Improving Music Recommendation Using Distributed Representation

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ABSTRACT

In this paper, a music recommendation approach based on distributed representation is presented. The proposed approach firstly learns the distributed representations of music pieces and acquires users' preferences from listening records. Then, it recommends appropriate music pieces whose distributed representations are in accordance with target users' preferences. Experiments on a real world dataset demonstrate that the proposed approach outperforms the state-of-the-art methods.

Keywords

music recommendation; distributed representation

1. INTRODUCTION

Nowadays, digital music market is growing rapidly due to the prevalence of mobile devices and advance in the Internet technology. It is more important than ever to help people find the interested music pieces from massive music contents available on the Internet. How to extract the feature of music and incorporate them into music recommendation is still a challenging task. To address this problem, we present a music recommendation approach based on distributed representation. Firstly, the proposed approach learns the distributed representations (vectors in real-valued, low-dimensional space) of music pieces from all users' historical listening records. Then, it infers users' music preferences from their listening records with these distributed representations. Finally, our approach recommends appropriate music pieces according to target users' preferences to satisfy their requirements.

2. PROPOSED APPROACH

Music recommendation is to find music pieces that the target user would probably enjoy. Formally, let $U = \{u_1, u_2, ..., u_{|U|}\}$ be the user set and $M = \{m_1, m_2, ..., m_{|M|}\}$ be the music set. For each user u, his/her historical listening record is denoted as $H^u = \{m_1^u, m_2^u, ..., m_{|H^u|}^u\}$, where $m_i^u \in M$. Music in H^u are sorted according to the corresponding playing time. Then, our task specifies to be seeking for music that user u may enjoy given his/her listening record H^u. To address this task, we propose a music recommendation approach, which consists of three steps: distributed representation learning, users' preferences acquisition, and recommendation.

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Firstly, we propose the *music2vec* model to learn the distributed representations of all music pieces. Specifically, the *music2vec* model adopt a skip-gram model [1], which is much more efficient as well as memory-saving than other approaches, to learn the distributed representation by maximizing the objective function over music sequences in all users' listening records. The underlying idea of *music2vec* is that similar music pieces should have similar contexts. Formally, the objective function is defined as follows:

$$\mathcal{L} = \sum_{u \in U} \sum_{m_i^u \in H^u} \sum_{-c \le j \le c, j \ne 0} \log p(m_{i+j}^u \mid m_i^u) \tag{1}$$

where c is the length of the context window. $p(m_{i+j}^u \mid m_i^u)$ represents the probability of observing a neighbor music piece m_{i+j}^u given the current music item m_i^u in u's record H^u, which is formally defined using the soft-max function as follows:

$$p(m_{i+j}^u \mid m_i^u) = \exp(\mathbf{v}_{m_i^u}^T \cdot \mathbf{v}'_{m_{i+j}^u}) \Big/ \sum_{m \in M} \exp(\mathbf{v}_{m_i^u}^T \cdot \mathbf{v}'_m) \tag{2}$$

where $\mathbf{v}_m$ and $\mathbf{v}'_m$ are the input and output distributed representations of music m, respectively. In the learning phase, we need to maximize the objective function defined in Equation 1 over all users' historical listening records. However, the complexity of computing corresponding soft-max function defined in Equation 2 is proportional to the music set size, which can reach millions easily. In this paper, we adopt negative sampling [1] to increase computation efficiency by generating a few noise samples for each input music to estimate the target music. Therefore, the training time yields linear scale to the number of noise samples. Finally, the distributed representations of all music pieces can be obtained.

Then, music preference of the target user is inferred from his/her historical listening record using the following formula:

$$\mathbf{p}_u = \frac{1}{|H^u|} \sum_{m_i^u \in H^u} \mathbf{v}_{m_i^u} \tag{3}$$

where $\mathbf{v}_{m_i^u}$ is the learned distributed representation of music m_i^u using *music2vec* model.

Finally, we propose a music recommendation method which can recommend music pieces appropriate music pieces whose distributed representations are in accordance with target users' preferences. Specifically, the predicted interest *pi* of the target user *u* in music piece *m* is the cosine similarity between *u*'s music preference $\mathbf{p}_u$ and *m*'s distributed representation $\mathbf{v}_m$, which is defined as follows:

$$pi(m \mid u, \mathbf{p}_u) = \cos(\mathbf{p}_u, \mathbf{v}_m) \tag{4}$$

Therefore, the ranking of music pieces $>_{u,\mathbf{p}_u}$ in our approach is defined as

$$m_i >_{u,\mathbf{p}_u} m_i' :\Leftrightarrow pi(m_i \mid u, \mathbf{p}^u) > pi(m_i' \mid u, \mathbf{p}^u) \tag{5}$$

We then can recommend the music pieces with high ranking scores (similar to user's musical preference) to the target user.

3. EXPERIMENTS

The experiments consist of two parts: evaluation of *music2vec* and the comparison of the proposed approach with baselines.

Firstly, we illustrate the effect of *music2vec* model by visualizing similarity among music pieces given in Table 1. As shown in Figure 1, music pieces with similar styles, such as singers, tags, and genres, have similar distributed representations. For example, "Summer" and "Moonlit Sea of Clouds", which have the same genre and player, do lie nearby in the real-valued distributed representation space. Besides, neither of these two music pieces has similar distributed representations with the other music pieces in Table 1. Therefore, the learned distributed representations with *music2vec* capture useful features effectively and depict music pieces well.

Table 1. Basic information of music examples

No	Name-Singer	Tags
1	Hero-Mariah Carey	pop, female vocalists, 90s, ballad
2	Without You-Mariah Carey	pop, female vocalists, soul, love
3	Drowning-Backstreet Boys	pop, boy bands, ballad
4	My Love-Westlife	pop, boy bands, Irish
5	Don't Cry-Guns N' Roses	classic rock, hard rock, ballad
6	Hotel California-Eagles	classic rock, rock, 70s
7	Fall Again-Kenny G	smooth jazz, R&B, Soul
8	Heart and Soul-Kenny G	smooth jazz, Rhythm and blues
9	Summer-Joe Hisaishi	sound track, Japanese, anime, instrumental, classical
10	Moonlit Sea of Clouds-Joe Hisaishi	sound track, Japanese, anime, instrumental, classical

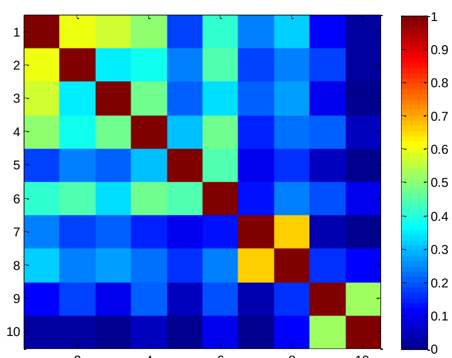

Figure 1. Similarity visualization of music examples with distributed representations

Then, we compare the proposed method with three state-of-the-art recommendation algorithms, including Bayesian Personalized Ranking (BPR) [2], FISMauc (FISM) [3], and user based collaborative filtering method (UserKNN) [4] on a real world dataset collected from Xiami Music (http://www.xiami.com/). From the comparison results in Table 2, we can see that our approach outperforms baselines in terms of F1 score and hitrate. Taking the F1 score as an example, when compared with BPR, FISM, and UserKNN with the recommending number being 10, the relative performance improvement achieved by the proposed approach is around 33.3%, 20.7%, and 42.2%, respectively. The improvements indicate that our approach is more effective than baselines in acquiring users' preference and assisting music recommendation.

In conclusion, the proposed approach can effectively recommend music pieces appropriate for target users and satisfy their preferences well.

Table 2. Comparisons with baselines

Methods	F1, %		Hitrate, %	
	@10	@20	@10	@20
Our approach	**7.88**	**9.23**	**36.65**	**43.14**
BPR	5.91	7.13	26.96	30.21
FISM	6.53	7.50	29.68	33.52
UserKNN	5.54	6.34	22.72	25.61

4. CONCLUSIONS AND FUTURE WORK

We present a music recommendation approach, which learns the distributed representations of music pieces from users' historical listening records, and utilizes these distributed representations to acquire users' music preferences and recommend appropriate music pieces. Experimental results show the effectiveness of the proposed approach. There are two possible future directions. Firstly, we plan to combine the distributed representation with more advanced recommendation techniques [5, 6], to further improve the performance. Secondly, we will try to evaluate our approach by online experiments.

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