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A Context-Aware Music Recommendation

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ABSTRACT

The world is facing a drastic change in a way music's are consumed by people. This is to mean that public music streaming collections that contain not less than a million tracks which generate tons of data are preferred by people than those private collections which contain less. Recommender systems support users in discovering music from such streaming services based on their preference. This is the reason why the field of music information retrieval as well as music recommendation is highly in demand for industry and academia. In this paper, we propose a context-aware music recommender system that makes the recommendation based on finding similarities among users linked by similar interests, music as well as users contextual information by exploiting a social network data. Social tag information is utilized as context data which are source of human generated contextual knowledge about music.

I. INTRODUCTION

Music has played a major role throughout the history of human cultures, and is still an integral part of our daily lives. We consume music either actively by listening to the radio or playing records, or passively by being exposed to music in public areas. Music is played in the background of almost any conceivable situation; specifically, a study on the musical experience in everyday life among nearly 350 people indicated that most people were exposed to music on a daily basis and that music was mostly experienced during some activity rather than during deliberate listening.

The ability to listen to background music in any situation has increased as portable music players like Apple's iPod, Microsoft's Zune, and Nokia's and Sony Ericsson's MP3 playing mobile phones become more popular. Still, the choice and organization of music based on situations can be a time-consuming process. Traditionally, a stream of appreciated music can be obtained by creating playlists and manually adding suitable tunes, or by just playing all tunes at random, skipping tunes when one comes along that is not suitable for the situation. Regardless of the method, getting the right music to play at the right time requires time and effort.

Recommender Systems (RSs) are software tools and techniques providing suggestions for items to be use to a User. In the music domain recommender systems can support information search and discovery tasks by helping the user to find relevant music items, for instance, new music tracks, or artists that the user may not even know.

We propose a recommender music system that offers, in addition to the conventional search techniques, some support for context-aware search of music, based on tag information.

One source for this contextual knowledge is the set of social tags that humans apply to music. Social tags are the result of collaborative tagging. In a social tagging system, an individual applies short, free text annotations (tags) to items, typically to organise their personal content. These tags can be combined with those created by other individuals to form a collective body of social tags. With a large enough set of taggers generating many tags, a very rich view of the tagged items emerges. Social tags are typically used to facilitate searching for items, exploring for new items, finding similar items, and finding other listeners with similar interests.

In the last few years, a number of music discovery and recommendation web sites have been supporting the social tagging of music. Commercial sites such as Last.fm, MyStrands and Qloud allow their users to apply social tags to tracks, albums, artists and playlists. These tags capture a great deal of information that is highly relevant to information including information about genre, mood, instrumentation and quality.

II. RELATED WORK

The availability of data from social networks, and in particular the ones that allow to build dynamic users profiles, opens the way for a more extensive concept of context, which could include both data generated by the interaction of users with a specific front-end of a service-based system and the ones derived from different activities of the same users in different virtual contexts (such as social networks).

When contextual information is used to explicitly suggest music of potential interest, a significant role is assumed by recommendation algorithms.

Starting from the idea that people tend to follow suggestions from other people with similar needs, the collaborative filtering is often used in literature as a technique to indirectly infer interests [3] [4]. Juuso Kaitila et al. [5] A content-based music recommender system. M. Sunitha Reddy et al. [6] employ User Based Collaborative Filtering for Music Recommendation System. The papers in [7], [8] apply the idea of Item-based Collaborative Filtering Recommendation Algorithms. [9] exploit a Music recommendation system based on matrix factorization technique –SVD. Ja-Hwung Su, et. Al [10] Personalized Music Recommendation by Mining Social Media Tags. Paul Lamere [11]social tagging and music information retrieval.

Several techniques have been proposed but most of the available systems use either content or collaborative approaches.

A collaborative-based approaches the system ignores the items' descriptions, i.e., their features. It tries to find users with music preferences that are similar to those of the target user. Two users are estimated as similar by observing only the co-occurrences of the items in the sets of items liked/purchased by the two users. Then, the system recommends to the target user items liked by these similar users and novel to the target user.

III. METHODOLOGY

To model user's context-sensitive preferences and generate recommendations, our project adopts existing collaborative filtering methods to context-aware recommendation settings. Collaborative filtering is the technology that focuses on the relationships between users and between items to make a prediction. The goal of the recommender system is to compute a scoring function that aggregates the result of computing similarities between users and between items. It works by combining the opinions of people who have expressed inclinations similar to uses in the past to make prediction. CF can be applied to web applications for which the context is defined. Based on the concept we have mentioned, the methodology we would follow for this project is first we explicitly extracted a music dataset from online social network services. This music collection contain four important data for this project: the music, the user data, the rating given by the user and the tag collection explicitly provided for each music. The next methodology we follow would be finding the similarity between items and users based on their preferences for both music discovery as tagging recommendations. The similarity calculation will be done by using a cosine similarity; and finally, based on the similarity result we obtain, we recommend music as well as the tag for the user.

The algorithms assume that if a user already listens an artist, it is reasonable to suggest music which offer similar content.

Moreover, starting from the idea that people tend to follow suggestions from other people with similar interests or needs, the algorithms take into consideration also users affinity.

A. Architecture

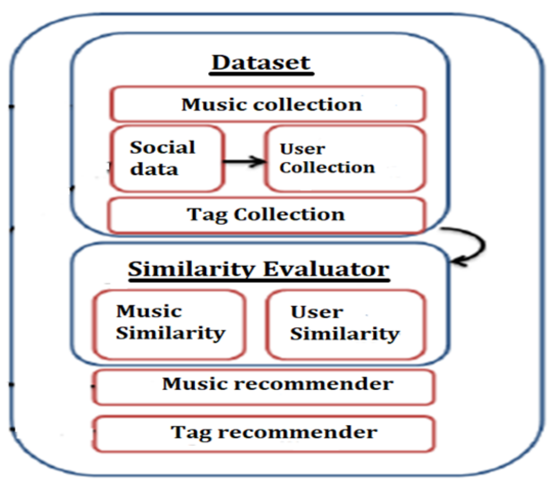

Fig.1 Architecture of our Recommender System

The architecture of the system is conceptual depicted in Fig.1. The Similarity Evaluator is the core component of the recommender, since it hosts all the algorithms to recommend music and tags to the user in context.

This module uses the Dataset as input, since it contains all the artist metadata, including the tags assigned by users.

B. Region Definition

Given U users and M artists, which can have multiple T tags, the relationship between users and artists can be denoted by an U ×M user-item matrix, while the relationship between artists and tags can be denoted by an M ×T item-tag matrix. An entry in the first matrix umi,j is 1 if the user i uses the artist j, 0 otherwise. In the same way, the second matrix can have an entry mtj,k which is equal to 1 if the artist j has the tag k associated, 0 otherwise.

An artist region is defined as a group of artists with similar context. A region is used to discover potential music and to recommend them to users in context. Artist regions can be derived by an M ×M item-item matrix, where an entry mmx,y represents the similarity value between artists x and y, and a sub-row of elements not equal to zero in this matrix represents a artist region.

A user region is defined as a group of users who have similar music usage experience. User regions can be derived by an U × U user-user matrix: here an entry uua,b represents the similarity value between a user a and a user b, and a sub-row of elements not equal to zero represents a user region.

A tag region is defined as a group of tags which are given to similar artists. Tag regions can be derived by an T × T tag-tag matrix: here an entry tta,b represents the similarity value between a tag a and a tag b, and a sub-row of elements not equal to zero represents a tag region.

Building regions (and the related matrices) helps the recommender to easily identify relationships in the dataset. Details of building user regions and artist regions are presented below section.

IV. SIMILARITY CRITERIA

To produce a recommendation, the algorithms work in three steps:

1) User region creation

2) Artist region creation

3) Artist or tag recommendation.

The similarity between two users a and b is done by cosine similarity. Which calculates the cosine measure between two vectors or between all column vectors of a matrix. Cosine() calculates a similarity matrix between all column vectors of a matrix x.

Artist similarities are evaluated by item-item matrix. Artist similarities are evaluated by comparing music (i.e., id, name, tags) through cosine similarity that produce a score between 0 and 1 derived by artist is assigned to a different dimension; therefore a artist is characterized by a vector whose elements are terms frequency. The cosine between vectors then gives a useful measure of the distance between them.

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In the following subsection, some usage scenarios are considered to explain the recommender functions.

A. Music Recommender

We use a User-based collaborative filter (UBCF) to recommender music to user based on context(contextual tags). This approach is to calculate distances to quantify how closely two users match each other in respect with a certain common item. For example, if user1 and user2 put in same ratings in the same item, the distance will be 0. On the other hand, assuming they give different ratings, the distance will be farther depending on the difference.

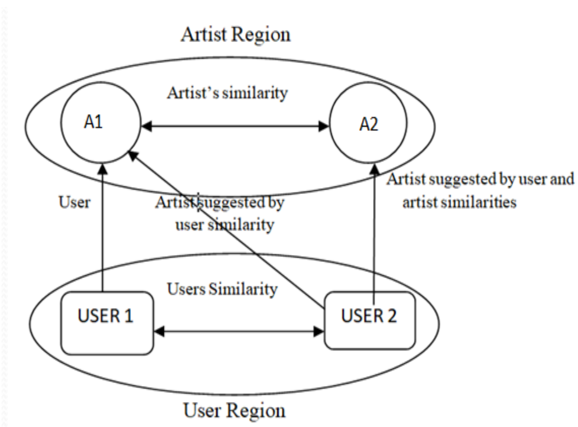

Fig.2 schema for Music recommender system

The main recommendation in this paper is recommending artists for similar users. The first scenario is related to the explicit use of a artist by the current user (as shown in Fig.2). The event triggers the computation of artist belonging to the same region (i.e., similar artist) for suggestions to:

a. The current user,

b. Users belonging the same user region of the current one (i.e., similar users).

a. **Similar Artist Recommendation for the current user**

Our recommenders system recommends similar artists to a specific artist. Given a collection of artists denoted as A1;A2;A3 belonging to the same artist region, as shown in Fig.3, the current user decides to use a artist m1. The music recommender module triggered in this scenario suggests, to the current user, all the other artist belonging to that region, by presenting scores in descending order. Each recommendation score is based on similarity

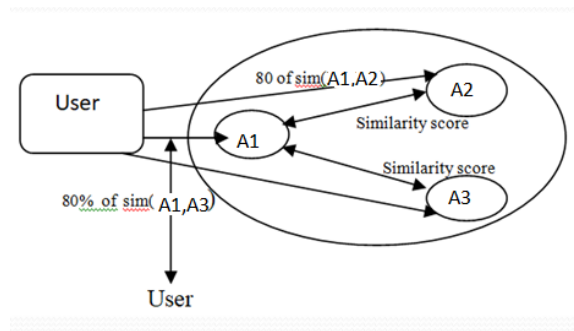

Fig.3 Similar music recommendation for current user

between the artist used and each other in the same region (evaluated through the cosine similarity). This approach takes into account that if a user uses a artist, it is reasonable to suggest artists with similar content.

b. Recommending similar artists to similar users

Considering the example in Fig.4, when the current user uses a artist A1, this artist is suggested to all the users belonging to the same user region, proportionally to the user

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similarity evaluated through cosine similarity (where a is the current user).

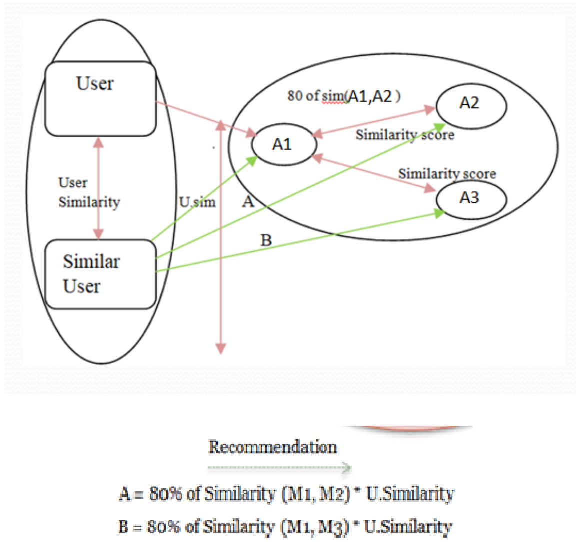

Fig.4 Artist recommendation schema for similar users

Considering the same example in Fig.4, when a current user uses a artist A1, other artists belonging to the same region are suggested not only to the current user, but, in the same way (i.e., considering the similarity score between the artist used and the other ones in the same region), also to other users belonging to the same User region of the current one, proportionally to user similarities evaluated through Cosine similarity.

B. Tag Recommender

The last scenario we take into consideration is related to the recommendation of tags, performed by the Tag recommender module shown in Fig.1 This scenario is triggered when a user wishes to tag a artist.

Considering the schema in Fig.5, given a collection of artists belonging to the same

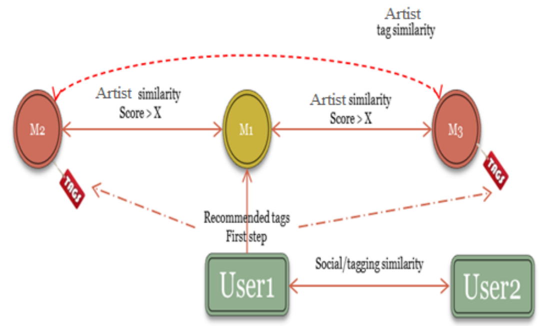

Fig.5 Schema of our Tag recommender system

region, denoted by m1, m2, m3, and tags related to the last two artists, the current user wishes to tag artist m1.

The main objective of this module is to facilitate the tagging action, in order to simplify search classifying artists by topics. The idea is to support users in selecting the proper set of tags with the aim of using a limited, shared and reliable dictionary. This approach avoids also mistakes for tag writing.

The tag recommendation algorithm is based mainly on dynamic artist regions and is organized into different steps.

In the first step, the algorithm collects the tags belonging to the artists whose similarity scores are higher than a threshold X (e.g. the average of scores). The tags already tied to the tagging artist are excluded from the collection.

In the next step, the score of each tag is evaluated by taking into account the:

• Number of times the tag is discovered;

• Number of times the tag is used by the current user;

• Artists similarity

By considering the above the steps we recommend tags to the user.

The recommender is implemented by using the Rstudio. We prefer to think of it of an environment within which statistical techniques are implemented. R can be extended (easily) via *packages*. There are about eight packages supplied with the R distribution and many more are available through the CRAN family of Internet sites covering a very wide range of modern statistics.

The interface used in the system is shinny application.The **Shiny** application includes the use of the **DT** package, which itself is a wrapper for the **Javascript** library provided within the **DataTables** package, as well as the use of **Cascading Style Sheets** (CSS).

V. EXPERIMENTAL SETUP

Data used by the recommender are Last.fm dataset..The Last.fm dataset is one of the largest available music recommendation system datasets. This dataset contains 359, 347 unique users and 17, 559, 530 total lines and includes user–artist–plays-tuples collected from the Last.fm API. This dataset contains user profile information such as gender, age, subscription date, country, and name. The dataset also contains information regarding which user listened to which artist and how many times based on data such as the user name, artist ID, artist name, and number of plays. Dataset contains only the artist information for the songs to which a user has listened. It also contain the artist Tag information. By analyzing the number of plays, one can determine the most popular artists for each user and the similarities among users' preferences. However, it is not possible to assess the similarities among artists or songs. Therefore, this dataset is best suited for training collaborative filtering methods for music recommendations.

VI. CONCLUSION AND FUTURE WORK

In this paper, we put forward a context aware music recommendation based on contextual tag information by making full use of the user's information and music,tag information. The paper focuses on three algorithms to suggest music and tags. The first one is used to find artist similarities by using an cosine similarity equation; the second one is used to find users similarities by using data which is explicity extracted from social networks; (c) the third one is used to select tags already assigned to artist that could be useful to characterize the artist in context. When tags are assigned, they contribute to extend artist data that improve precision and recall of search.

Experimental results show that the algorithm proposed in this paper can effectively improve the accuracy and speed of the algorithm so as to improve the quality of music recommendation and user experience. In the future, we will exploit all the information in the dataset (including additional data coming from specific social networks) to infer domain related interests, which could improve recommendation precision.

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