User-Dependent Learning to Debias for Recommendation

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Motivation

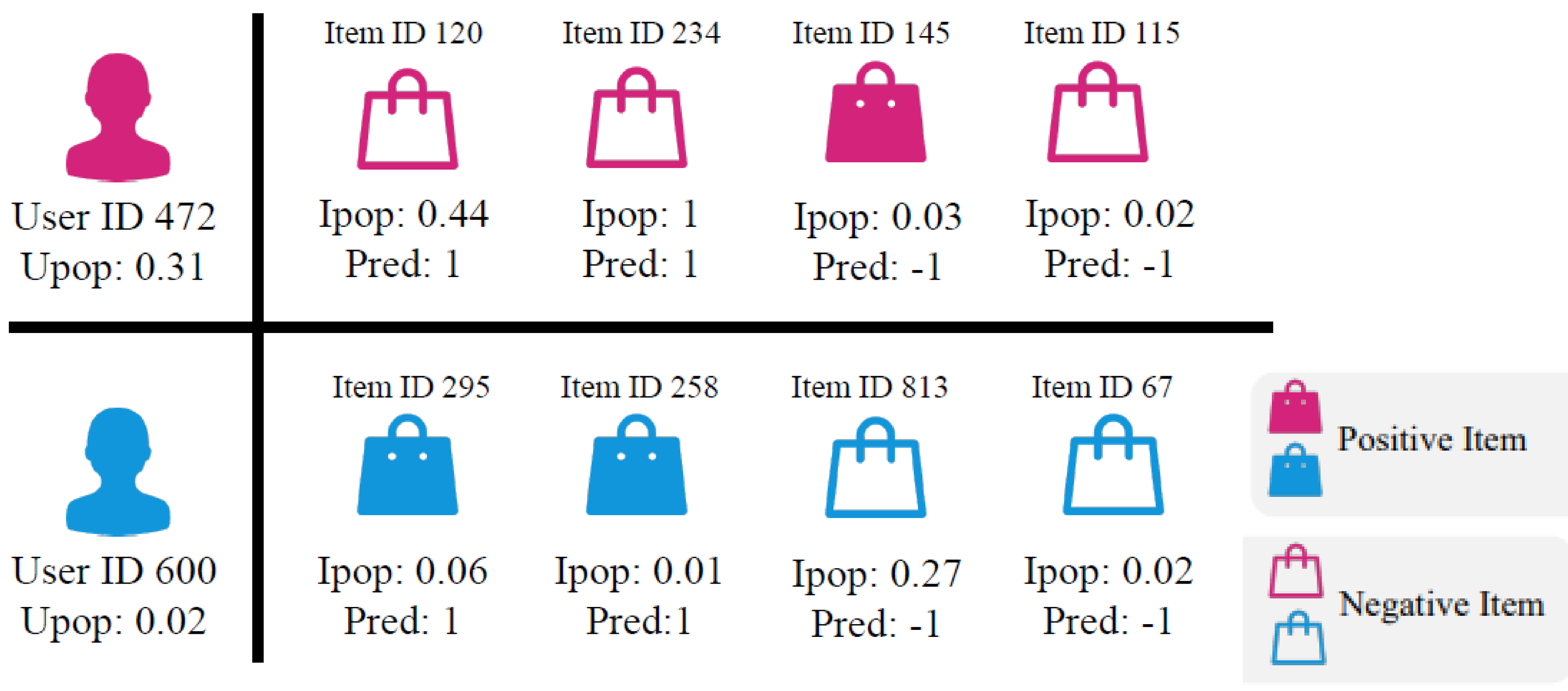


Figure 1: A case study of MF on Yahoo! R3 dataset

Popularity-Sensitive (PS) user ID 472 (0.31) is more prone to click items with high popularity, even if they are false positives, such as item ID 120 and 234. On the contrary, Popularity-Insensitive (PI) user ID 600 (0.02) is less influence by items' popularity. Despite the high popularity of item ID 813 (0.27), the user shows a low interest in it. It verifies that it is sub-optimal to treat all users equally and necessary to take into account users' popularity sensitivity, which has not been studied in unbiased recommender learning.

Method

➢ Propensity Estimation

item popularity: $Ipop_i = \frac{\sum_{u \in \mathcal{U}} \mathbb{I}(r_{ui}=1)}{max\_Ipop}$,

users' popularity sensitivity:

$$\rho_{ui} = Upop_u = \frac{\sum_{i \in \Omega_u} Ipop_i}{|\Omega_u|},$$

➢Unbiased Learning Objective

$$\mathcal{L}_{UDIPS} = \frac{1}{|\mathcal{U}||\mathcal{I}|} \sum_{(u,i):O_{ui}=1} \left(\frac{\alpha_u}{\rho_{ui}} \cdot \delta(\hat{r}_{ui}, r_{ui}) + (1-\alpha_u) \cdot \delta(\hat{r}_{ui}, r_{ui}) \right),$$

where $\alpha_u \in \{0, 1\}$ is a binary variable which is used to determine whether a user is sensitive to item popularity. Empirically, we set $\alpha_u = 1$ when users' popularity is larger than a threshold θ; otherwise, $\alpha_u = 0$.

➢Unbiasedness Analysis

$\alpha_u = 1$

$$\mathbb{E}\left[\mathcal{L}_{UDIPS}(\hat{\mathbf{R}}|\alpha_u=1)\right] = \mathbb{E}\left[\frac{1}{|\mathcal{U}||\mathcal{I}|} \sum_{(u,i):O_{ui}=1} \alpha_u \cdot \frac{1}{\rho_{ui}} \cdot \delta(\hat{r}_{ui}, r_{ui})\right]$$

$$= \frac{1}{|\mathcal{U}||\mathcal{I}|} \sum_{u\in\mathcal{U}} \sum_{i\in\mathcal{I}} \frac{\mathbb{E}[O_{ui}]}{\rho_{ui}} \cdot \delta(\hat{r}_{ui}, r_{ui})$$

$$= \frac{1}{|\mathcal{U}||\mathcal{I}|} \sum_{u\in\mathcal{U}} \sum_{i\in\mathcal{I}} \frac{\rho_{ui}}{\rho_{ui}} \cdot \delta(\hat{r}_{ui}, r_{ui}) = \frac{1}{|\mathcal{U}||\mathcal{I}|} \sum_{u\in\mathcal{U}} \sum_{i\in\mathcal{I}} \delta(\hat{r}_{ui}, r_{ui}).$$

$\alpha_u = 0$

$$\mathbb{E}\left[\mathcal{L}_{UDIPS}(\hat{\mathbf{R}}|\alpha_u=0)\right] = \mathbb{E}\left[\frac{1}{|\mathcal{U}||\mathcal{I}|} \sum_{(u,i):O_{ui}=1} (1-\alpha_u) \cdot \delta(\hat{r}_{ui}, r_{ui})\right]$$

$$= \frac{1}{|\mathcal{U}||\mathcal{I}|} \sum_{u\in\mathcal{U}} \sum_{i\in\mathcal{I}} \mathbb{E}(O_{ui}) \cdot \delta(\hat{r}_{ui}, r_{ui}) = \frac{1}{|\mathcal{U}||\mathcal{I}|} \sum_{u\in\mathcal{U}} \sum_{i\in\mathcal{I}} \delta(\hat{r}_{ui}, r_{ui})$$

Experiments

➢Datasets

Dataset	#Users	#Items	#NB-Tr	#UB-Tr	#Val	#NB-Te	#UB-Te
Yahoo! R3	15.4k	1.0k	249k	5.4k	33.8k	31.2k	48.6k
Coat	290	300	5.6k	464	928	696	4.1k

➢Results

- Comparison with SOTA

Model		Yahoo! R3 NDCG	Yahoo! R3 Presicion	Yahoo! R3 Recall	Yahoo! R3 AUC	Coat NDCG	Coat Presicion	Coat Recall	Coat AUC
Unbiased Test (UB-Te)	MF	0.547	0.256	0.730	0.649	0.492	0.327	0.537	0.667
	MF-IPS	0.548	0.257	0.730	0.649	0.494	0.329	0.539	0.665
	MF-UDIPS	**0.579**	**0.263**	**0.753**	**0.677**	**0.499**	**0.332**	**0.547**	**0.673**
	InterD	0.669	0.288	0.822	0.753	0.519	0.337	0.558	0.682
	InterD-UDIPS	**0.676**	**0.291**	**0.833**	**0.762**	**0.526**	**0.342**	**0.570**	**0.692**
	KD_Label	0.575	0.259	0.751	0.674	0.502	0.325	0.540	0.679
	KDLabel-UDIPS	**0.585**	**0.263**	**0.759**	**0.681**	**0.506**	**0.328**	**0.555**	**0.686**
	DR	0.548	0.256	0.731	0.650	0.493	0.328	0.540	0.667
	DR-UDIPS	**0.552**	**0.261**	**0.749**	**0.660**	**0.504**	**0.334**	**0.563**	**0.670**
Normal Biased Test (NB-Te)	MF	0.825	0.313	0.970	0.652	0.810	0.267	0.995	0.667
	MF-IPS	0.815	0.311	0.966	0.626	0.809	0.265	0.986	0.636
	MF-UDIPS	**0.830**	**0.314**	**0.971**	**0.661**	**0.820**	**0.270**	**0.995**	**0.660**
	InterD	0.837	0.316	0.973	0.673	0.830	0.271	0.994	0.669
	InterD-UDIPS	**0.841**	**0.319**	**0.976**	**0.683**	**0.832**	**0.274**	**0.995**	**0.671**
	KD_Label	0.814	0.313	0.968	0.628	0.814	0.263	0.991	0.620
	KDLabel-UDIPS	**0.827**	**0.316**	**0.969**	**0.655**	**0.820**	**0.268**	**0.995**	**0.640**
	DR	0.791	0.308	0.957	0.571	0.812	0.259	0.986	0.638
	DR-UDIPS	**0.825**	**0.317**	**0.970**	**0.651**	**0.823**	**0.274**	**0.991**	**0.656**

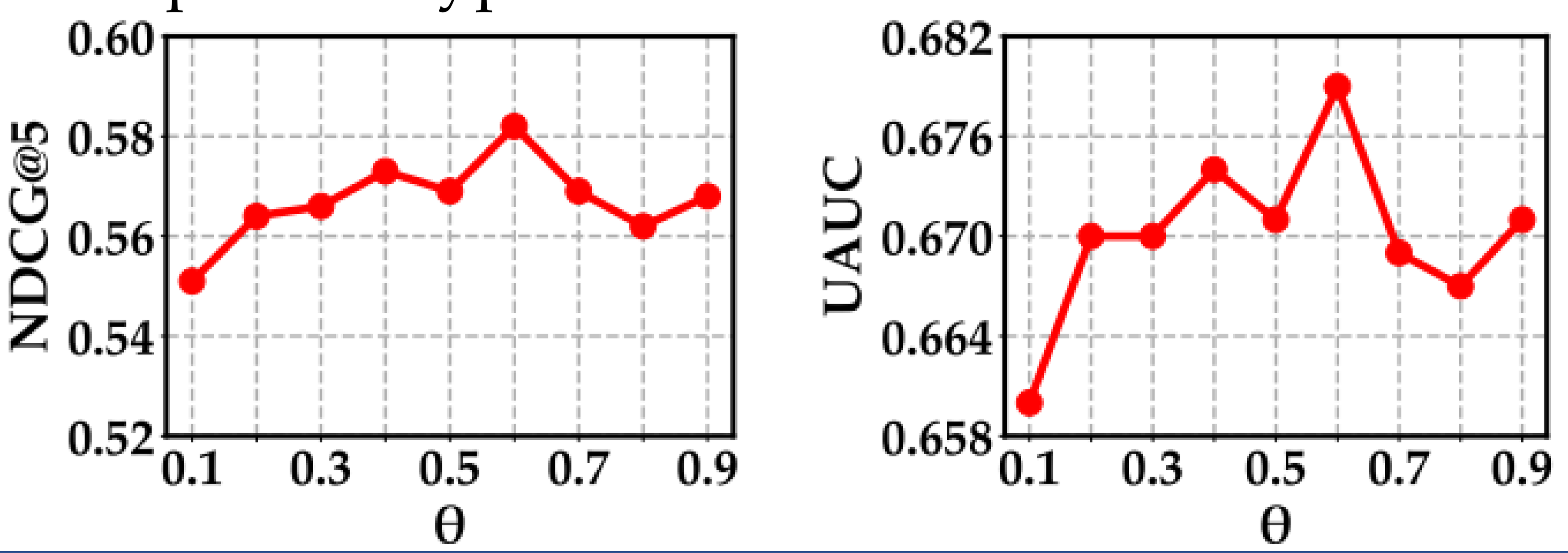
- UDIPS-based methods consistently outperforms existing models on UB-Te and NB-Te across two datasets.

- Comparison in terms of PI/PS users

		NDCG	Recall	Precision	AUC
MF-IPS	PI users	0.53435	0.69128	0.25156	0.62877
	PS users	0.56170	0.72476	0.24195	0.65501
MF-UDIPS	PI users	0.57058	0.73551	0.26484	0.66592
	Gain(%)	**6.78%**	**6.40%**	**5.28%**	**5.91%**
	PS users	0.60515	0.78583	0.25957	0.70340
	Gain(%)	**7.74%**	**8.43%**	**7.28%**	**7.39%**

- The performance gain from PS users is larger than that from PI users. It indicates that UDIPS is more effective in handling under-debiasing of PS users compared with the over-debiasing of PI users.

- Impact of Hyper-Parameter.



Conclusion

In this work, we propose a user-dependent inverse propensity score method that takes into account users' popularity sensitivity. Specifically, it can adaptively conduct propensity estimation for each user-item pair based on the user's sensitivity to item popularity. Also, the proposed loss function converges to the ideal loss function by effectively eliminating popularity bias.

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