A MUSIC RECOMMENDATION SYSTEM USING MUSIC ATTRIBUTES

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Abstract: -.In this modern world providing listening platform for music to users is critical task. An efficient source is to built a music recommendation system. These systems use recommendation methods by extracting data. Recommendation is mostly done on the meta data of the song but the availability of huge amount of existing genres and recommending a new song with no meta data to the user's cold start problem are the major difficulties. The following predicts a model in a content based approach for Music Recommendation System. In this paper the recommendation is done basing on user's MUSIC attributes of song. These five attributes namely: Mellow, Unpretentious, Sophisticated Intense and Contemporary (MUSIC). For the recommendation, analysis is done on the dataset with song features taken from music service (spotify) and its respective MUSIC attributes. Regression techniques-Support Vector Regression(SVR), Isotonic Regression(IR) are used for estimating MUSIC attributes and Classification technique(Random Forest) to examine a better Regression technique and cosine similarity to find similarity among users. The accuracy and root mean square error (RMSE)demonstrate the effectiveness of MUSIC model in music recommendation and also solve a cold start problem.

Keywords: Music Recommendation System, Spotify, Isotonic Regression, Machine learning.

1. INTRODUCTION

Music recommendation systems have made music accessible to users ,they are a class of recommendation systems which predicts user's preference on the songs and recommend music .Music recommendation systems use following filtering methods for music recommendation.Filtering is based on the ratings of users or behaviour of others users in the system. Based on the user similarity which provide a reasonable prediction of the active user’s preference or item similarity found by using user rating .This method faces difficulties 1)A typical taste user or user with a rare taste can't get best benefits. 2)Presence of large number of items, a matrix of user item can be sparse which does not yield a good result. Other technique , Context filtering uses context and meta data of the song which enhances the recommendation efficiency. Meta data (genre) is widely used for user preferences, according to the genre the songs are grouped and recommendation is done basing on genre but using them leads to following problems: Existence of large number of genres. There are approx 1301 echonest genres .Most genres are similar to one another No adequate understanding of genre definitions .Above all problems can be solved by Content based data ,the content of the song is extracted from the audio signal. Recommendations are done specific to a single user. The major difficulty is complexity of the process because requires deep domain knowledge and Music Information Retrieval platforms. This paper introduces a simpler content based approach. In this approach the music can be learned by its underlying properties of the song, like the audio features i.e. danceability ,energy, mode , speechiness ,acousticness , instrumentalness, liveness , valance ,tempo which are audio features taken from spotify which are unique for each song . [3]In this paper enhancement of content based filtering is done by introducing MUSIC model which even solves the cold start problem .The music recommendations are done on MUSIC attributes of the users.[2]The user preferences are learned by playlist of user in the MUSIC database.

The rest of the paper is organised into 6 sections. Related work presented in section2, Methodology explained in section 3, Experimentation details described in section 4, Results and comparison discussed in section 5 and finally conclusion in section 6.

2. RELATED WORKS

[5]P. J. Rentfrow, L. R. Goldberg, D. “The song remains the same: A replication and extension of the MUSIC model,” this work extended the understanding of musical preferences and results are conceptualized in five music factors. [4] Rentfrow et al. (2011), the psychological effects that music has on people to use the musical listening habits as self-identifying personality features. The researcher examined different aspects of a musical composition what specifically is the impact of the listener towards one specific type of music over another. Rentfrow performed several studies on underlying psychological factors are the basis for musical preference. [8] Dionysios N. Sotiropoulos et al (2007) content-based system which constructs music similarity models of its users by associating different music similarity measures to different users. Specifically, a user-supplied relevance feedback procedure and related neural network-based incremental learning allows the system to determine which subset of a set of objective features approximates more accurately the subjective music similarity perception of a specific user.[10]VadenHoven et al.", explains how spotify data have interesting patterns found in the data be used to overcome the problems while applying model of choice and analyze the spotify data by performing some statistics on the entire dataset and to determine the worth of the Spotify data for data science.

3. METHODOLOGY

The methodology described in this paper involves following algorithms.

Support Vector Regression

The Support Vector Regression (SVR) uses the same as that of SVM, with very less differences. SVR produces real n umber output which is too difficult to envision the information which has countless possibilities. With the help of SVR one can reduces the error rate and maximizes the margin for individual hyper plane.

Isotonic Regression

Isotonic regression is a technique which doesn't depend on parameters to build a function. Due to non-parametric feature of this regression it doesn't assume the linearity among the variables. This reduces the error rate of mean squared.

Random Forest Classifier:

Random forest classification is used to classify the songs according to the user. For depicting the performance difference between the results of both Regression techniques. This is the step in the process where the dataset of both the users is merged with adding a owner name and owner id .This is split into training and testing set to calculate the accuracy of the Support Vector Regression , Isotonic Regression.

4. EXPERIMENTATION

4.1 Dataset

The dataset is taken from spotify datasets. The audio features of these songs are captured from spotify. These songs are new. According to the users preferenced songs in the dataset the taste of users is identified. The dataset consists of 101 songs with 3 columns of meta data(id ,name ,artist) and 13 columns of audio features(danceability ,energy ,key ,loudness , mode speechiness ,acousctiness ,instumentalness ,liveness ,valence ,tempo ,duration_ms ,time signature).The analysis involves following features as the content of the song

4.2 The Five Factors Of The Music Model

Rentfrow et al.(2011) developed a five-factor model for music preference , many other studies i.e. four-factor ,seven-factor models lead to inconsistent conclusions. This is best for understanding music based on psychological effects of music on listeners[6]. The following are the five factors:[5] Mellow Attribute describes relaxedness, slowness, sadness, quietness. Unpretentious Attribute describes the lack of complexity, unaggressive, softness and acoustic nature. Sophisticated Attribute describes the complexity, intelligence, and dynamic nature of a piece. Intensity Attribute describes the distortion, tenseness and aggression of a piece. Contemporary Attribute describes the percussive nature, rhythmic nature, the current mood. These factors better describes the user taste.

4.3 Modeling The Music Factors With Spotify Features

An analysis is done with classifiers of Weka, on songs from Rentfrow et al. (2011).[4]This analysis is performed on various regression classifiers in which is one of it is linear regression. The linear regression which used ,yielded an output which is a equation with audio features.[1]This equation gives a relation between the audio features and MUSIC attributes. The songs from Rentfrow et al. are picked by the experts for learning underlying features, correlation between the variables is calculated before the regression to find the features used for individual MUSIC attributes. Each attribute involves different combination of features.

4.4 Procedure

- ✓ The music database consists of songs and audio features with the respective music factors calculated.
- ✓ Regression techniques are used for predicting the MUSIC attributes. The predicted attributes are added to database by adding a additional column which determines the technique.(discussed in next section)
- ✓ Two users playlists are selected by the user according to their tastes .This creates two samples from the music database for each user.
- ✓ These two samples are merged by adding a column for Owner/user identification .
- ✓ MUSIC attributes are calculated for each individual by their respective playlists.
- ✓ When a new song enters the database ,the MUSIC attributes are predicted using the regression techniques. The new song MUSIC attributed are compared to the user MUSIC attributes.
- ✓ Similarity metric is used find the similarity between the new song and the user .According to the similarity the new song is recommended to one of the user .

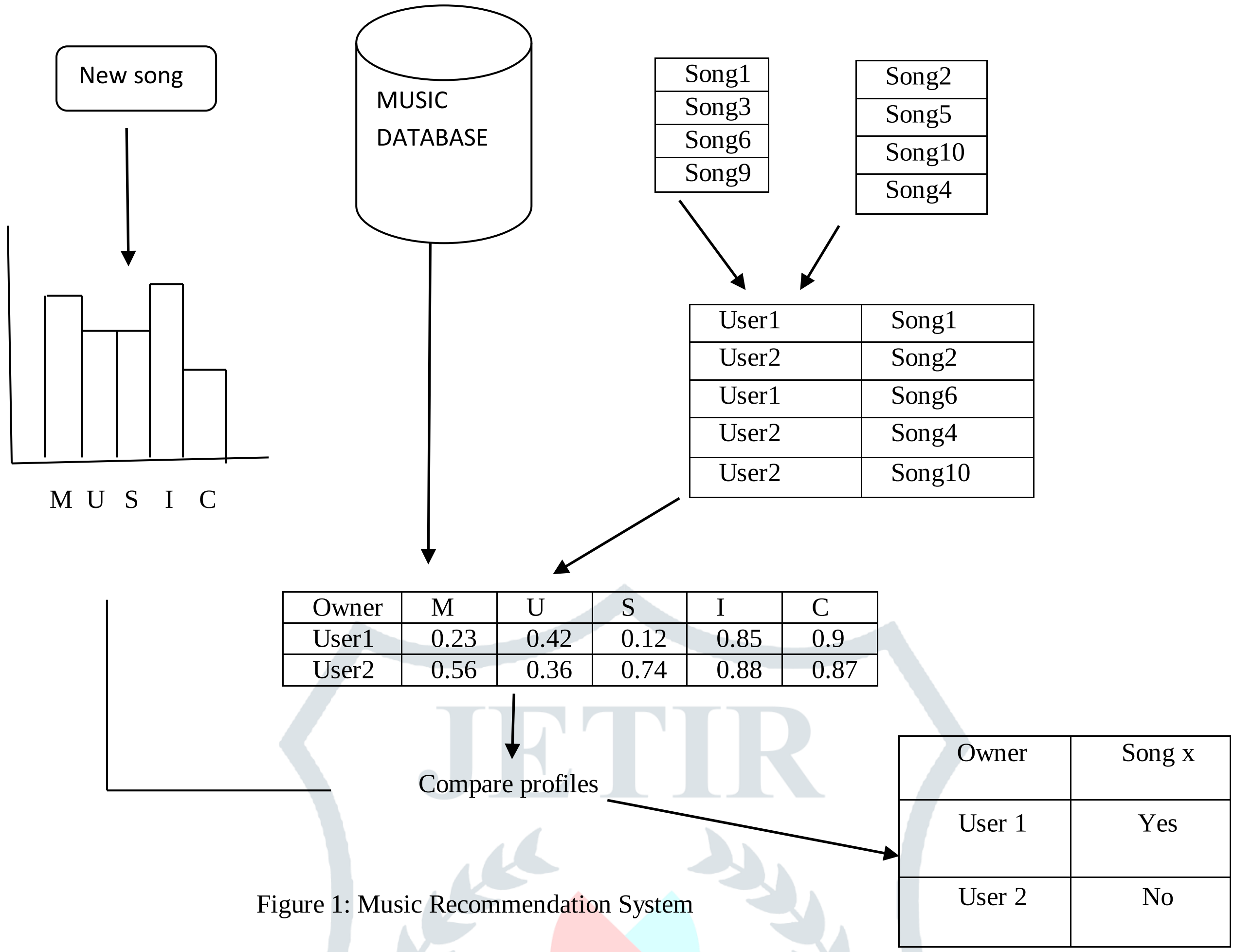

Figure 1: Music Recommendation System

4.5 FEATURE SELECTION

In this paper two Regression techniques for predicting MUSIC attributes and a single classifier is used to check and examine the performance of the Regression applied. For Music Recommendation based on MUSIC attributes, the new song similarity[7][8]is calculated by using Cosine similarity. The feature selection for the dataset is done according to the regression RMSE(Root mean square error).

a) Comparison of RMSE values using SVR

The process discussed here is to find the most relevant combination of audio features for each MUSIC attribute[4].Baseline represents all the audio features' RMSE(root mean square error) values .These are compared to feature columns (No danceability, No energy, No speechiness, No acousticness, No liveness, No valence, No tempo, where , No danceability represents all features taken except the one listed, here i.e. danceability and so do the other columns) and the RMSE values which are greater than baseline are not to be ignored, so we consider only those features. They are calculated individually for MUSIC attributes(A).

Table 1: Comparison of RMSE values

A	Baseline	No Danceabiity	No Energy	No Speechiness	No Acousticnes	No Liveness	No Valence	No Tempo
M	0.0995581	0.0987623	0.1016939	0.1024868	0.0982789	0.0983154	0.103587	0.0730217
U	0.0711755	0.0719700	0.0716008	0.0723104	0.0706723	0.0707442	0.0755824	0.0560587
S	0.0641481	0.0643390	0.0643437	0.0642874	0.0648931	0.0642548	0.0644835	0.0613558
I	0.095732	0.0963620	0.0979288	0.0959972	0.0950081	0.0939946	0.0981868	0.0689306
C	0.0635243	0.0641472	0.0639201	0.0636594	0.0638013	0.0638903	0.0642088	0.0559277

M Attribute:

X = [['energy','speechiness','valence']]

Y = ['M']

U Attribute:

X = [['danceability', 'energy', 'speechiness', 'valence']]

Y = ['U']

S Attribute:

X = [['danceability', 'energy', 'speechiness','acousticness', 'liveness', 'valence']]

Y = ['S']

I Attribute:

X = [['danceability', 'energy', 'speechiness', 'valence']]

Y = ['I']

C Attribute:

X = [['danceability', 'energy', 'speechiness', 'acousticness', 'liveness', 'valence']]

Y = ['C']

b) Comparison of RMSE values with IR

Isotonic Regression involves only one independent variable for Regression process. The relevant audio features are selected by finding the least RMSE value compared to all audio features. The variables involved in the Regression process are the only variables used to find the MUSIC attributes in user's preferenced list of songs ,since the preferenced songs are selected from this dataset .This process is to learn which attributes describe the best for each individual MUSIC attributes(A).

Table 2:Comparision of RMSE values

A	Danceabiity	Energy	Speechiness	Acousticness	Liveness	Valence	Tempo
M	0.1472076	0.1473419	0.1478423	0.1475753	0.1462070	0.1478423	0.1311426
U	0.0757132	0.0992930	0.1003815	0.0967774	0.0978563	0.0696598	0.0979410
S	0.0985420	0.0983411	0.1001873	0.0617262	0.0994673	0.0825917	0.1002160
I	0.1561020	0.1377768	0.1238720	0.1558883	0.1539400	0.1556674	0.1223594
C	0.0274144	0.0910535	0.0898439	0.0914802	0.0901661	0.0759099	0.0916648

M Attribute: X = [['tempo']]

Y = ['M']

U Attribute: X = [['valance']]

Y = ['U']

S Attribute: X = [['acousticness']]

Y = ['S']

I Attribute: X = [['tempo']]

Y = ['I']

C Attribute: X = [['danceability']]

Y = ['C']

The predicted MUSIC attributes are added to the dataset by adding additional columns (M_svr,M_ir).. and so on. This dataset which is created by adding the additional columns is used for further analysis.In this experiment, user preferences are captured user's playlist by selecting songs list from the given dataset which are quite unique .The above dataset with additional columns (M_svr ,M_ir ,U_svr ,U_ir ,S_svr ,S_ir ,I_svr ,I_ir ,C_svr ,C_ir) where _svr , the MUSIC attributes predicted by Support vector Regression and _ir , the MUSIC attributes by Isotonic Regression ,while comparing results following metric are used.

Figure 2: The Mean Audio Features of two users.

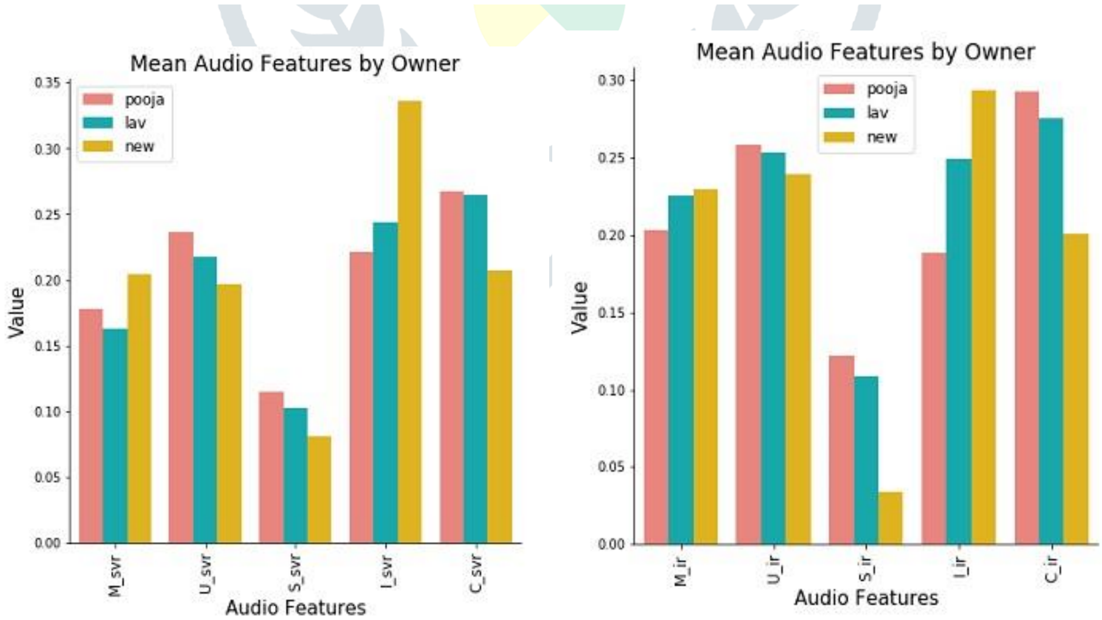

Figure 3: The Mean Audio Features of the two users and the new song.

5 RESULTS AND COMPARISON

The performance of the existing system methodology i.e. recommendation with the audio features alone is outshined by proposed system i.e. recommendation with MUSIC attributes. The accuracy of the existing system is 57.7[9].In this paper for the Regression techniques a Random forest classifier for Support Vector Regression and Isotonic Regression for the dataset which contains MUSIC attributes predicted using both the regression techniques are used for performance validation. The results are compared based on Accuracy ,RMSE ,ROC(Receiver Operating Characteristic Curve)_AUC(area under curve)_Score . Among the proposed Isotonic Regression yields the best results compared to support vector regression.

Table 3: Performance metrics comparison

Random forest	Accuracy	RMSE	Roc_auc_score
MUSIC_SVR	71.42	0.534	0.783
MUSIC_IR	85.71	0.377	0.833

ACCURACY: Accuracy is the no of predictions that the model is correct. It is one of the metric for classification model for evaluating the result and calculate errors in the model.

ROOT MEAN SQUARE ERROR: This value is the prediction error which performing the Regression process. Its the error between the predicted with the actual values ,which explains deviation or residual value while predicting.

ROC_AUC_SCORE: The area under the curve of ROC. The ROC curves are obtained from Support Vector Regression and Isotonic Regression are compared

COSINE SIMILARITY: Cosine similarity is to find the similarity between the new song and the users by finding the cosine similarity for MUSIC attributes of both users with the MUSIC attributes predicted for the new song.

Table 4: Cosine Similarity result

USER	MUSIC_SVR(cos)	MUSIC_IR(cos)
User1	0.87	0.91
User2	0.84	0.87

In the above table the cosine similarity value is compared to recommend the new song to the user in both the Regression algorithms the new is song recommended to User1 because the similarity metric is more compared to User2.

6. CONCLUSION

In this paper a music recommendation is modelled for recommending songs to the user using a content based approach, by using songs features. They are analyzed for understanding the user preference and pattern in songs .The MUSIC FACTORS in the content based approach is analyzed and how many features used to predict MUSIC attributes for enhancing the recommendation. For prediction two regression techniques are used ,this paper has the comparison of accuracy of support vector regression and isotonic regression.

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