MODELING ARTIST PREFERENCES FOR PERSONALIZED MUSIC RECOMMENDATIONS

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EXTENDED ABSTRACT

Music recommender systems have become central parts of popular streaming platforms such as Last.fm, Pandora, or Spotify to help users find music that fits their preferences. These systems learn from the past listening events of users to recommend music a user will likely listen to in the future. While music recommender systems can provide quality recommendations to listeners of mainstream music artists, recent research [2] has shown that they tend to underserve listeners of unorthodox, low-mainstream artists. This is foremost due to the scarcity of usage data of low-mainstream music as music consumption patterns are biased towards popular artists (i.e., popularity bias) [3].

Thus, the objective of our work[1] is to provide a novel approach for modeling artist preferences of users with different music consumption patterns and listening habits. We focus on three user groups: (i) LowMS (i.e., listeners of unorthodox, niche music), (ii) HighMS (i.e., listeners of mainstream music), and (iii) MedMS (i.e., listeners of music that lies in between). The main problem we address in this work is how to exploit variations in listening habits to better serve users, whose listening behavior differs significantly from the mainstream. With that, we aim to realize music recommendations that are not biased towards the mainstream prevalent in a community.

In our work, we model user listening behavior on the level of music artists to describe a user's music taste. Since a user's music artist preferences may change over time [5], we take temporal drifts of a user's music listening habits into consideration. To do so, we utilize the Base-Level Learning (BLL) equation from the cognitive architecture ACT-R [1] to model music listening habits. The BLL equation accounts for the time-dependent decay of item exposure in human memory. It quantifies the usefulness of a piece of information based on how frequently and how recently it was accessed by a user and models this time-dependent decay using a power-law distribution [4]. In the present paper, we adopt the BLL equation to model the listening habits of users in the three groups and predict their music artist preferences. We name our approach BLL_u and demonstrate the efficacy of BLL_u using the *LFM-1b* dataset [6], which contains listening histories of more than 120,000 Last.fm users, amounting to 1.1 billion individual listening events over nine years: `http://www.cp.jku.at/datasets/LFM-1b/`.

Additionally, the dataset contains demographic data such as age and gender as well as a "mainstreaminess" factor, which relates a user's artist preferences to the aggregated preferences of all users (i.e., the mainstream). Based on this factor, we assign the users in our dataset (a subset of LFM-1b) to one of the three groups: (i) LowMS, (ii) MedMS, and (iii) HighMS. Thus, the 1000 users with the lowest mainstreaminess are in the LowMS group, the 1000 users with a mainstreaminess value centered around the median are in the MedMS group, and the users with the highest values are in the HighMS group.

The contributions of our work are two-fold. Firstly, we introduce BLL_u, an approach to model and predict artist preferences with the aim to provide personalized music recommendations. As our intention is to generate recommendations that are not biased towards the mainstream of the Last.fm community, we model the user's preference for an artist by considering how often this individual user has listened to this artist. Addi-

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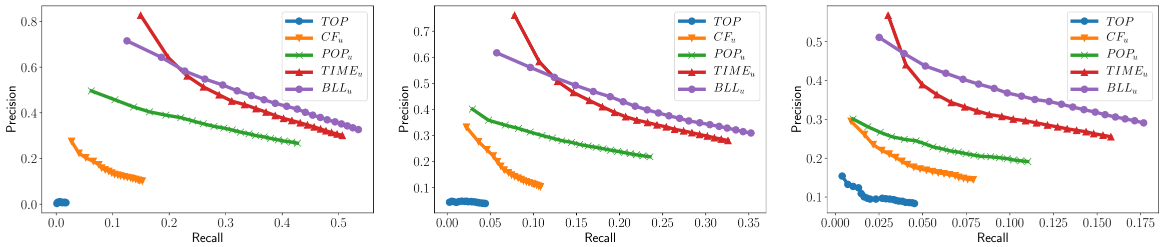

(a) User group: LowMS (b) User group: MedMS (c) User group: HighMS

Figure 1. Recall/precision plots of the baselines and our BLL_u approach for the three user groups LowMS, MedMS, and HighMS, and for $k = 1 \ldots 20$ predicted artists.

tionally, since music preferences are dynamic, we incorporate the user's temporal drifts of artist preferences into our model. Secondly, we evaluate our approach on three different groups of Last.fm users based on the distance of their listening behavior to the mainstream: (i) LowMS, (ii) MedMS, and (iii) HighMS.

For our evaluation, we split the user groups into train and test sets. We employ a time-based split, and we put the 1% most recent listening events of each user into the test set and keep the remaining listening events for training. This procedure leads to three test sets with 68,651 listening events for LowMS, 78,511 listening events for MedMS, and 82,030 listening events for HighMS. For each user, we aim to predict the artists in these listening events using our evaluation framework TagRec: `https://github.com/learning-layers/TagRec`.

Figure 1 illustrates the results of our evaluation in form of recall/precision plots. Here, we compare BLL_u to four baselines: (i) TOP, which recommends the most popular artists of all users, (ii) CF_u, which recommends artists using collaborative filtering, (iii) POP_u, which recommends the most popular artists of a specific user, and (iv) $TIME_u$, which recommends the artists a particular user has listened to most recently. We find that for all groups, BLL_u leads to the best accuracy results for predicting music artists and provides especially good results for the LowMS group. Interestingly, we also find that the time-based approach $TIME_u$ provides even better accuracy results than BLL_u when only predicting 1 or 2 artists.

We plan to extend our analysis to include more sophisticated mainstreaminess measures based on rank-order correlation or Kullback-Leibler divergence [2] since our current mainstreaminess measure is rather simplistic. Furthermore, we aim to integrate our findings into personalized music recommendation algorithms (e.g., for songs), with particular attention to avoid popularity bias and to better serve the low mainstreaminess group. The reason is that standard collaborative filtering approaches typically do not provide suitable music recommendations for this user group.

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