# **Estimating Propensity for Causality-based Recommendation without Exposure Data**

## Zhongzhou Liu<sup>1</sup>, Yuan Fang<sup>1</sup>, Min Wu<sup>2</sup> Singapore Management University<sup>1</sup>, A\*STAR<sup>2</sup>

#### **Background & Motivation**

#### **Causal effect of recommendation**

	Shampoo	Nintendo Switch
<b>Recommended</b> $Y_{u,i}^1$ <b>Not recommended</b> $Y_{u,i}^0$	95% 90%	50% 10%
Causal affect $\mathcal{T}_{ab}$	507	1097

#### • Traditional RS: award item with higher interaction probability

• Causal RS: award items with higher causal effect.

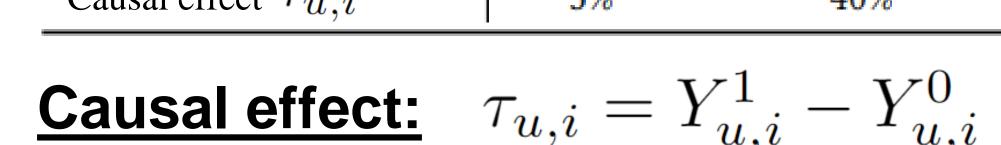
#### **Motivation**

 Existing causal RS assume that exposure data<sup>#</sup> or propensity scores<sup>\$</sup> are observable. In most public RS datasets, they are not.

<sup>#</sup>Whether an item has been recommended to a user or not

<sup>\$</sup> The probability of recommending/exposing an item 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?* 

- Other propensity score estimation methods:
  - Require exposure data to train propensity estimator, or
  - Lack prior knowledge (e.g., popularity), less robust estimation.

#### Preliminaries & Core assumption & Method

#### **Observed variables**

#### **Core Assumption**

- Interactions:  $Y_{u,i} \in \{0,1\}$
- Popularity of item *i*: *pop<sub>i</sub>*

#### **Unobserved variables**

- Exposure:  $Z_{u,i}$
- Propensity:  $p_{u,i} = P(Z_{u,i} = 1)$

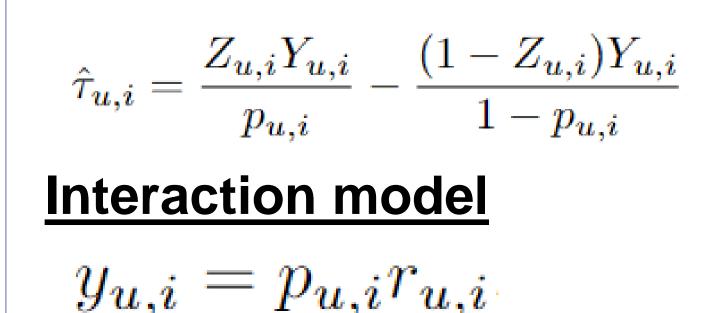
Consider a user u and a pair of items (i, j). Suppose the popularity of item i is greater than that of j, and their interaction probabilities with user u are similar. Then it follows that item i is more likely to be exposed to user u than item j is.

#### **Overall loss for propensity learning**

$$\min_{\Theta} \mathcal{L} = \sum_{u,i,j} (\mathcal{L}_{\text{na\"ive}} + \lambda \mathcal{L}_{\text{pop}}) + \mu \text{KL}(Q \| \text{Beta}(\alpha, \beta))$$

- Interaction (**not** exposed):  $Y_{u,i}^0$
- Interaction (exposed):  $Y_{u,i}^1$

#### **Causal effect estimation** [2]



#### Estimating propensity and exposure $\hat{p}_{u,i} = f_p(\mathbf{x}_{u,i}), \quad \hat{Z}_{u,i} = \operatorname{Norm}(\hat{p}_{u,i}) > \epsilon$

 $Pu, i \quad Jp(\mathbf{A}u, i), \quad u, i = \Pi(Pu, i) < C$ 

Integrating the assumption into propensity score modelling

 $\mathcal{L}_{pop} = -\kappa_{u,i,j} \log \left[ \sigma(\operatorname{sgn}_{i,j} \cdot (f_p(\mathbf{x}_{u,i}) - f_p(\mathbf{x}_{u,j}))) + \sigma(\operatorname{sgn}_{i,j} \cdot (f_r(\mathbf{x}_{u,j}) - f_r(\mathbf{x}_{u,i}))) \right]$ 

**Causality-based recommendation** [2]

$$\frac{Z_{u,i}Y_{u,i}}{\max(p_{u,i},\chi^1)}\log\left(1+e^{-\omega(\hat{s}_{u,i}-\hat{s}_{u,j})}\right) + \frac{(1-Z_{u,i})Y_{u,i}}{\max(1-p_{u,i},\chi^0)}\log\left(1+e^{\omega(\hat{s}_{u,i}-\hat{s}_{u,j})}\right)$$

### **Experiment & Conclusion**

\* PropCare requires no propensity or exposure data in training/reference. They are used only for evaluation.

Methods	DH_original		DH_personalized			ML			
	<b>CP@10</b> ↑	<b>CP</b> @100↑	CDCG↑	<b>CP@10</b> ↑	<b>CP@100</b> ↑	CDCG↑	<b>CP</b> @10↑	<b>CP</b> @100↑	CDCG↑
Ground-truth	$.0658 {\pm} .001$	$.0215 {\pm} .001$	$1.068 {\pm}.000$	$.1304 \pm .001$	$.0445 \pm .001$	1.469±.003	.2471±.001	$.1887 {\pm} .000$	$16.29 \pm .006$
Random						.8316±.039			

#### **Conclusion**

 PropCare enables more generalizability of causal RS without accessing

POP<br/>CJBPR<br/>EM $.0200\pm.000$  $.0113\pm.000$  $.7877\pm.001$  $.0457\pm.000$  $.0096\pm.001$  $.8491\pm.002$  $-.142\pm.001$  $-.092\pm.001$  $11.43\pm.005$ CJBPR<br/>EM $.0263\pm.001$  $.0087\pm.001$  $.7769\pm.002$  $.0564\pm.008$  $.0106\pm.005$  $.8528\pm.032$  $-.410\pm.002$  $-.187\pm.001$  $9.953\pm.006$ EM<br/>PROPCARE $.0118\pm.001$  $.0067\pm.001$  $.7247\pm.001$  $.0507\pm.002$  $.0121\pm.001$  $.8779\pm.003$  $-.437\pm.002$  $-.194\pm.002$  $10.21\pm.011$ PROPCARE $.0351\pm.002$  $.0156\pm.001$  $.9268\pm.005$  $.1270\pm.001$  $.0381\pm.000$  $1.426\pm.001$  $.0182\pm.002$  $.0337\pm.002$  $13.80\pm.011$ 

\*Results are reported as the average of 5 runs (mean±std). Best results except Ground-truth are bolded, and runners-up are underlined.

PropCare: Drops only 6.6% from ground-truth; Outperforms other baselines w.r.t. causal recommendation. ground-truth exposure & propensity.

 Core assumption that integrates prior knowledge can improve causal RS.

**ACKNOWLEDGEMENT & REFERENCES** 

[1] Xu Xie, et al. CausCF: Causal collaborative filtering for recommendation effect estimation. CIKM 2021.
[2] Masahiro Sato, et al. Unbiased learning for the causal effect of recommendation. RecSys 2020.

For complete references please refer to https://arxiv.org/abs/2310.20388

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