J. Inf. Technol. Appl. Manag. 23(1): 33~43, March 2016
http://dx.doi.org/10.21219/jitam.2016.23.1.033

ISSN 1598-6284 (Print)
ISSN 2508-1209 (Online)

Bayesian Learning through Weight of Listener's Prefered Music Site for Music Recommender System

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Abstract

Along with the spread of digital music and recent growth in the digital music industry, the demands for music recommender are increasing. These days, listeners have increasingly preferred to digital real-time streamlining and downloading to listen to music because it is convenient and affordable for the listeners to do that. We use Bayesian learning through weight of listener's prefered music site such as Melon, Billboard, Bugs Music, Soribada, and Gini. We reflect most popular current songs across all genres and styles for music recommender system using user profile. It is necessary for us to make the task of preprocessing of clustering the preference with weight of listener's preferred music site with popular music charts. We evaluated the proposed system on the data set of music sites to measure its performance. We reported some of the experimental result, which is better performance than the previous system.

Keywords : Bayesian Networks, Machine Learning, Clustering, Collaborative Filtering

Received : 2015. 12. 02. Revised : 2016. 03. 16. Final Acceptance : 2016. 03. 22.

※ Funding for this paper was provided by Namseoul University in 2016.

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1. Introduction

Music (songs, albums etc) is something that we all take pleasure to listening in and everybody has their own preferences for different kinds of music, such as pop, country, rhythm and blues, jazz, and hip-hop. It is convenient for us to find all genres and styles on music portal sites with its popular music charts on trends and free online music streaming sites. We are now able to choose and listen from thousands of artists from all over the world. We have collected a list including 20 more of the best and free online music streaming sites, which will definitely cater to all your music needs and even help you to discover new artists. Along with the spread of digital music and recent growth in the digital music industry, the demands for music recommender are increasing. It is becoming a part of our common life style that the demands for enjoying the digital music life using intelligent portable device such as mp3 players and mp3 phone, are increasing anytime or anyplace without any restriction of time and place [Miyahara et al., 2000]. These days, listeners have increasingly preferred to digital real-time streamlining and downloading to listen to music because this is convenient and affordable for the listeners. While online digital music has become a new communication channel to listen to music, where digital files can be delivered over various online networks to people's computing devices. They can enjoy listening to great music from these free online music streaming sites. The demands for music portal sites and many different digital music pieces on music portal site are increasing rapidly. Billboard and its popular music charts have evolved into the primary source of information on trends and innovation in music, serving music fans, artists, top executives, tour promoters, publishers, radio programmers, lawyers, retailers, digital entrepreneurs and many others. A music recommender system has been actually processed the researches to satisfy the needs for listeners and even help you to discover new artists. But it is currently lack of music recommending method in online portal site environment. In this paper, we propose a new music recommender system through Bayesian learning through weight of listener's prefered music site. We can access various music databases through music sites to find favorite musical pieces by using retrieval systems, and then we have to execute queries repeatedly by ourselves. To solve this problem, it is desirable that it is neccessay for us to take the task of preprocessing of clustering of weight based music site with its popular music charts on trends in music database in order to reflect probably-preferred pieces from the database by estimating listener's preferences using listener's user profile. The next section briefly reviews the literature related to studies. Section 3 is described a new method for music recommender system in detail, such as system architecture with sub modules, the algorithm for proposing system, and the procedure of processing the recommender. Section 4 describes the evaluation of this system in order to prove the criteria of logicality and efficiency through the implementation and the experiment. In section 5, finally it is described the conclusion of paper and further research direction.

2. Related works

2.1 Collaborative Filtering(CF)

The CF is based on the ratings of other users who have similar preferences and is widely used for such recommender as Amazon.com and IMDb.com. It also have the first rater problem because they recommend based on the interest of users in items, not considering the items' contents. Also, in case users estimate preference on a lot of items, systems have a shortcoming that the accuracy of prediction is fallen due to the sparsity of {user-item} matrix [Miyahara et al., 2000; Balabanovic et al., 1997]. The other reason of sparsity for {user-item} matrix in the recommender system is the missing value caused from partial rating on items. It is used weighting of the five-point scale, a measure of likert in the explicit method. In general, it is performed in four steps.

〈Table 1〉 Matrix to Predict Preference of Rating

	Item A	Item B	Item C	Item D
User	3	1	3	5
User	1	3	1	4
User		3	1	2
New User	3	1		?
step 1	To define and calculate the weighted of similarity with new users and neighbors.			
step 2	To predict a preference of New user for particular item, it is determine how many neighbors with high similarity and how many people by which criterion you will select.			
step 3	New users' preference predicts a value of preference for items which have not been input on the basis of preference for item of neighbors with similar preference.			
step 4	To evaluate the result of collaborative filtering with preference of item which has not input a preference of new users and predicted preference by proper evaluation criterion.			

The explicit method can not only reflect exact attributes of item, but also still has the problem of sparsity and scalability, though it has been practically used to improve these defects [Park et al., 2013]. To resolve this problem, this paper suggests the preference through Bayesian learning through weight of listener's prefered music site with most popular current songs across all genres and styles, ranked by for music recommender systems. It is necessary for us to make the task of preprocessing of clustering listener's preference with weight of music site with its popular music charts on trends in the music data reflected by most popular current songs across all genres and styles using listener's user profile for music recommender systems.

2.2 Clustering

Clustering is the process of grouping physical or abstract objects into classes of similar objects. It is the process of organizing objects in a database into clusters. It involves classifying or segmenting the data into groups based on the natural structure of the data. Its techniques [Hand et al., 2001; Griffiths et al., 2006] fall into a group of undirected data mining tools. The principle of clustering is maximizing the similarity inside an object group and minimizing the similarity between the object groups. Its algorithm is a kind of user's segmentation methods commonly used in data mining, can often use to k-means clustering algorithm. K-means is the most well-known and commonly, used partition methods are the simplest clustering algorithm. In the k-means algorithm, cluster similarity is measured in regard to the mean value of the objects in a cluster, which can be viewed as the cluster's center of gravity. This algorithm uses as input a predefined number of clusters that is the k from its name. Mean stands for an average, an average location of all the members of a particular cluster. The euclidean norm is often chosen as a natural distance which user a between k measure in the k-means algorithm [Griffiths et al., 2006]. The a_i means the preference of attribute i for user a.

$$d_{a,k} = \sqrt{\sum_i (a_i - k_i)^2} \quad (1)$$

There are two part of k-means algorithm. The 1st part is that partition the objects into k clusters. The 2nd part is that iteratively reallocate objects to improve the clustering. The system can use Euclidean distance metric for similarity.

2.3 Bayesian Networks(BNs)

BNs can be used to model the joint probability distribution of multiple random variables. BN model is well known that classic machine learning methods like Hidden Markov models (HMMs), neural networks. BNs became extremely popular models in the last decade. They have been used for applications in various areas, such as machine learning, text mining, natural language processing, speech recognition, signal processing, bio informatics, error-control codes, medical diagnosis, weather forecasting, and cellular networks [Pearl et al., 2000]. Specific types of BN models were developed to address stochastic processes, known as dynamic BN, and counterfactual information, known as functional BN [Pearl et al., 2000]. With the BNs, we formulate a item preference model in the form of a joint probability distribution. In the case of music recommender, the problem is finding items that a given user is likely to rate highly. For this purpose, we calculate the conditional probability for the target user U = u, the candidate item C = c and then recommend items in order of probability. Alternatively, we may calculate the conditional probability for the target user and rating to find items that are highly likely to obtain a positive rating. The recommender system may receive user feedback for final purchase behavior, and periodically, the system updates the parameters of the item preference. BNs model using final purchase data by using the Bayesian inference engine as the decision of behavior of buying additional item in order to increase the precision of the recommender. Although the preference model can be used in many ways, here, we explain the typical ways for item recommender. Here, since a recommender system can use the same item preference Bayesian network model can have two type of the calculation of probability, one is prior probability, the other is posterior probability. The users can be commonly used to update the parameters of the model and thus increase the precision of both the recommender and promotion. Bayesian probability measures a degree of belief. Bayes theorem then links the degree of belief in a proposition before and after accounting for evidence. For proposition C_i and evidence X,

- P(C_i), the prior, is the initial degree of belief in C_i

- P(C_i|X), the posterior, is the degree of belief having counted for X.
- the quotient P(X|C_i)/P(X) represents the support X provides for C_i

Bayes' theorem gives the relationship between the probabilities of C_i and X, P(C_i) and P(X), and the conditional probabilities of C_i given X and X given C_i, P(C_i|X) and P(X|C_i). For example, suppose an experiment is performed many times. P(C_i) is the proportion of outcomes with property C_i, and P(X) that with property X. P(X|C_i) is the proportion of outcomes with property X out of outcomes with property C_i, and P(C_i|X) the proportion of those with C_i out of those with X. In Bayesian inference, the posterior distribution is proportional to the product of the likelihood and the prior distribution. For parameters C_i and data X. It is most common form as follows [Hand et al., 2001]. For events C_i and X, provided that P(X) ≠ 0,

$$P(C_i \mid X) = \frac{P(X|C_1)P(C_1)}{P(X)},\ 1 \le i \le m \quad (2)$$

The denominator is the marginal likelihood of the data, which is the integral of the likelihood against the prior distribution. In many applications, the event X is fixed in the discussion, and we wish to consider the impact of its having been observed on our belief in various possible events C_i. In such a situation the denominator of the last expression, the probability of the given evidence X, is fixed. For more on the application of Bayes' theorem under the Bayesian interpretation of probability, we can apply it in the application using Bayesian learning. We can apply the algorithms for the preference of user-item using Bayesian theorem in previous paper [Cheung et al., 1996]. For any set of random variables, the probability of any member of a joint distribution can be calculated from conditional probabilities using the chain rule (given a topological ordering of X) as follows :

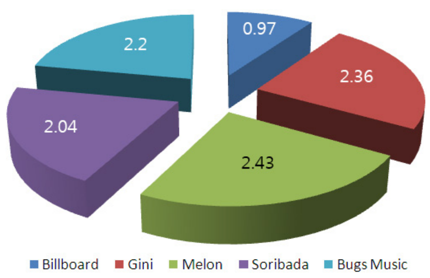
$$\begin{aligned} P(X \mid C_l) &= P(x_1, x_2, \cdots, x_n, C_l) \quad (3)\\ P(x_1 \mid C_l) &= P(x_1|C_l)P(x_2|C_l) \cdots P(x_n|C_l)P(C_l) \\ &= P(C_l)\prod_{k-1}^{n} P(x_k \mid C_l) \end{aligned}$$

BNs became extremely popular models in the last decade. They have been used for applications in various areas, such as machine learning, text mining, natural language processing, speech recognition, signal processing, bio informatics, error-control codes, medical diagnosis, weather forecasting, and cellular networks. In general, the case of learning with known structure and partial observability, one can use the EM (expectation maximization) algorithm to find a locally optimal maximum-likelihood estimate of the parameters [Pearl et al., 2000]. There are two main applications of the EM algorithm. The first occurs when the data indeed has missing values, due to problems with or limitations of the observation process. The second occurs when optimizing the likelihood function is analytically intractable but when the likelihood function can be simplified by assuming the existence of and values for additional but missing (or hidden) parameters. The latter application is more common in the computational pattern recognition community.

3. Our proposal for a Music Recommender System

3.1 Clustering with Weight of Listener's Prefered Music Site

In this section, we suggest the music recommender system using Bayesian learning through weight of listener's prefered music site with most popular current songs across all genres and styles for music recommender systems. We have 1,000 listeners in user profile, who have experienced to listen songs and have downloaded the mp3 music files from online music site. As a result of that, we have 1,000 listeners who have listened or downloaded and we use 500 song titles. There are 5 rates weighted by listener's prefered music site to reflect most popular current songs across all genres and styles on music portal sites, which have its popular music charts on trends, such as Melon, Billboard, Bugs Music, Soribada, and Gini. The following <Figure 1> show the result with statistics of the result for possession of users by each listener's prefered music site. In case of each rate, it is shown that the result of output for possession of prefered music site. It is shown that the weight for possession of prefered music site.



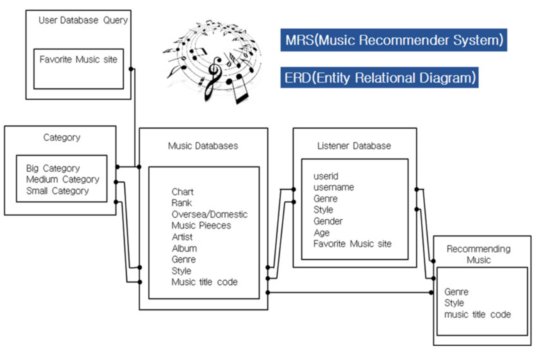
〈Figure 1〉 The Result of the Graphical Statistics of the Weight for Possession of Prefered Music Site

The music database created after suitable preprocessing for structure of content based users' music according to ERD, was grouped and ordered by each music genre and music style based on big/medium/small category as the following <Table 2>.

〈Table 2〉 The List of Category for Music Site

music sites with rank	Melon realtime Top 100, Billboad Hot 100, Sorobada popular chart, Gini Top 100, Bugs Daily Top 100
genre	R&B, Ballad, Dance, Folk, Electronica, Drama, Pop, Rock, Hip Hop, Ani, Pop, Country, Rap, Soul, Soft Pop
Style	R&B Ballad, 00' Ballad, Urban, Soft Pop/Rock, 00' Dance, Pop Rap, Medium, Folk Pop, Soft Dance, Electronica, Rap/Hip-Hop, Pop, R&B Dance, Pop Rock, Neo Soul, Urban, Club Dance, Punk Rock, Modern Folk, Dance Pop, Country Pop, Reggae, Korea TV Drama, Soul, CM Song, Alternative Pop, Indiem etc.

The big category is based on music sites with rank. The medium category is based on genre of music. The small category is based on style of music. The music database created after suitable preprocessing for structure of content based users' music according to ERD as the following <Figure 2>.



〈Figure 2〉 The ERD of Music Recommender System

The system can create the cluster of music data sorted by music genre and music style for the preprocessing task on the analytical agent. The system can compute listener's probability of preference of all categories of music genre and music style in clustering data which is selected by social variable such as age, gender, occupation, and music propensity. As a result of that, the system has finished the ready to recommend songs with high probability in music category belonged to brand songs. There are two type of the preprocessing task. One is the effective clustering of music genre and music style for music recommender system via Bayesian learning through weight of listener's prefered music site. The other is creating of clusters with neighborhood user-group by listeners' social code such as age, gender, occupation, and music propensity via the task of preprocessing for the effective clustering of music genre and music style for music recommender system via Bayesian learning through weight of listener's prefered music site by listeners' propensity on the purpose of recommending song in the music recommender system. We make the task of preprocessing of clustering of music genre and music style for music recommender system with Bayesian suggestion via Bayesian learning through weight of listener's prefered music site with most popular current songs across all genres and styles, to adjust the result through Bayesian learning with weight of listener's prefered music site. The procedural preprocessing steps for music recommender system using Bayesian suggestion is depicted as the following <Table 3>.

〈Table 3〉 The Procedural Pre-Processing Steps for Music Recommender System

Step 1 :	The login user reads user profile as listener's profile. And then recognizes the classification code, music propensity in listener's profile.
Step 2 :	The system selects the cluster classified with social code of login user, as the basis of the social such as age, gender, an occupation, music propensity.
Step 3 :	The system scans user's probability of preference of the categories of music site in the selected cluster.
Step 4 :	First, the system recommends the songs using prior probability according to the preference in the selected cluster.
Step 5 :	Then, the system recommends the songs according to the information of recommender which is applied by posterior probability through Bayesian learning, if a listener wanted to obtain any songs as additional request.
Step 6 :	The system makes user's TOP-4 of songs in the list of songs to recommend songs which is similar to music propensity of login user.
Step 7 :	The system executes the cross comparison with recommending data in order to avoid the duplicated recommender which it has ever taken.

We apply the effective clustering of music genre and music style in the music site to recommender system through Bayesian learning with weight of listener's prefered music site.

4. The Environment of Implementation and Experiment and Evaluation

4.1. Experimental Data for Evaluation

We used 1,000 listeners in user profile, who had experienced to listen to songs and had downloaded the mp3 music files from online music site with its popular music charts on trends in the music data reflected by most popular current songs across all genres and styles. They had listened or downloaded from online music site and had used 500 song titles. It was necessary for us to make the task of clustering listener's preference with weight of music site using user profile. For doing that, we made the implementation for prototyping of music recommender system. The experimental dataset for music recommender system was collected by each 5 music sites for proving of the proposed. We have finished the system implementation about prototyping music recommender system. We'd try to carry out the experiments in the same condition with dataset collected in online portal music sites such as Melon, Billboard, Bugs Music, Soribada, and Gini. It has been difficult for us to do the performance evaluation of proposing method as comparing with other method because proposing system uses new method to reflect weight of online music sites. So we have tried to do the performance evaluation for proposing method using various music sites with one hand tied behind our back. The 1st system is proposing system using BN learning through listener's preferred with weight of music site using user profile, called by "proposal", the 2nd system is the previous system called by "previous", without weight of listener's prefered music site by listeners' propensity. Our proposing system is new music recommender system based on listener's prefered online potal music site such as Melon, Billboard, Bugs Music, Soribada, and Gini. Thererfore, it is meaningful to present a new music recommending method in online portal site environment.

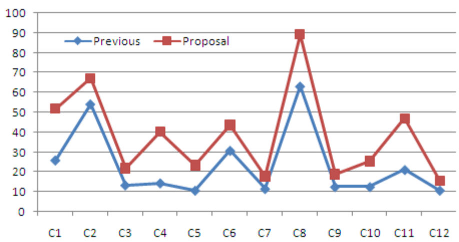
4.2 Experiment and Evaluation

The system's overall performance evaluation is used by the metrics of evaluation for music recommender system, such as precision, recall and F-measure for proposing system in clusters. For performance evaluation of the system, we used metrics most widely used for recommender systems using learning data set and testing data set, precision, recall and F-measure defined as follows : Precision = recommended relevant songs/all recommended songs, Recall = recommended relevant songs/total relevant songs, F-measure = 2(Precision×Recall)/(Precision+Recall). The metrics of evaluation for music recommender system in our system was used in the field of information retrieval commonly [Herlocker et al., 1999].

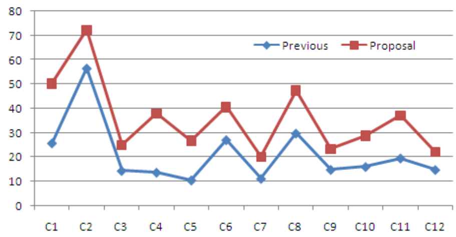
The <Table 4> presents the result of music recommender system by evaluation metrics (precision, recall and F-measure). The proposing system is better performance than the previous system. Our proposing system with BN learning through weight of listener's prefered music site is higher 10.64% in precision than the previous system without weight of listener's prefered music site by listeners' propensity. It is higher 6.11% in recall than previous system, generally, it is higher 6.53% in F-measure than existing system. As a result, we could have the music recommender system to be able to recommend the songs with an immediate effect. The <Figure 6> is shown in the screen of music recommending site on a smart phone. The proposing system is better performance than the previous system.

〈Table 4〉 The Result of Music Recommender System by the Metrics of Evaluation

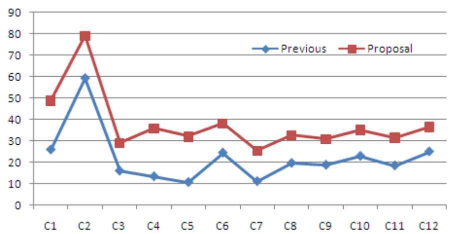
Cluster	Category	Proposal			previous(without weight)		
		Precision1	Recall1	F-measure1	Precision2	Recall2	F-measure2
C1	Ani	25.88	25.88	25.88	26.00	23.12	24.48
C2	Balla	54.18	59.26	56.61	13.00	19.92	15.73
C3	Count	13.29	15.95	14.50	8.67	13.04	10.41
C4	Dance	14.33	13.31	13.80	26.00	22.66	24.22
C5	Drama	10.63	10.63	10.63	13.00	21.53	16.21
C6	Elect	30.73	24.39	27.19	13.00	13.94	13.45
C7	Folk	11.46	11.05	11.25	6.50	14.51	8.98
C8	Hip h	63.13	19.56	29.87	26.00	13.31	17.61
C9	Pop	12.46	18.69	14.95	6.50	12.35	8.52
C10	R&B	12.46	22.85	16.13	13.00	12.40	12.69
C11	Rap	21.04	18.41	19.64	26.00	13.16	17.48
C12	Rock	10.63	24.94	14.91	5.20	11.73	7.21



〈Figure 3〉 The Result of Music Recommender System by Precision



〈Figure 5〉 The Result of Music Recommender System by F-measure



〈Figure 4〉 The Result of Music Recommender System by Recall

〈Figure 6〉 The Screen of Music Recommending Site

5. Conclusions

These days, listeners have increasingly preferred to digital real-time streamlining and downloading to listen to music because it is convenient and affordable for the listeners to do that. Listeners can access various music databases through the Internet to find favorite musical pieces by using retrieval systems. Billboard and its popular music charts have evolved into the primary source of information on trends and innovation in music, serving music fans, artists, top executives, tour promoters, publishers, radio programmers, lawyers, retailers, digital entrepreneurs and many others. Along with the spread of digital music and recent growth in the digital music industry, the demands for music recommender are increasing. But the portal music sites have few music recommender methods, with the exception of major music site and to a certain extent famous music site because of large amounts of music data in real time environment. It will be meaningful to present a new music recommender method based on online potal music site. Moreover, we reflected most popular current songs across all genres and styles in order to improve the accuracy of recommender method, to reduce listeners' searching effort to find out the songs using weight of listener's prefered music sites. Our proposing system was a new music recommender system using Bayesian learning through weight of listener's prefered music site. We carried out experiments with dataset of collecting from online portal music sites to measure its performance. The previous system did not yet reflect the importance, i.e., without weight of listener's prefered music site by listeners' propensity. It was crucial to have different value via Bayesian learning through weight of listener's prefered music site by listeners' propensity. We have described that the performance of the proposing system with weight of listener's prefered music site is better performance than the previous system. We will concern about the future research of music recommender system using listeners' propensity in order to reflect the personal sensitivity state according to time zone, weather and season listeners' propensity in detail.

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