Music Recommendation Based on Label Correlation

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Abstract. The Web is becoming the largest source of digital music and users often find themselves exposed to a huge collection of items. How to effectively help users explore through massive music items creates a significant challenge that must be properly addressed in the era of E-Commerce. For this purpose, a number of music recommendation systems have been proposed and implemented, which can identify music items that are likely to be appealing to a specific user. This paper presents a hybrid music recommendation system based on the labels associated with each music album, which also explicitly takes into account the correlation among labels. Experimental results on a real-world sales dataset show that our approach can achieve a clear advantage in terms of *precision* and *recall* over traditional methods in which labels are treated as independent keywords.

Keywords: music recommendation, similarity matrix, label, correlation

1 Introduction

Information recommendation has become an important research area since the first paper on collaborative filtering (CF) published in the 1990s [1]. Extensive work has been conducted in both industry and academia on developing new techniques and algorithms for building recommendation systems over the last decades [2]. Recently, more attentions are being devoted to this topic due to the success of several practical systems deployed at Amazon[1] (book), Pandora[2] (music) and MovieLens[3] (movie).

As the Web becomes the largest source of digital music, massive music items have been made accessible to users. For example, users can now enjoy and share music with others in online music communities while more and more online music stores are open for music fans. Since it is an ever increasingly difficult and time-consuming task to search through the diverse music collection, it is almost compulsory for successful music websites to implement an efficient music recommendation system to provide good user experience (e.g., Douban[4] and Xiami[5]).

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[1] http://www.amazon.com
[2] http://www.pandora.com
[3] http://www.movielens.umn.edu
[4] http://www.douban.com
[5] http://www.xiami.com

Most of the existing music recommendation systems are based on the similar idea as other recommendation systems used in E-Commerce, relying on the historical records or behaviors of users. For example, the widely used rating matrix stores the preference of users given to various products, which can be used to discover users with similar behaviors (collaborative filtering). However, the CF method may face significant difficulty when the matrix is sparse, which is often the case in practice. On the other hand, labels or tags can be used to describe the contents or features of products and identify other products with similar properties (content-based recommendation). However, labels are traditionally treated as a set of independent keywords and their relationships are largely ignored.

In this paper, we propose a hybrid music recommendation system based on labels and, more importantly, the correlation among labels to identify similar music items and users. Each music album is represented by a set of labels assigned to it by various users (music description) and each user is also represented by a set of labels associated with the set of albums that he/she has purchased (music preference). The correlation between two labels is defined according to the frequency that they are attached to the same user and is taken into account when calculating the distance between two sets of labels. By contrast, without this correlation information, two label sets without any common labels are regarded as being completely different. In the experiments, a real-world sales dataset from an online music store is used as the benchmark problem and a comparative study is conducted against the traditional method without considering the correlation among labels.

The rest part of the paper is organized as follows. Section 2 gives a brief review on music recommendation and the use of label information in recommendation. The architecture of our system and the proposed techniques based on label correlation are detailed in Section 3. The experiment results are presented in Section 4 and this paper is concluded in Section 5 with some discussions for future work.

2 Related Work

2.1 Music Recommendation

In general, there are two types of music recommendation systems: content-based and collaborative recommendations [2]. Content-based recommendation systems analyze the acoustic features of music and calculate the similarity between two music items in terms of acoustic features and recommend music items that are most similar to those known to be attractive to a specific user. For good recommendation accuracy, a lot of manual efforts are required to extract acoustic features.

The collaborative recommendation systems recommend items that other users in the same user group with similar preferences have purchased or favored [3]. A typical application of this method is by amazon.com in which 20% - 30% of the profits are claimed to be due to recommendation. One of the major issues is that, with the increasing number of users and music items, the issue of data sparseness becomes inevitable, resulting in low accuracy and efficiency. Another fundamental challenge is that, when a new user or a new item enters in to a recommendation system based on the collaborative method, it is impossible for the system to respond properly due to the lack of historical data [2, 4, 5].

Several music recommendation systems are currently available online, which are used to recommend new music items to users or help them find potentially interesting music items. Fig. 1 shows a screenshot of Douban Music.

Fig. 1. An illustration of the recommendation results in Douban Music

2.2 Recommendation Based on Label

As far as music is concerned, labeling is an effective way to describe the properties of music items and also accurately classify music items [6-9]. With the use of labels, the original user-item structure is extended to user-label-item (i.e., not only the items that a user has purchased but also the properties of the items are available). However, traditionally, labels are used as independent keywords in most of the music recommendation systems [10] and their correlation has not yet been fully exploited. The correlation information between two labels can reflect their underlying semantic relationship and can help better calculate the similarity between two music items. After all, in the era of Web 2.0, it is increasingly easier to get the labels of music items [11]. For example, they can be tagged by either music experts or through the collaborative efforts of millions of users.

3 Recommendation Based on Label Correlation

3.1 System Architecture

The general framework of the proposed music recommendation system based on label correlation is shown in Fig. 2. For new users, they are allowed to manually select a set of labels for themselves and the system will recommend music items with similar label sets (content-based). For existing users, the system will create two recommended lists. Given the set of labels associated with the user (the set of labels of music items purchased by this user) and the label correlation information based on historical data, the first list is created by finding music items with similar label sets (content-based). The second list is created by finding a set of users with similar label sets and then selecting some items from their purchase records (CF).

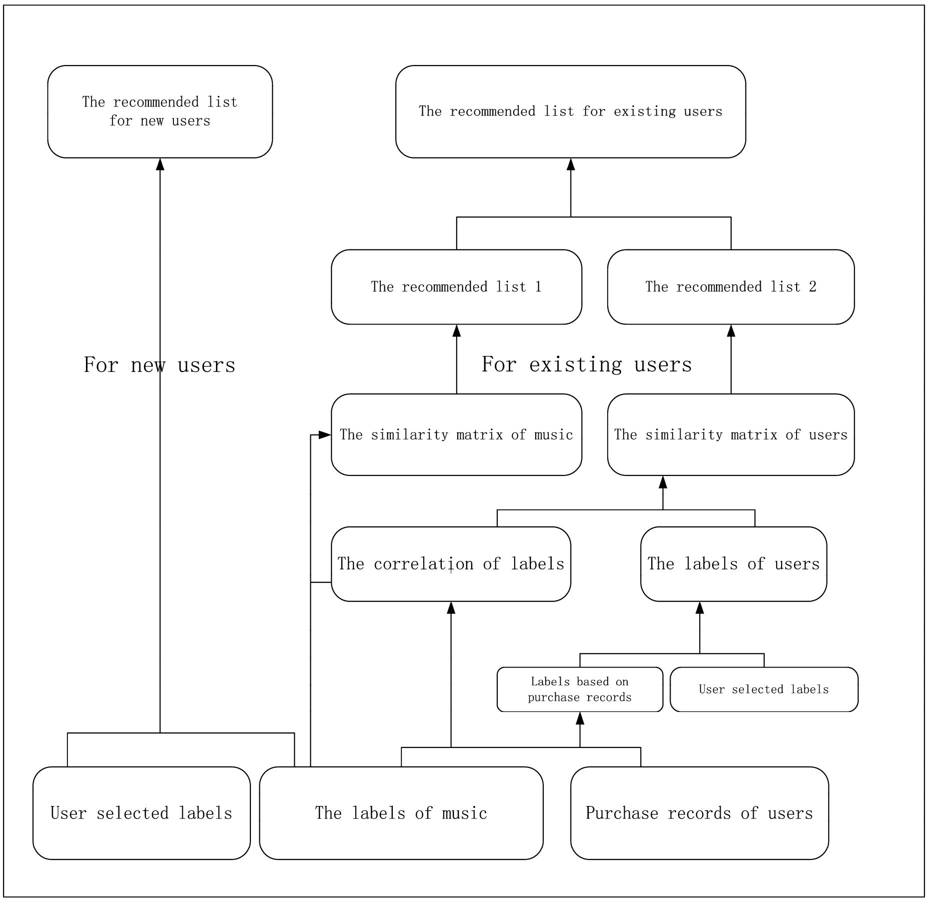

Fig. 2. The general framework of the music recommendation system based on label correlation. Note that new users and existing users are treated differently.

3.2 Methodology

The labels of the music items purchased by a user represent this user's interest or preference. For each user, according to the sales record and the complete label list, a four-element tuple (*user*, *label*, *num_label*, *num_item*) is created as the most basic relationship between users and labels where *num_label* is the number of times that *label* has appeared in the purchased items by *user*, and *num_item* is the number of purchased items by *user* (see Table 1 for an example).

Table 1. The four-element tuple representing the relationship among user, label and item

user	label	num_label	num_item
u_i	l_m	3	3
u_i	l_n	1	3
u_i	l_o	1	3
u_j	l_m	2	3
…	…	…	…

The representation power of a label to a user is defined as $describe(user, label)$, which describes the importance of the label to the user (Table 2).

$$describe(user, label) = num\_label/num\_item \quad (1)$$

Table 2. The importance of labels to users

user	label	describe
u_i	l_m	3/3
u_i	l_n	1/3
u_i	l_o	1/3
u_j	l_m	2/3
…	…	…

For u_i, the correlation between two labels is defined as:

$$label\_cor_i(l_m, l_n) = describe(u_i, l_m) \cdot describe(u_i, l_n) \quad (2)$$

Note that for m=n, the value of $label\_cor_i$ is set to 1. Over the entire set of users, the correlation between two labels is defined as:

$$label\_cor(l_m, l_n) = \sum_i label\_cor_i(l_m, l_n) \quad (3)$$

The similarity between two users is given by equation (4) where L_i and L_j are the two corresponding label sets:

$$user\_sim(u_i, u_j) = \sum_{l_1 \in L_i} \sum_{l_2 \in L_j} label\_cor(l_1, l_2) \cdot describe(u_i, l_1) \cdot describe(u_j, l_2) \quad (4)$$

The similarity between two music items is defined as:

$$item\_sim(item_i, item_j) = \sum_{l_1 \in L_i} \sum_{l_2 \in L_j} label\_cor(l_1, l_2) \quad (5)$$

The similarity between a user and a music item is defined as:

$$user\_item\_sim(u_i, item_j) = \sum_{l_1 \in L_i} \sum_{l_2 \in L_j} label\_cor(l_1, l_2) \cdot describe(u_i, l_1) \cdot describe(u_i, l_2) \quad (6)$$

The advantage of this approach is that it is straightforward to calculate the distance between users or music items with different numbers of labels. Also, our approach is flexible as the distance calculation does not simply depend on the existence or absence of a label. Instead, all relationships among labels are taken into account, which is expected to exploit more information hidden in the label sets.

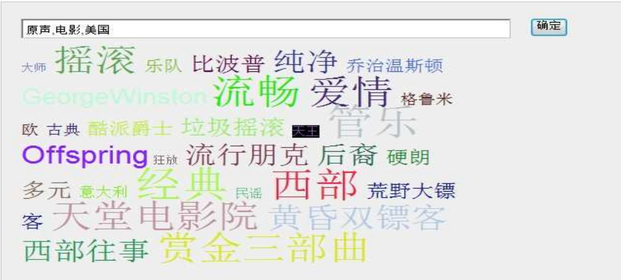

Fig. 3. An example of the label cloud in our system

For new users, since there is no personalized information in the system, the label cloud can be used to guide the user to choose the labels for themselves. The size of each displayed label is determined by the number of times that this label has been used. According to the selected label set, the similarity between the label set and the music items can be calculated and the most similar items will appear in the recommended list.

The recommended list for existing users consists of two parts. The first part of the list is created by finding music items similar to those that have been purchased by the user. Denote the set of purchased items by $\{item_1, item_2, \ldots, item_w\}$. For each item in this set, 5 most similar music items are retrieved, resulting in 5w items in total. If an item appears k times, its similarity value will be multiplied by k. All items are sorted by the similarity (items that have already been purchased before are removed) and the top n items are selected. For the second part of the list, m users that are most similar to the given user are identified. Next, the similarity between the given user and each of the items that have been purchased by this set of m users is calculated. At last, all items are sorted based on the similarity and up to 50 items are selected (items that have already been purchased before are removed). The final recommended list is created by appending the second part of the list to end of the first part of the list.

4 Experiments

4.1 Dataset

The dataset used in this paper was obtained from a LP (Long Play) album store on Taobao Marketplace[6], the most popular online platform in China for small businesses

[6] http://www.taobao.com

and individual entrepreneurs to open retail stores, which was founded by Alibaba Group[7]. The dataset contained the purchase record of each customer and a list of all albums in stock. The time range of the dataset was from 2009-12-16 to 2012-01-12, which was divided by the time point of 2011-12-04 into the training set and the test set. Each album was labeled by a group of music funs according to its information such as singer, region, music style, melody, rhythm, emotion etc.

4.2 Experimental Results

For evaluating recommendation systems, *recall* and *precision* have been widely used as the performance metric [12, 13]. Suppose S, M and N are the length of the recommended list, the number of albums purchased by all users and the number of albums purchased by all users that also appeared in the recommended list. *Recall* is defined as N/M, which is equal to the proportion of actually purchased albums that have also been recommended. *Precision* is defined as N/S, which is equal to the proportion of recommended albums that have been actually purchased.

In the experiments, we considered three parameters: n, m, L, representing the number of items in the first part of the recommended list, the number of similar users and the maximum length of the recommended list respectively. For comparison, the content-based recommendation system based on TF-IDF and Jaccard similarity [14] was implemented. The Jaccard similarity was defined as the size of intersection divided by the size of the union of the two label sets while TF-IDF was used for measuring the importance of a label to an album.

Table 3. The experiment results of recommendation based on label correlation and TF-IDF

			label correlation			**TF-IDF**	
n	**m**	**L**	**recall**	**precision**	**L**	**recall**	**precision**
2	1	5	20.32%	15.21%	5	13.20%	9.78%
2	2	8	24.71%	20.36%	8	18.52%	13.41%
3	2	10	29.63%	23.32%	10	20.61%	16.75%
4	2	10	33.54%	23.96%			
5	3	15	41.23%	22.78%	15	24.33%	14.38%
5	4	15	43.56%	22.91%			
5	5	20	44.37%	19.83%	20	25.24%	13.22%

From Table 3, we can see that with the increasing value of n, m and L, the *recall* value increased monotonically, as more and more albums appeared in the recommended list. In the meantime, the *precision* value increased from around 15% to nearly 24% before dropping back to under 20%, which shows that parameter tuning is important for recommendation systems in order to achieve satisfactory performance.

[7] http://www.alibaba.com

By contrast, our method achieved unanimously better results across various parameter settings compared to the traditional method in which each label was treated as an independent keyword.

5 Conclusion

This paper addressed a research question of significant practical value: how to effectively use label information in the scenario of music recommendation? Different from traditional recommendation systems where labels are only treated as independent keywords, we proposed to exploit the correlation among labels and use the label set to represent both the music items and users. The similarity measures for user-to-user, item-to-item and user-to-item were also defined. Experiment results on a real-world sales dataset show that, with this type of correlation information, the connection among users and music items can be better described and the quality of recommendation in terms of *precision* and *recall* were both improved compared to traditional methods based on the Jaccard distance and TF-IDF.

As to future work, we will investigate and compare other ways to define the label correlation and calculate the similarity among users and music items, which may hopefully extract more useful information from the original dataset and better reflect the interest of users. More importantly, most existing studies on recommendation are based on the assumption of stationary user behaviors by treating all purchase records as an unordered list. However, it is likely that the interest of a user on music may change during time. Consequently, we may explicitly incorporate the time factor into the framework of recommendation by tracking the change of labels associated with a user (e.g., change of frequency, new labels).

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