An MPD Player with Expert Knowledge-based Music Recommendation

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Abstract

This work demonstrates a music player based on Music Player Daemon (MPD), a protocol popular for audiophiles, with personalized music recommendation. Different from collaborative filtering based recommendation, which relies on usage patterns from a large number of users, we propose a novel approach that does not require other users' information. We formulate the recommendation as a task of knowledge base completion and exploit the expert knowledge from a music knowledge base. The effectiveness of our approach is evaluated, and the player is released as an open-source software for music lovers.

1 Introduction

Modern approaches to music recommendation are mainly developed for online content distribution platforms such as Spotify.[1] For example, collaborative filtering extracts the association between customers and items (i.e. albums or tracks) from a large amount of logs from numerous users [Chen *et al.*, 2016]. On the other hand, content-based approach that models the association between customers and the acoustic features extracted from a wide range of audio contents [van den Oord *et al.*, 2013]. Whether it is a large number of user logs or a full coverage of audio contents, both are exotic resources exclusive to the large-scale music content providers or distributors. The preference of music being controlled by a few giant companies can be a serious issue both for the progress of the music industry and for the freedom of customers: Choices are limited by the commercial cooperation, and the diversity is clamped down.

Some music lovers keep away from online music services and still lend toward maintain their own recording collections. They purchase hi-definition audio files from the Internet or rip the tracks from CDs and store the audio files in their own computer or NAS. For music listening, they play an album from their collections with standalone music players, no giant company is involved in monitoring and controlling their behaviors. For these users, however, suggestions about the next album to purchase or the next artist to explore are still somewhat desired. For this reason, we present an alternative approach to music recommendation without the need of others' logs and audio contents.

This work investigates the music recommendation from a novel perspective. Instead of collaborative filtering-based and content-based approaches, our model predicts the next album to purchase or the next artist to explore by knowledge base inference. We formulate the recommendation as a special case of knowledge base completion. A music knowledge base is constructed by extracting expert knowledge from a long-established online music database, All Music Guide,[2]. All musicians and recordings are entities in the knowledge base, and their relations are labeled in several types. Our knowledge base contains not only the fundamental information such as styles, genres, themes, and moods of musicians and recordings, but also the social network of musicians. The relationships among musicians such as similar, influenced by, and followed by are taken as important information for modeling the knowledge base inference.

Our recommendation model is integrated into a cross-platform, open-source music player, which is based on the Music Player Daemon (MPD)[3] protocol and can be easily used as a client for playing one's music collection. The contributions of this work are threefold as follows.

1. We present an alternative approach to music recommendation. By integrating expert knowledge, experimental results show the effectiveness of our model.
2. The approaches based on collaborative filtering suffer from the issue of bandwagon effects [Sundar *et al.*, 2008]. In contrast, our model for personalized music recommendation is free from the impact of the crowd.
3. We release our MPD player with the music recommendation model as an open-source software for the research community and the music lovers who object to be controlled by the giant companies.[4]

2 Music Knowledge Base

The music knowledge base plays the crucial role in our system. We construct a music knowledge base with the data

[1] www.spotify.com

[2] www.allmusic.com

[3] https://www.musicpd.org

[4] https://github.com/hhhuang/mpd_player

Type	Instances	Samples
Artist	11,162	The Beatles, Bob Dylan, U2
Album	79,488	Revolver, The Wall, Achtung Baby
Theme	187	Introspection, Reflection, Late Night
Mood	295	Playful, Reflective, Earnest
Style	776	Alternative, Indie Rock
Genre	21	Pop/Rock, R&B, Electronic, Jazz

Table 1: Statistics of the entities in our music knowledge base

crawled from All Music Guide, a large online music database comprised of the information of three millions of albums with metadata such as the styles, themes, genres, and ratings well-annotated by experts since 1991. One important information available from the database is the social network of artists. The social relations among artists are labeled in six categories, including SIMILARS, INFLUENCERS, FOLLOWERS, GROUPMEMBERS, ASSOCIATEDWITH, and COLLABORATORWITH. Specifically, an artist is either a musician or a group. For example, the Beatles is an artist, John Lennon is also an artist, and their relations are denoted as GROUPMEMBER(The Beatles, John Lennon). Table 1 shows the entities in the current version of our music knowledge base, which covers a total of 91,929 entities and 527,121 factual triples.

3 Method

Knowledge base completion is aimed at predicting the missing relation between two entities. For example, a musician's membership of a rock band is not labeled in a knowledge base, and the model for knowledge base completion is expected to inference the fact $h + r \approx t$, where the head entity h is the rock band, the tail entity t is the musician, and r is their relation, GROUPMEMBERS.

Approaches to knowledge base completion are roughly categorized into embedding-based method like TransE [Bordes *et al.*, 2013] and path-based method like path ranking [Kotnis *et al.*, 2015]. In this work, we formulate music recommendation as a task of knowledge base completion by considering the user as a special entity in the knowledge base with relations to preferred artists/albums. As illustrated in Figure 1, we add the user as an entity into the knowledge base and also add the LIKE relations between the user and those albums most played, since the log of each track has been played is captured by the MPD player. Then, we perform the knowledge embedding algorithm to model the relations among a variety of entities. In other words, we treat the user behaviour as facts and train the knowledge embedding model to inference user's preference. For the case in Figure 1, Pink Floyd's album *The Wall* will be recommended since the user enjoys the albums of the same and the similar artists.

4 Evaluation

We split an eight-year user log into two parts chronologically. The log records from the first five years are used for training the knowledge base, and the log records from the last three years are reserved for testing. We train the knowledge embeddings with the OpenKE package [Han *et al.*, 2018], which consists of a number implementations of famous algorithms

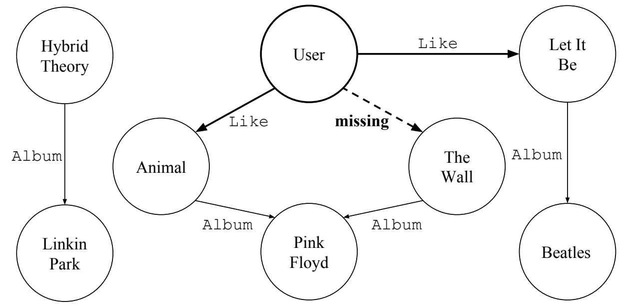

Figure 1: Recommendation made by recovering the missing link between the user and an album

Task	k	Accuracy	MRR
Next Artist	4	0.667	0.799
Next Artist	10	0.500	0.638
Next Artist	50	0.167	0.290
Next Album	4	0.619	0.802
Next Album	10	0.476	0.666
Next Album	50	0.333	0.475

Table 2: Performance of link prediction for next artist to explore and next album to purchase

for knowledge base representation. The TransE [Bordes *et al.*, 2013] model is employed in our system. The dimension of knowledge embeddings is 50, and the batch size is 100.

We evaluate our model with the task of link prediction at $k \in \{4, 10, 50\}$, denoting the number of candidates. For example, the model has to rank the positive instance (i.e. an album was frequently played from the last three years) higher than other three negative instances for the evaluation at $k = 4$. Table 2 reports the performance of our recommendation model in Accuracy and MRR. The performance remains robust even though a number of negative instances are added to mix up. We also explore more recent knowledge embedding models such as Bilinear-Diag[Yang *et al.*, 2014] and Complex Embeddings [Trouillon *et al.*, 2016], however, the simple TransE model outperforms the advanced ones in our application.

5 Conclusion

Modern technologies for music recommendation are mostly exclusive to the giant companies that possess countless user logs or audio contents. This paper demonstrates an alternative approach to personalized music recommendation for the music lovers who keep away from the music service platforms. Our recommendation system is smoothly integrated into an audiophile player based on the MPD protocol. Without the need of numerous users' logs, our novel approach exploits the single individual's log with expert knowledge. To the best of our knowledge, this is the first attempt to formulate music recommendation as a task of knowledge base completion. A comprehensive evaluation and user study will be conducted in the future work.

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