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Estimating Propensity for Causality-based Recommendation without Exposure Data

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Background

	Shampoo	Nintendo Switch
Recommended	95%	50%
Not recommended	90%	10%
Recommendation effect	5%	40%

Exposure: whether the target item is exposed (recommended) to a user.
Propensity: The probability of an item is exposed (recommended) to a user.

If an item already has a high probability of being interacted by a user without being recommended, ***is there really a need to recommend the item to this user?***

Introduction

- Causality-based recommendation
  - Traditional RS award items with higher interaction probabilities
  - Causality RS award items with higher causal effect
- Limitations of existing methods
  - Require exposure and/or propensity to be known during training and/or inference
  - Fail to incorporate prior knowledge
- Our contribution
  - Propose a propensity estimation method for causality-based RS **without** ground-truth data.
  - Build a pairwise relationship between propensity and item popularity with a key assumption.

Naïve method

- Interaction model

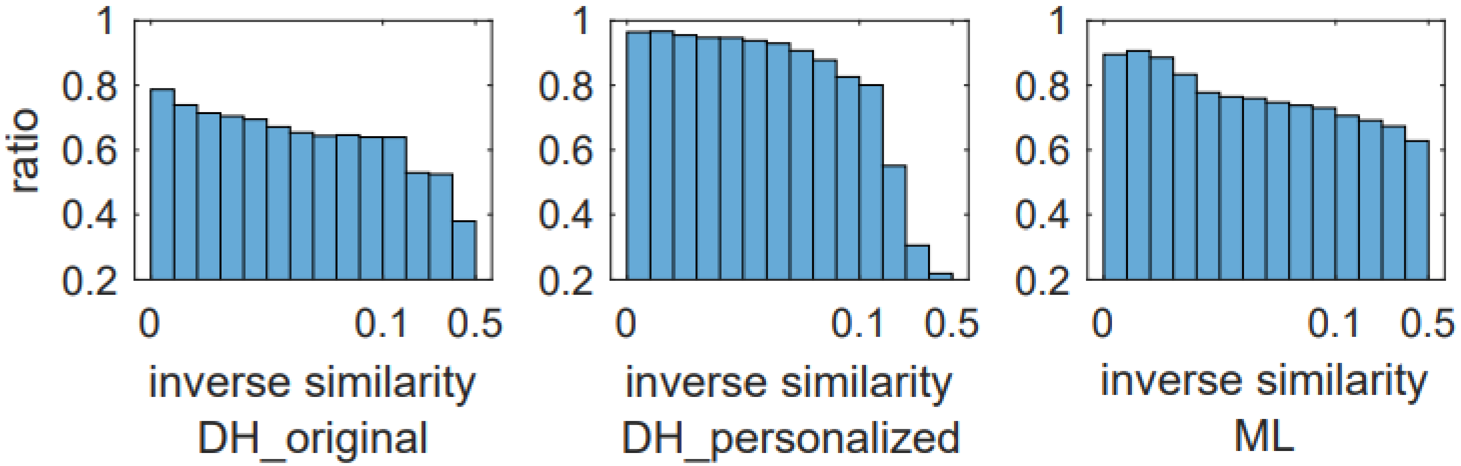
$$y_{u,i} = p_{u,i} r_{u,i},$$

$y_{u,i}$	Interaction (observed)
$p_{u,i}$	Propensity (unobserved)
$r_{u,i}$	Relevance (unobserved)

But directly estimating with interaction model is not robust.

Assumption

- Consider a user u and a pair of items (i, j). Suppose the popularity of item i is greater than that of j, and their interaction probabilities with user u are similar. Then it follows that item i is more likely to be exposed to user u than item j is.



item pairs (i, j) that satisfy the assumption

Method

- item popularity as a *proxy* (core assumption)

$$-\log\left[\sigma(f_p(\mathbf{x}_{u,i}) - f_p(\mathbf{x}_{u,j}))\right] \ \text{s.t.}\ \text{pop}_i > \text{pop}_j,\ y_{u,i} \approx y_{u,j},$$

- Relationship between propensity and interaction (interaction model)

$$-Y_{u,i} \log f_p(\mathbf{x}_{u,i};\Theta_p) f_r(\mathbf{x}_{u,i};\Theta_r) - (1 - Y_{u,i}) \log(1 - f_p(\mathbf{x}_{u,i};\Theta_p) f_r(\mathbf{x}_{u,i};\Theta_r))$$

- Regularization

$$\mu \mathrm{KL}(Q \| \mathrm{Beta}(\alpha, \beta))$$

Experiments

Methods	DH_original			DH_personalized			ML		
	CP@10↑	CP@100↑	CDCG↑	CP@10↑	CP@100↑	CDCG↑	CP@10↑	CP@100↑	CDCG↑
Ground-truth	.0658±.001	.0215±.001	1.068±.000	.1304±.001	.0445±.001	1.469±.003	.2471±.001	.1887±.000	16.29±.006
Random	.0154±.001	.0071±.002	.7390±.004	.0479±.004	.0107±.005	.8316±.039	.0124±.002	.0135±.005	13.16±.076
POP	.0200±.000	.0113±.000	.7877±.001	.0457±.000	.0096±.001	.8491±.002	-.142±.001	-.092±.001	11.43±.005
CJBPR	.0263±.001	.0087±.001	.7769±.002	.0564±.008	.0106±.005	.8528±.032	-.410±.002	-.187±.001	9.953±.006
EM	.0118±.001	.0067±.001	.7247±.001	.0507±.002	.0121±.001	.8779±.003	-.437±.002	-.194±.002	10.21±.011
PROPCARE	**.0351**±.002	**.0156**±.001	**.9268**±.005	**.1270**±.001	**.0381**±.000	**1.426**±.001	**.0182**±.002	**.0337**±.002	**13.80**±.011

Methods	DH_original			DH_personalized			ML		
	KLD↓	Tau↑	F1 score↑	KLD↓	Tau↑	F1 score↑	KLD↓	Tau↑	F1 score↑
Random	.5141±.001	.0002±.000	.4524±.013	3.008±.002	.0001±.000	.4463±.021	.0363±.002	.0002±.000	.4511±.022
POP	.5430±.000	**.4726**±.000	.2851±.000	4.728±.000	**.6646**±.000	.2772±.000	.0615±.000	**.4979**±.000	.5050±.000
CJBPR	.3987±.008	.3279±.011	.2853±.005	2.650±.022	.6477±.013	.2825±.005	.0230±.006	.4956±.045	**.5189**±.020
EM	.6380±.002	.0834±.000	.4974±.001	2.385±.001	.0934±.002	.4954±.009	.0517±.001	.1321±.002	.3653±.005
PROPCARE	**.3851**±.023	.3331±.065	**.5846**±.006	**1.732**±.038	.4706±.072	**.6059**±.017	**.0204**±.005	.3889±.034	.4847±.020

Takeaways

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- Our proposed method can estimate propensity for causality-based RS **without** the need to access ground-truth propensity and exposure data.

- we formulated a key assumption and incorporated it as prior information to enhance our estimation, thereby improving causality-based recommendation.