# GEOGRAPHICAL REGION MAPPING SCHEME BASED ON MUSICAL PREFERENCES

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## ABSTRACT

Many countries and cities in the world tend to have different types of preferred or popular music, such as pop, K-pop, and reggae. Music-related applications utilize geographical proximity for evaluating the similarity of music preferences between two regions. Sometimes, this can lead to incorrect results due to other factors such as culture and religion. To solve this problem, in this paper, we propose a scheme for constructing a music map in which regions are positioned close to one another depending on the similarity of the musical preferences of their populations. That is, countries or cities in a traditional map are rearranged in the music map such that regions with similar musical preferences are close to one another. To do this, we collect users' music play history and extract popular artists and tag information from the collected data. Similarities among regions are calculated using the tags and their frequencies. And then, an iterative algorithm for rearranging the regions into a music map is applied. We present a method for constructing the music map along with some experimental results.

## 1. INTRODUCTION

To recommend suitable music pieces to users, various methods have been proposed and one of them is the joint consideration of music and location information. In general, users in the same place tend to listen to similar kinds of music and this is shown by the statistics of music listening history. Context-aware computing utilizes this human tendency to recommend songs to a user.

However, the current approach of exploring geographical proximity for obtaining a user's music preferences might have several limitations due to various factors such as region scale, culture, religion, and language. That is, neighboring regions can show significant differences in music listening statistics and vice versa.

In fact, the geographical distance between two regions is not always proportional to the degree of difference in music preferences. For instance, assume that there are two neighboring countries having different music preferences. In the case of two regions near the border of the two countries, the people might show very different music preferences from those living in a region far from the border but in the same country. The degree of preference differences can be varied because of the difference in the sizes of the countries. Furthermore, the water bodies that cover 71% of the Earth's surface can lead to a disjunction of the differences.

Music from countries that have a high cultural influence might gain global popularity. For instance, pop music from the United States is very popular all over the world. Countries that have a common cultural background might have similar musical preferences irrespective of the geographical distance between them. Language is another important factor that can lead to different countries, such as the US and the UK, having similar popular music charts.

For these reasons, predicting musical preferences on the basis of geographical proximity can lead to incorrect results. In this paper, we present a scheme for constructing a music map where regions are positioned close to one another depending on the musical preferences of their populations. That is, regions such as cities in a traditional map are rearranged in the music map such that regions with similar musical preferences are close to one another. As a result, regions with similar musical preferences are concentrated in the music map and regions with distinct musical preferences are far away from the group.

The rest of this paper is organized as follows: In Section 2, we present a brief overview of the related works. Section 3 presents the scheme for mapping a geographical region to a new music space. Section 4 describes the experiments that we performed and some of the results. In the last section, we conclude the paper with directions for future work.

## 2. RELATED WORK

Many studies have tried to utilize location information for various music-related applications such as music search and recommendation. Kaminskas et al. presented a context-aware music recommender system that suggests music items on the basis of the users' contextual conditions, such as the users' mood or location [1]. They defined the term "place of interest (POI)" and considered the selection of suitable music tracks on the basis of the POI. In [2], Schedl et al. presented a music recommenda-

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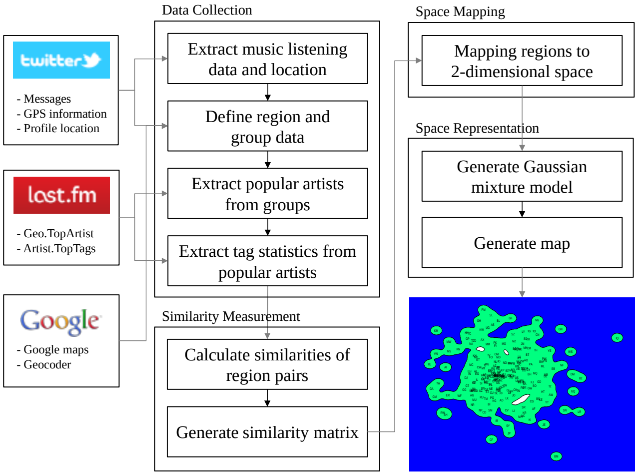



**Figure 1.** Overall scheme

**Figure 2.** Collected data from twitter

tion algorithm that combines information on the music content, music context, and user context by using a data set of geo-located music listing activities. In [3], Schedl et al derived and analyzed culture-specific music listening patterns by collecting music listening patterns of different countries (cities). They utilized social microblog such as Twitter and its tags in order to collect music-related information and measure the similarities between artists. Jun et al. presented a music recommender that considers personal and general musical predilections on the basis of time and location [4]. They analyzed massive social network streams from twitter and extracted the music listening histories. On the basis of a statistical analysis of the time and location, a collection of songs is selected and blended using automatic mixing techniques. These location-aware methods show a reasonable music search and recommendation performance when the range of the place of interest is small. However, the aforementioned problems might occur when the location range increases. Furthermore, these methods do not consider the case where remote regions have similar music preferences, which is often the case.

On the basis of these observations, in this paper, we propose a new data structure called a "music map", where regions with similar musical preferences are located close to one another. Some pioneering studies to represent music by using visualization techniques have been reported. Lamere et al. presented an application for exploring and discovering new music by using a three-dimensional (3D) visualization model [5]. Using the music similarity model, they provided new tools for exploring and interacting with a music collection. In [6], Knees et al. presented a user interface that creates a virtual landscape for music collection. By extracting features from audio signals and clustering the music pieces, they created a 3D island landscape. In [7], Pampalk et al. presented a system that facilitates the exploration of music libraries. By estimating the perceived sound similarities, music pieces are organized on a two-dimensional (2D) map so that similar pieces are located close to one another. In [8], Rauber et al. proposed an approach to automatically create an organization of music collection based on sound similarities. A 3D visualization of music collection offers an interface for an interactive exploration of large music repositories.

## 3. GEOGRAPHICAL REGION MAPPING

In this paper, we propose a scheme for geographical region mapping on the basis of the musical preferences of the people residing in these regions. The proposed scheme consists of three parts as shown in Figure 1. Firstly, the music listening history and the related location data are collected from Twitter. After defining regions, the collected data are refined to tag the statistics per region by querying popular artists and their popularities from last.fm. Similarities between the defined regions are calculated and stored in the similarity matrix. The similarity matrix is represented into a 2D space by using an iterative algorithm. Then, a Gaussian mixture model (GMM) is generated for constructing the music map on the basis of the relative location of the regions.

### 3.1 Music Listen History and Location Collection

By analyzing the music listening history and location data, we can find out the music type that is popular in a certain city or country. In order to construct a music map, we need to collect the music listening history and location information on a global scale. To do this, we utilize last.fm, which is a popular music database. However, last.fm has several limitations related to the coverage of the global music listening history. The most critical one is that the database provides the listening data of a particular country only. In other words, we cannot obtain the data for a detailed region. Users in some countries (not all countries) use last.fm, and it does not contain sufficient data to cover the preferences of all the regions of these countries. Because of this, we observed that popular music in the real world does not always match with the last.fm data.

On the other hand, an explosive number of messages are generated all over the world through Twitter. Twitter is one of the most popular social network services. In this study, we use Twitter for collecting a massive amount of music listening history data. By filtering music-related messages from Twitter, we can collect various types of

| | | |
|---|---|---|
| #nowplaying | #np | #music |
| #soundcloud | #musicfans | #listenlive |
| #hiphop | #musicmondays | #pandora |
| #mp3 | #itunes | #newmusic |

Table 1. Music-related hashtags.

| |
|---|
| <Phrase A> by < Phrase B> |
| < Phrase A> - < Phrase B > |
| < Phrase A > / < Phrase B > |
| “< Phrase A >” - < Phrase B > |

Table 2. Typical syntax for parsing song title and artist

music-related information, such as artist name, song title, and the published location. Figure 2 shows the distribution of the collected music-related tweets from around the world.

We used the Tweet Stream provided through a Twitter application processing interface (API) for collecting tweets. In order to select only the music-related tweets, we used music-related hashtags. Hashtags are very useful for searching the relevant tweets or for grouping tweets on the basis of topics. As shown in Table 1, we used the music-related hashtag lists that have been defined in [4]. Music-related tweet messages contain musical information such as song title and artist name. These textual data are represented in various forms. In particular, we considered the patterns shown in Table 2 for finding the artist names and the song titles. We employed a local MusicBrainz [9] server to validate the artist names.

For collecting location information, we gathered global positioning system (GPS) data that are included in tweet messages. However, we observed that the number of tweets that contain GPS data is quite small considering the total number of tweets. To solve this, we collected the profile location of the user who published a tweet message. Profile location contains the text address of the country or the city of the user. We employed the Google Geocoding API [10] for validating the location name and converting the address to GPS coordinates.

### 3.2 Region Definition and Tag Representation

Using the collected GPS information, we created a set of regions on the basis of the city or country. For grouping data by city name or country name, the collected GPS information is converted into its corresponding city or country name. In this study, we got 1327 cities or 198 countries from the music listening history collected through Twitter.

For each region, we collect two sets $A_r$ and $AC_r$ of referred artist names and their play counts, respectively:

$$A_r = \{a_1, \dots, a_n\} \quad (1)$$

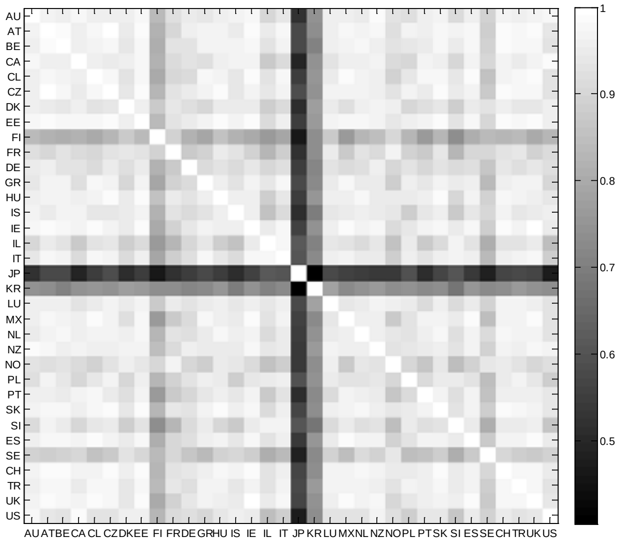



**Figure 3**. Tag similarity matrix of 34 countries

$$AC_r = \{ac_1, \dots, ac_n\} \quad (2)$$

where $n$ is the number of referred artists. Also, using an artist name, we can collect his/her tag list. For a region $r$, we construct a set $T_r$ of top tags by querying top tags to last.fm using the artist names of the region $r$ as follows:

$$T_r = \{getTopTags(a_1) \cup \dots \cup getTopTags(a_n) \mid a_i \in A_r\} \\ = \{t_1, \dots t_m\} \quad (3)$$

where *getTopTags*($a$) returns a list of top tags of artist $a$ and $m$ is the number of collected tags for the region $r$. We define a function *RTC*($r$, $t$) that calculates the total count of tag $t$ in region $r$ using the following equation:

$$RTC(r,t) = \sum_{a_i \in A_r} ac_i \times getTagCount(a_i, t) \quad (4)$$

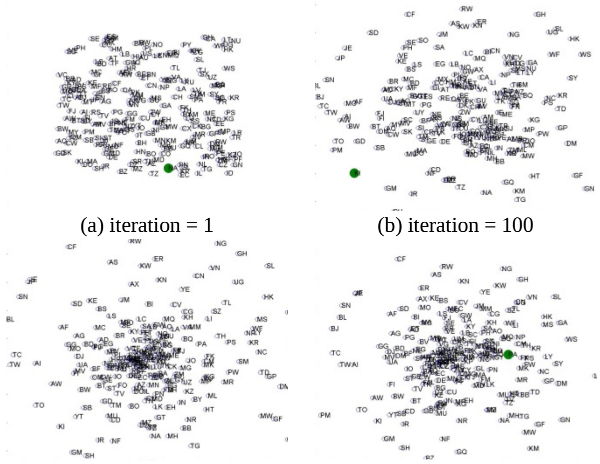
Here, *getTagCount*($a$, $t$) returns the count of tag $t$ for the artist $a$ in last.fm. In the same vein, *RTC* can return a set of tag counts when the second argument is a tag set $\boldsymbol{T}$.

$$RTC(r, \boldsymbol{T}) = \{RTC(r,t_1), \dots, RTC(r,t_m) \mid t_i \in \boldsymbol{T}\} \quad (5)$$

### 3.3 Similarity Measurement

To construct a music map of regions, we need a measurement for estimating musical similarity. In this paper, we assume that music proximity between regions is closely related to the artists and their tags because the musical characteristics of a region can be explained by the artists’ tags of the region. In particular, in order to measure the similarity among the regions represented by the tag groups, we employed a cosine similarity measurement as shown in the following equation:

$$TSM(r_1, r_2) = \frac{RTC(r_1, \boldsymbol{T}_u) \times RTC(r_2, \boldsymbol{T}_u)}{|RTC(r_1, \boldsymbol{T}_{r_1})| \times |RTC(r_2, \boldsymbol{T}_{r_2})|} \quad (6)$$



(a) iteration = 1 (b) iteration = 100

(c) iteration = 400 (d) iteration = 1000

**Figure 4**. Example of mapped space in iterations

$$\boldsymbol{T}_u = \boldsymbol{T}_{r_1} \cap \boldsymbol{T}_{r_2} \tag{7}$$

The cosine similarities of all possible pairs of regions were calculated and stored in the tag similarity matrix TSM. Hence, if there were m regions in the collection, we obtained a TSM of $m \times m$. A sample TSM for 34 countries is shown in Figure 3.

### 3.4 2D Space Mapping

On the basis of the TSM, we generated a 2D space for a music map by converting tag similarities between regions into proper metric for 2D space mapping. In this paper, this conversion is done approximately using an iterative algorithm. The proposed algorithm is based on the computational model such as a self-organizing map and an artificial neural network algorithm. By using an iterative phase, the algorithm gradually separates the regions in inverse proportion to the tag similarity.

#### *3.4.1 Initialization*

In the initialization phase, 2D space is generated where X-axis and Y-axis of the space have ranges from 0 to 1. Each region is randomly placed on the 2D space. We observed that our random initialization does not provide deterministic result of the 2D space mapping.

#### *3.4.2 Iterations*

In each iteration, a region in the 2D space is randomly selected and the tag distance *TD* between the selected region $r_s$ and any other region $r_i$ is computed using the similarity matrix.

$$TD(r_s, r_i) = 1 - TSM(r_s, r_i) \tag{8}$$

Subsequently, Euclidean distances *ED* between the selected region $r_s$ and other region $r_i$ is computed using the following equation

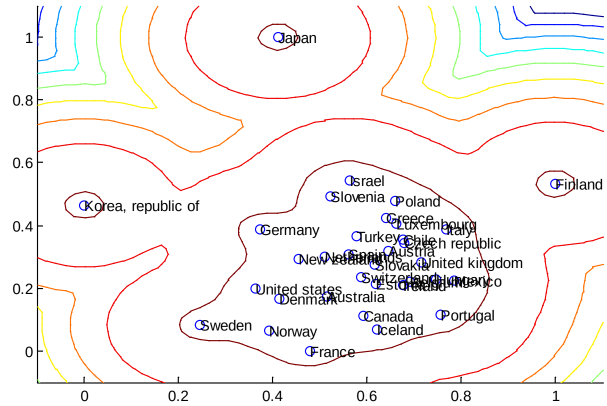




**Figure 5**. Gaussian mixture model of 34 countries

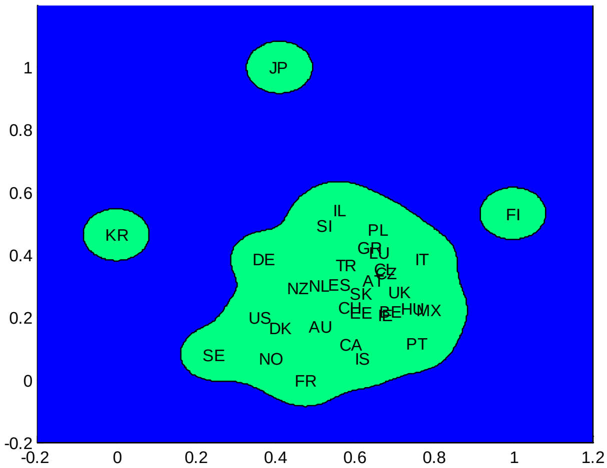




**Figure 6.** Music map of 34 countries

$$ED(r_s, r_i) = \sqrt{\left(x(r_s) - x(r_i)\right)^2 + \left(y(r_s) - y(r_i)\right)^2} \tag{9}$$

where $x(r_i)$ and $y(r_i)$ returns x and y positions of the region $r_i$ in 2D space, respectively. In order for *TD* and *ED* to have same value as much as possible, the following equation is applied

$$x(r_i) = x(r_i) + \lambda(t)\left(ED(r_s, r_i) - TD(r_s, r_i)\right)\frac{(x(r_s) - x(r_i))}{ED(r_s, r_i)} \tag{10}$$

$$y(r_i) = y(r_i) + \lambda(t)\left(ED(r_s, r_i) - TD(r_s, r_i)\right)\frac{(y(r_s) - y(r_i))}{ED(r_s, r_i)} \tag{11}$$

Here, $\lambda(t)$ is a learning rate in *t*-th iteration. The learning rate is monotonically decreased during iteration according to the following equation

$$\lambda(t) = \lambda_0 \exp(-t/T) \tag{12}$$

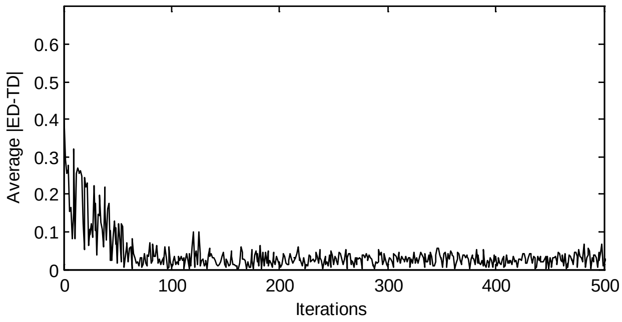



**Figure 7**. Average difference of distances in iterations

$\lambda_0$ denotes the initial learning rate, and T represents the total number of iterations. After each iteration, regions having higher TD are located far away from the selected region and regions having lower TD are located closer. Figure 4 shows examples of the mapped space after iterations.

### 3.5 Space Representation

After 2D space mapping, the regions are mapped such that regions having similar music preferences are placed close to one another. As a result, they form distinct crowds in the 2D space. In contrast, regions having unique preferences are placed apart from the crowds. To represent them as a map, a 2D distribution on the space is not sufficient. In this paper, in order to represent the information like a real world map, we employed the GMM. The Gaussian with diagonal matrix is constructed using the following equations:

$$\mu(\mathrm{i}) = \{x(r_i), y(r_i)\} \qquad (13)$$

$$\sigma(\mathrm{i}) = \begin{bmatrix} {}^{1}/_{8n} & 0 \\ 0 & {}^{1}/_{8n} \end{bmatrix} \qquad (14)$$

$$p(\mathrm{i}) = \frac{1}{nn(r_i)} \qquad (15)$$

Here, $n$ is total number of regions and $nn(r_i)$ returns the number of neighboring regions of region $r_i$ in the 2D space. To model the GMM in the crowded area of 2D space, mixing proportion $p(i)$ is adjusted based on the number of neighbors $nn(r_i)$. In other words, $nn(r_i)$ has a higher value when $p(i)$ is crowded and it reduces the proportion of $i$-th Gaussian. It helps to prevent Gaussian from over-height. An example of generated GMM is shown in Figure 5.

To generate a music map using the GMM, the probabilistic density function (pdf) of the GMM is simplified by applying a threshold. By projecting the GMM on the 2D plane after applying the threshold to the pdf, the boundaries of the GMM are created. We empirically found that the threshold value 0 gives an appropriate boundary. A boundary represents regions as a continent

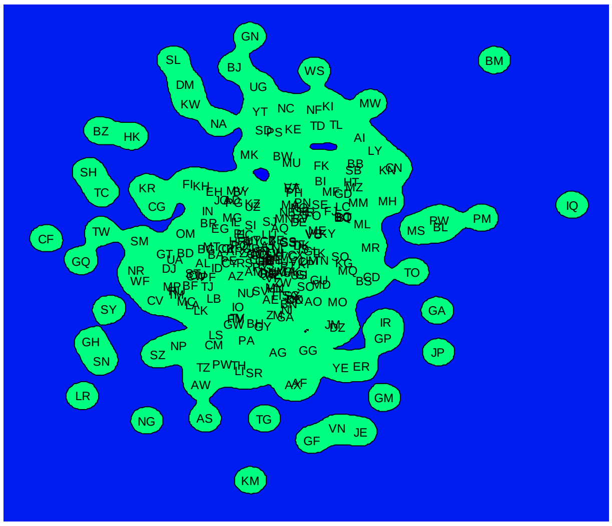


**Figure 8**. Music map of 239 countries

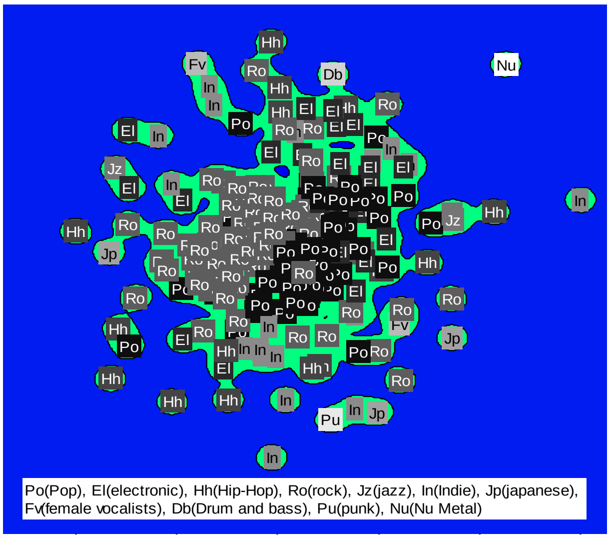



**Figure 9**. Top tags of music map.

or a small island on the basis of their distribution. As a result, the mapped result is visualized as a music map having an appearance similar to that of a real world map. An example of a music map for 34 countries is shown in Figure 6. Although the generated music map contains less information than the contour graph of GMM, it could be more intuitive to the casual users to understand the relations between regions in terms of music preferences.

## 4. EXPERIMENT

### 4.1 Experiment Setup

To collect the music-related tweets, we gathered the tweet streams from the Twitter server in real time in order to collect the music information of Twitter users. During one week, we collected 4.57 million tweets that had the hashtags listed in Table 1. After filtering the tweets through regular expressions, 1.56 million music listening history records were collected. We got 1327 cities or 198 countries from the music listening history collected through Twitter. We collected the lists of the top artists for 249 countries from last.fm. For these countries, 2735 artists and their top tags were collected from last.fm.

### 4.2 Differences of ED and TD

In the proposed scheme, the iterative algorithm gradually reduces the difference between ED and TD, as mentioned above. In order to show that the algorithm reduces the difference and moves the regions appropriately, the average difference between ED and TD is measured in each iteration. Figure 7 shows the average distances during 500 iterations. The early phases in the computation show high average distance differences due to the random initialization. As the iteration proceeds, the average distance differences are gradually reduced and converged.

### 4.3 Map Generation for 249 Countries

In order to evaluate the effectiveness of the proposed scheme, we defined a region group that contained 249 countries. After collecting the music listening history from Twitter and last.fm, we generated a music map by using the proposed scheme. Figure 8 shows the resulting music map. We observed that the map consisted of a big island (continent) and a few small islands. In the center of the big island, countries that had a high musical influence, such as the US and the UK, were located. On the other hand, countries having unique music preferences such as Japan and Hong Kong were formed as small islands and located far away from the big island.

### 4.4 Top Tag Representation

A music map is based on the musical preferences between regions, and these preferences were calculated on the basis of the similarities of the musical tags. In the last experiment, we first find out the top tag of each country and show the distribution of the top tags in the music map. Figure 9 shows the top tags of the map in Figure 8. In the map, “Rock” and “Pop”, which are the most popular tags in the collected data, are located in the center and occupies a significant portion of the big island. On the north side of the big island, “Electronic” tag is located and in the south, “Indie” tag is placed. The “Pop” tag, which is popular in almost every country, is located throughout the map.

## 5. CONCLUSION

In this paper, we proposed a scheme for constructing a music map in which regions such as cities and countries are located close to one another depending on the musical preferences of the people residing in them. To do this, we collected the music play history and extracted the popular artists and tag information from Twitter and last.fm. A similarity matrix for each region pair was calculated by using the tags and their frequencies. By applying an iterative algorithm and GMM, we reorganized the regions into a music map according to the tag similarities. The possible application domains of the proposed scheme span a broad range—from music collection, browsing services, and music marketing tools, to a worldwide music trend analysis.

## 6. ACKNOWLEDGEMENT

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