in the million song dataset. For this, we processed each of these datasets seperately and applied the user's information on the million song dataset via a matching algorithm.

VI. RESULTS

We performed clustering on all the songs based on the loudness, pitch and timbre attributes using K-means Clustering. We classified the songs into ten different clusters to recommend new songs based on a queried song/limited playlist. The User taste profile data set is proceesed to obtain the user's listening history. Each user's listeing history is then further processed based on song Ids. Song Ids in User Taste profile is mapped to the song Ids in million song data set to obtain the meta data of User's playlist. The user's listening history is applied onto clusters via a matching algorithm to find out which cluster a User's song belongs to.

Recommendations were achieved by applying the user playlist information (User's playlist songs mapped with their song Meta data from million song data set) over the clusters. To do this, we first found out which cluster each song from user's playlist belongs to. This gave us the user's most favorite cluster. We based our analytic on the hypothesis that a user might like songs closer to this cluster, which we called the user's favourite cluster. As the clustering is based on song similarity, we know that the song coordinates that are in and around this cluster will become strong candidates for a recommendation to this user.

Therefore, once we obtained the most favourite cluster for each user, we computed pair-wise distances between each song of the cluster to the songs in the User's playlist. This way, we reduced the dimensionality by limiting the distance comparisons only to a cluster level. We derived the median distance of each song in the user's playlist with every other song in the cluster. We recommended one song for every song in the playlist based on this analytic. For example, if a user has 7 songs in his playlist, 7 recommendations are provided to the user. These songs are sorted or presented to the user based on the ranking achieved by weighing the play counts of corresponding songs in the playlist. The songs in the User's playlist have play Count Information. The recommendations corresponding to each song in the playlist is ranked against its play Count.

The following figures show the pictorial representation of our results. The stars in the picture are plotted based on the User's playlist information. The Traingles in the picture are the recommendations provided by our model. We see that most of the recommended songs are quite close to the songs that user likes and listens.

We used Big data technologies like HDFS, Spark, and HIVE database as part of our project

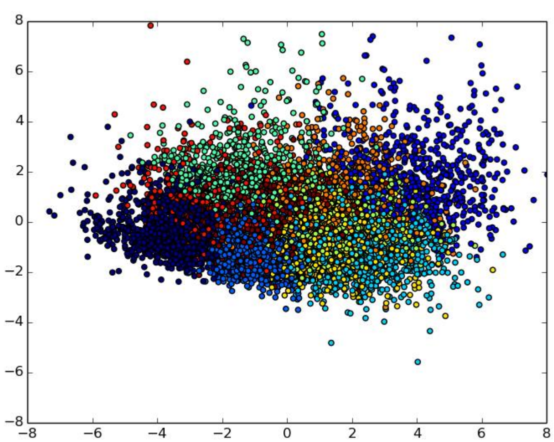


Fig. Clusters based on song similarity

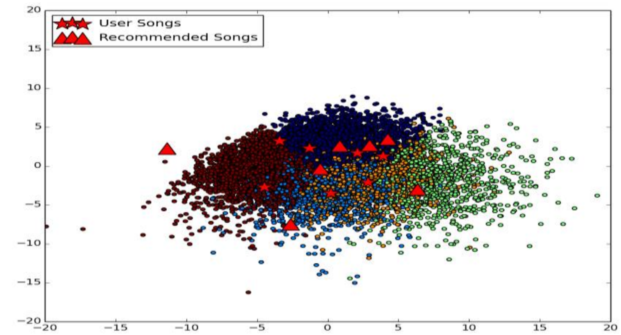


Fig. Recommendations based on Songs in User's Playlist

There were many challenges that we faced while working on this project. The complete Million song data set was about 300GB and the data format was in hdf5. The data extraction from the hdf5 files was very time consuming. We had to experiment different approaches to reduce the time complexity involved in processing the million song dataset into spark understandable format. We finally processed the data successfully by running multiple jobs on HPC, parallelizing the computation. This reduced the processing time by around 80%.

The spectral features of a song are 2D arrays with 12 coefficients for each segment. Each of these 12 coefficients are 12 different dimension of each spectral property of a song. The number of segments varied across all the songs. We spent considerable amount of time in researching about data preprocessing techniques, which was important for minimizing data loss on dimensionality reduction. We approached the project with the hypothesis that averages across each coefficient would standardize the data. We, therefore, normalized the data across each segment and obtained a 25 dimension vector for each song. We used this data to perform clustering of all songs on these 25 dimensions.

We executed our project in NYU HPC. There were multiple environment issues that we faced. Setting up a development environment in python was a challenge as there were many compatibility issues.

VII. Future Work

In this paper, songs are classified into clusters based on the three audio features namely pitch, timbre and loudness. This has been achieved by using the k-means algorithm.

We can expand this project by adding in additional metrics to provide better recommendations to the user. We intend to do this by performing sentiment classification of songs themselves, primarily based on lyrics and title, but some based on music analytic features as well.

Similar analysis can be conducted to build recommender system that can also be implemented on movie databases.

VIII. CONCLUSION

We tested our analytic based on a test and training set obtained by dividing each user's play list information. We divided the user playlist data in a 60-40 proportion. We trained our analytic on the 60% data and measured the analytic on the rest of the 40% data for each user.

We applied the training set on the processed song clusters to obtain recommendations. We evaluated these recommendations by comparing their similarity with the rest 40% of the user playlist data i.e., the test set. This comparison is done by computing pair-wise distances between the recommended songs and songs in the test-set. We placed a threshold value for the maximum distance that each song can be from the other and generated a similarity score. We calculated accuracy based on this similarity score; by making a recommendation valid if the similarity score is greater than 0.7. We got an overall accuracy measurement of approximately 65%.

We will get a better picture of the performance after releasing the model on a pilot run over a set of users.

IX. ACKNOWLEDGMENT

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