Modeling Artist Preferences for Fair Music Recommendations

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Problem

- While music recommender systems can provide quality recommendations to listeners of mainstream music artists, research has shown that they tend to discriminate listeners of low-mainstream artists.
- We provide a novel approach for modeling artist preferences of users with different music consumption patterns and listening habits.

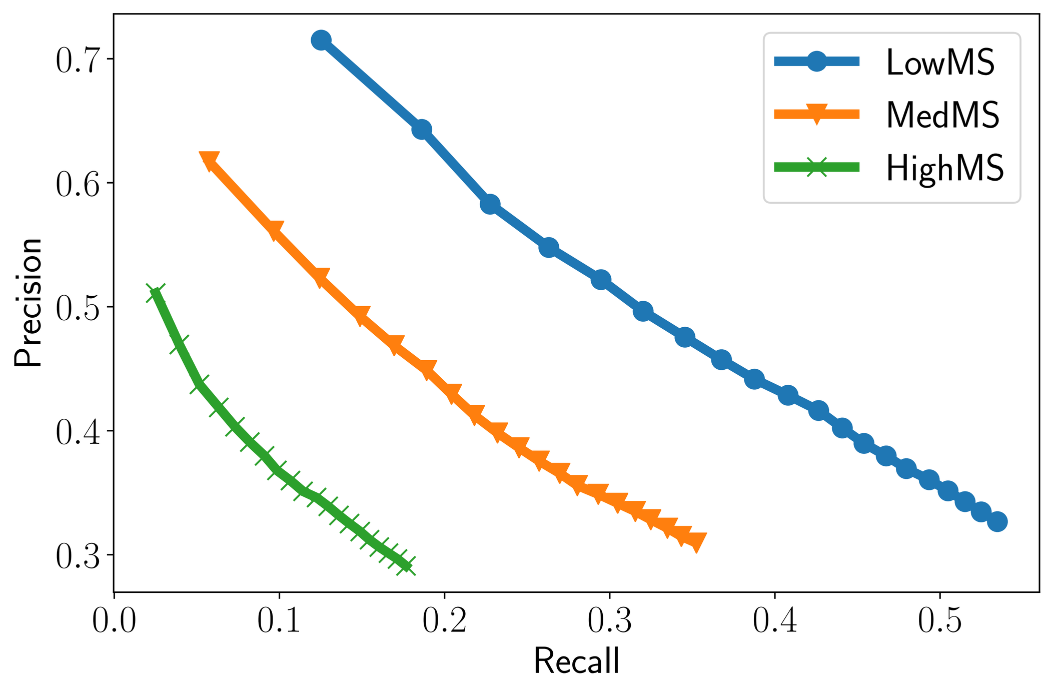
Approach

- Our proposed approach utilizes the Base-Level Learning (BLL) equation from the cognitive architecture ACT-R to describe music listening habits.
- The BLL equation accounts for the time-dependent decay of item exposure in human memory using a power-law function.
- It quantifies the usefulness of a piece of information (e.g., an artist a) based on how frequently and how recently it was accessed by a user u:

$$B_{u,a} = ln\left(\sum_{j=1}^{n} t_{u,a,j}^{-d}\right)$$

Conclusion

- BLL_u leads to the best accuracy results for predicting music artists and provides especially good results for the LowMS group.
- We reach a performance improvement with BLL_u over TOP of 50 times in the LowMS setting but only of 4 times in the HighMS setting.
- We plan to use the $B_{u,a}$ values we calculate for u and a as a context dimension in context-aware recommendation approaches.



Dataset & Framework

[1] Schedl, M. The LFM-1b Dataset for Music Retrieval and Recommendation In *Proc. of ICMR'2016*. ACM.

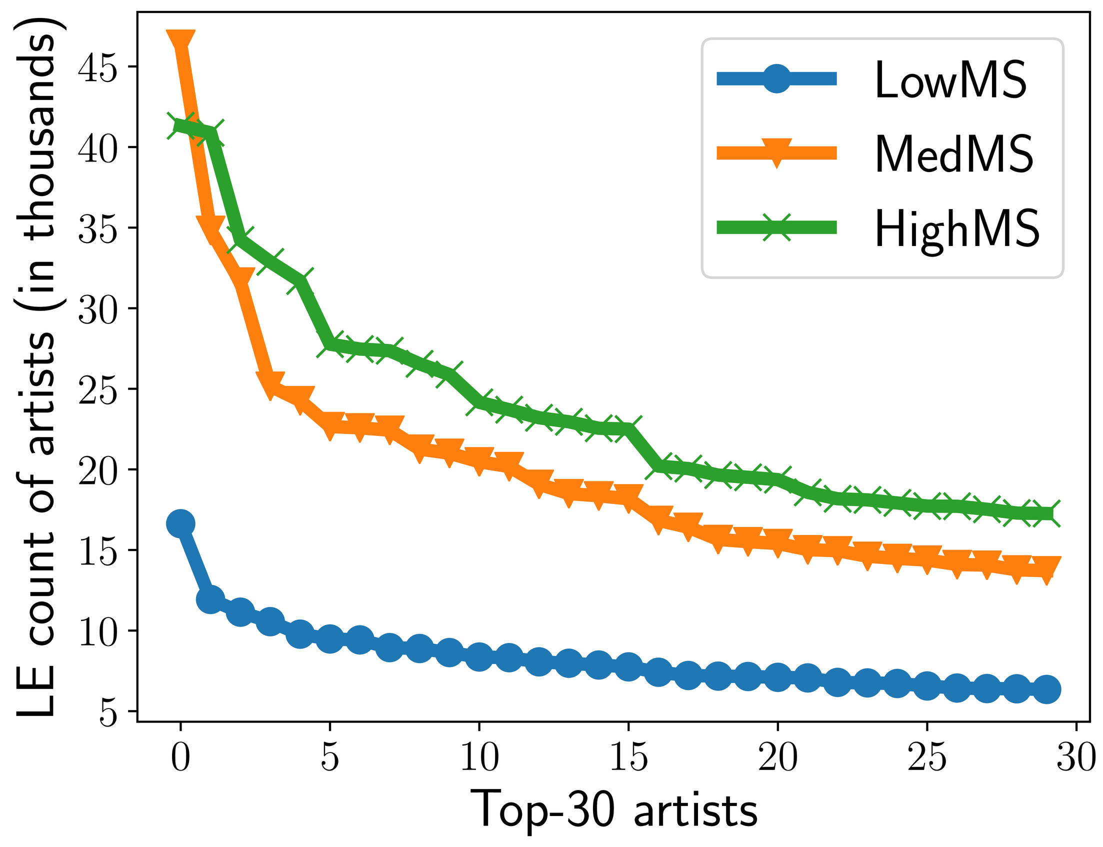
[2] Kowald, D., Kopeinik, S., and Lex., E. The TagRec Framework as a Toolkit for the Development of Tag-Based Recommender Systems. In *Proc. of UMAP'2017*. ACM.

LastFM User Groups Based on Mainstreaminess

Using the mainstreaminess scores (MS) of the LFM-1b dataset [1], we put the 1,000 users with lowest MS into the LowMS group, the 1,000 users with MS around the median into the MedMS group, and the 1,000 users with highest MS into the HighMS group.

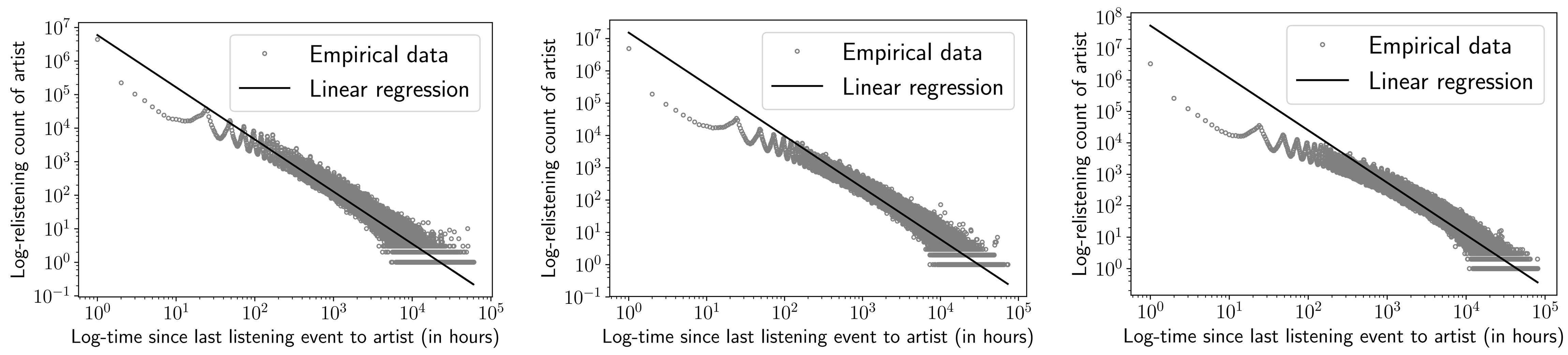
User Group	$\|U\|$	$\|A\|$	$\|LE\|$	$\|Avg.A/U\|$	$\|Avg.MS\|$	$\|Avg.Age\|$	M/F
LowMS	1,000	82,417	6,915,352	239	.125	24.582	74%/26%
MedMS	1,000	86,249	7,900,726	496	.379	25.352	68%/32%
HighMS	1,000	92,690	8,251,022	1,194	.688	21.486	65%/35%

The number of listening events (LE) for the top-30 artists of LowMS, MedMS and HighMS. While the artist distribution is balanced for LowMS, there are dominating artists for HighMS.



Temporal Drifts of Music Artist Preferences

The effect of time on artist relistening behavior of LastFM user groups. We find that the shorter the time since the last LE of an artist, the higher its relistening count.



(a) User group: LowMS
Linear reg.: R^2 = .893, α = -1.555

(b) User group: MedMS
Linear reg.: R^2 = .901, α = -1.599

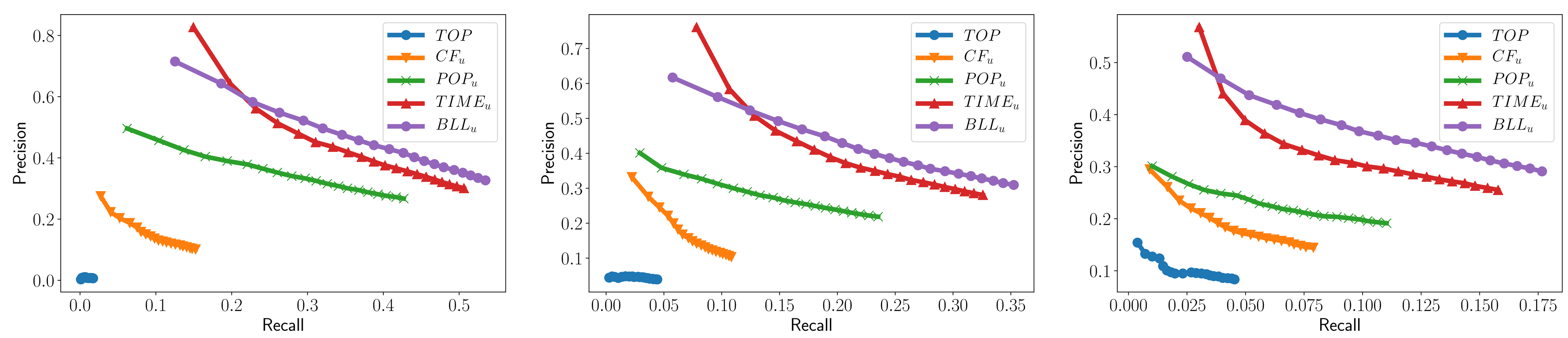
(c) User group: HighMS
Linear reg.: R^2 = .899, α = -1.664

Prediction of Music Artist Preferences

BLL_u outperforms 4 baselines: mainstream-aware modeling (TOP), collaborative-filtering (CF_u), popularity-aware modeling (POP_u) and time-aware modeling ($TIME_u$).

User group	Metric	TOP	CF_u	POP_u	$TIME_u$	BLL_u
LowMS	$F1@20$	.009	.121	.328	.377	**.405**
	$MAP@20$	.003	.069	.244	.381	**.391**
	$nDCG@20$	.011	.152	.395	.535	**.545**
MedMS	$F1@20$	.041	.105	.226	.301	**.329**
	$MAP@20$	.010	.055	.122	.228	**.231**
	$nDCG@20$	.040	.135	.248	.382	**.388**
HighMS	$F1@20$	.058	.102	.139	.195	**.219**
	$MAP@20$	.014	.034	.050	.102	**.110**
	$nDCG@20$	.059	.107	.139	.216	**.233**

Recall/precision plots of the baselines and our BLL_u approach for $k = 1 \ldots 20$ predicted artists. The evaluation was conducted using our TagRec framework [2].



(a) User group: LowMS

(b) User group: MedMS

(c) User group: HighMS