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Emotion Based Music Recommendation System Using Navie Bayes Classification

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Abstract

Along with the rapid extension of digital music system and formats, the searching and managing the music system based on the users preference has been very significant. Inorder to improve the users listening experience based on their music preference a recommender can be used. The number of choices of users also overwhelming, so it requires to filter, prioritize and effectively deliver relevant music based on the users choice. Recommending the music based on the user choice based on location, time of day, music listening history and their emotional state is a tedious task. Recommender system solves the problem by incisiving the large volume of spontenously generated information to provide users with personalized content and services.Though music retrieval system is evolved in recent years, but recommending songs based on the user interests is not evolved so far. In this paper, we proposed a emtion based Muisc Recommendation System (MRS) to find the correleation between the users data and music. To address such issue the proposed work provides a novel framework for recommending the music based on the user interest using Navie Bayes classification algorithm. The probability of an event with strong independence assumption between the features were applied to Navie Bayes algorithm. In this proposed system, the emotional state of a user is taken using the users search history and the results were evaluted with the exisiting recommender system.

Keywords: *Music Recommendation System (MRS), Navie Bayes, Correleation and Classification*

1. Introduction

In the current times music industry has shifted more advance towards digital distribution through online music stores and online streaming services namely iTunes, Grooveshark, Saavan, Gana, etc,. Automatic music recommendation is a tedious task. The aforementioned applications learns the user preferences by analyzing the users music listening history for providing music recommendation to the user[1]. The music recommendation to the user is listing the set of songs recommended to the user. The Content Based (CB) [2], Collaborative Filtering (CF) [3] and hybrid approach [4] are used to build the personalized music recommendation system. The content based recommendation system recommends similar songs to the user based on the songs presented in the users music listening histroy. The music listening history represents the previously listented songs by the user. The collaborative filtering recommends songs to the user based on the songs listened by the group of people those who have the similar preference to that of the user. The hybrid approach combines the knowledge obtained by content based and collaborative based approaches for recommending songs to the user.

A good music recommendation system should be able to automatically detect the preferences and generate playlist accordingly [4]. Navie Bayesian classifiers and cluster analysis is used to determine the features of the item can be used to classify it. Alajanki et al [5] developed a system to extract the users preferences from the user listening history. This system is limited to extract the users preferences based on age, gender, location, ambient, time of data and emotions, etc,. In this prposed work considers only three emotions such as happy, normal and sad. For example one may feel relaxed when seeing scenery or may feel sad when seeing a horror things. The relationship between the song and the user emotions from the philosophical, pyschological and anthropological

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perceptions were identified [6]. The user emotions and user listening history are also influcned by the timings [6].

The proposed work uses the search history and make recommendation based on the emotional state of the user. The search engine provides the user search history and the history is classified based on the emotional state of the user namely happy, normal and sad. The probability to recommend the music is calculated using navie bayes classifier, the emotion which has highest state of probability is recommended by the Muisc Recommender System (MRS).

2. Related work

Researchers used SVM [4] and linear regression [2] to classify the songs based on the audio features of the songs [9,10]. The traditional approache namely Mel – Frequency Cepstral Coefficients (MFCC) were used to extract audio features from song. Schedl et al. [11] proposed the text mining approach for calculating the artist similarites in songs. Humprehy et al. [12] proposed a method for extracting latent features from the audio signals presented in the song. The MFCC approach do not include metadata such as artists_familiarity, artist_location, duration, mode, year, tempo, song_id, etc,. The song trach were classified into positive and negative classes based on the latent features extracted from the song [10]. The classification results is used to extract the relationship between the airtst and music track. Social tagging services also allow user to provide tags descrbing the genres, moods, instrumentation etc, to classify songs. Ignatov et al. [13] proposed a method that correlates the social tags and the keywords mined from the artist profiles to calculate artist relationship scores. These approaches use traditional approaches to extract latent music features to understand users to music relationship. However, these approaches are time-consuming and involves a lot of user interference.

Researchers proved that using the DCNN for extracting latent music features gives better performance when compared to traditional approaches [14,15]. They proved that the DCNN approaches outperforms the traditional machine. learning techniques such as the SVM [1] and the linear regression [2] in terms of classifying songs. The deep neural networks (DNN) approach such as the DCNN [16], the gated recurrent unit (GRU) and the long short-term memory (LSTM) [17] have the capability to work on the huge amount of data in a distributed manner. Oord, Dieleman, and Schraumen [14] proposed usage of the DCNN approach for classifying the songs by identifying the latent music features presented in the songs.

Salamon and Bello [15] proposed usage of DCNN for environmental sound classifications. The existing PMRS algorithms [14,15] are limited to recommending songs based on latent music features presented in the user's music listening history. The latent music features for each song are obtained from the audio signal presented in that song. In the proposed EPMRS, we extract the latent features presented in the user's data (containing the user's information and the user's music listening history) and the music data. The EPMRS uses these latent features to recommend songs to the user.

3. Proposed System

The Proposed system will use the traditional filtering technique and album art of the song to recommend new songs. The hybrid Recommender System will scan the album art of the song for unique labels. A recommender system is created using text analysis. The search history of user is collected from the search engine and suitable dataset is extracted for prediction. For this step we have used FMA and million song dataset. The dataset is preprocessed and classification has been done. The classification packages readr, dplyr and caTools while pandas and numpy were used in recommendation system analysis. In addition social media data of person have also been used, where people express their views on different matters, share their opinions and thoughts. Such expressions of thoughts and opinions can be leveraged to study the personality traits of the person and hence use this information to try to enhance existing user to user collaborative filtering techniques for music recommendation. Personality traits of the users can be studied in terms of

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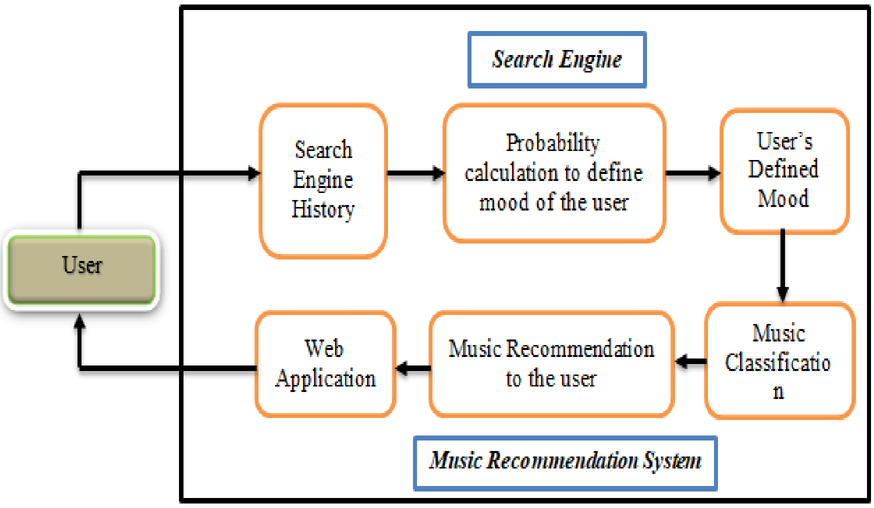
standard Big Five Personality Traits defined as Openness to experience Conscientiousness, Extraversion, Agreeableness, and Neuroticism. The users search engine history is taken as input, probability of the user is calculated using Navie Bayes algorithm then user mood is defined. Based on the mood music classification is done and music is recommended to the user. With this proposed system, we are able to determine the current status (mood) of the user based on the search history and social media data. Based on the status, MRS will recommend the song to the user. The Fig.1 shows the proposed system architecture of Music Recommendation System (MRS)



4. Implementation

4.1 Emotion Classification

Emotion are both prevalent in and essential to all aspects of our lives. It influences our decision-making. Dr.Paul Ekman is an American psychologist who is a pioneer in study of emotion based[14] and facial expression.His research findings led him to classify six basic emotions: anger, disgust, fear, happiness, sadness and surprise.

4.2Search Annotation

All searches in the proposed work are manaually annotated with nine tags namely anger, disgust, fear, happiness, sadness, surprise, emotion, non – emotion and junk using an annotation tool.

4.3 Tokenization and Preprocessing

The collected comments are processed with the following four pre-processing procedures. First, segment each comment into a set of word tokens. A token is a string with an assigned and thus identified meaning. It is structured as a pair consisting of a token name and an optional token value.

The token name is a category of lexical unit. A stop word [18] is a commonly used word such as "the", "a", "an", "in" that a search engine has been programmed to ignore, both when indexing entries for searching and when retrieving them as the result of a search query. After that, remove HTML tags and then stemming occurs. A tokenizer is used to convert a sequence of characters into a sequence of tokens.

4.4 Feature Selection

The word frequency is set for keyword identification, i.e if a word appears more than the minimum threshold it will treated as keyword for feature identification and selection. The two process is done in term feature classification process, term frequency (TF) and term frequency inverse document frequency (TF – IDF) [19]. Term Frequency (TF) is a value of how often a term occurs in documents. Term – Frequency Inverse Document Frequency (TF-IDF) is a statistic value that shows the important a term in documents. For weight adjustment, we compute term frequency tf (t, d) equals f (t, d). That is, a frequency of term t in a document d. The inverse document frequency idf (t,D) shows if the term is common or rare of all documents. The Fig.2 shows the emotion classification framework.

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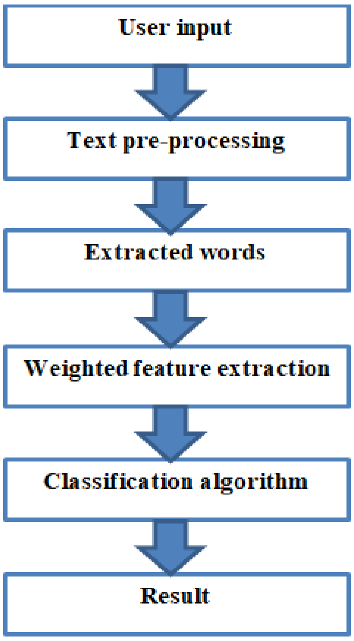

Figure 2: Emotion Classification Framework

5. Modules

The implementation of emotion-based music recommendation system consists of two modules: 1. Search Engine module 2. Music Recommendation [20] Web App module. In each module there is a registration and login page for the user and the admin. If the login is valid then the home page will be displayed. The admin add content in both modules. The backend process is taken care by the admin.

User Input

The user input is the user's search in the search engine. The search history will be matched with the song genre for recommendation.

Text Preprocessing

Converting all letters to lower or upper case converting numbers into words or removing numbers removing punctuations, accent marks and other diacritics removing white spaces expanding abbreviations removing stop words, sparse terms, and particular words text canonicalization [20].

Extraction of Words

The text preprocessing result is taken as the extracted word. It will be used to get the music according to the users search. The stop words and other unwanted symbols will be removed for accuracy.

Weighted Feature

Assign weights to various features of the dataset as all of them being zero or with random values. Based on the values assigned to the weights, the model being used will calculate the output. The actual output will be labelled with each example in the dataset. Consider it as T. Obviously, since the weights assigned during the initialization will not lead to the exact target output, there will be some error(E).E=O - T. This error will translate itself into the alteration of weights. Depending on the number of iterations and the desired error threshold, O will either start emulating T or the model will be exhausted trying to learn weights.

Classification Algorithm

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The naive bays classification [21] algorithm is the most efficient algorithm which is been implemented in the music recommendation system. The probability of the searches will be taken into calculation for this method.

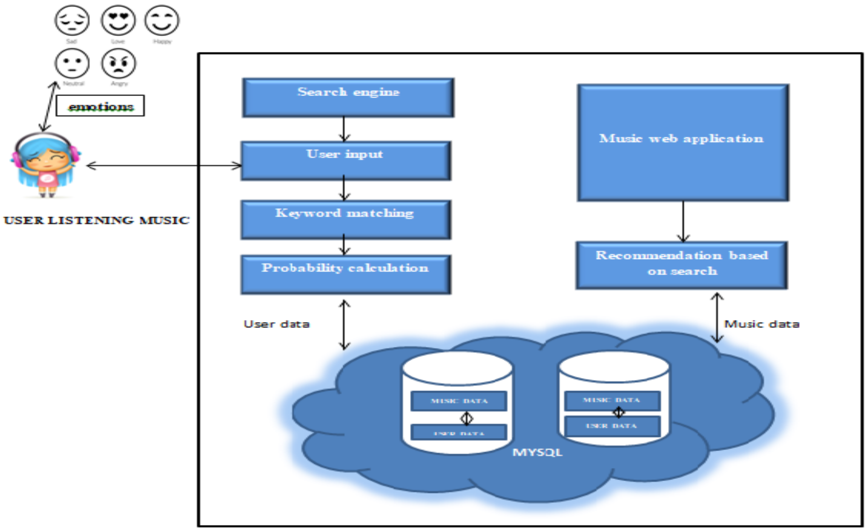

Figure 3. Over all Architecture of MRS

6. NAIVE BAYES PROBABILITY MODEL CALCULATION

Given a problem instance to be classified, represented by a vector representing some *n* features (independent variables), it assigns to this instance probabilities

$$p\,(C_k \mid x_1 ,\ldots\ldots, x_n) \qquad (1)$$

for each of *K* possible outcomes or *classes* C_k.

The problem with the above formulation is that if the number of features *n* is large or if a feature can take on a large number of values, then basing such a model on probability tables is infeasible. We therefore reformulate the model to make it more tractable. Using Bayes' theorem, the conditional probability can be decomposed as

$$P(C_k \mid x) = \frac{p(C_k)\, p(x \mid C_k)}{p(x)} \qquad (2)$$

By using Bayesian probability terminology, the above equation can be written as

$$\text{posterior} = \frac{prior \text{ x } likelihood}{evidence} \qquad (3)$$

The numerator is equivalent to the joint probability model :

$$p\,(C_{k,}\, x_{1,} \ldots\ldots, x_n) \qquad (4)$$

which can be rewritten as follows, using the chain rule for repeated applications of the definition of conditional probability:

$$p\,(C_k , x_1 ,\ldots\ldots, x_n) \;= p\,(x_1 \mid x_2,\ldots, x_n, C_k)\; p\,(x_2 \mid x_3,\ldots, x_n, C_k) \qquad (5)$$

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Assume that all features in **x** are mutually independent, conditional on the category C_k. Under this assumption,

$$\text{p}\ (x_i \mid x_{i+1}, \dots, x_n, C_k) = \text{p}\ (x_i \mid C_k) \tag{6}$$

Thus, the joint model can be expressed as,

$$\text{p}\ (C_k \mid x_{1,} \dots, x_n)\ \alpha\ \ \text{p}\ (C_k) \prod_{i=1}^{n} p(x_i \mid C_k) \tag{7}$$

where α denotes proportionality.

This means that under the above independence assumptions, the conditional distribution over the class variable C is,

$$\text{p}\ (C_k \mid x_{1,} \dots, x_n) = \frac{1}{Z}\ \text{p}\ (C_k) \prod_{i=1}^{n} p(x_i \mid C_k) \tag{8}$$

where the evidence Z = p(x) = $\sum_k$ p (C_k) $p(x \mid (C_k)$ is a scaling factor dependent only on $x_{1,} \dots, x_n$, that is, a constant if the values of the feature variables are known.

Considering $x_{1,} \dots, x_n$ as the data collected from the history and that corresponds to emotional state of the user. Using the Probability Calculation the state (mood) which has the highest probability is taken into account and are linked via SQL server and send to the recommendation system to recommend the song of particular emotion state of the user.

7. Results

The user searched the sad quotes in the search engine. The history of the search is taken into account and the Naive Bayes classifier classifies the emotional state of the user by calculating the probability model. The calculated model gives the emotional state that has the highest probability. The sad mood has the highest probability and it is recommended in the music web application. In the recommendation column, sad song is recommended as result. The Fig.4 & 5 shows the results of the proposed Music Recommendation System.

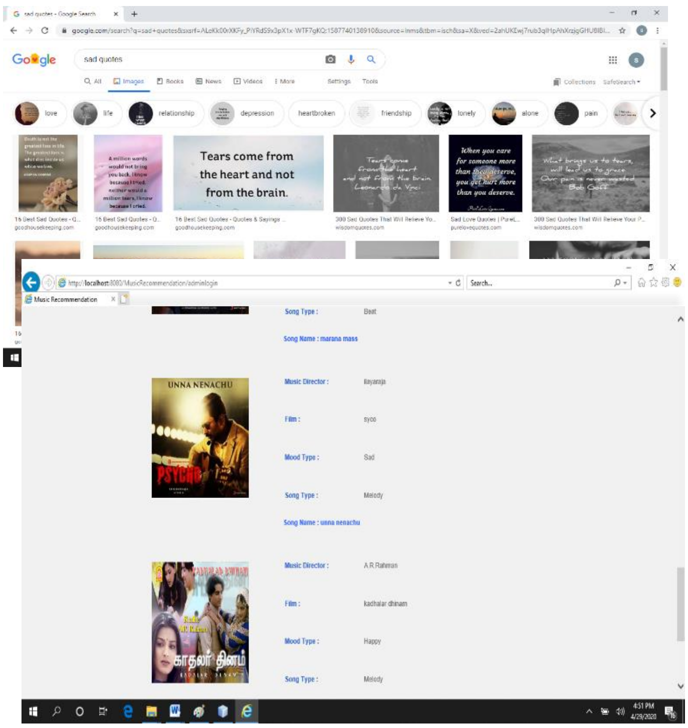

Figure 5. Song recommendation by MRS

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8. Conclusion

The prposed work focuses on the emotion classification and music recommendation. Emotion is classificated based on the six classifiers and based on the classifier MRS will recommend songs to the user. User search history is collected from the search engine and it is classified, based on the classfication the MRS will recommended song to the user.

References

[1]. Hyung, Z.; Park, J.S.; Lee, K. Utilizing context-relevant keywords extracted from a large collection of user-generated documents for music discovery. Inf. Process. Manag. 2017, 53, 1185–1200.

[2]. Pazzani,M.J.;Billsus,D.Contentbasedrecommendationsystems. InTheAdaptiveWeb: MethodsandStrategies ofWebPersonalization; Springer Science & Business Media: Berlin/Heidelberg, Germany, 2007; pp. 325–341.

[3]. Schafer, J.B.; Frankowski, D.; Herlocker, J.; Sen, S. Collaborative filtering recommender systems. In The Adaptive Web: Methods and Strategies of Web Personalization; Springer Science & Business Media: Berlin/Heidelberg, Germany, 2007; pp. 291–324.

[4]. Yading Song, Marcus Pearce:A Survey of Music Recommendation Systems and Future Perspectives; ,: Queen Mary, University of Londo; Conference Paper .June 2012.

[5]. Aljanaki, A.; Wiering, F.; Veltkamp, R.C. Studying emotion induced by music through a crowdsourcing game. Inf. Process. Manag. 2016, 52, 115–128.

[6]. Shan, M.K.; Kuo, F.F.; Chiang, M.F.; Lee, S.Y. Emotion-based music recommendation by affinity discovery from film music. Expert Syst. Appl. 2009, 36, 7666–7674 .

[7]. F.-F. Kuo and M.-K. Shan, “A personalized music filtering system based on melody style classification,” Proc. IEEE Int. Conf. on Data Mining, pp. 649-652, 2002.

[8]. P. Cano, et al., “Content-based music audio recommendation,” Proc. ACM Multimedia, pp. 212-212, 2005.

[9]. Hsu, C.W.; Lin, C.J. A comparison of methods for multiclass support vector machines. IEEE Trans. Neural Netw. 2002, 13, 415–425.

[10]. Fan, R.E.; Chang, K.W.; Hsieh, C.J.; Wang, X.R.; Lin, C.J. LIBLINEAR: A library for large linear classification. J. Mach. Learn. Res. 2008, 9, 1871–1874.

[11]. Schedl, M.; Pohle, T.; Knees, P.; Widmer, G. Exploring the music similarity space on the web. ACM Trans. Inf. Syst. 2011, 29, 1–24.

[12]. Humphrey, E.J.; Bello, J.P.; LeCun, Y. Moving beyond feature design: Deep architectures and automatic feature learning in music informatics. In Proceedings of the 13th International Society for Music Information Retrieval Conference, Porto, Portugal, 8 October 2012; pp. 403–408.

[13]. Ignatov, D.I.; Nikolenko, S.I.; Abaev, T.; Poelmans, J. Online recommender system for radio station hosting based on information fusion and adaptive tag-aware profiling. Expert Syst. Appl. 2016, 55, 546–558.

[14]. McFee, B.; Lanckriet, G.R. Learning multi-modal similarity. J. Mach. Learn. Res. 2011, 12, 491–523.

[15]. Haupt, J. Last.fm: People-powered online radio. Music Ref. Serv. Q. 2009, 12, 23–24.

ISSN: 2233-7857 IJFGCN

[16]. Ignatov, D.I.; Nikolenko, S.I.; Abaev, T.; Poelmans, J. Online recommender system for radio station hosting based on information fusion and adaptive tag-aware profiling. Expert Syst. Appl. 2016, 55, 546–558.

[17]. Oord, A.V.; Dieleman, S.; Schrauwen, B. Deep content-based music recommendation. In Proceedings of the 26th Neural Information Processing Systems, Lake Tahoe, CA, USA, 5–10 December 2013; pp. 2643–2651.

[18]. Luhn, H. P. (1959). "Keyword-in-Context Index for Technical Literature (KWIC Index)". American Documentation. Yorktown Heights, NY: International Business Machines Corp. 11 (4): 288–295. doi:10.1002/asi.5090110403.

[19]. Wu, H.C.; Luk, R.W.P.; Wong, K.F.; Kwok, K.L. Interpreting TF-IDF term weights as making relevance decisions. Proc. ACM Trans. Inf. Syst. 2008, 26, 13:1–13:37.

[20]. Ignatov, D.I.; Nikolenko, S.I.; Abaev, T.; Poelmans, J. Online recommender system for radio station hosting based on information fusion and adaptive tag-aware profiling. Expert Syst. Appl. 2016, 55, 546–558.

[21]. https://en.wikipedia.org/wiki/Naive_Bayes_classifier.

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