中国科学技术大学 University of Science and Technology of China
NUS National University of Singapore
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THE WEB CONFERENCE ACM

Causal Recommendation: Progresses and Future Directions

Lecture Tutorial for The Web Conference 2022

Organizers: Yang Zhang, Wenjie Wang, Peng Wu, Fuli Feng, Xiangnan He

26 April 2022
Web page: https://causalrec.github.io/

Outline

- Part 1 (90 Min, 9:00—10:30)
  - Introduction (Fuli Feng, 15 Min)
  - Potential outcome framework for recommendation (Peng Wu, 60~70 Min)
  - Q&A (5 Min)
- Part 2 (90 Min, 10:45-12:15)
  - Structural causal model-based recommendation (Yang Zhang and Wenjie Wang, 60~70 Min)
  - Comparison (Wenjie Wang, 2 Min)
  - Open problems, future directions and conclusion (Fuli Feng, 20 Min)
  - Q&A (5 Min)

• Information Seeking

Information explosion problem?

- Information seeking requirements
  - ❖ E-commerce (Taobao/PDD/Amazon)
  - ❖ Social networking (Facebook/Weibo/Wechat)
  - ❖ Content sharing platforms (Tiktok/Kwai/Pinterest)

12 million items in Amazon

2.8 billion users in Facebook

720,000 hours videos uploaded per day in Youtube

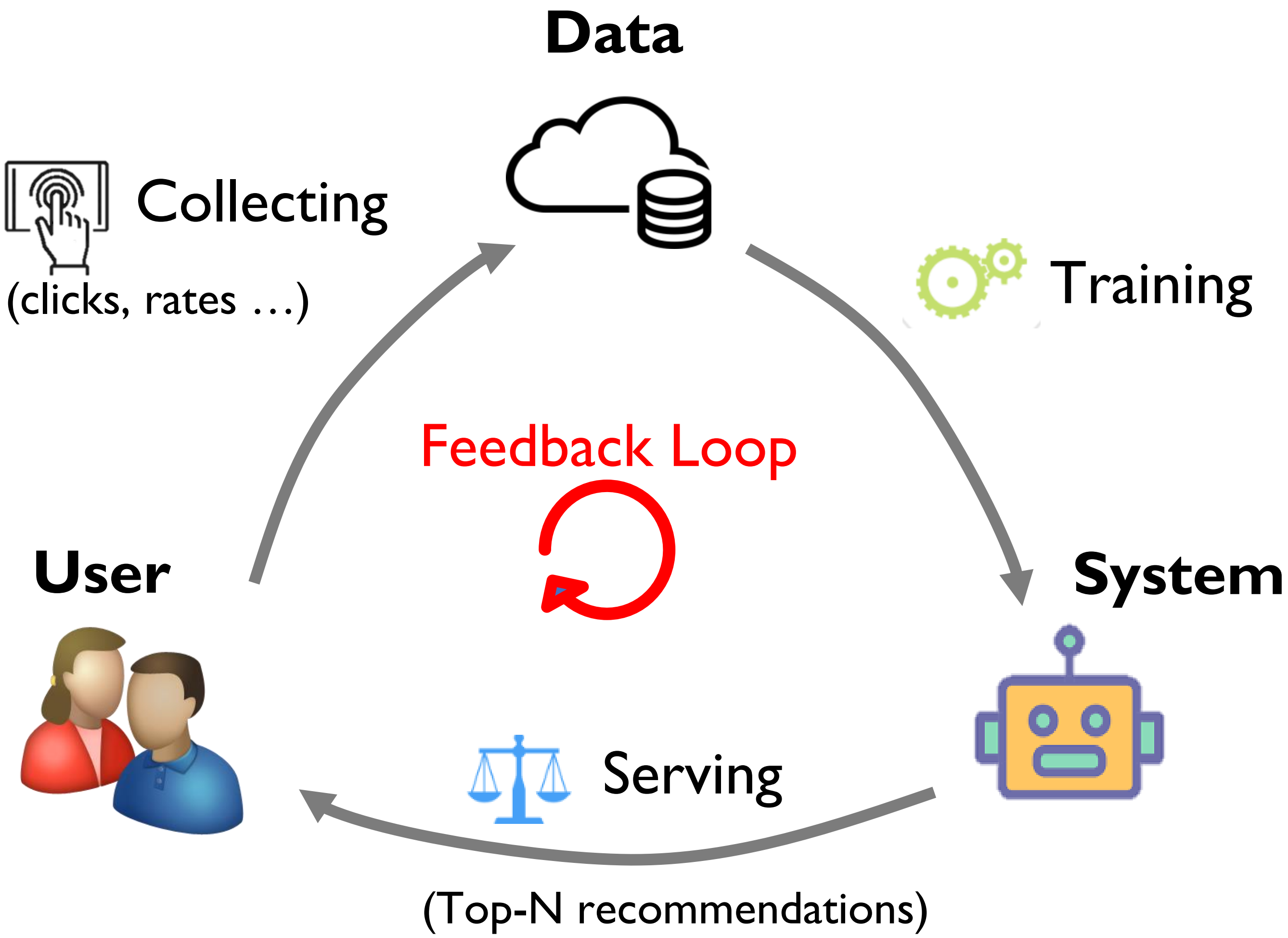
Recommender system has been recognized as a powerful tool to address information overload.

You may like?

How to handle?

• Ecosystem of Recsys

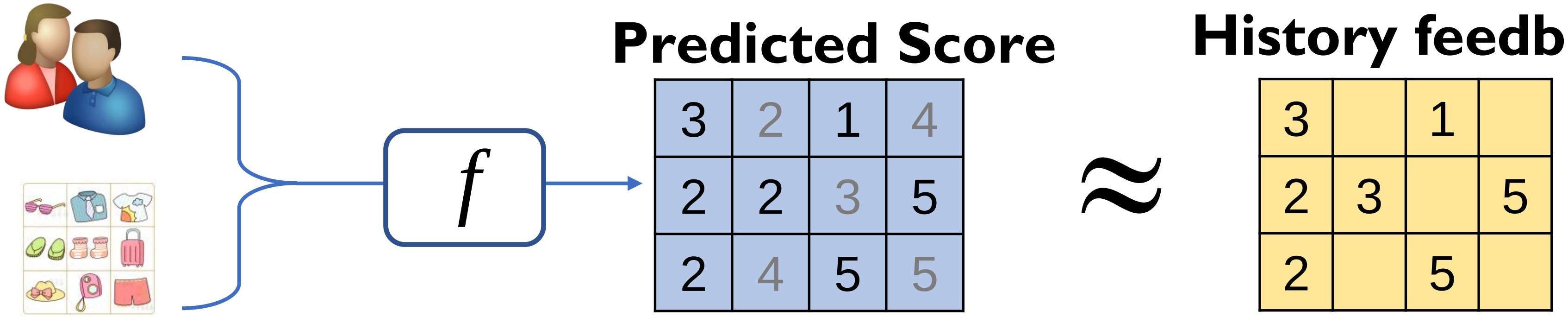
- Workflow of RS
  - **Training**: RS is trained/updated on observed user-item interaction data.
  - **Serving**: RS infers user preference over items and exposes top-n items.
  - **Collecting**: User actions on exposed items are merged into the training data.
- Forming a Feedback Loop



Chen et al. arxiv 2021. Bias and Debias in Recommender System: A Survey and Future Directions

Mainstream Models: Fitting Historical Data

- Minimizing the difference between historical feedback and model prediction



Predicted Score

3	2	1	4
2	2	3	5
2	4	5	5

≈

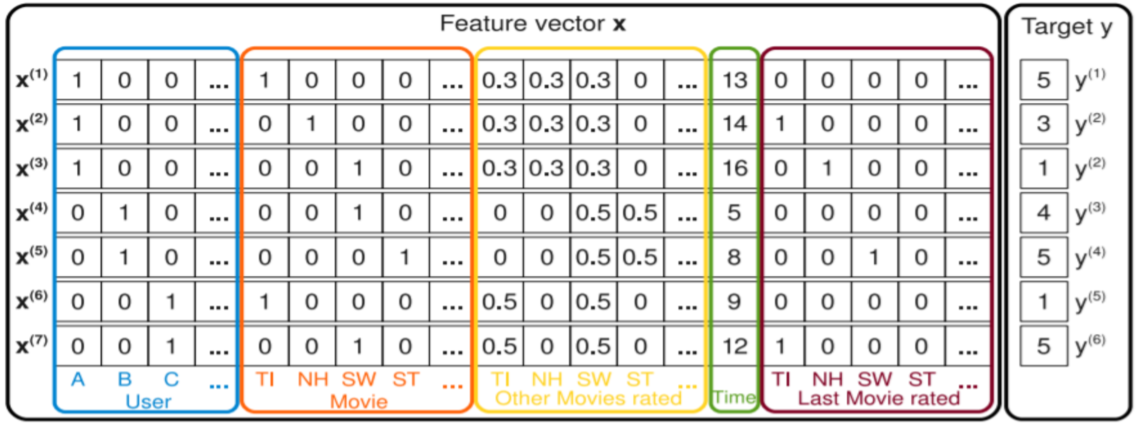
History feedback

3		1	
2	3		5
2		5	

- **Collaborative filtering:** Similar users perform similarly in future

Shallow representation learning

- Matrix factorization & factorization machines



Feature vector **x**

	User				Movie					Other Movies rated					Time	Last Movie rated					Target y	
	A	B	C	...	TI	NH	SW	ST	...	TI	NH	SW	ST	...		TI	NH	SW	ST	...		
$\mathbf{x}^{(1)}$	1	0	0	...	1	0	0	0	...	0.3	0.3	0.3	0	...	13	0	0	0	0	...	5	$y^{(1)}$
$\mathbf{x}^{(2)}$	1	0	0	...	0	1	0	0	...	0.3	0.3	0.3	0	...	14	1	0	0	0	...	3	$y^{(2)}$
$\mathbf{x}^{(3)}$	1	0	0	...	0	0	1	0	...	0.3	0.3	0.3	0	...	16	0	1	0	0	...	1	$y^{(2)}$
$\mathbf{x}^{(4)}$	0	1	0	...	0	0	1	0	...	0	0	0.5	0.5	...	5	0	0	0	0	...	4	$y^{(3)}$
$\mathbf{x}^{(5)}$	0	1	0	...	0	0	0	1	...	0	0	0.5	0.5	...	8	0	0	1	0	...	5	$y^{(4)}$
$\mathbf{x}^{(6)}$	0	0	1	...	1	0	0	0	...	0.5	0	0.5	0	...	9	0	0	0	0	...	1	$y^{(5)}$
$\mathbf{x}^{(7)}$	0	0	1	...	0	0	1	0	...	0.5	0	0.5	0	...	12	1	0	0	0	...	5	$y^{(6)}$

Neural representation learning

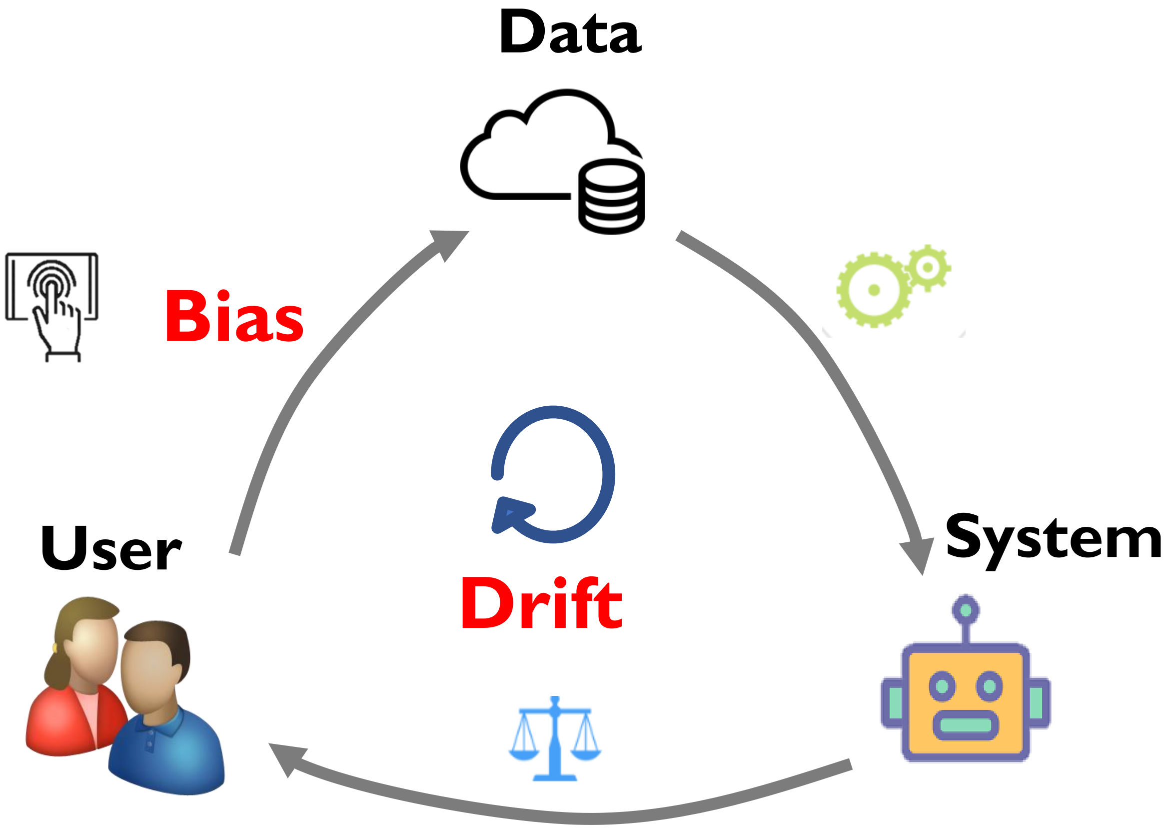
- Neural collaborative filtering
- Graph neural networks
- Sequential model
- Textual & Visual encoders

Learning correlations between input features and interaction labels

Shortcomings of Data-Driven Methods

- Bias in data (Collecting):
  - Data is observational rather than experimental (missing-not-at-random)
  - Affected by many hidden factors:
    - Public opinions

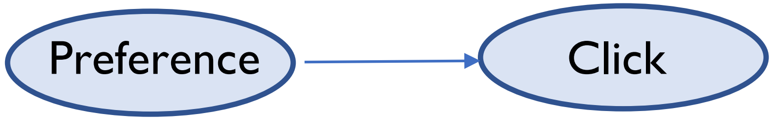
    ……
- Drift along time:
  - User/item feature changes
    - Income, marriage status
    - iPhone 12 (2021→2022)
  - Preference evolution



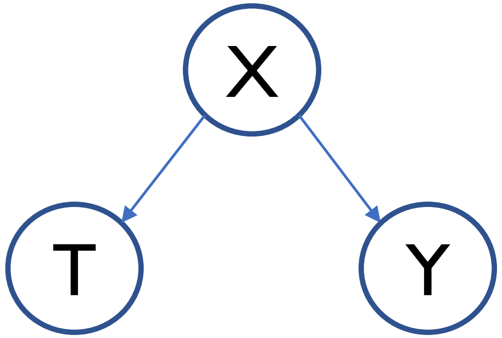
Shortcomings of Data-Driven Methods

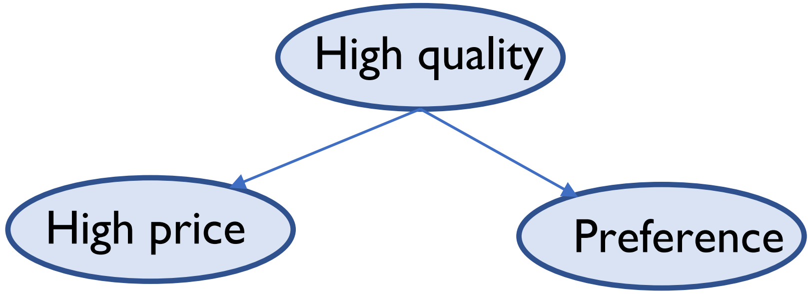
- Learning correlation != Learning preference: Correlations may not reflect the true causes of interaction.

- Three basic types of correlations:
  - **Causation**
    - Stable and explainable

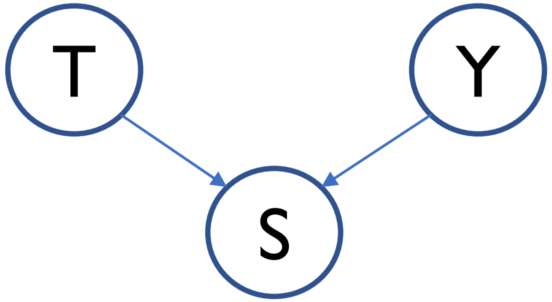


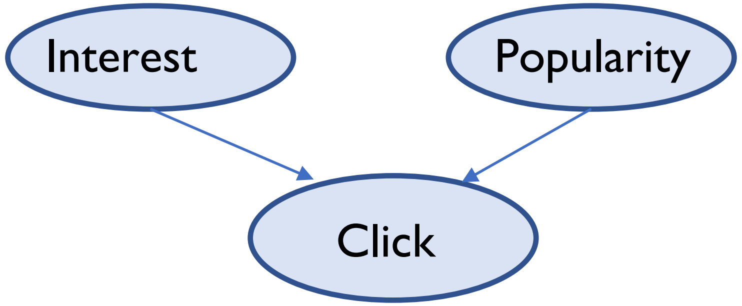
  - **Confounding**
    - Ignoring X
    - Spurious correlation





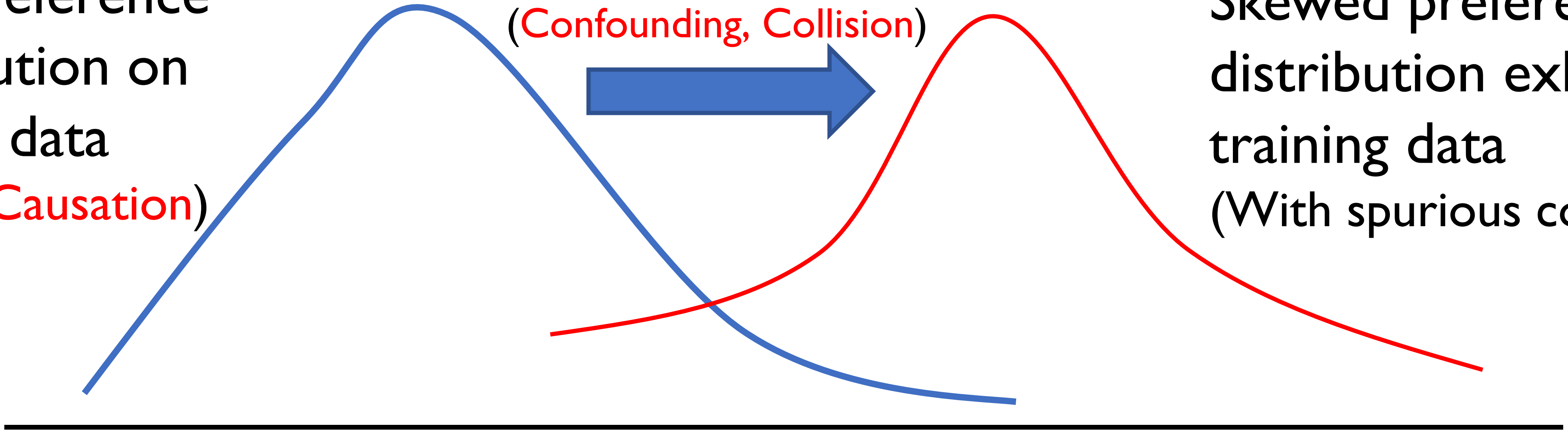
  - **Collision**
    - Condition on S
    - Spurious correlation





• Shortcomings of Data-Driven Methods

- Data-driven methods would learn skewed user preference:



True preference distribution on testing data
(Stable Causation)

Biases
(Confounding, Collision)

Skewed preference distribution exhibited on training data
(With spurious correlation)

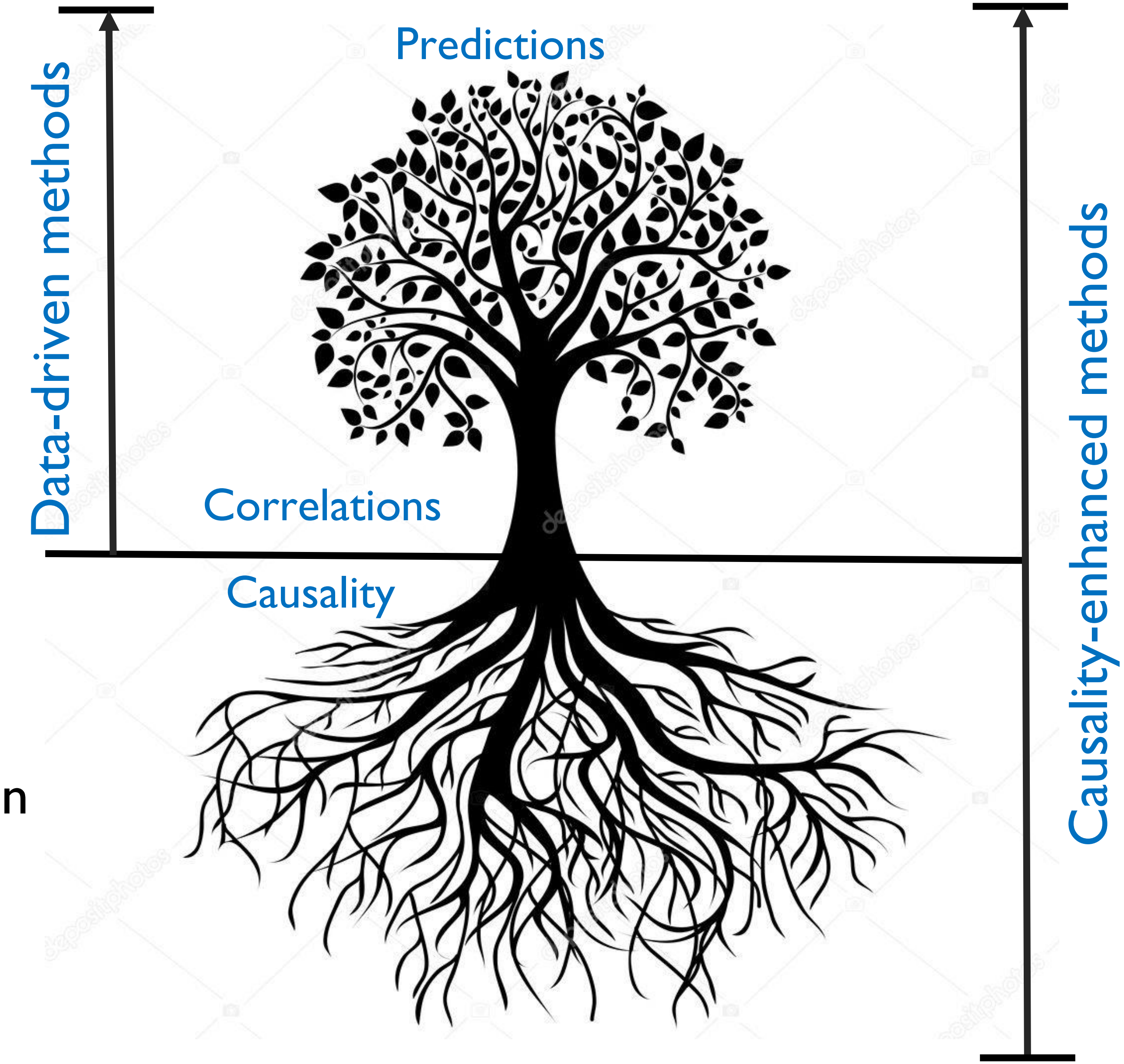
- Data-driven methods may infer spurious correlations, which are deviated from reflecting user true preference and lack interpretation.

Chen et al. arxiv 2021. Bias and Debias in Recommender System: A Survey and Future Directions

• Why Causal Inference?

- Aim: Understanding the inherent causal mechanism of user behavior
    - Capturing user true preference

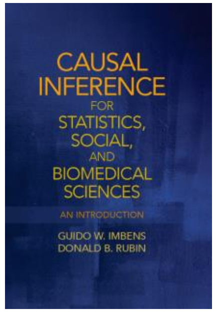
- Making reliable & explainable recommendations
    - Correlation + Causality > Correlation



Classification of Causal Recommendation

- Potential Outcome Framework

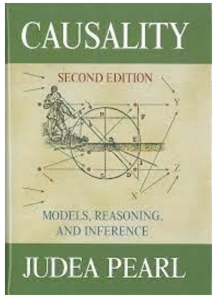
(Donald B. Rubin)



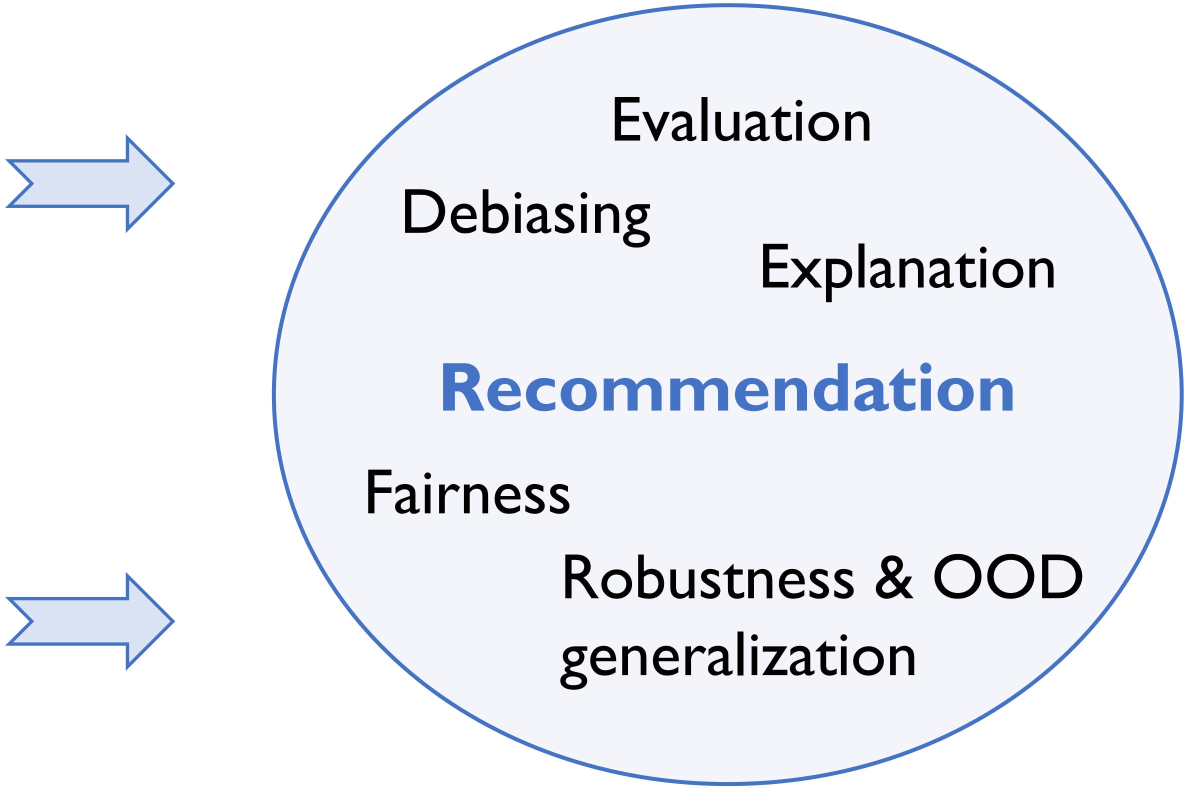
CAUSAL
INFERENCE
FOR
STATISTICS,
SOCIAL,
AND
BIOMEDICAL
SCIENCES
AN INTRODUCTION
GUIDO W. IMBENS
DONALD B. RUBIN

- Structural Causal Model (SCM)

(Judea Pearl)



CAUSALITY
SECOND EDITION
MODELS, REASONING, AND INFERENCE
JUDEA PEARL



Evaluation

Debiasing

Explanation

Recommendation

Fairness

Robustness & OOD generalization

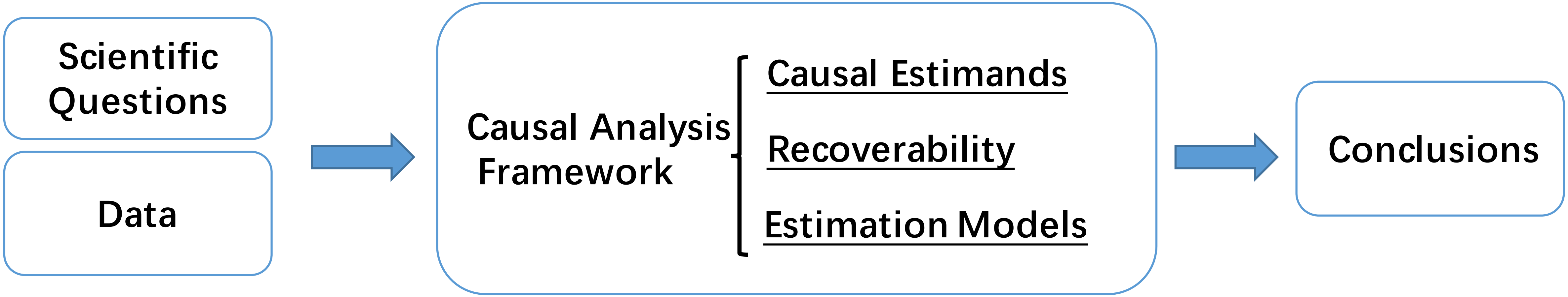
Outline

- Introduction
- Potential outcome framework for recommendation
- Structural causal model-based recommendation
- Comparison
- Open problems, future directions and conclusions

Contents

Contents

• Causal analysis framework



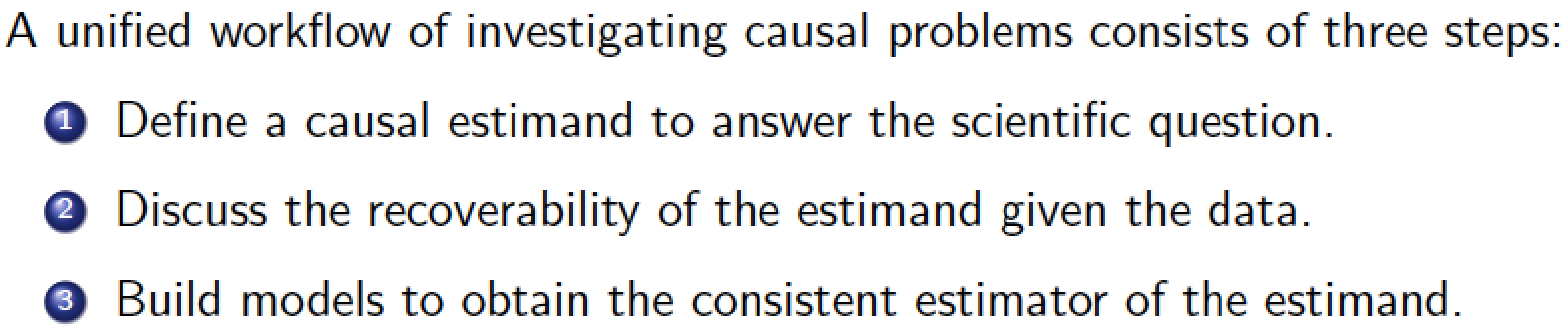
Scientific Questions

Data

Causal Analysis Framework

- Causal Estimands
- Recoverability
- Estimation Models

Conclusions

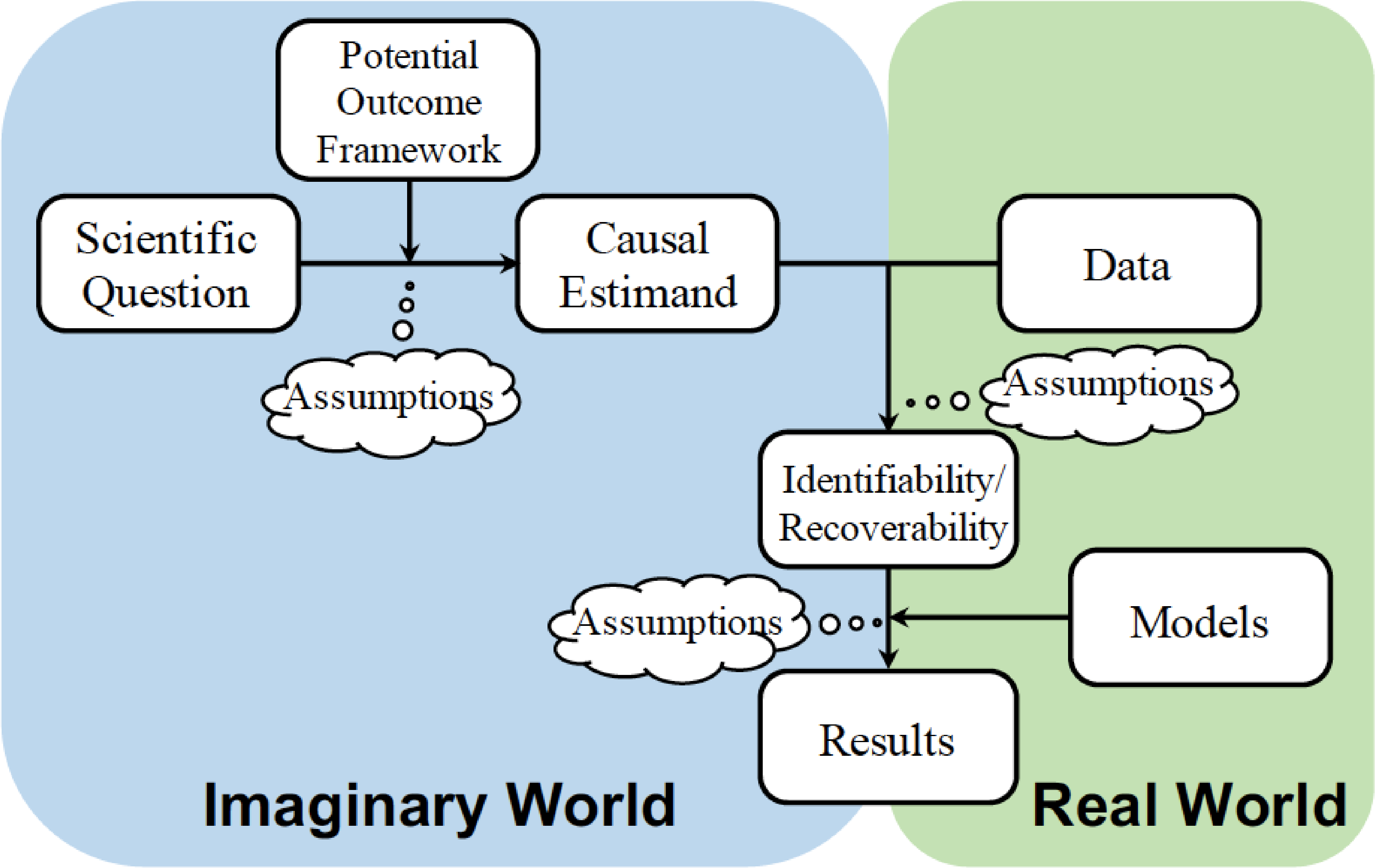


A unified workflow of investigating causal problems consists of three steps:

1. Define a causal estimand to answer the scientific question.
2. Discuss the recoverability of the estimand given the data.
3. Build models to obtain the consistent estimator of the estimand.

Peng Wu, Haoxuan Li, Yuhao Deng, Wenjie Hu, Quanyu Dai, Zhenhua Dong, Jie Sun, Rui Zhang, Xiao-Hua Zhou (2021), ``Causal Analysis Framework for Recommendation'', arXiv:2201.06716. (To appear in IJ-CAI)

• Causal analysis framework


Potential Outcome Framework

Scientific Question

Causal Estimand

Data

Assumptions

Assumptions

Identifiability/ Recoverability

Assumptions

Models

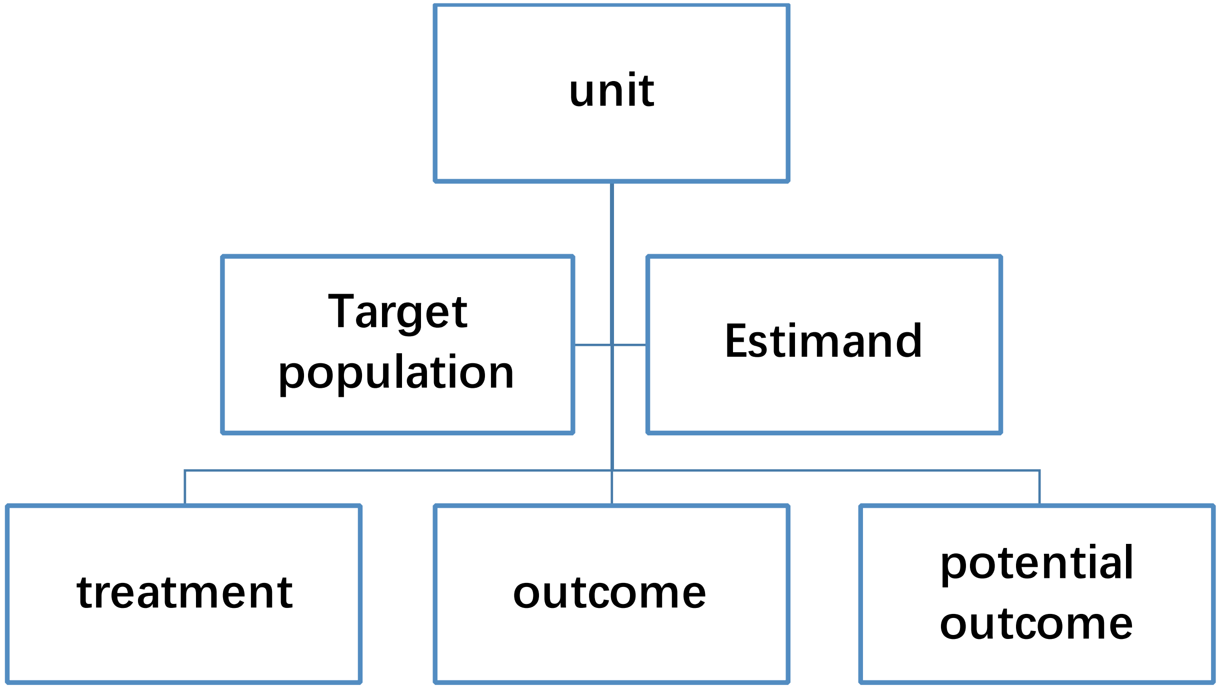
Results

Imaginary World

Real World

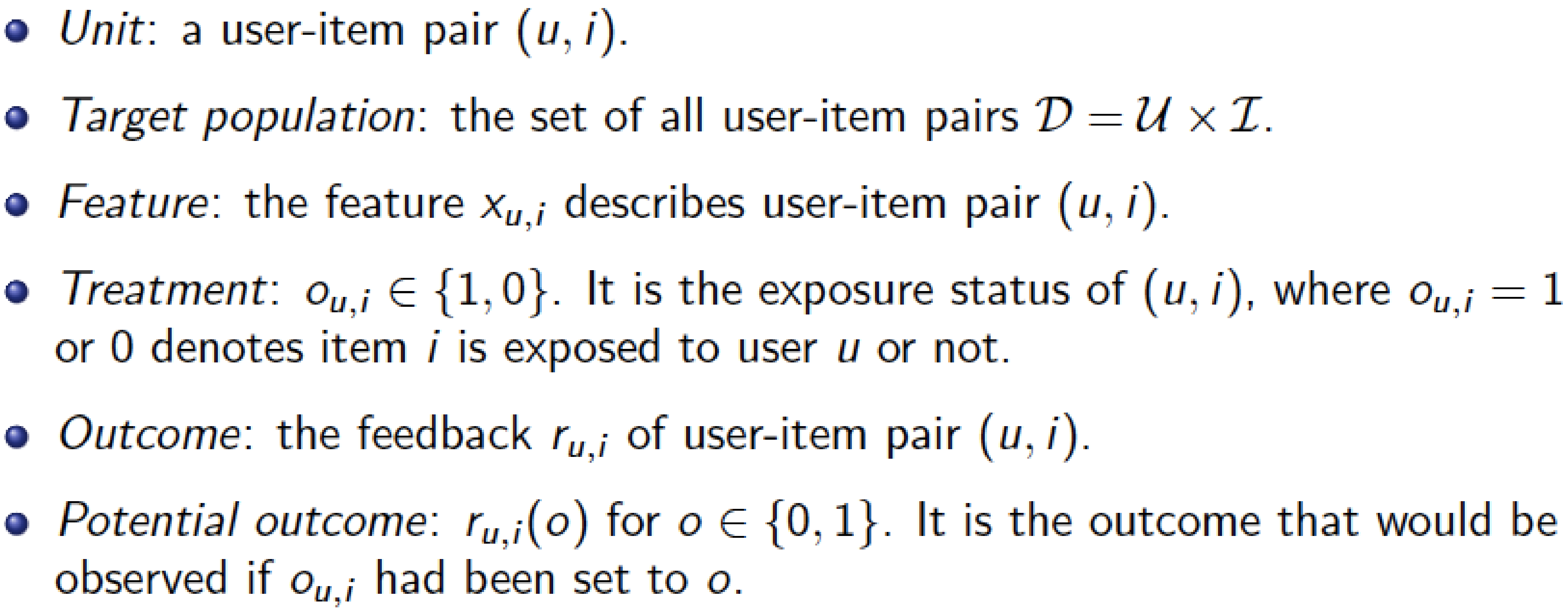
Peng Wu, Haoxuan Li, Yuhao Deng, Wenjie Hu, Quanyu Dai, Zhenhua Dong, Jie Sun, Rui Zhang, Xiao-Hua Zhou (2021), ``Causal Analysis Framework for Recommendation'', arXiv:2201.06716. (To appear in IJ-CAI)

• Key elements in PO framework



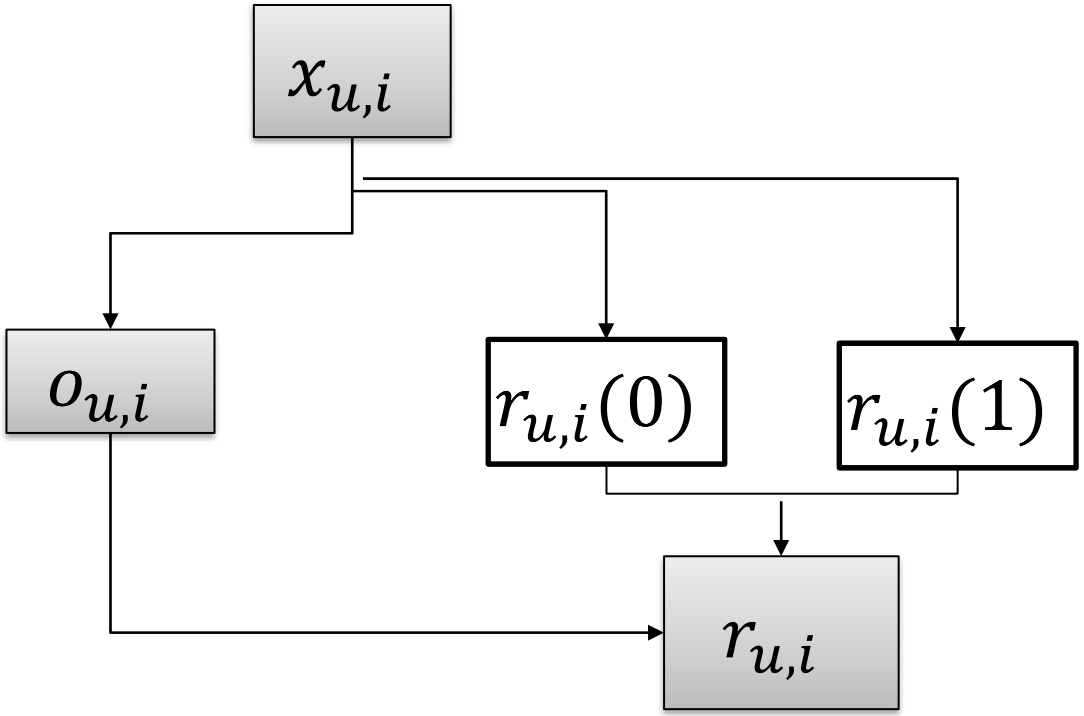
- **Unit**: the most fine-grained research subject.
- **Target population**: the population that we want to make an inference/prediction on.
- **Causal estimand**: the causal parameter, providing a recipe for answering the scientific question of interest from any hypothetical data whenever it is available.

• PO framework in RS



- *Unit*: a user-item pair (u, i).
- *Target population*: the set of all user-item pairs $\mathcal{D} = \mathcal{U} \times \mathcal{I}$.
- *Feature*: the feature $x_{u,i}$ describes user-item pair (u, i).
- *Treatment*: $o_{u,i} \in \{1, 0\}$. It is the exposure status of (u, i), where $o_{u,i} = 1$ or 0 denotes item i is exposed to user u or not.
- *Outcome*: the feedback $r_{u,i}$ of user-item pair (u, i).
- *Potential outcome*: $r_{u,i}(o)$ for $o \in \{0, 1\}$. It is the outcome that would be observed if $o_{u,i}$ had been set to o.

- PO framework in RS

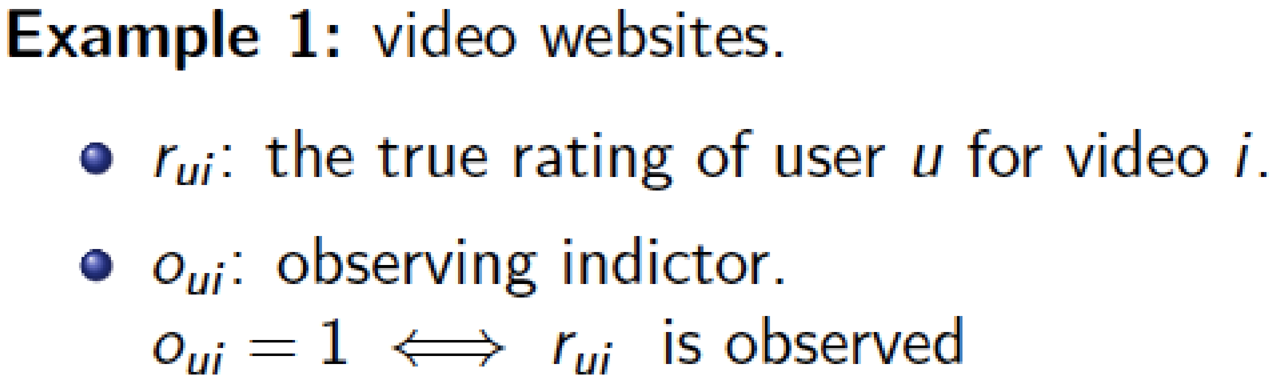


In RS, we often want to answer the intervention question "if recommending an item to a user, what would the feedback be". Formally, the estimand is

$$\mathbb{E}(r_{u,i}(1) \mid x_{u,i}), \qquad (1)$$

it requires to predict the potential outcome $r_{u,i}(1)$ using feature $x_{u,i}$.

• PO framework in RS



Example 1: video websites.

- r_{ui}: the true rating of user u for video i.
- o_{ui}: observing indictor.
  $o_{ui} = 1 \iff r_{ui}$ is observed

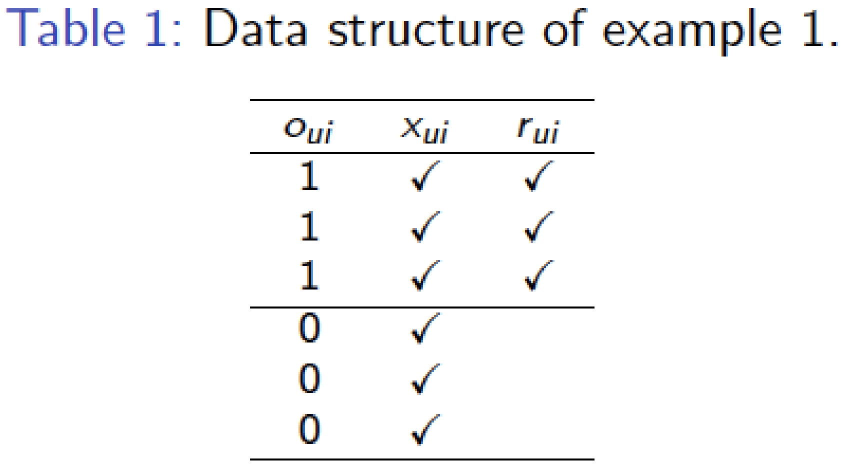


Table 1: Data structure of example 1.

o_{ui}	x_{ui}	r_{ui}
1	✓	✓
1	✓	✓
1	✓	✓
0	✓	
0	✓	
0	✓	

We can regard the observing indicator $o_{u,i}$ as the treatment, and define $r_{u,i}(1)$ as the true rating if $o_{u,i} = 1$ for all user-item pairs. Here we use $r_{u,i}(1)$ instead of $r_{u,i}$ is to underline that the outcome is part of observable.

Goal: predict the potential outcome $r_{u,i}(1)$ using feature $x_{u,i}$.

Example 2: advertising CTR Predication.

- r_{ui}: $r_{ui} = 1$ if u clicks on item i; $r_{ui} = 0$ otherwise.
- o_{ui}: $o_{ui} = 1$ if item i is exposed to u; $o_{ui} = 0$ otherwise.
- CTR: $\mathbb{E}[r_{ui}(1)|x_{u,i}] = \mathbb{P}(r_{ui}(1) = 1|x_{u,i})$.

o_{ui}	x_{ui}	r_{ui}	$r_{ui}(1)$
1	✓	✓	✓
1	✓	✓	✓
1	✓	✓	✓
0	✓	✓	
0	✓	✓	
0	✓	✓	

Example 3: advertising post-click CVR Predication.

- r_{ui}: $r_{ui} = 1$ if user u purchases item i; $r_{ui} = 0$ otherwise.
- o_{ui}: $o_{ui} = 1$ if user u clicks item i $o_{ui} = 0$ otherwise.
- post-click CVR: $\mathbb{E}[r_{ui}(1)|x_{u,i}] = \mathbb{P}(r_{ui}(1) = 1|x_{u,i})$.

• Remarks

- The definition of the causal estimand does not involve the data collected and the model adopted.
- It also doesn't not involve the relationship between $x_{u,i},\ o_{u,i}\ \text{ and } r_{u,i}$. In other word, when defining causal estimand, it needn't distinguish confounder, collider, instrument variable, etc.

Significance: Through formalizing the scientific question into a causal estimand, we can answer the following questions: what exactly is being estimated and for what purpose.

Contents

• Challenges

- Missing data:
  selection bias
  or confounding bias.

o_{ui}	x_{ui}	r_{ui}	$r_{ui}(1)$
1	✓	✓	✓
1	✓	✓	✓
1	✓	✓	✓
0	✓	✓	
0	✓	✓	
0	✓	✓	

- Data sparsity:

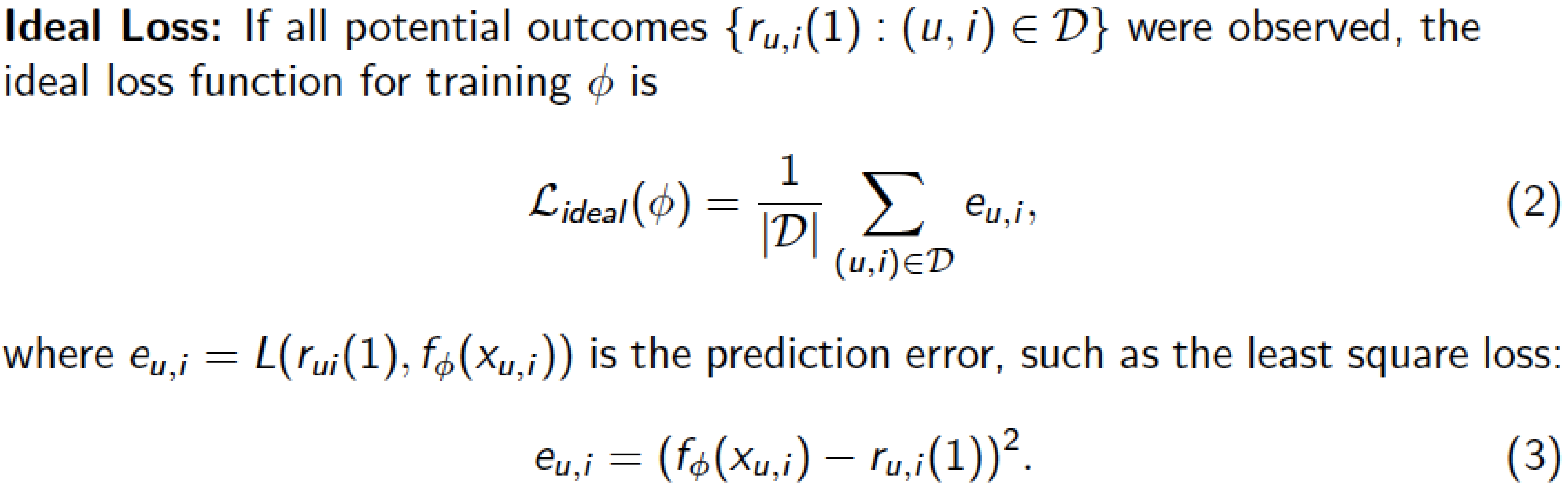
	ML 100K	Coat Shopping	Yahoo! R3
#users	943	290	15400
#items	1682	300	1000
#MNAR ratings	100000	6960	311704
#MAR ratings	0	4640	54000

Missing rate is very high:

- ML 100K: $100000/(943 * 1682) = 0.063$;
- Coat Shopping: $6960/(290 * 300) = 0.080$;
- Yahoo! R3: $311704/(15400 * 1000) = 0.020$.

Ideal Loss

Let $f_\phi(x_{u,i})$ be a recommender model with parameter ϕ and $\hat{r}_{u,i}(1) = f_\phi(x_{u,i})$ be the predicted $\mathbb{E}[r_{u,i}(1)|x_{u,i}]$.



Ideal Loss: If all potential outcomes $\{r_{u,i}(1) : (u,i) \in \mathcal{D}\}$ were observed, the ideal loss function for training ϕ is

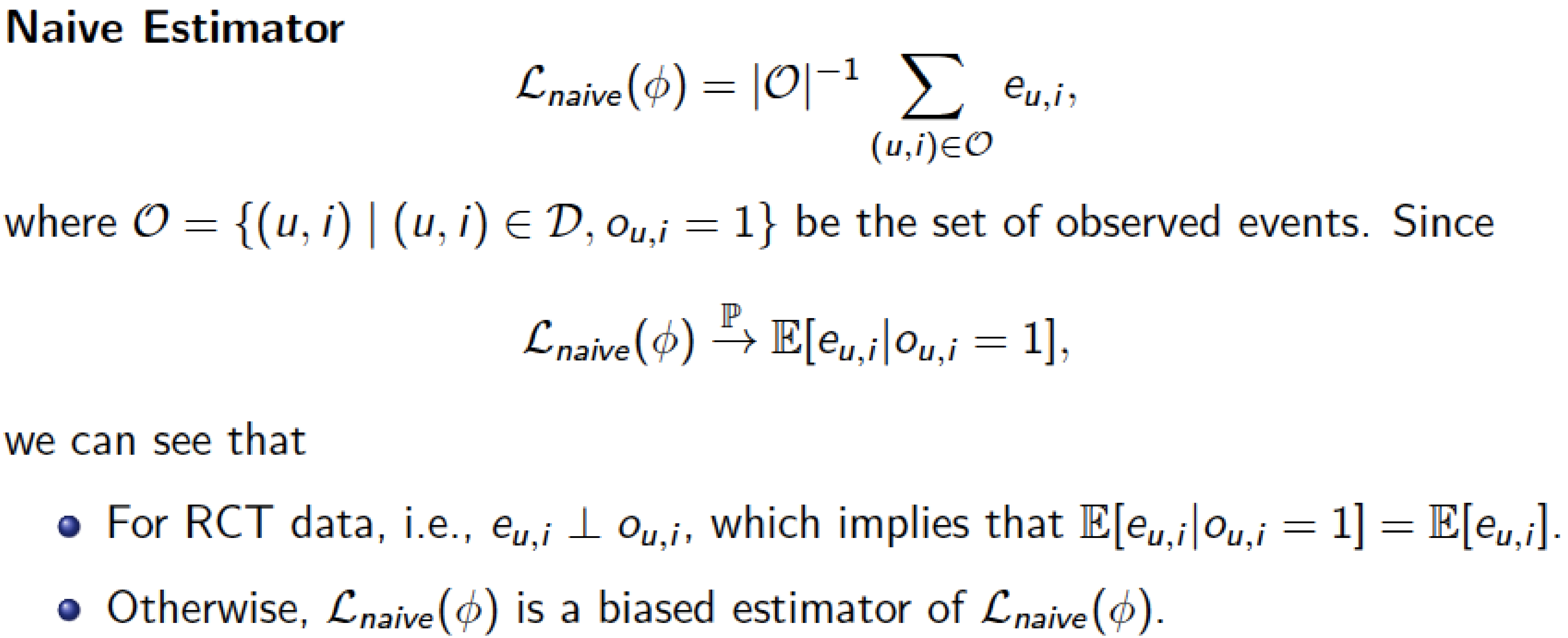
$$\mathcal{L}_{ideal}(\phi) = \frac{1}{|\mathcal{D}|} \sum_{(u,i)\in\mathcal{D}} e_{u,i}, \tag{2}$$

where $e_{u,i} = L(r_{ui}(1), f_\phi(x_{u,i}))$ is the prediction error, such as the least square loss:

$$e_{u,i} = (f_\phi(x_{u,i}) - r_{u,i}(1))^2. \tag{3}$$

Noticing that $e_{u,i}$ is computable only when $o_{u,i} = 1$, $L_{ideal}(\phi)$ is infeasible. As such, our target is constructing estimators that approximate to $L_{ideal}(\phi)$.

• Naïve Estimator



Naive Estimator

$$\mathcal{L}_{naive}(\phi) = |\mathcal{O}|^{-1} \sum_{(u,i)\in\mathcal{O}} e_{u,i},$$

where $\mathcal{O} = \{(u,i) \mid (u,i) \in \mathcal{D}, o_{u,i} = 1\}$ be the set of observed events. Since

$$\mathcal{L}_{naive}(\phi) \xrightarrow{\mathbb{P}} \mathbb{E}[e_{u,i}|o_{u,i} = 1],$$

we can see that

- For RCT data, i.e., $e_{u,i} \perp o_{u,i}$, which implies that $\mathbb{E}[e_{u,i}|o_{u,i} = 1] = \mathbb{E}[e_{u,i}]$.
- Otherwise, $\mathcal{L}_{naive}(\phi)$ is a biased estimator of $\mathcal{L}_{naive}(\phi)$.

When the estimator is biased, the corresponding recommendation model is in general sub-optimal.

• Inverse Propensity Score (IPS)

$$\mathcal{L}_{IPS}(\phi) = \frac{1}{|\mathcal{D}|} \sum_{(u,i)\in\mathcal{D}} \frac{o_{u,i} e_{u,i}}{\hat{p}_{u,i}}, \tag{4}$$

where $p_{u,i} := \mathbb{P}(o_{u,i} = 1 \mid x_{u,i})$ is the propensity score.

The unbiasedness property of IPS estimator is based on the following assumption

$$r_{u,i}(1) \perp o_{u,i} \mid x_{u,i}, \tag{5}$$

which implies that $e_{u,i} \perp o_{u,i} \mid x_{u,i}$. Then if $\hat{p}_{u,i} = p_{u,i}$,

$$\begin{aligned}
\mathbb{E}[\mathcal{L}_{IPS}(\phi)] &= \mathbb{E}[\frac{o_{u,i} e_{u,i}}{p_{u,i}}] = \mathbb{E}[\mathbb{E}\{\frac{o_{u,i} e_{u,i}}{p_{u,i}} \mid x_{u,i}\}] \\
&= \mathbb{E}[\frac{\mathbb{E}(o_{u,i}|x_{u,i}) \cdot \mathbb{E}(e_{u,i}|x_{u,i})}{p_{u,i}}\}] \\
&= \mathbb{E}[\mathbb{E}(e_{u,i}|x_{u,i})] = \mathbb{E}[e_{u,i}]
\end{aligned}$$

Tobias Schnabel, Adith Swaminathan, Ashudeep Singh, Navin Chandak, Thorsten Joachims (2016). “Recommendations as treatments: Debiasing learning and evaluation”, ICML.

• Self-Normalized IPS (SNIPS)

$$\mathcal{L}_{SNIPS}(\phi) = \frac{\sum_{(u,i)\in\mathcal{D}} \frac{o_{u,i}e_{u,i}}{\hat{p}_{u,i}}}{\sum_{(u,i)\in\mathcal{D}} \frac{o_{u,i}}{\hat{p}_{u,i}}}.$$

The SNIPS estimator often has lower variance than the IPS estimator but has a small bias.

Tobias Schnabel, Adith Swaminathan, Ashudeep Singh, Navin Chandak, Thorsten Joachims (2016). “Recommendations as treatments: Debiasing learning and evaluation”, ICML.

• Error Imputation-Based (EIB) Method

$$\mathcal{L}_{EIB}(\phi, \theta) = |\mathcal{D}|^{-1} \sum_{(u,i)\in\mathcal{D}} [o_{u,i}e_{u,i} + (1 - o_{u,i})\hat{e}_{u,i}], \tag{6}$$

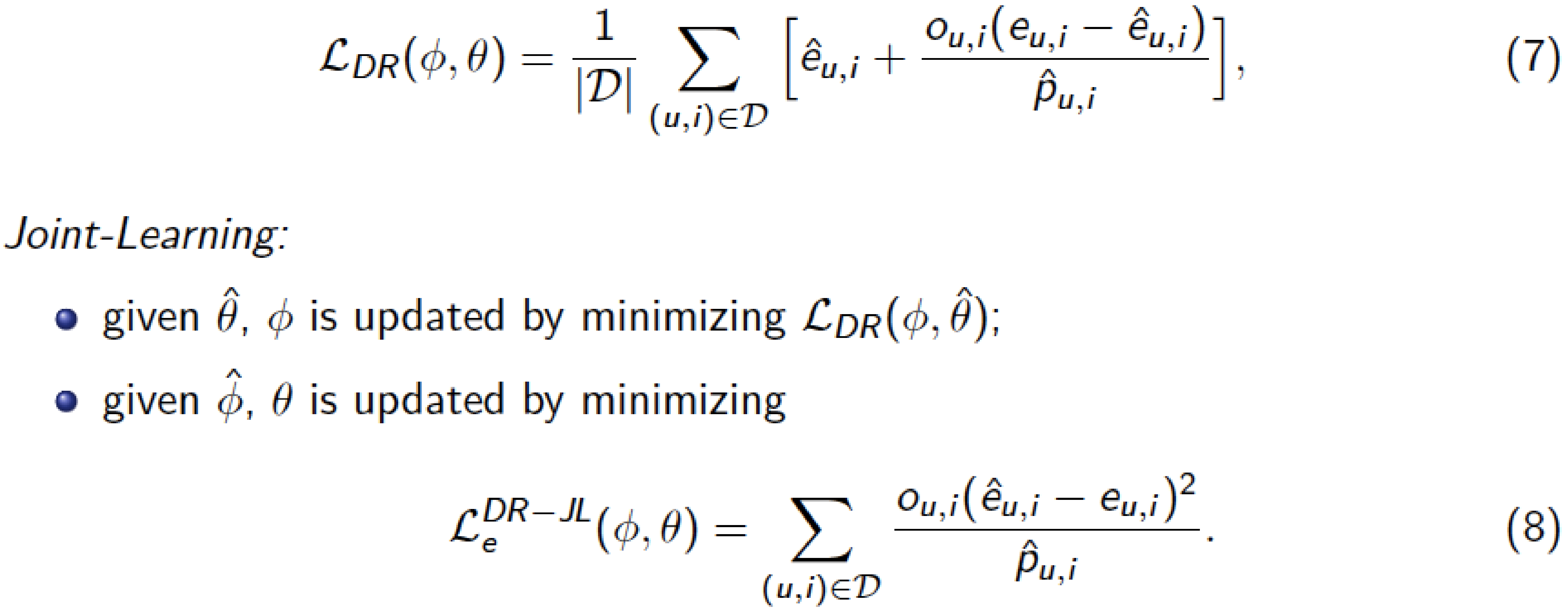
where $\hat{e}_{u,i} = g_\theta(x_{u,i})$ fits the prediction error $e_{u,i}$ using $x_{u,i}$, i.e., it estimates $g_{u,i} := \mathbb{E}[e_{u,i}|x_{u,i}]$.

Given $\hat{e}_{u,i}$, we have

$$\begin{aligned}
\mathbb{E}[\mathcal{L}_{EIB}(\phi, \theta)] &= \mathbb{E}[o_{u,i}e_{u,i} + (1 - o_{u,i})\hat{e}_{u,i}] \\
&= \mathbb{E}[e_{u,i}] + \mathbb{E}[(1 - o_{u,i})(\hat{e}_{u,i} - e_{u,i})] \\
&= \mathbb{E}[e_{u,i}] + \mathbb{E}[\mathbb{E}\{(1 - o_{u,i})(\hat{e}_{u,i} - e_{u,i})|x_{u,i}\}] \\
&= \mathbb{E}[e_{u,i}] + \mathbb{E}[\mathbb{E}(1 - o_{u,i}|x_{u,i}) \cdot \mathbb{E}(\hat{e}_{u,i} - e_{u,i}|x_{u,i})] \\
&= \mathbb{E}[e_{u,i}] + \mathbb{E}[(1 - p_{u,i})(\hat{e}_{u,i} - g_{u,i})].
\end{aligned}$$

If $\hat{e}_{u,i} = g_{u,i}$, EIB estimator is unbiased.

• Doubly Robust Joint Learning (DR-JL)



$$\mathcal{L}_{DR}(\phi, \theta) = \frac{1}{|\mathcal{D}|} \sum_{(u,i) \in \mathcal{D}} \left[\hat{e}_{u,i} + \frac{o_{u,i}(e_{u,i} - \hat{e}_{u,i})}{\hat{p}_{u,i}} \right], \tag{7}$$

Joint-Learning:

- given $\hat{\theta}$, ϕ is updated by minimizing $\mathcal{L}_{DR}(\phi, \hat{\theta})$;
- given $\hat{\phi}$, θ is updated by minimizing

$$\mathcal{L}_{e}^{DR-JL}(\phi, \theta) = \sum_{(u,i) \in \mathcal{D}} \frac{o_{u,i}(\hat{e}_{u,i} - e_{u,i})^2}{\hat{p}_{u,i}}. \tag{8}$$

Xiaojie Wang, Rui Zhang, Yu Sun, Jianzhong Qi (2019), “Doubly Robust Joint Learning for Recommendation on Data Missing Not at Random”, ICML.

• Doubly Robust Property

Given $\hat{p}_{u,i}$ and $\hat{e}_{u,i}$, we have

$$\begin{aligned}
\mathbb{E}[\mathcal{L}_{DR}(\phi,\theta)] &= \mathbb{E}[\hat{e}_{u,i} + \frac{o_{u,i}(e_{u,i} - \hat{e}_{u,i})}{\hat{p}_{u,i}}] \\
&= \mathbb{E}[e_{u,i} + \frac{(o_{u,i} - \hat{p}_{u,i})(e_{u,i} - \hat{e}_{u,i})}{\hat{p}_{u,i}}] \\
&= \mathbb{E}[e_{u,i}] + \mathbb{E}[\frac{\mathbb{E}\{(o_{u,i} - \hat{p}_{u,i})(e_{u,i} - \hat{e}_{u,i})|x_{u,i}\}}{\hat{p}_{u,i}}] \\
&= \mathbb{E}[e_{u,i}] + \mathbb{E}[\frac{\mathbb{E}(o_{u,i} - \hat{p}_{u,i}|x_{u,i}) \cdot \mathbb{E}(e_{u,i} - \hat{e}_{u,i}|x_{u,i})}{\hat{p}_{u,i}}] \\
&= \mathbb{E}[e_{u,i}] + \mathbb{E}[\frac{(p_{u,i} - \hat{p}_{u,i}) \cdot (g_{u,i} - \hat{e}_{u,i})}{\hat{p}_{u,i}}].
\end{aligned}$$

Thus, If either $\hat{e}_{u,i} = g_{u,i}$ or $\hat{p}_{u,i} = p_{u,i}$,

$$\mathbb{E}[\mathcal{L}_{DR}(\phi,\theta)] = \mathbb{E}[e_{u,i}].$$

Contents

1 Potential Outcome Framework

2 Basic Methods: IPS, EIB and DR

3 Limitations of Basic Methods

4 Enhanced DR Methods

5 Uniform Data-Aware Methods

6 Causal Analysis Framework

• Limitations of IPS and DR methods

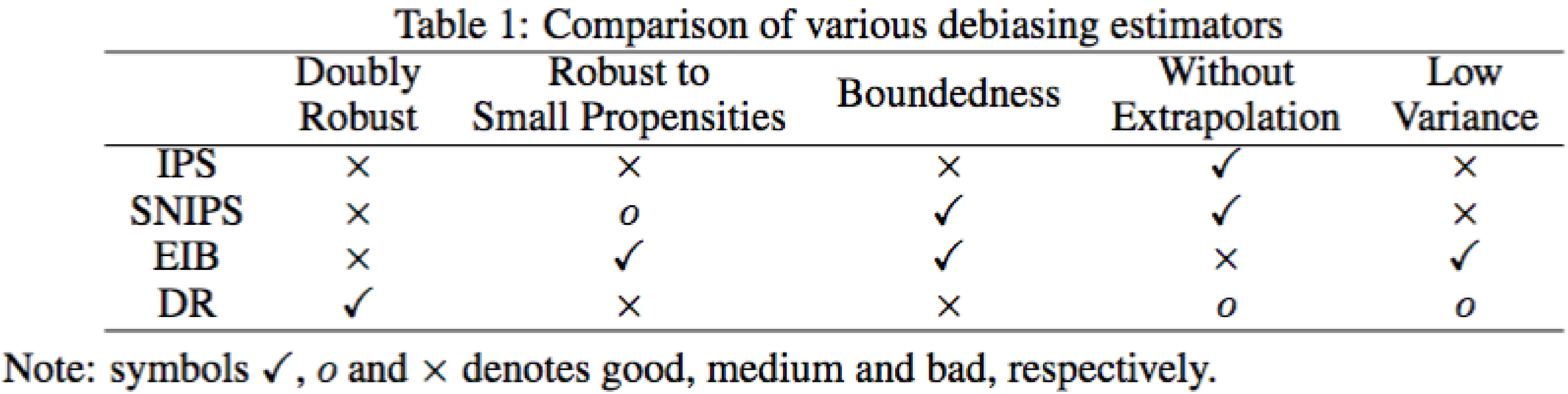


Table 1: Comparison of various debiasing estimators

	Doubly Robust	Robust to Small Propensities	Boundedness	Without Extrapolation	Low Variance
IPS	×	×	×	✓	×
SNIPS	×	*o*	✓	✓	×
EIB	×	✓	✓	×	✓
DR	✓	×	×	*o*	*o*

Note: symbols ✓, *o* and × denotes good, medium and bad, respectively.

Peng Wu, Haoxuan Li, Yan Lyu & Xiao-Hua Zhou (2022), ’Doubly Robust Collaborative Targeted Learning for Recommendation on Data Missing Not at Random’, arXiv:2203.10258.

• Five Desired Properties

- **Doubly robust**: DR enjoys the property of double robustness; In contrast, IPS and EIB do not meet the property of double robustness.

- **Robust to small propensities**: Both the IPS and DR use $1/\hat{p}_{u,i}$ as the weight to recover the target distribution. In the presence of small propensities, the weights will become extremely large and cause instability. In contrast, EIB does not suffer from such a problem.

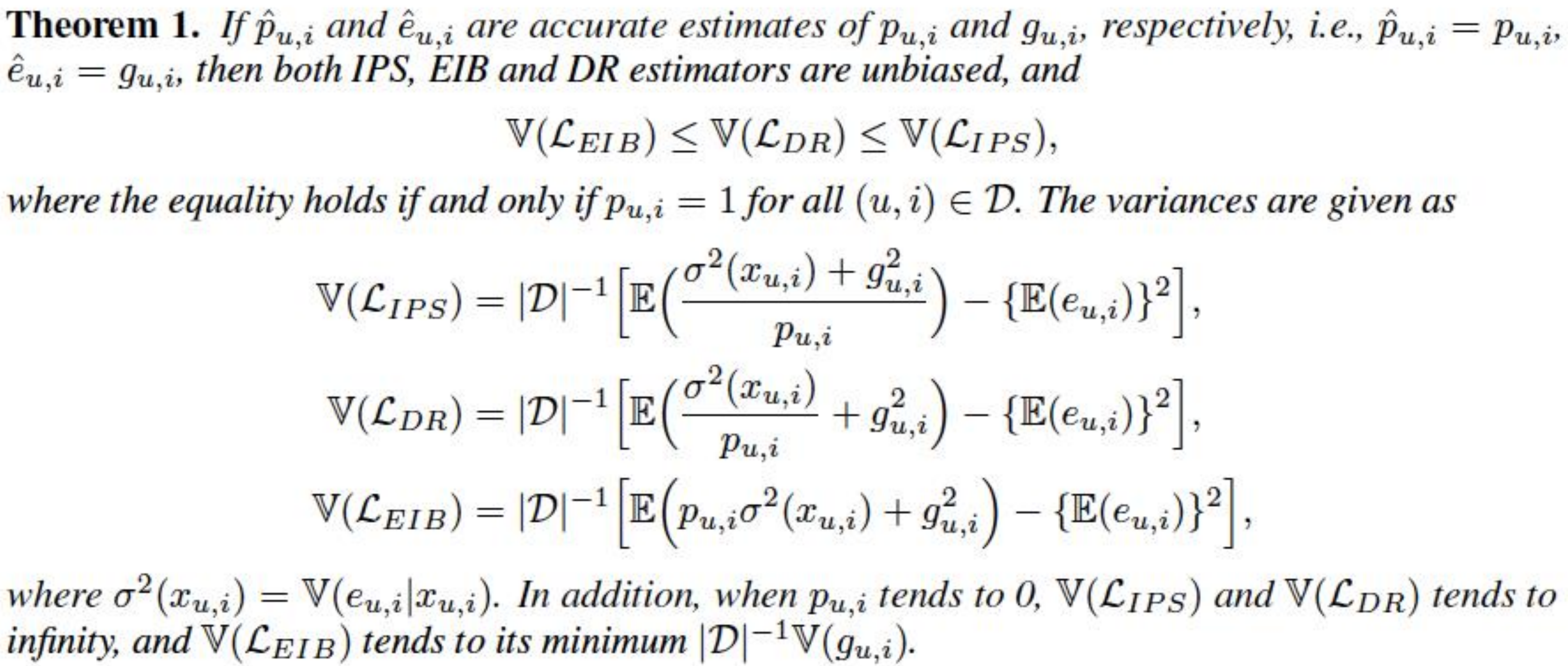
- **Boundedness**: Both the IPS and DR may lie outside the range of $L_{ideal}(\phi)$, i.e., they do not enjoy the property of boundedness. For example, if we set $e_{u,i} \in [0,1]$, then $L_{ideal}(\phi) \in [0,1]$, while $L_{IPS}(\phi)$ and $L_{DR}(\phi, \theta)$ may not be within the range. The EIB can guarantee boundedness property easily if the error imputation model is chosen appropriately.

• Five Desired Properties

- **Without extrapolation** (small bias): EIB usually has a large bias, which is a consequence of making implicitly extrapolation. Specifically, the error imputation model is trained with exposed events while using the predicted values for unexposed events. This relies heavily on extrapolation since the exposed events are sparse and there may exist a significant difference between the distributions of exposed events and unexposed events. Thus, it is hard to obtain accurate error imputation and leads to poor performance. In comparison, the estimation of propensity score doesn't rely on extrapolation.

- **Low variance**: It can be shown that EIB has the smallest variance among these methods.

Five Desired Properties



Theorem 1. *If $\hat{p}_{u,i}$ and $\hat{e}_{u,i}$ are accurate estimates of $p_{u,i}$ and $g_{u,i}$, respectively, i.e., $\hat{p}_{u,i} = p_{u,i}$, $\hat{e}_{u,i} = g_{u,i}$, then both IPS, EIB and DR estimators are unbiased, and*

$$\mathbb{V}(\mathcal{L}_{EIB}) \leq \mathbb{V}(\mathcal{L}_{DR}) \leq \mathbb{V}(\mathcal{L}_{IPS}),$$

where the equality holds if and only if $p_{u,i} = 1$ for all $(u, i) \in \mathcal{D}$. The variances are given as

$$\mathbb{V}(\mathcal{L}_{IPS}) = |\mathcal{D}|^{-1}\Big[\mathbb{E}\Big(\frac{\sigma^2(x_{u,i}) + g_{u,i}^2}{p_{u,i}}\Big) - \{\mathbb{E}(e_{u,i})\}^2\Big],$$

$$\mathbb{V}(\mathcal{L}_{DR}) = |\mathcal{D}|^{-1}\Big[\mathbb{E}\Big(\frac{\sigma^2(x_{u,i})}{p_{u,i}} + g_{u,i}^2\Big) - \{\mathbb{E}(e_{u,i})\}^2\Big],$$

$$\mathbb{V}(\mathcal{L}_{EIB}) = |\mathcal{D}|^{-1}\Big[\mathbb{E}\Big(p_{u,i}\sigma^2(x_{u,i}) + g_{u,i}^2\Big) - \{\mathbb{E}(e_{u,i})\}^2\Big],$$

where $\sigma^2(x_{u,i}) = \mathbb{V}(e_{u,i}|x_{u,i})$. In addition, when $p_{u,i}$ tends to 0, $\mathbb{V}(\mathcal{L}_{IPS})$ and $\mathbb{V}(\mathcal{L}_{DR})$ tends to infinity, and $\mathbb{V}(\mathcal{L}_{EIB})$ tends to its minimum $|\mathcal{D}|^{-1}\mathbb{V}(g_{u,i})$.

Contents

• Three Enhanced Methods

- **More Robust Doubly Robust (MRDR)**: bias-variance trade-off.
- **Doubly robust targeted learning**: capture the merits of both EIB and DR.
- **Multi-task learning**: parameter sharing.

• More Robust Doubly Robust (MRDR)

MRDR enhances the robustness of DR-JL by optimizing the variance of the DR estimator with the imputation model.

$$\mathcal{L}_{DR}(\phi,\theta)=\frac{1}{|\mathcal{D}|}\sum_{(u,i)\in\mathcal{D}}\left[\hat{e}_{u,i}+\frac{o_{u,i}(e_{u,i}-\hat{e}_{u,i})}{\hat{p}_{u,i}}\right],$$

DR-JL

- given $\hat{\theta}$, ϕ is updated by minimizing $\mathcal{L}_{DR}(\phi,\hat{\theta})$;
- given $\hat{\phi}$, θ is updated by minimizing

$$\mathcal{L}_e^{DR-JL}(\phi,\theta)=\sum_{(u,i)\in\mathcal{D}}\frac{o_{u,i}(\hat{e}_{u,i}-e_{u,i})^2}{\hat{p}_{u,i}}.$$

MRDR

- given $\hat{\theta}$, ϕ is updated by minimizing $\mathcal{L}_{DR}(\phi,\hat{\theta})$;
- given $\hat{\phi}$, θ is updated by minimizing

$$\mathcal{L}_e^{MRDR}(\theta)=\sum_{(u,i)\in\mathcal{D}}\frac{o_{u,i}(\hat{e}_{u,i}-e_{u,i})^2}{\hat{p}_{u,i}}\cdot\frac{1-\hat{p}_{u,i}}{\hat{p}_{u,i}}.$$

MRDR substitutes the loss function of the imputation model.

Idea of More Robust Doubly Robust (MRDR)

This substitution can help reduce the variance of $L_{DR}(\phi, \theta)$ and hence a more robust estimator might be achieved.

$$\mathbb{V}_{\mathcal{O}}[\mathcal{L}_{DR}(\phi,\theta)] = \frac{1}{|\mathcal{D}|^2}\mathbb{E}_{\mathcal{O}}[\underbrace{\sum_{(u,i)\in\mathcal{D}} \frac{o_{u,i}(1-p_{u,i})(\hat{e}_{u,i}-e_{u,i})^2}{\hat{p}_{u,i}^2}}_{\mathcal{L}_e^{MRDR}(\theta)}].$$

Siyuan Guo, Lixin Zou, Yiding Liu, Wenwen Ye, Suqi Cheng, Shuaiqiang Wang, Hechang Chen, Dawei Yin, and Yi Chang (2021), “Enhanced Doubly Robust Learning for Debiasing Post-Click Conversion Rate Estimation”. SIGIR

Motivation of DR-TMLE

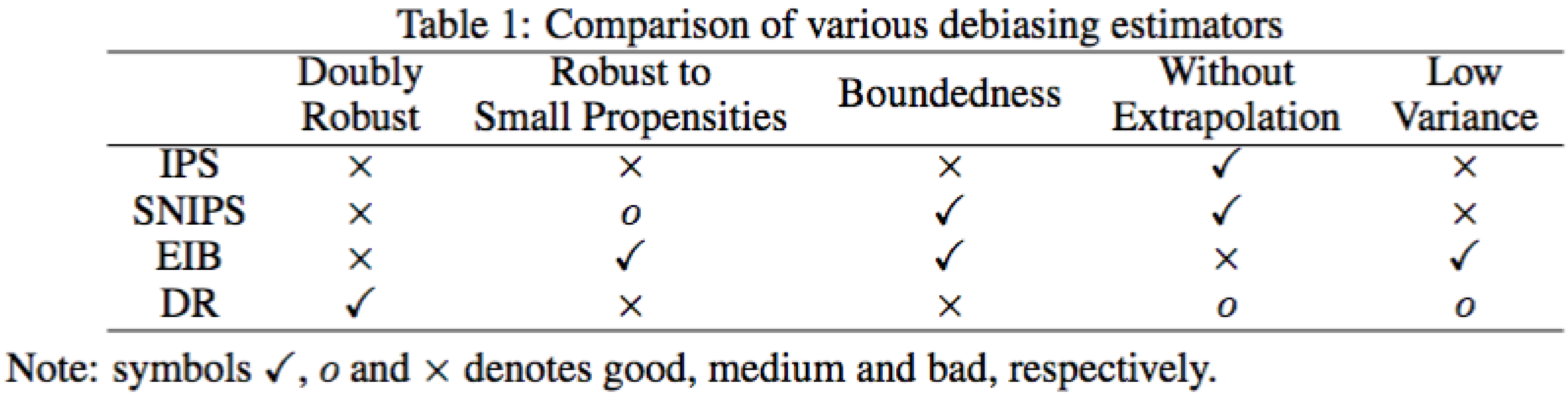


Table 1: Comparison of various debiasing estimators

	Doubly Robust	Robust to Small Propensities	Boundedness	Without Extrapolation	Low Variance
IPS	×	×	×	✓	×
SNIPS	×	*o*	✓	✓	×
EIB	×	✓	✓	×	✓
DR	✓	×	×	*o*	*o*

Note: symbols ✓, *o* and × denotes good, medium and bad, respectively.

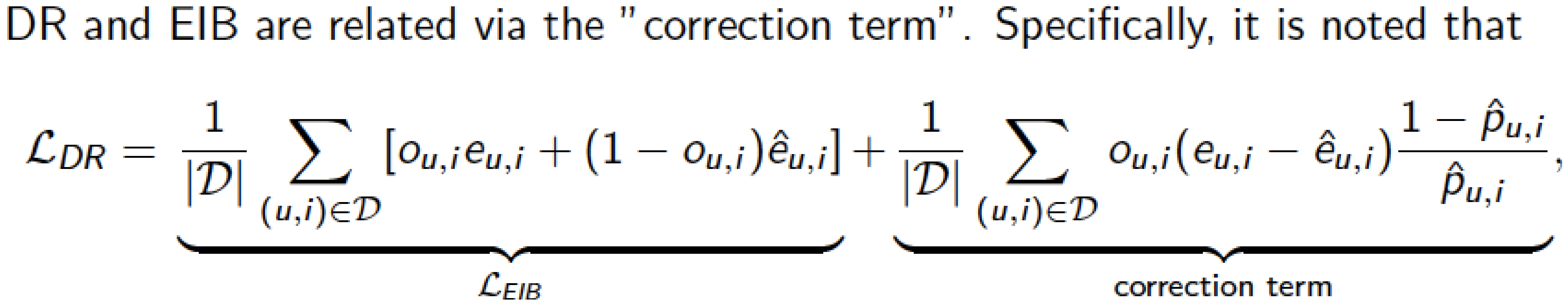
- DR outperforms IPS in terms of both bias and variance.

- When compared with EIB, DR tends to have a smaller bias, while EIB has a smaller variance. It involves the bias-variance trade-off.

- Ideally, it is desirable to develop a method that can capture the merits of both DR and EIB.

Peng Wu, Haoxuan Li, Yan Lyu & Xiao-Hua Zhou (2022), 'Doubly Robust Collaborative Targeted Learning for Recommendation on Data Missing Not at Random', arXiv:2203.10258.

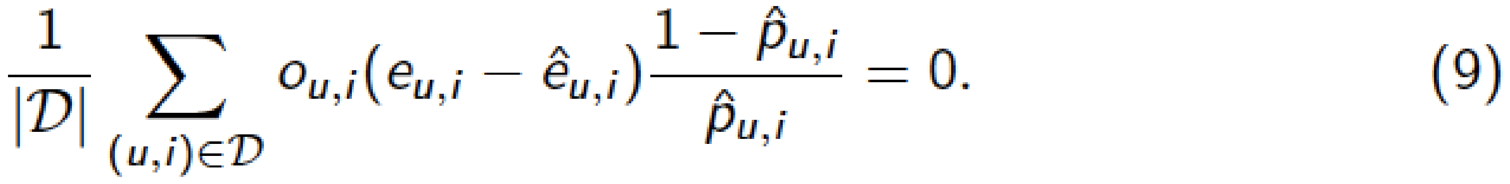
• Basic idea of DR-TMLE



DR and EIB are related via the "correction term". Specifically, it is noted that

$$\mathcal{L}_{DR} = \underbrace{\frac{1}{|\mathcal{D}|}\sum_{(u,i)\in\mathcal{D}}\left[o_{u,i}e_{u,i} + (1-o_{u,i})\hat{e}_{u,i}\right]}_{\mathcal{L}_{EIB}} + \underbrace{\frac{1}{|\mathcal{D}|}\sum_{(u,i)\in\mathcal{D}} o_{u,i}(e_{u,i}-\hat{e}_{u,i})\frac{1-\hat{p}_{u,i}}{\hat{p}_{u,i}}}_{\text{correction term}},$$

which indicates that the correction term uses propensity score to estimate how much L_{EIB} overestimates or underestimates L_{ideal} and then subtracts it. As a compromise, the correction term will increase the variance of the DR estimator according to Theorem 1. Thus, if $\hat{e}_{u,i}$ is computed in a manner that ensures that



$$\frac{1}{|\mathcal{D}|}\sum_{(u,i)\in\mathcal{D}} o_{u,i}(e_{u,i}-\hat{e}_{u,i})\frac{1-\hat{p}_{u,i}}{\hat{p}_{u,i}} = 0. \qquad (9)$$

Then the EIB would have small bias and the DR would have small variance.

Merits of DR-TMLE

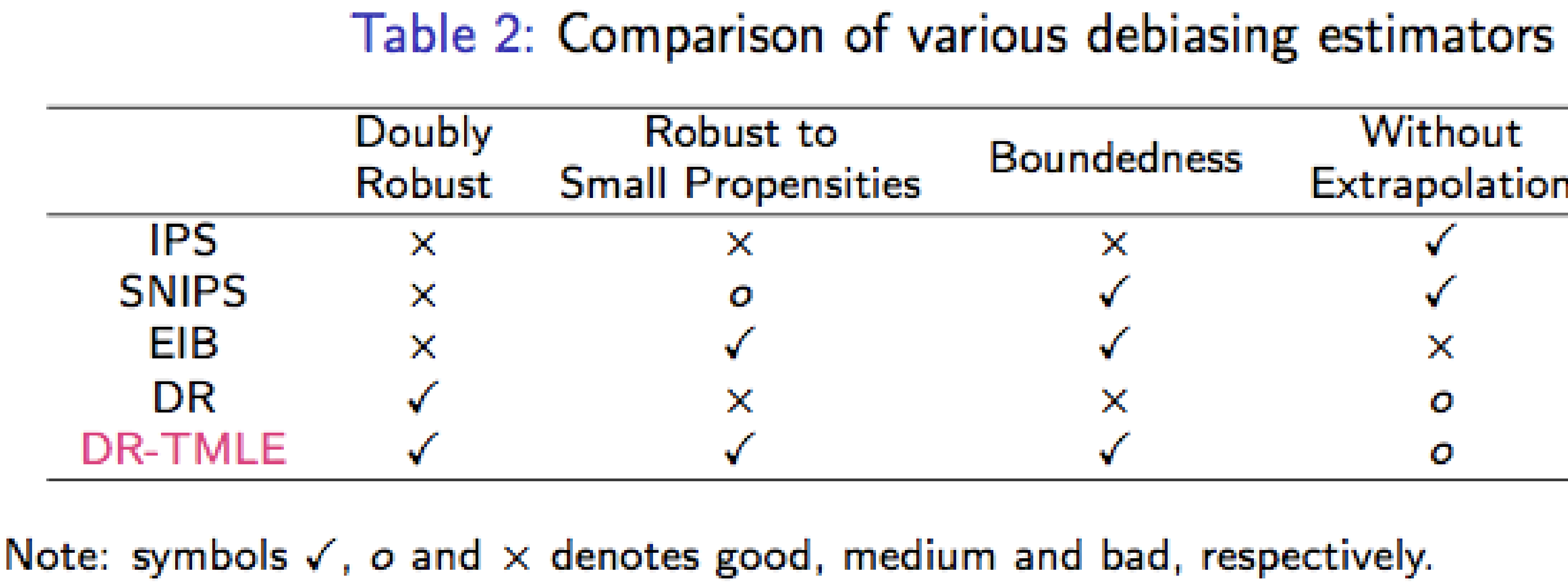


Table 2: Comparison of various debiasing estimators

	Doubly Robust	Robust to Small Propensities	Boundedness	Without Extrapolation	Low Variance
IPS	×	×	×	✓	×
SNIPS	×	o	✓	✓	×
EIB	×	✓	✓	×	✓
DR	✓	×	×	o	o
DR-TMLE	✓	✓	✓	o	✓

Note: symbols ✓, o and × denotes good, medium and bad, respectively.

- Some may argue that the constraint (9) may degrade the accuracy of $\hat{e}_{u,i}$.
- By leveraging the targeted maximum likelihood estimation (TMLE) technique, DR-TMLE obtain an estimate of $\hat{e}_{u,i}$ that satisfies equation (9), without sacrificing the accuracy of error imputation model.

• TMLE Technique

Assume the error imputation model can be presented as

$$\hat{e}_{u,i} = \varphi\{h_{\phi}(x_{u,i})\},$$

where h is an arbitrary function, φ is a known function, such as identity, sigmoid.

The basic idea of TMLE consists of two steps:

- **Step 1 (Initialization)**: pre-train an initial imputation estimator, denoted as

$$\hat{e}_{u,i}^{(0)} = \varphi\{\hat{h}^{(0)}(x_{u,i})\}$$

- **Step 2 (Targeting)**: update $\hat{e}_{u,i}^{(0)}$ by fitting an extended one-parameter model

$$e_{u,i}^{new}(\eta) = \varphi\{\hat{h}^{(0)}(x_{u,i}) + \eta(1/\hat{p}_{u,i} - 1)\}$$

The DR-TMLE estimator is given as

$$\mathcal{L}_{DR-TMLE} = |\mathcal{D}|^{-1} \sum_{(u,i)\in\mathcal{D}} \left[\hat{e}_{u,i}^{new} + o_{u,i}(e_{u,i} - \hat{e}_{u,i}^{new})/\hat{p}_{u,i}\right].$$

• TMLE Technique

- It can be shown that the TMLE technique would ensure that $\hat{e}_{u.i}^{new}$ satisfies equation (9).

- Since the targeting step updates the imputation model by adding an error correction term $\frac{1}{\hat{p}_{u,i}} - 1$ to approximate $e_{u,i}$ better and hence does not sacrifice the accuracy of imputation model.

Collaborative Targeted Learning

- DR-TMLE requires a pre-trained propensity model, however, a concern is that if $\hat{p}_{u,i}$ is inaccurate, the targeting step in TMLE cannot be guaranteed to provide a correct direction of debiasing and variance-reduction.

- To cope with the problem, a novel TMLE-based collaborative targeted learning approach (TMLE-TL) was developed, which pursues an optimal strategy for estimation of the propensity score and error imputation model.

Peng Wu, Haoxuan Li, Yan Lyu & Xiao-Hua Zhou (2022), ’Doubly Robust Collaborative Targeted Learning for Recommendation on Data Missing Not at Random’, arXiv:2203.10258.

Numeric Experiments

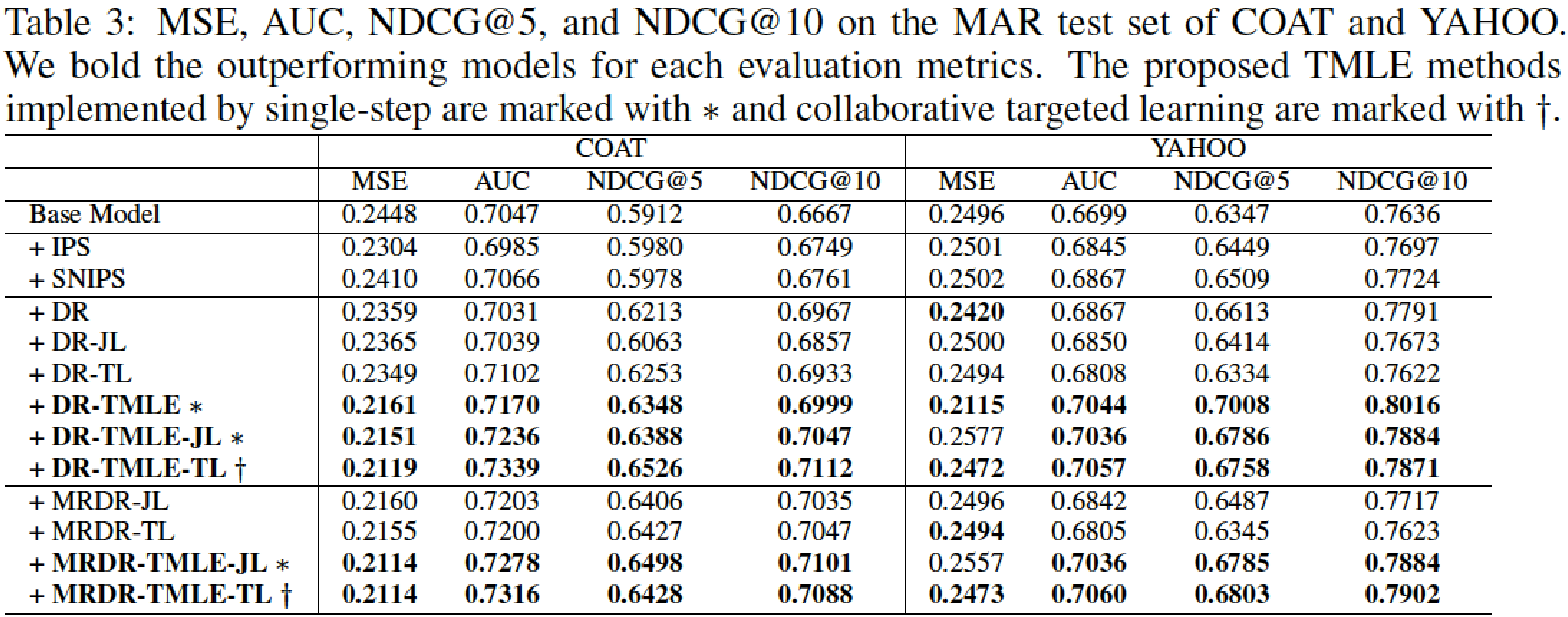
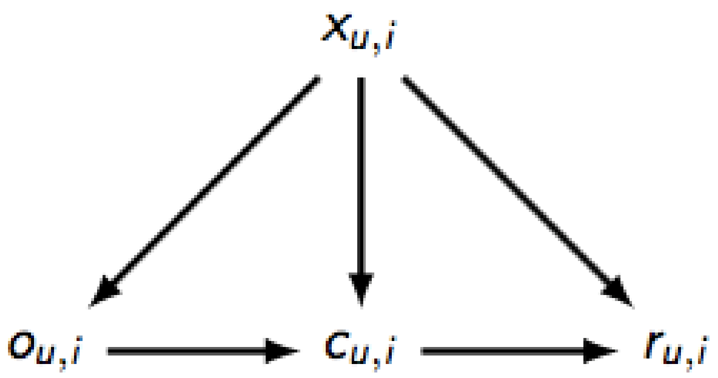


Table 3: MSE, AUC, NDCG@5, and NDCG@10 on the MAR test set of COAT and YAHOO. We bold the outperforming models for each evaluation metrics. The proposed TMLE methods implemented by single-step are marked with $*$ and collaborative targeted learning are marked with †.

	COAT				YAHOO			
	MSE	AUC	NDCG@5	NDCG@10	MSE	AUC	NDCG@5	NDCG@10
Base Model	0.2448	0.7047	0.5912	0.6667	0.2496	0.6699	0.6347	0.7636
+ IPS	0.2304	0.6985	0.5980	0.6749	0.2501	0.6845	0.6449	0.7697
+ SNIPS	0.2410	0.7066	0.5978	0.6761	0.2502	0.6867	0.6509	0.7724
+ DR	0.2359	0.7031	0.6213	0.6967	**0.2420**	0.6867	0.6613	0.7791
+ DR-JL	0.2365	0.7039	0.6063	0.6857	0.2500	0.6850	0.6414	0.7673
+ DR-TL	0.2349	0.7102	0.6253	0.6933	0.2494	0.6808	0.6334	0.7622
+ DR-TMLE $*$	**0.2161**	**0.7170**	**0.6348**	**0.6999**	**0.2115**	**0.7044**	**0.7008**	**0.8016**
+ DR-TMLE-JL $*$	**0.2151**	**0.7236**	**0.6388**	**0.7047**	0.2577	**0.7036**	**0.6786**	**0.7884**
+ DR-TMLE-TL †	**0.2119**	**0.7339**	**0.6526**	**0.7112**	**0.2472**	**0.7057**	**0.6758**	**0.7871**
+ MRDR-JL	0.2160	0.7203	0.6406	0.7035	0.2496	0.6842	0.6487	0.7717
+ MRDR-TL	0.2155	0.7200	0.6427	0.7047	**0.2494**	0.6805	0.6345	0.7623
+ MRDR-TMLE-JL $*$	**0.2114**	**0.7278**	**0.6498**	**0.7101**	0.2557	**0.7036**	**0.6785**	**0.7884**
+ MRDR-TMLE-TL †	**0.2114**	**0.7316**	**0.6428**	**0.7088**	**0.2473**	**0.7060**	**0.6803**	**0.7902**

Multi-Task Learning

A typical e-commerce transaction has the following sequential events:



- o_{ui}: $o_{ui} = 1$ if item i is exposed to u; $o_{ui} = 0$ otherwise.
- c_{ui}: $c_{ui} = 1$ if u clicks on item i; $c_{ui} = 0$ otherwise.
- r_{ui}: $r_{ui} = 1$ if user u purchases item i; $r_{ui} = 0$ otherwise.

Multiple Tasks:

- Post-view click-through rate: take $o_{u,i}$ as treatment,

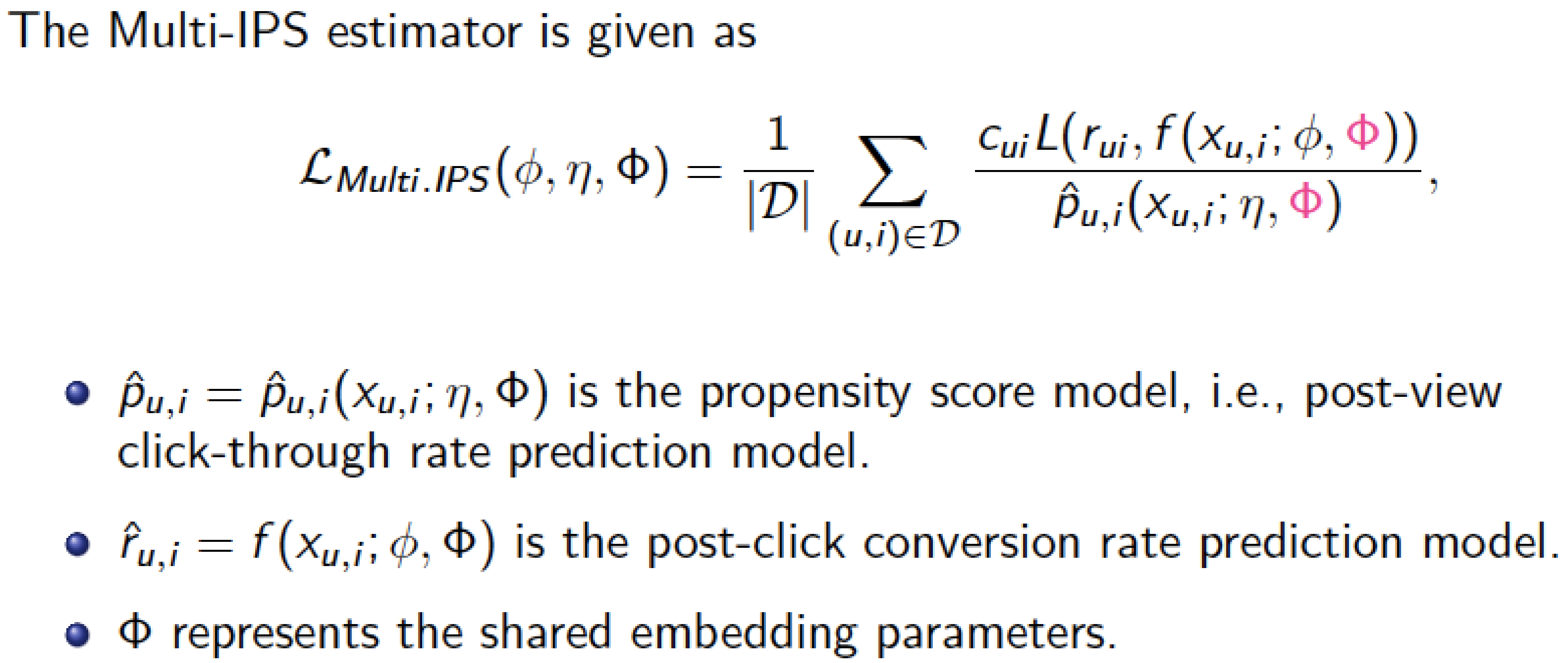
$$\mathbb{P}(c_{u,i}(1) = 1 | x_{u,i}) = \mathbb{P}(c_{u,i} = 1 | x_{u,i}, o_{u,i} = 1)$$

- Post-click conversion rate: take $c_{u,i}$ as treatment

$$\begin{aligned}\mathbb{P}(r_{u,i}(1) = 1 | x_{u,i}) &= \mathbb{P}(r_{u,i} = 1 | x_{u,i}, c_{u,i} = 1) \\ &= \mathbb{P}(r_{u,i} = 1 | x_{u,i}, o_{u,i} = 1, c_{u,i} = 1)\end{aligned}$$

The last equation holds if $c_{u,i} = 1 \implies o_{u,i} = 1$.

Multi-Task Learning: Multi-IPS



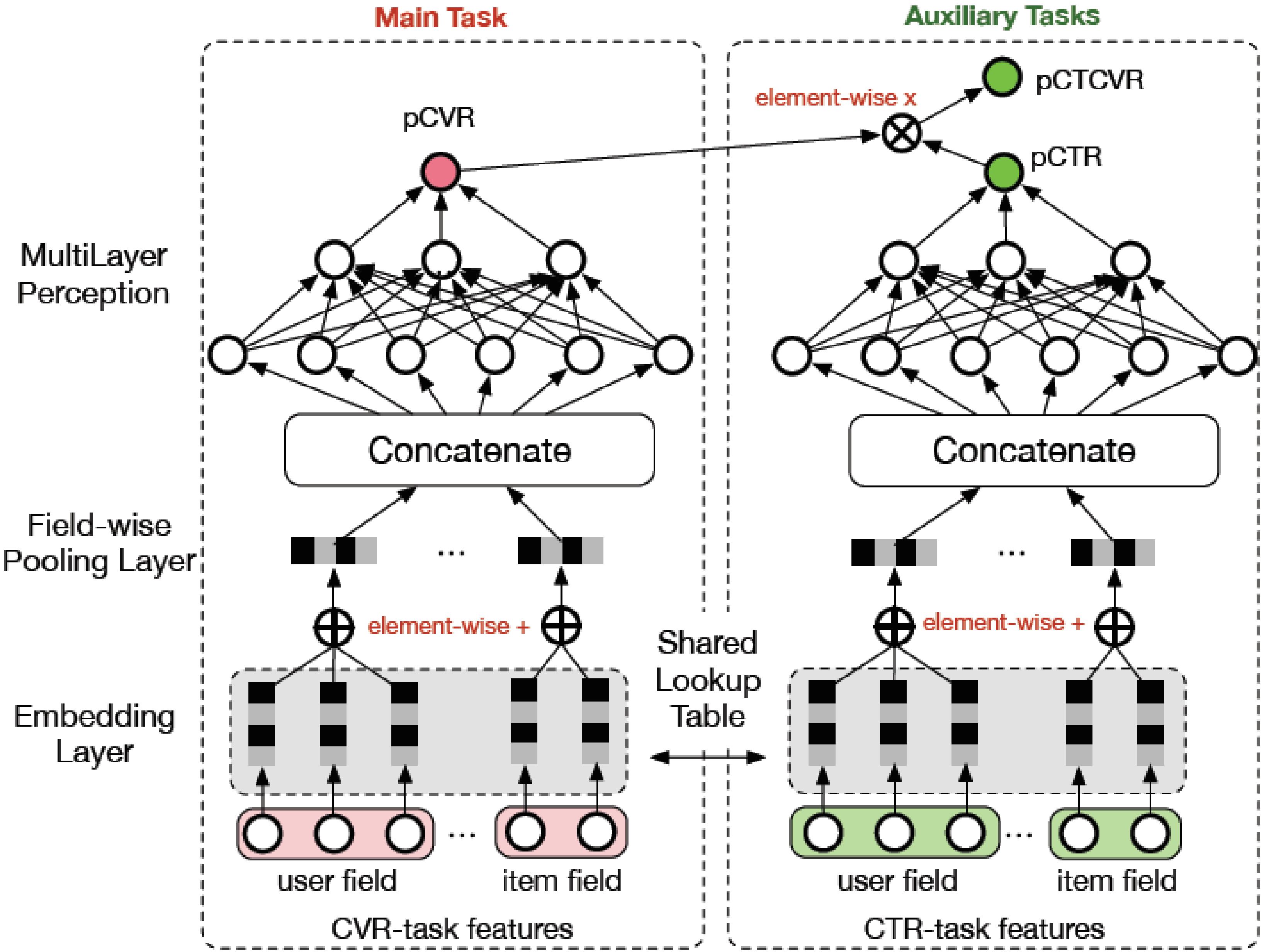
The Multi-IPS estimator is given as

$$\mathcal{L}_{Multi\_IPS}(\phi, \eta, \Phi) = \frac{1}{|\mathcal{D}|} \sum_{(u,i)\in\mathcal{D}} \frac{c_{ui} L(r_{ui}, f(x_{u,i}; \phi, \Phi))}{\hat{p}_{u,i}(x_{u,i}; \eta, \Phi)},$$

- $\hat{p}_{u,i} = \hat{p}_{u,i}(x_{u,i}; \eta, \Phi)$ is the propensity score model, i.e., post-view click-through rate prediction model.
- $\hat{r}_{u,i} = f(x_{u,i}; \phi, \Phi)$ is the post-click conversion rate prediction model.
- Φ represents the shared embedding parameters.

Wenhao Zhang, Wentian Bao, Xiao-Yang Liu, Keping Yang, Quan Lin, Hong Wen, Ramin Ramezani (2020), “Large-scale Causal Approaches to Debiasing Post-click Conversion Rate Estimation with Multi-task Learning”. WWW

• Multi-Task Learning: Multi-IPS



• Intuition of Parameter Sharing

- Training samples with all exposures for pCTR task is relatively much richer than pCVR task.

- Thus, parameter sharing mechanism enables pCVR network to learn from un-clicked exposures and provides great help for alleviating the data sparsity trouble.

Wenhao Zhang, Wentian Bao, Xiao-Yang Liu, Keping Yang, Quan Lin, Hong Wen, Ramin Ramezani (2020), “Large-scale Causal Approaches to Debiasing Post-click Conversion Rate Estimation with Multi-task Learning”. WWW

• Multi-Task Learning: Multi-DR

The Multi-DR estimator is given as

$$\mathcal{L}_{Multi.DR}(\phi, \eta, \Phi) = \frac{1}{|\mathcal{D}|} \sum_{(u,i)\in\mathcal{D}} \Big\{ g_{u,i}(x_{u,i}; \theta, \Phi) + \frac{c_{ui}\,(L(r_{ui}, f(x_{u,i}; \phi, \Phi)) - g_{u,i}(x_{u,i}; \theta, \Phi))}{\hat{p}_{u,i}(x_{u,i}; \eta, \Phi)} \Big\},$$

- $g_{u,i}(x_{u,i}; \theta, \Phi)$ is the error imputation model.
- $\hat{p}_{u,i} = \hat{p}_{u,i}(x_{u,i}; \eta, \Phi)$ is the propensity score model, i.e., post-view click-through rate prediction model.
- $\hat{r}_{u,i} = f(x_{u,i}; \phi, \Phi)$ is the post-click conversion rate prediction model.
- Φ represents the shared embedding parameters among CTR task, CVR task, and imputation task.

Contents

• Estimation of Propensity Score

- Without using uniform dataset: Logistic regression or matrix factorization,

$$p_{u,i} = \mathbb{P}(o_{u,i} = 1 \mid x_{u,i}),$$

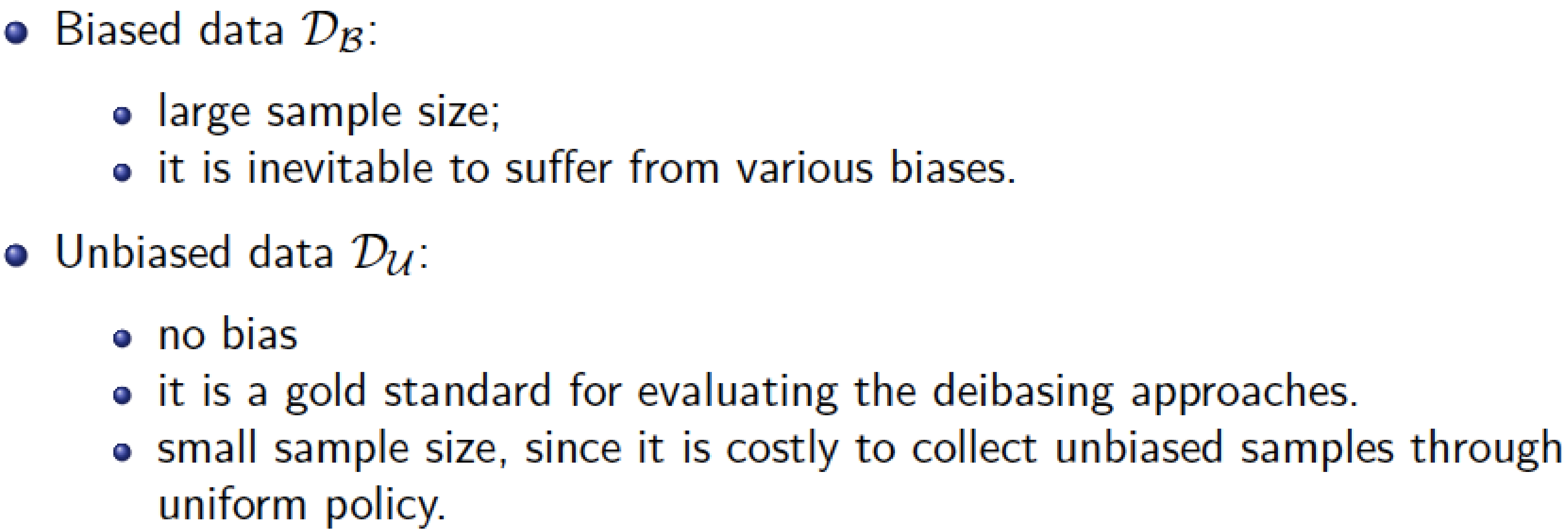
i.e., estimating $o_{u,i}$ using $x_{u,i}$.

- Using a small uniform dataset: Naive Bayes

$$p_{u,i} = \mathbb{P}(o_{u,i} = 1 \mid x_{u,i}, r_{u,i}(1)) = \frac{\mathbb{P}(r_{u,i}(1) \mid x_{u,i}, o_{u,i} = 1) \cdot \mathbb{P}(o_{u,i} = 1, x_{u,i})}{\mathbb{P}(x_{u,i}, r_{u,i}(1))},$$

  - $\mathbb{P}(x_{u,i}, r_{u,i}(1))$ can be trained with uniform data;
  - $\mathbb{P}(r_{u,i}(1) \mid x_{u,i}, o_{u,i} = 1)$ and $\mathbb{P}(o_{u,i} = 1, x_{u,i})$ can be obtained by using the biased data.

• Characters of Biased Data and Unbiased Data



- Biased data $\mathcal{D}_{\mathcal{B}}$:
  - large sample size;
  - it is inevitable to suffer from various biases.
- Unbiased data $\mathcal{D}_{\mathcal{U}}$:
  - no bias
  - it is a gold standard for evaluating the deibasing approaches.
  - small sample size, since it is costly to collect unbiased samples through uniform policy.

Only using the unbiased ratings to train the rating model may cause severe overfitting due to the small sample size.

A compromised and pragmatic method is to combine two dataset: a big biased observed ratings and a small unbiased ratings.

• Intuition of Combining Biased Data and Unbiased Data

- A natural question is: whether the unbiased data is helpful to improve the quality of recommendations?

- Intuitively, the unbiased data provides a better way to evaluate the resulting recommendation model, and hence it may give a better optimizing direction for training the model parameters.

- The key point is how to use the unbiased data.

- In general, the unbiased data are applied to obtain better propensity score model or error imputation model.

Bi-Level Optimization

- Wang et al. (2021) use the unbiased data to train the propensity score model, parameterized with η, such that the recommendation model performs well on the unbiased data.

- Formally, this goal can be formulated as a Bi-level optimization problem

$$\begin{aligned} \eta^* &= \arg\min_{\eta} \mathcal{L}(\phi^*(\eta); \mathcal{D}_{\mathcal{U}}) \\ s.t. \quad \phi^*(\eta) &= \arg\min_{\phi} \mathcal{L}(\phi, \eta; \mathcal{D}_{\mathcal{B}}). \end{aligned}$$

where

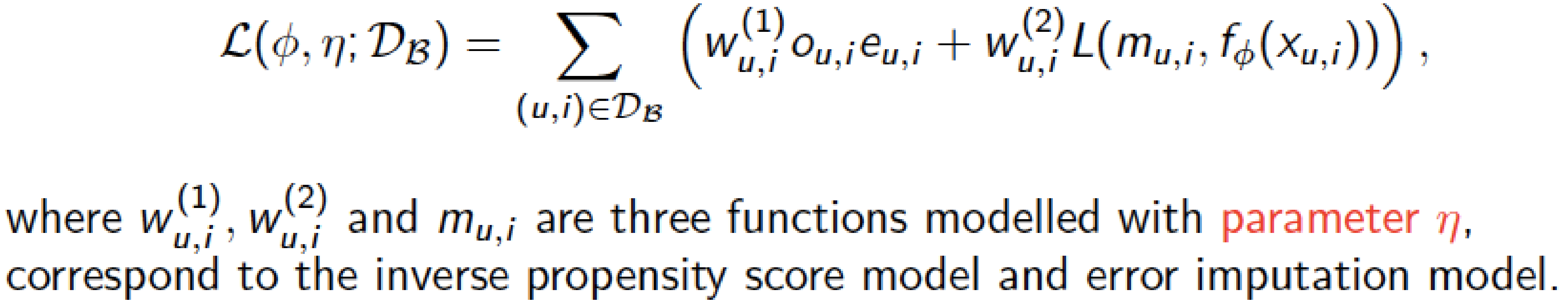
$$\mathcal{L}(\phi^*(\eta); \mathcal{D}_{\mathcal{U}}) = \sum_{(u,i)\in\mathcal{D}_{\mathcal{U}}} \left(r_{u,i} - f_{\phi^*(\eta)}(x_{u,i})\right)^2,$$

$L(\phi, \eta; D_B)$ can be chosen as the same form of IPS estimator or DR estimator.

Xiaojie Wang, Rui Zhang, Yu Sun, Jianzhong Qi (2021), “Combating Selection Biases in Recommender Systems with a Few Unbiased Ratings”, WSDM.

AutoDebias

- AutoDebias applys the unbiased data to train the propensity score model and error imputation model. Thus, it has a more flexile form of $L(\phi, \eta; D_B)$.



$$\mathcal{L}(\phi,\eta;\mathcal{D}_{\mathcal{B}}) = \sum_{(u,i)\in\mathcal{D}_{\mathcal{B}}} \left(w^{(1)}_{u,i} o_{u,i} e_{u,i} + w^{(2)}_{u,i} L(m_{u,i}, f_{\phi}(x_{u,i})) \right),$$

where $w^{(1)}_{u,i}$, $w^{(2)}_{u,i}$ and $m_{u,i}$ are three functions modelled with parameter η, correspond to the inverse propensity score model and error imputation model.

Jiawei Chen, Hande Dong, Yang Qiu, Xiangnan He, Xin Xin, Liang Chen, Guli Lin, Keping Yang (2021), “AutoDebias: Learning to Debias for Recommendation”. SIGIR.

Contents

• Motivation

- The introduction of causal techniques into recommender systems (RS) has brought great development to this field and has gradually become a trend.

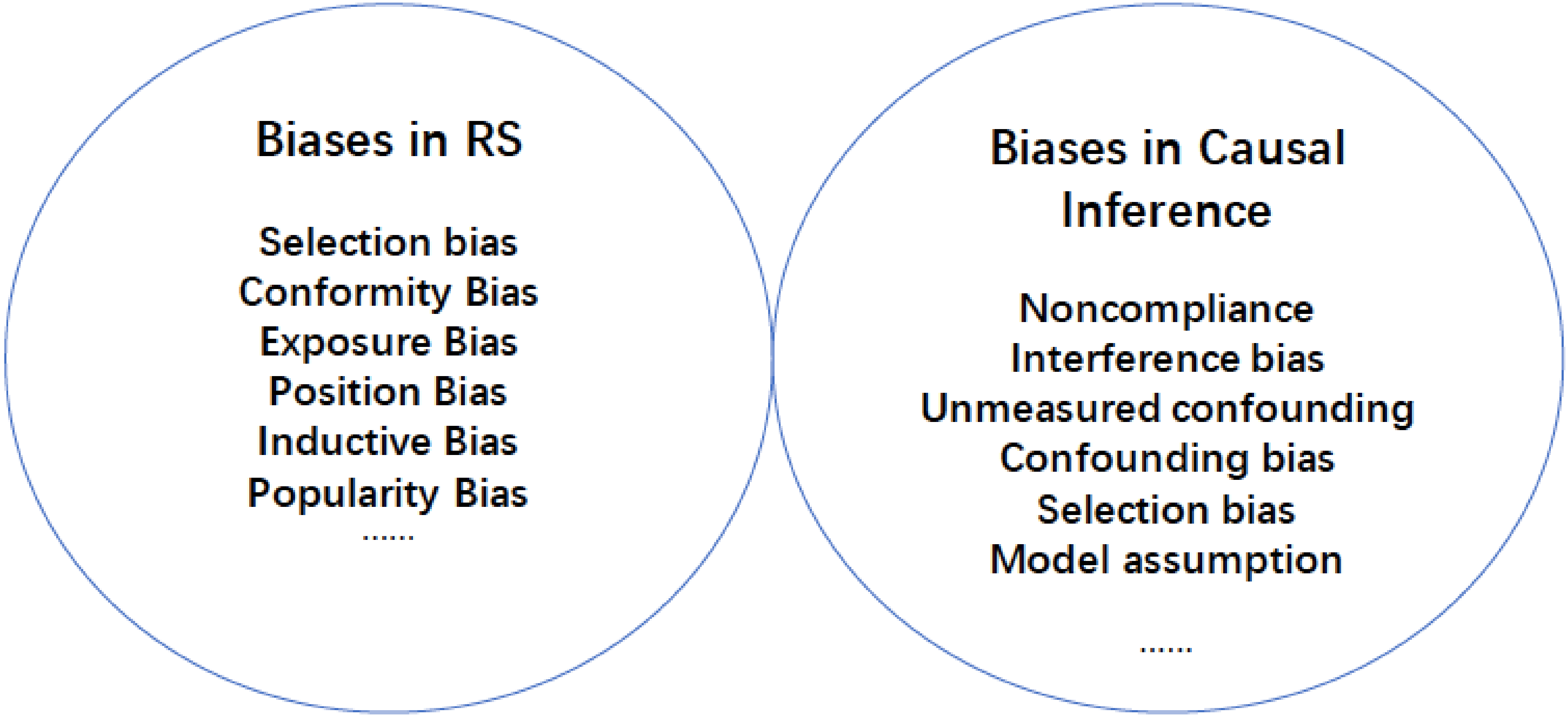
- Technically speaking, the existence of various biases is the main obstacle to drawing causal conclusions from observed data. Yet, formal definitions of the biases in RS are still not clear, which leads to difficulty in discussing theoretical properties and limitations of various debiasing approaches.

- This greatly hinder the development of RS.

Jiawei Chen and Hande Dong and Xiang Wang and Fuli Feng and Meng Wang and Xiangnan He (2020), ’ Bias and Debias in Recommender System: A Survey and Future Directions’, arXiv:2010.03240.

Peng Wu, Haoxuan Li, Yuhao Deng, Wenjie Hu, Quanyu Dai, Zhenhua Dong, Jie Sun, Rui Zhang, Xiao-Hua Zhou (2021), ``Causal Analysis Framework for Recommendation‘’, arXiv:2201.06716. (To appear in IJ-CAI)

• Goal



Biases in RS

Selection bias
Conformity Bias
Exposure Bias
Position Bias
Inductive Bias
Popularity Bias
……

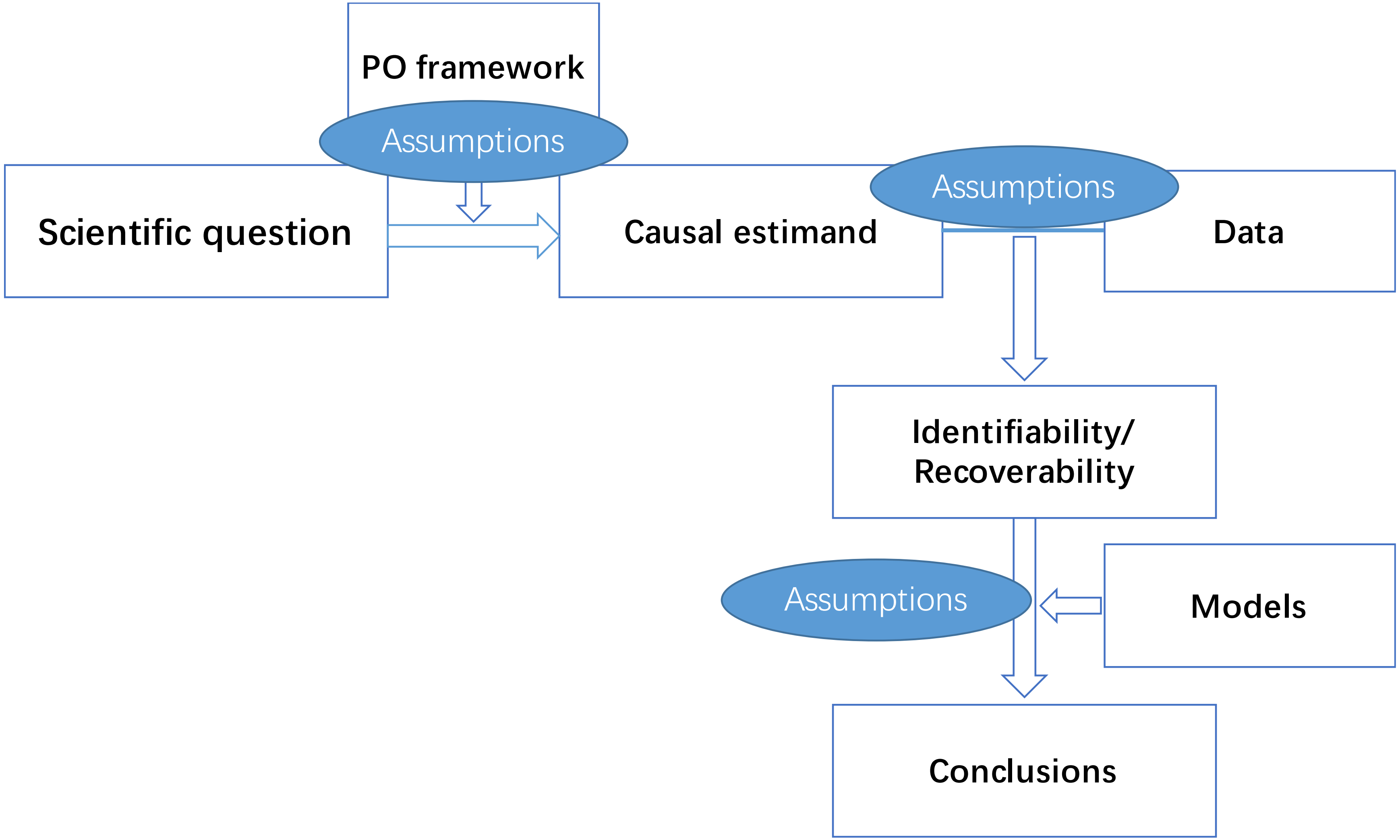
Biases in Causal Inference

Noncompliance
Interference bias
Unmeasured confounding
Confounding bias
Selection bias
Model assumption

……

- Provide formal definitions of various biases in RS.

• Biases in Causal Inference



PO framework

Assumptions

Scientific question

Causal estimand

Assumptions

Data

Identifiability/
Recoverability

Assumptions

Models

Conclusions

We need a variety of assumptions to climb from association (data) to causality (causal conclusions), violating these assumptions may result in various biases.

Conclusions

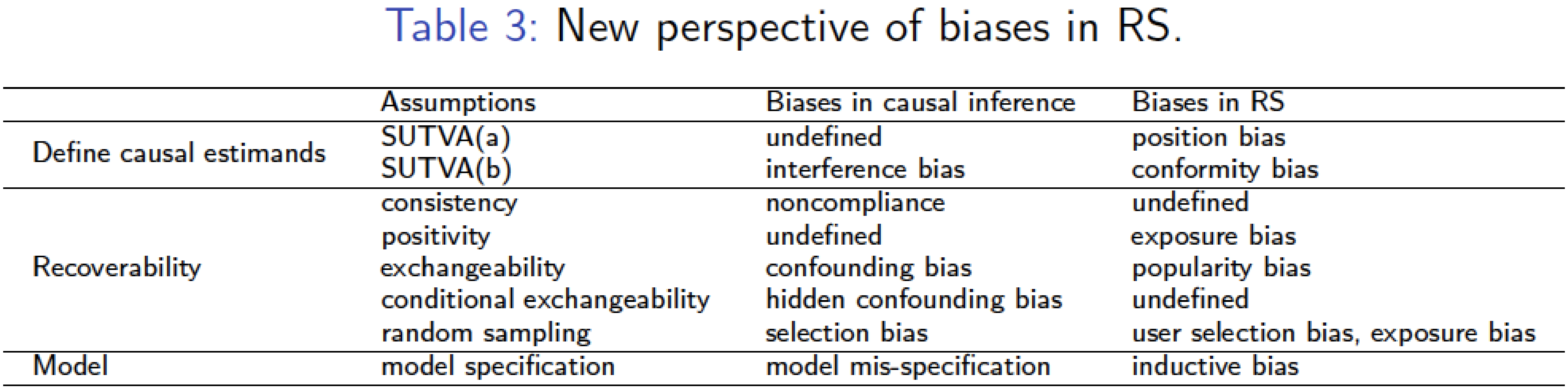


Table 3: New perspective of biases in RS.

	Assumptions	Biases in causal inference	Biases in RS
Define causal estimands	SUTVA(a)	undefined	position bias
	SUTVA(b)	interference bias	conformity bias
Recoverability	consistency	noncompliance	undefined
	positivity	undefined	exposure bias
	exchangeability	confounding bias	popularity bias
	conditional exchangeability	hidden confounding bias	undefined
	random sampling	selection bias	user selection bias, exposure bias
Model	model specification	model mis-specification	inductive bias

- According to Table 1, we can define the descriptive biases in RS formally using the rigorous syntax of causal inference.
- It also provides an opportunity to apply the existing causal inference methods to RS.
- In addition, for the unique characteristics of RS, we expect that a series of new methods will be developed by weakening or substituting the assumptions.

Jiawei Chen and Hande Dong and Xiang Wang and Fuli Feng and Meng Wang and Xiangnan He (2020), ’ Bias and Debias in Recommender System: A Survey and Future Directions’, arXiv:2010.03240.

Peng Wu, Haoxuan Li, Yuhao Deng, Wenjie Hu, Quanyu Dai, Zhenhua Dong, Jie Sun, Rui Zhang, Xiao-Hua Zhou (2021), ``Causal Analysis Framework for Recommendation‘’, arXiv:2201.06716. (To appear in IJ-CAI)

Outline

- Introduction
- Potential outcome framework for recommendation
- Structural causal model-based recommendation
  - Introduction (Yang Zhang)
  - Confounding and colliding in recommendation (Yang Zhang)
  - Counterfactual recommendation (Wenjie Wang)
- Comparison
- Open problems, future directions and conclusions

Structural Causal Model

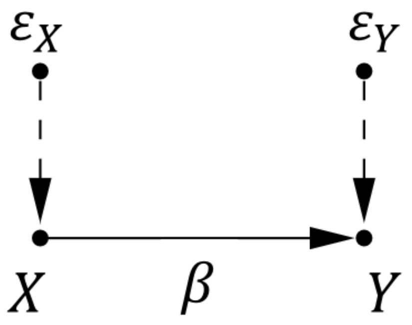
- How to express mathematically some common understandings, such as symptoms do not cause diseases?

X: disease Y: *symptom*

$$X = U_X$$
$$Y = \beta X + U_Y$$

U_X *and* U_Y: exogenous

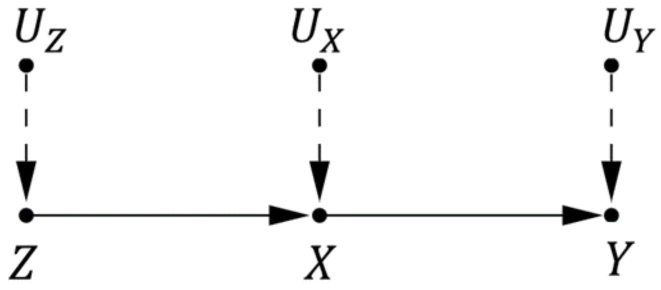
To express the inherent directionality



Causal Graph / Causal Diagram

Causal diagrams encodes causal assumption via missing arrows, representing claims of zero influences

- The straightforward generalization



Non-parametric interpretation

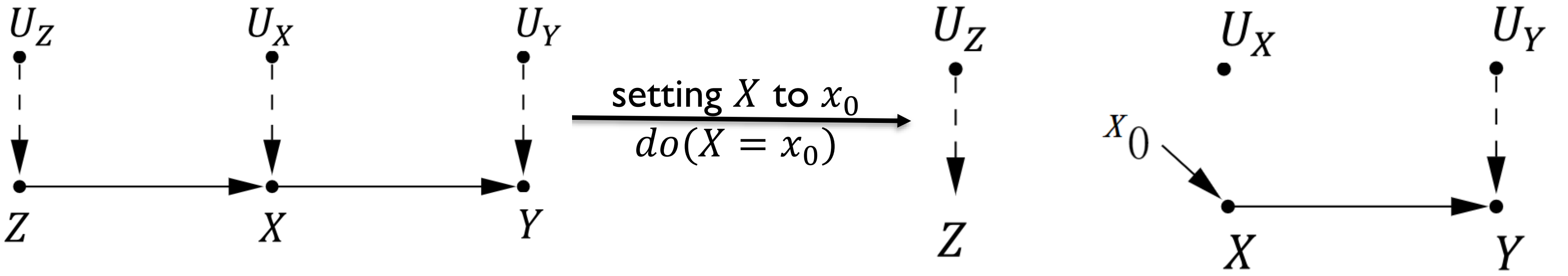
$$Z = f_Z(U_Z)$$
$$X = f_X(Z, U_X)$$
$$Y = f_Y(X, U_Y)$$

Pearl, Judea. "Causal inference." Causality: objectives and assessment (2010): 39-58.

Structural Causal Model

- Causal graph is important

Try to compute the expected effect of setting X to x_0, denoted as $E(Y|do(X = x_0))$



$$Z = f_Z(U_Z)$$
$$X = x_0$$
$$Y = f_Y(X, U_Y)$$

- According to the graph, we have

$E(Y|do(X = x_0)) = E(Y|x)$, regardless what $\{f_Z, f_X, f_Y\}$ is.

- The right hand side is estimable from the distribution of observed variables, i.e., $P(x, y, z)$,

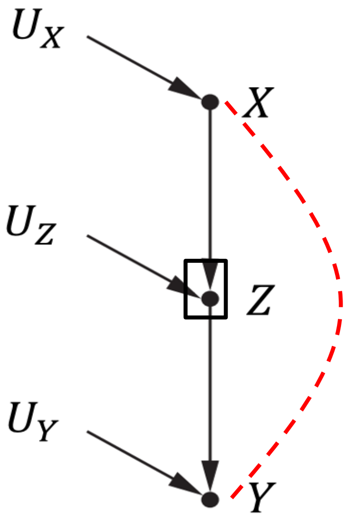
The causal graph encodes most causal assumptions between variables, the form of $\{f(\cdot)\}$ could be unknown.

Pearl, Judea. "Causal inference." Causality: objectives and assessment (2010): 39-58.

Structural Causal Model

- Basic causal structure in causal graph

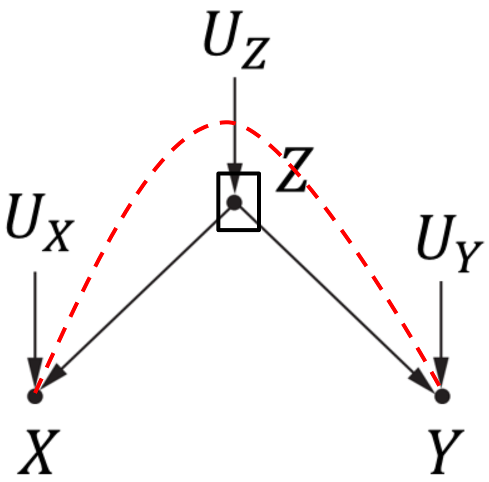
Chain



Z: **mediator**

- X and Y are associated.
- condition on Z, X and Y are independent

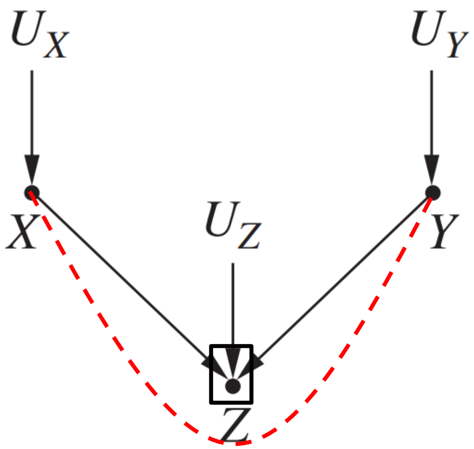
Confounding



Z: **confounder**

- X does not affect Y, but X and Y are correlated. Spurious correlations.
- condition on Z, X and Y are independent, blocking the spurious correlations.

Colliding



Z: **collider**

- X and Y are independent.
- Condition on Z, X and Y are correlated, bringing spurious correlations.

Structural Causal Model

- Correlation is not causation

Confounders and controlling colliders would bring spurious correlations between treatment and outcome.

It is impossible to answer causal question with correlation-level tools

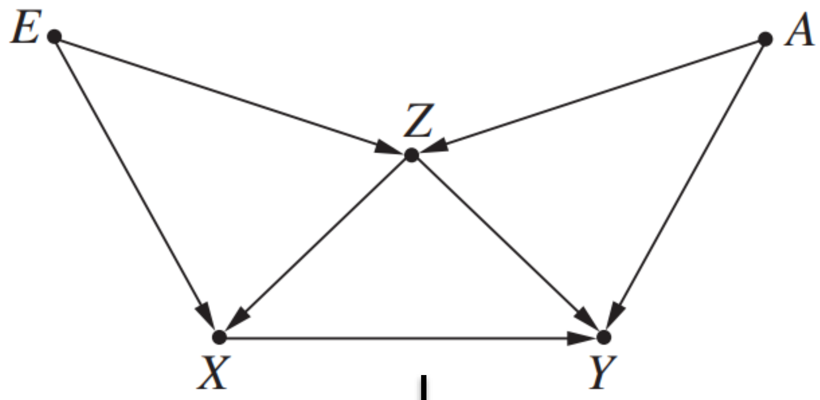
- SCM provides *do*-calculus

It provides various principles to identify target causal effect.
For example, utilize *the backdoor adjustment when confounders exist*

If no node in Z is a descendant of X, and blocks every path between X and Y that contains an arrow into X (backdoor path), then the average causal effect:

$$P(Y|do(X)) = \sum_Z P(Y|X,Z)P(Z)$$

Confounder E,Z,A will bring spurious correlation

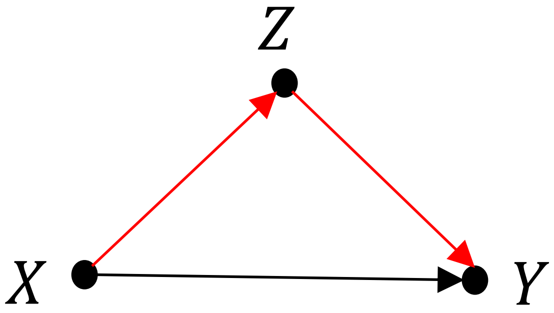


$$P(Y|do(X)) = \sum_{z,a} P(Y|X,z,a)P(z,a)$$

Structural Causal Model

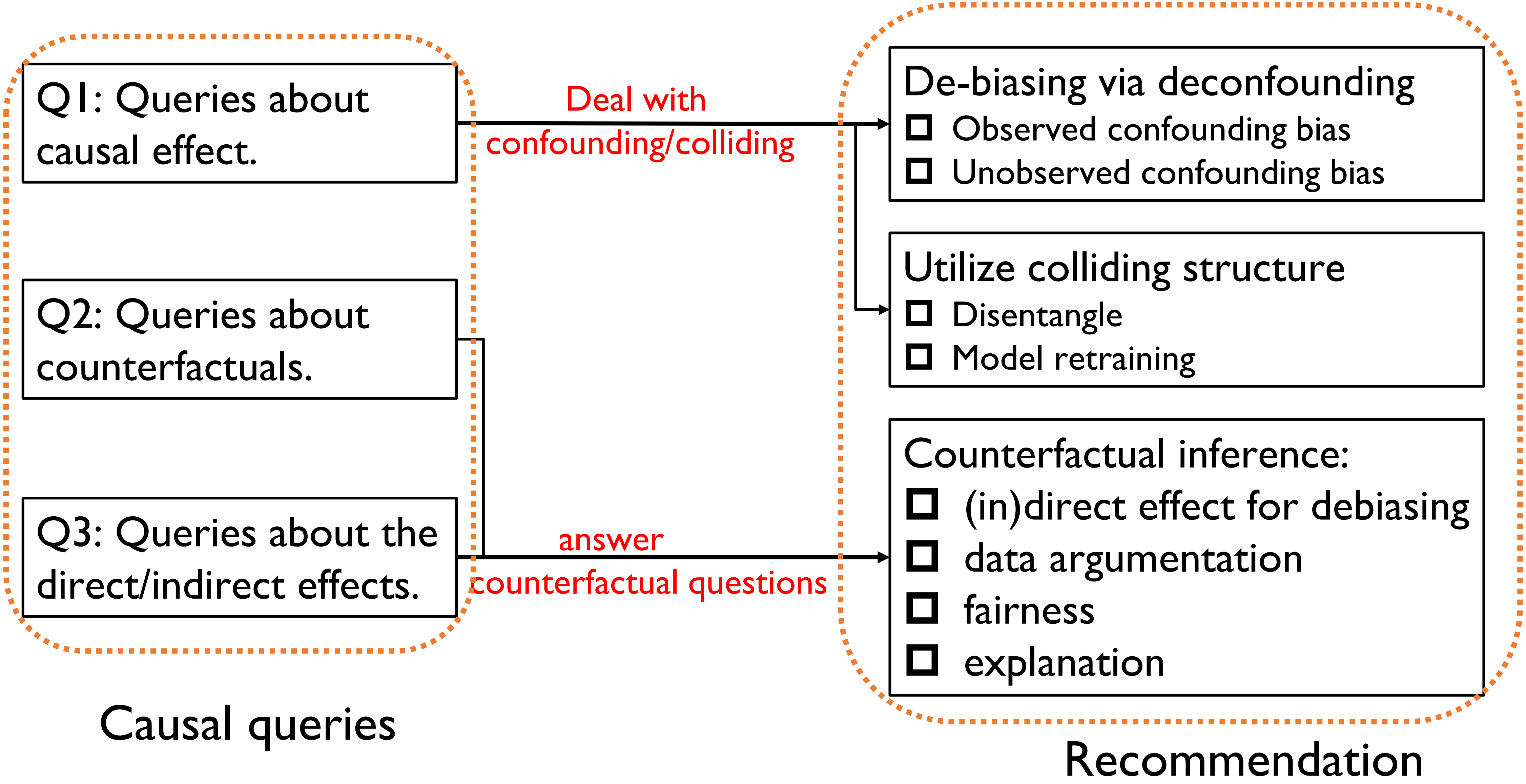
- SCM provides both a mathematical foundation and a friendly calculus for the analysis of causes and counterfactuals.
- It can deal with the estimation of three types of causal queries:

☐ Queries about the effect of potential interventions.
To compute causal effect, e.g., $P(Y|do(X))$
☐ Queries about counterfactuals.
e.g., whether event A would occur **had event B been different**?
☐ Queries about the direct / indirect effects. (based on counterfactuals)



the direct effects of X on Y: $X \rightarrow Y$
the indirect effects of X on Y: $X \rightarrow Z \rightarrow Y$

Recommendation based on SCM



Q1: Queries about causal effect.

Q2: Queries about counterfactuals.

Q3: Queries about the direct/indirect effects.

Causal queries

Deal with confounding/colliding

answer counterfactual questions

De-biasing via deconfounding
- ☐ Observed confounding bias
- ☐ Unobserved confounding bias

Utilize colliding structure
- ☐ Disentangle
- ☐ Model retraining

Counterfactual inference:
- ☐ (in)direct effect for debiasing
- ☐ data argumentation
- ☐ fairness
- ☐ explanation

Recommendation

Recommendation based on SCM

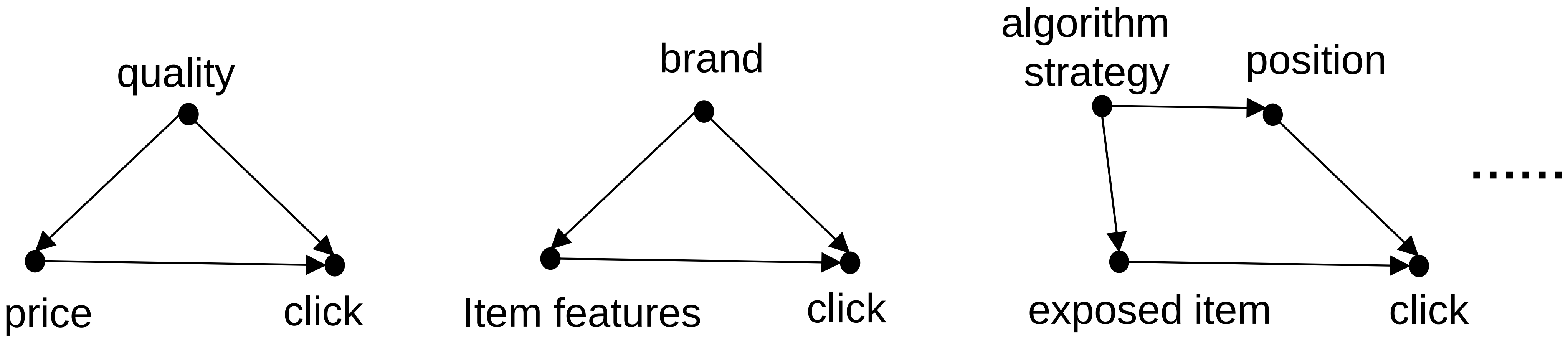
- Dealing with confounding structures in recommendation (Yang Zhang)
  - Confounding in recommendation.
  - Deal with observed confounders.
  - Deal with unobserved confounders.
- Considering colliding structures in recommendation (Yang Zhang)
  - Colliders in recommendation
  - Modeling the colliding effect
- Counterfactual recommendation (Wenjie Wang)
  - Counterfactual inference for recommendation
  - Counterfactual data augmentation
  - Counterfactual fairness
  - Counterfactual explanation

Recommendation based on SCM

- Dealing with confounding structures in recommendation
  - Confounding in recommendation.
  - Deal with observed confounders.
  - Deal with unobserved confounders.
- Considering colliding structures in recommendation
  - Colliders in recommendation
  - Modeling the colliding effect
- Counterfactual recommendation
  - Counterfactual inference for recommendation
  - Counterfactual data augmentation
  - Counterfactual fairness
  - Counterfactual explanation

Confounding in recommendation

- Are there confounders in recommendation?
  - There are some possible examples



quality

price

click

brand

Item features

click

algorithm strategy

position

exposed item

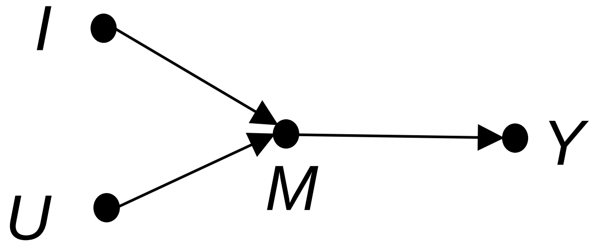
click

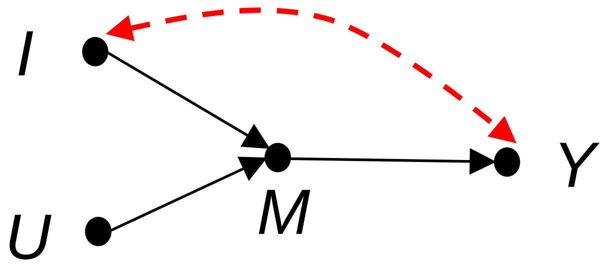
……

- What’s more, some confounder are observable/measurable, some confounder are unobservable/unmeasurable.
  e.g., company is measurable, quality is unmeasurable.

Confounding in recommendation

- Is it necessary to deal with confounding effects?
  - The goal of recommendation: estimate user preference. But user preference is implicit.
  - We estimate it as $P(Y|U,I)$, i.e., taking the correlations between (*U*,*I*) pair and click *Y* as the preference.





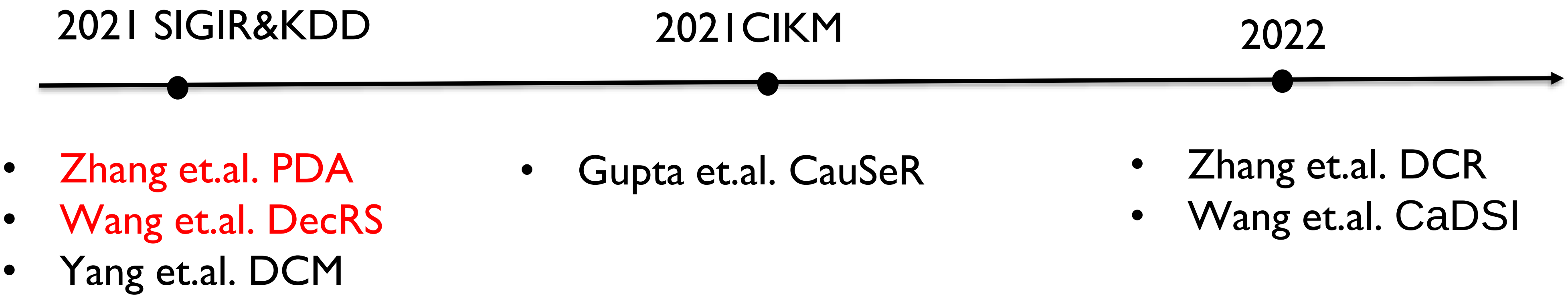
- However, when there are confounders between U/I and Y(red line), the confounding effect will also manifest as correlations, while it cannot reflect user preference.

Thus, we need to deal with the confounding problem in recommendation!
Next, we will show how to deal with confounding problem.

Existing work regarding observed confounders

- Existing work

The backdoor adjustment is obvious selection, and most work is based on it.



2021 SIGIR&KDD

- Zhang et.al. PDA
- Wang et.al. DecRS
- Yang et.al. DCM

2021CIKM

- Gupta et.al. CauSeR

2022

- Zhang et.al. DCR
- Wang et.al. CaDSI

The above work considers different problems caused by confounder, and has different strategies to implement the backdoor adjustment.

PDA: Confounding view of the popularity bias

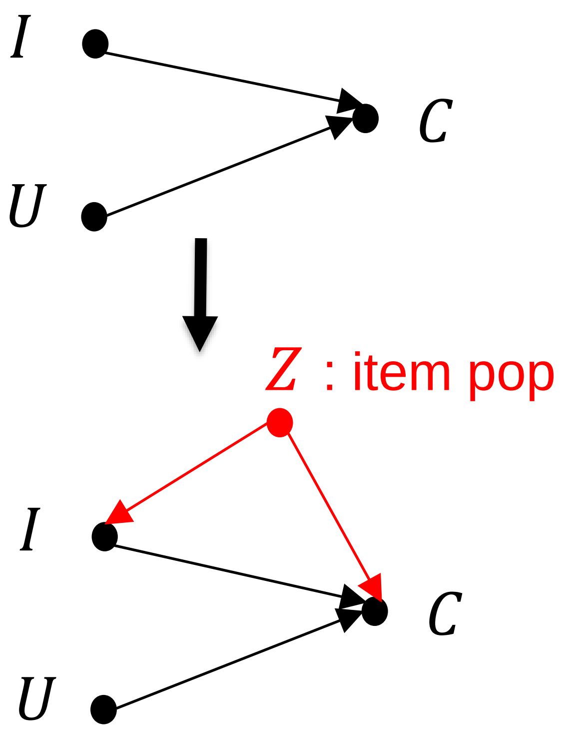
- Popularity bias
  - Favor a few popular items while not giving deserved attention to the majority of others
  - The popular items are recommended even more frequently than their popularity would warrant, amplifying long-tail effects.
- Previous methods ignore the underline causal mechanism and blindly remove bias to purchase an even distribution.
- But, not all popularity biases data are bad.
  - Some items have higher popularity because of better quality.
  - Some platforms have the need of introducing desired bias (promoting the items that have the potential to be popular in the future).

Zhang et al. SIGIR 2021. Causal Intervention for Leveraging Popularity Bias in Recommendation

PDA: Confounding view of the popularity bias

- What is the bad effect of popularity bias?
  - Common causal assumption
    - $(U, I) \rightarrow C$: user-item matching affects click.
    - Item popularity also has influence on the recommendation process, but is not considered.
  - Cofounding view
    - $Z \rightarrow I$: Popularity affects item exposure.
    - $Z \rightarrow C$: Popularity affects click probability.
    - Z is a confounder, bringing spurious (bad effect) correlation between I and C.
    - Take the causation $P(C|do(U, I))$, instead of the correlation $P(C|U, I)$, as user preference.

U: user; **I: exposed item;**
C: interaction label



Causation (backdoor adjustment):

$$\boldsymbol{P(C|do(U,I)) = \sum_Z P(C|U,I,Z)P(Z)}$$

Correlation:

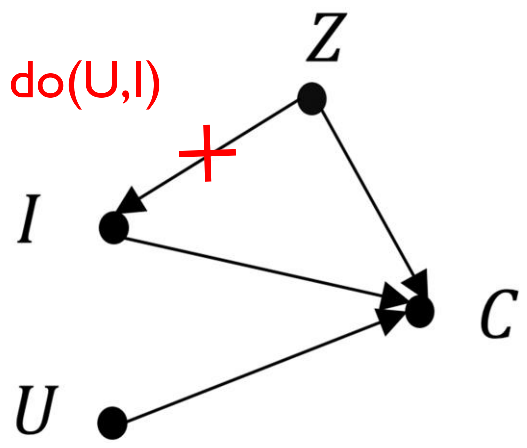
Bad effect

$$P(C|U,I) = \sum_Z P(C|U,I,Z)\boxed{P(Z|I)}$$
$$\propto \sum_Z P(C|U,I,Z)\boxed{P(I|Z)}P(Z)$$

Zhang et al. SIGIR 2021. Causal Intervention for Leveraging Popularity Bias in Recommendation

PDA: Confounding view of the popularity bias

- Training & Inference: Popularity De-confounding (PD, remove bad effect)



- To estimate $P(C|do(U,I)) = \sum_z P(C|U,I,z)P(z)$
  - **Step 1**. Estimate P(C|U,I,Z)
    - $P_\Theta(c=1|u,i,m_i^t) = f_\Theta(u,i) \times m_i^t$
    - m_i^t the popularity of item i in timestamp t
    - Learn with traditional loss
  - **Step 2**. Compute $P(\mathrm{C}|\mathrm{do}(\mathrm{U},\mathrm{I}))$
    - $\sum_Z P(C|U,I,Z)P(Z) \propto f_\Theta(u,i)$
    - Derivation sees the paper

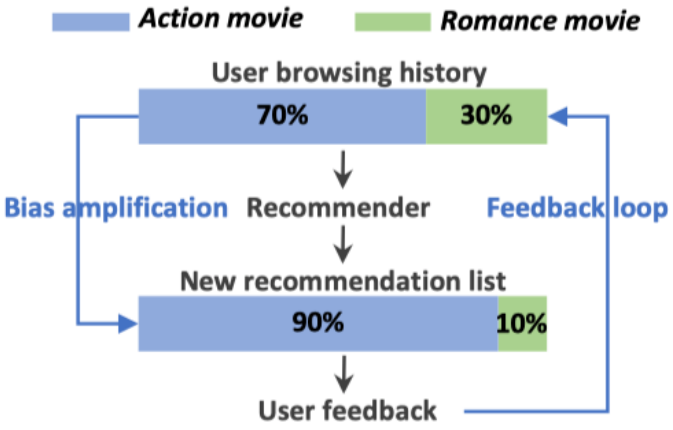
- Another Inference: Popularity Adjusting (inject desired popularity bias)
  - Inject the desired pop bias $\tilde{Z}$ by causal intervention

$$P(C|do(U,I),do(Z=\tilde{z})) \Longrightarrow f_\Theta(u,i) \times \tilde{m}_i$$

Zhang et al. SIGIR 2021. Causal Intervention for Leveraging Popularity Bias in Recommendation

DecRS: De-confounding for Alleviating Bias Amplification

- Bias amplification:
  - What is it?
  - Why?

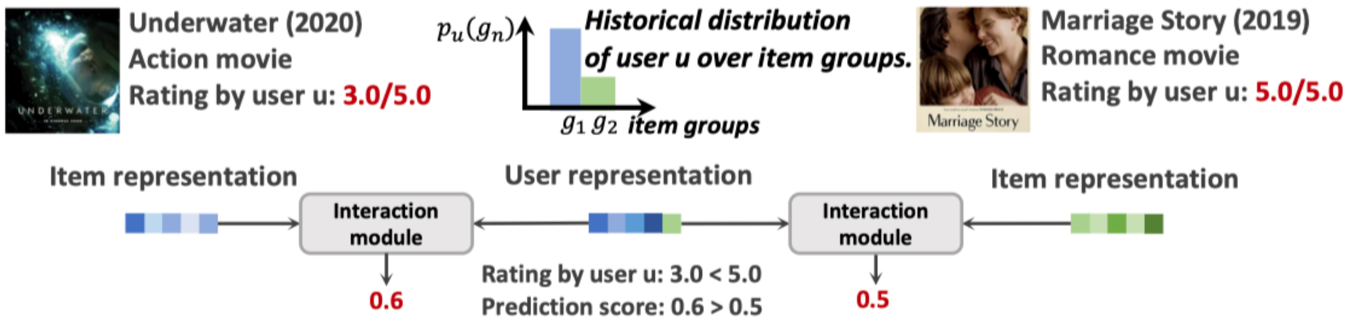


(a) An example of bias amplification.

over-recommend items in the majority group

- An item with low rating receives a higher prediction score because it belongs to the majority group.
- Intuitively, we can know that the user representation shows stronger preference to majority group.

(b) Prediction score difference between the items in the majority and minority groups over ML-1M.

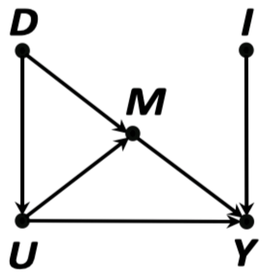


(c) An example on the cause of bias amplification.

Wang et al. SIGKDD 2021. Deconfounded recommendation for alleviating bias amplification.

DecRS: De-confounding for Alleviating Bias Amplification

- A Causal view of bias amplification



(a)

U	***User representation***
I	***Item representation***
D	***User historical distribution over item groups***
M	***Group-level user representation***
Y	***Prediction score***

- D: user historical distribution over **item group.** $d_u = [p_u(g_1), \dots, p_u(g_N)]$, e.g., $d_u = [0.8, 0.2]$.
- M: to describe how much the user likes different item groups, decided by D and U.
- $(U, M) \rightarrow Y$: an item i can have a high Y because: 1) user's pure preference over the item ($U \rightarrow Y$) or 2) the user shows interest in the item group ($U \rightarrow M \rightarrow Y$).

✓ D is a confounder between U and Y, bringing spurious correlations : given the item i in a group g, the more superior g is in u's history, the higher the prediction score Y becomes.

- Backdoor adjustment

$$
\begin{aligned}
&P(Y|U=\mathbf{u}, I=\mathbf{i}) \\
&= \frac{\sum_{\mathbf{d}\in\mathcal{D}}\sum_{\mathbf{m}\in\mathcal{M}} P(\mathbf{d})P(\mathbf{u}|\mathbf{d})P(\mathbf{m}|\mathbf{d},\mathbf{u})P(\mathbf{i})P(Y|\mathbf{u},\mathbf{i},\mathbf{m})}{P(\mathbf{u})P(\mathbf{i})} && \text{(1a)} \\
&= \sum_{\mathbf{d}\in\mathcal{D}}\sum_{\mathbf{m}\in\mathcal{M}} P(\mathbf{d}|\mathbf{u})P(\mathbf{m}|\mathbf{d},\mathbf{u})P(Y|\mathbf{u},\mathbf{i},\mathbf{m}) && \text{(1b)} \\
&= \sum_{\mathbf{d}\in\mathcal{D}} P(\mathbf{d}|\mathbf{u})P(Y|\mathbf{u},\mathbf{i},M(\mathbf{d},\mathbf{u})) && \text{(1c)} \\
&= P(\mathbf{d}_u|\mathbf{u})P(Y|\mathbf{u},\mathbf{i},M(\mathbf{d}_u,\mathbf{u})), && \text{(1d)}
\end{aligned}
$$

→

$$
\begin{aligned}
&P(Y|do(U=\mathbf{u}), I=\mathbf{i}) \\
&= \sum_{\mathbf{d}\in\mathcal{D}} P(\mathbf{d}|do(U=\mathbf{u}))P(Y|do(U=\mathbf{u}),\mathbf{i},M(\mathbf{d},do(U=\mathbf{u}))) && \text{(2a)} \\
&= \sum_{\mathbf{d}\in\mathcal{D}} P(\mathbf{d})P(Y|do(U=\mathbf{u}),\mathbf{i},M(\mathbf{d},do(U=\mathbf{u}))) && \text{(2b)} \\
&= \sum_{\mathbf{d}\in\mathcal{D}} \boxed{P(\mathbf{d})}P(Y|\mathbf{u},\mathbf{i},M(\mathbf{d},\mathbf{u})), && \text{(2c)}
\end{aligned}
$$

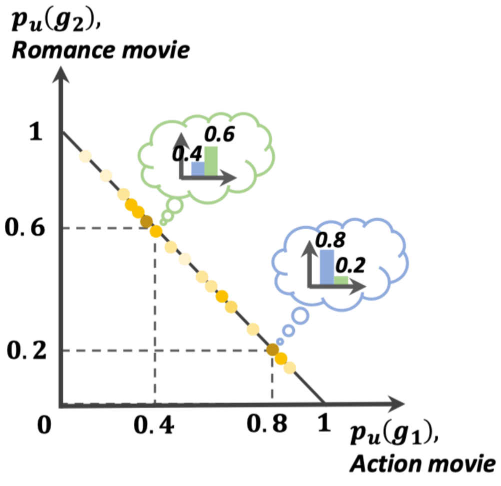
Wang et al. SIGKDD 2021. Deconfounded recommendation for alleviating bias amplification.

DecRS: De-confounding for Alleviating Bias Amplification

- Deconfounded Recommender System (DecRS)
  - To implement:

$$P(Y|do(U=\boldsymbol{u}), I=\boldsymbol{i}) = \sum_{\boldsymbol{d}\in\mathcal{D}} P(\boldsymbol{d})P(Y|\boldsymbol{u},\boldsymbol{i},M(\boldsymbol{d},\boldsymbol{u})) \quad (3)$$

Challenge: the sample space of D is infinite.



Infinite Sample Space

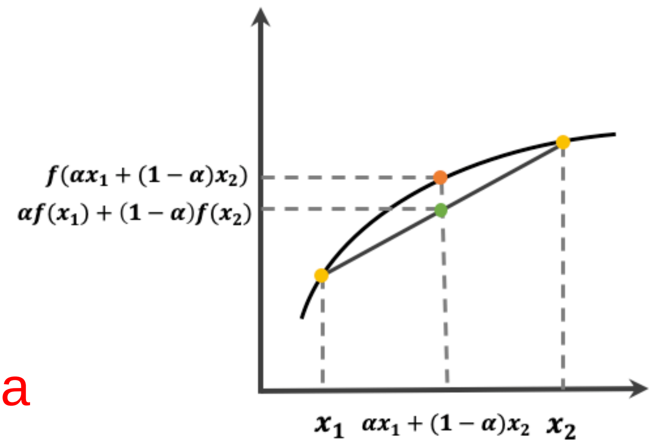
- Backdoor adjustment approximation:
  (1) Sampling distributions to represent $\mathcal{D}$;
  Use function $f(\cdot)$ (FM) to calculate $\mathrm{P}(Y|u,i,M(d,u))$.

$$\begin{aligned} P(Y|do(U=\boldsymbol{u}), I=\boldsymbol{i}) &\approx \sum_{\boldsymbol{d}\in\tilde{\mathcal{D}}} P(\boldsymbol{d})P(Y|\boldsymbol{u},\boldsymbol{i},M(\boldsymbol{d},\boldsymbol{u})) \\ &= \sum_{\boldsymbol{d}\in\tilde{\mathcal{D}}} P(d)f(\boldsymbol{u},\boldsymbol{i},M(\boldsymbol{d},\boldsymbol{u})) \end{aligned} \quad (4)$$

  (2) Approximation of $E_d[f(\cdot)]$.
  - Expectation of function $f(\cdot)$ of $\boldsymbol{d}$ in Eq. 4 is hard to compute because we need to calculate the results of $f(\cdot)$ for each $\boldsymbol{d}$.
  - **Jensen's inequality**: take the sum into the function $f(\cdot)$.

$$P(Y|do(U=\boldsymbol{u}), I=\boldsymbol{i}) \approx \boxed{f(\boldsymbol{u},\boldsymbol{i},M(\sum_{\boldsymbol{d}\in\tilde{\mathcal{D}}} P(\boldsymbol{d})\boldsymbol{d},\boldsymbol{u})).} \quad (5)$$

learn it with data



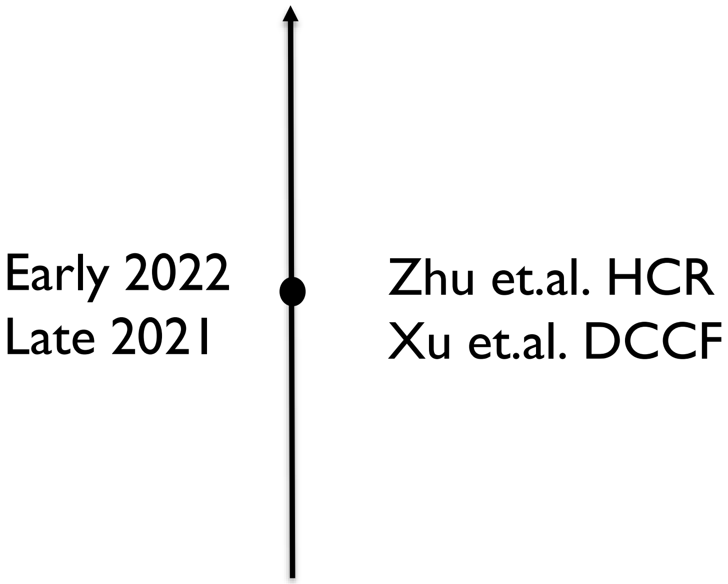
Approximation

Different to PDA, the learn one directly represents the target casual effect.

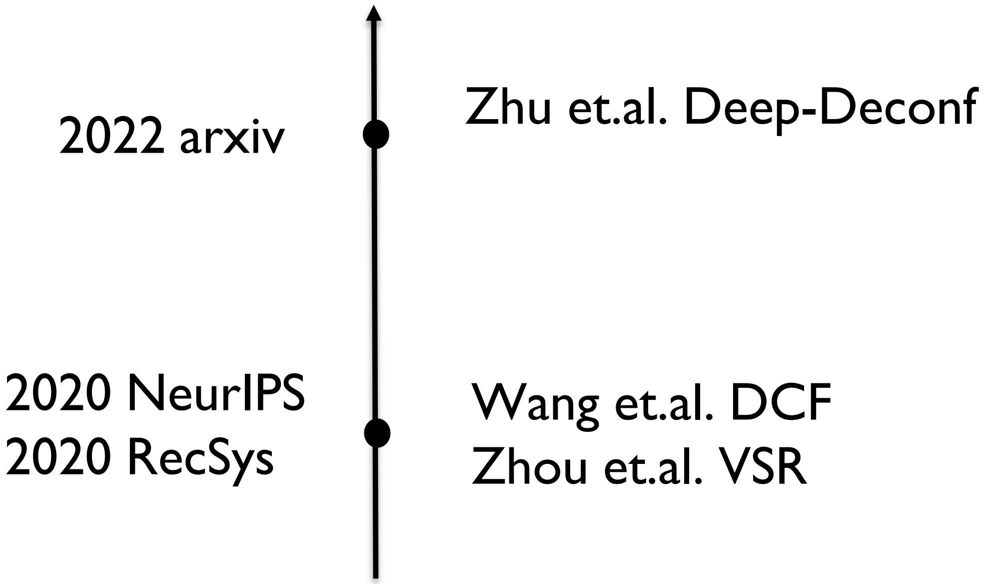
Wang et al. SIGKDD 2021. Deconfounded recommendation for alleviating bias amplification.

Existing Work for Unobserved Confounders

- The methods based on backdoor adjustment need the confounders could be observable and controllable.
- However, unobserved/unmeasurable/uncontrollable confounders exist in recommendation. How to deal with them?
  - There are two lines of work:



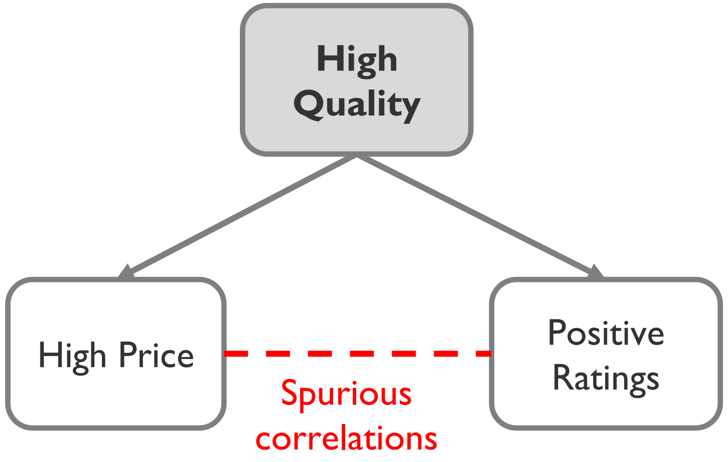
Front-door adjustment



Learning substitutes

HCR: The Front-door Adjustment-based Method

- Source of confounding bias is the **confounder** that **affects item attributes and user feedback** simultaneously.
- Some confounders are hard to measure.
  - Technical difficulties, privacy restrictions, *etc.*
  - E.g., product quality.



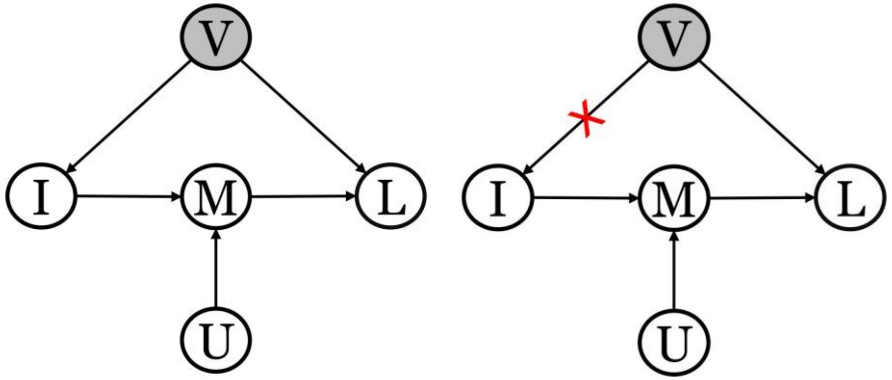
- Removing hidden confounders is hard:
  - Inverse Propensity Weighting
    - Based on strict assumption of no hidden confounder.
  - Backdoor Adjustment
    - Require the confounder's distribution.

Xinyuan Zhu et.al. "*Mitigating Hidden Confounding Effects for Causal Recommendation*" in 2022.

HCR: The Front-door Adjustment-based Method

- Abstract user feedback generation process into causal graph.
  - V: hidden confounder; L: like feedback; I: item; U: user.
  - M: a set of variables that act as mediators between $\{U, I\}$ and L, e.g., user-item feature matching, and click.
- Key:
  - Block the backdoor path $I \leftarrow V \rightarrow L$
  - Estimate the causal effect of I on L, i.e.,

$$P(L|U, \mathrm{do}(I)).$$



- Hidden Confounder Removal (HCR) framework.
  - Front-door adjustment
    - decompose causal effect of I on L into: 1) the effects of I on M and 2) the effect of M on L.

$$P(L|U, \mathrm{do}(I)) = \sum_M P(M|U, do(I))P(L|U, do(M))$$
$$= \sum_M P(M|U, I) \sum_{I'} P(I')P(L|M, U, I')$$

Xinyuan Zhu et.al. "*Mitigating Hidden Confounding Effects for Causal Recommendation*" in 2022.

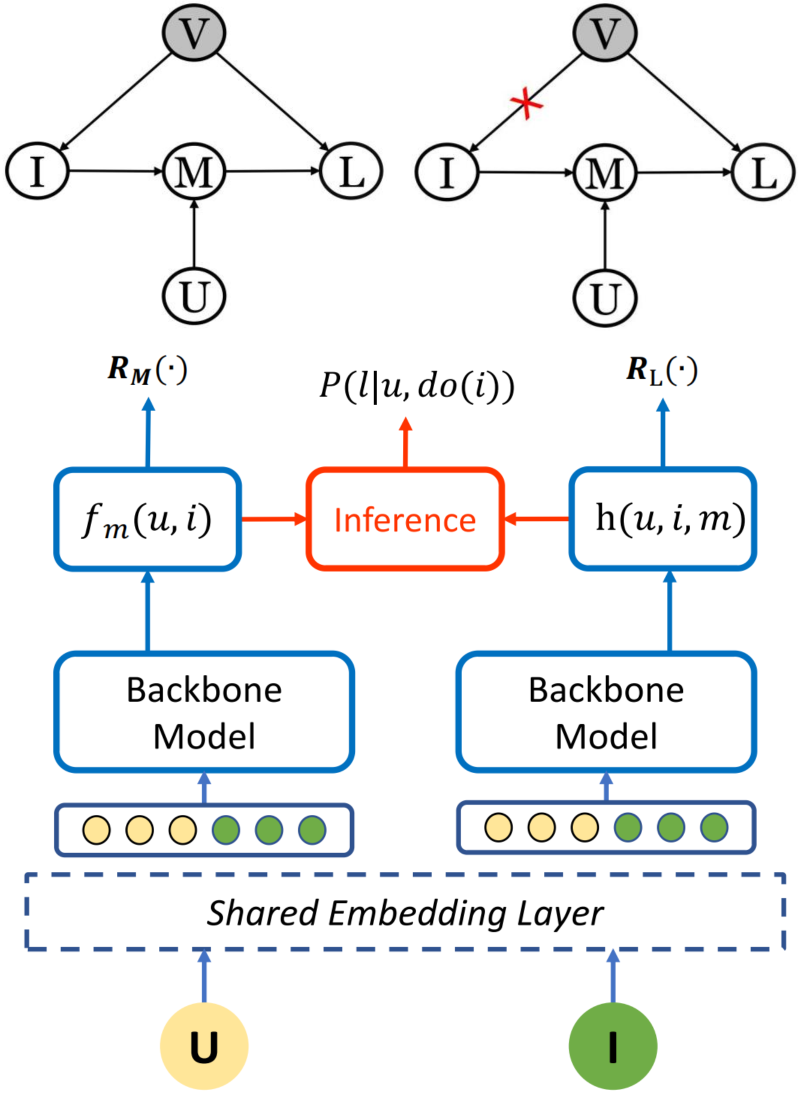
HCR: The Front-door Adjustment-based Method

- Hidden Confounder Removal (HCR) framework
  - $P(L|do(I),U) = \sum_M P(M|U,I) \sum_{I'} P(I')P(L|U,I',M)$
  - Multi-task learning
    - Learns $P(M|U,I) \coloneqq f_m(U,I)$
    - Learn

$$\begin{aligned} \mathrm{P}(L|M,U,I) &\coloneqq h(U,I,M) \\ &= h^1(U,M)h^2(U,I') \end{aligned}$$

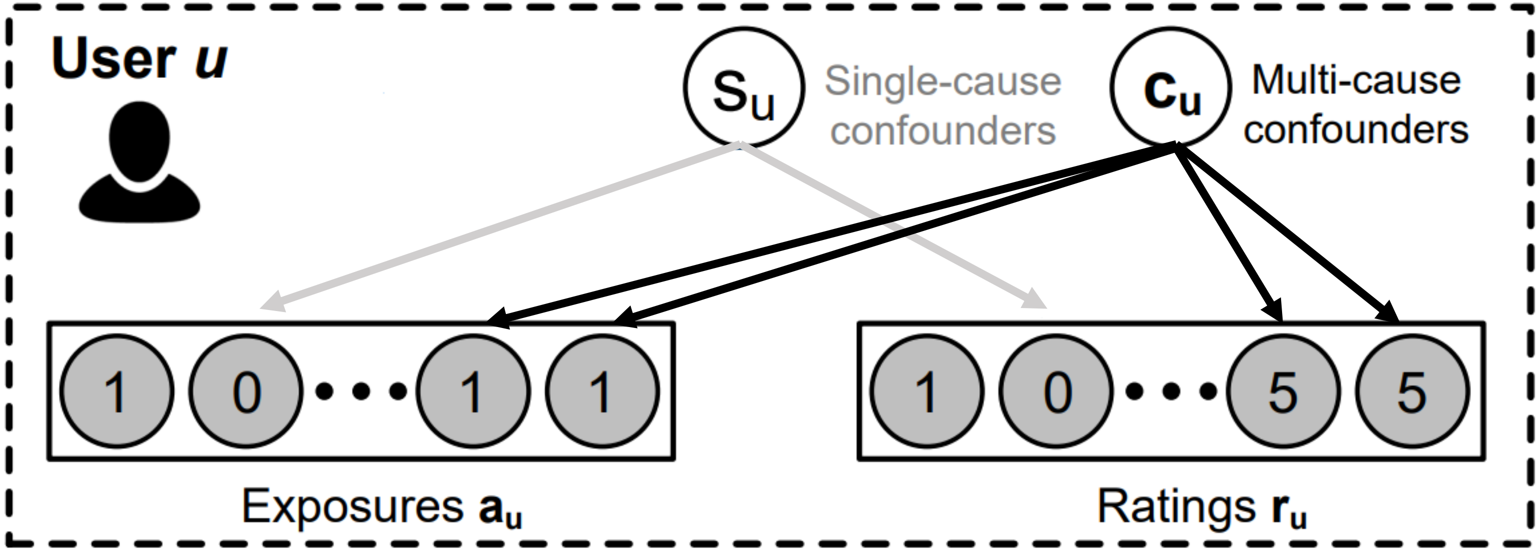
  - Inference
    - Infer $P(M|U,I)$ and $P(L|U,I,M)$
    - Get rid of the sum over I and obtain

$$\begin{aligned} &P(L|U,do(I)) \\ &= \sum_M f_m(U,I) \sum_{I'} P(I')h^1(U,M)h^2(U,I') \\ &= \sum_M f_m(U,I)h^1(U,M) \sum_{I'} P(I')h^2(U,I') \\ &= S_u \sum_M f_m(U,I)h^1(U,M) \end{aligned}$$



Learning Substitutes-based Method

- Multiple causes assumption for recommendation:
  - multiple causes: each user's binary exposure to an item a_{ui} is a cause(treatment), thus there are multiple causes.
  - There are multiple-cause confounders (confounders that affect ratings and many causes).
  - Single-cause confounders (confounders that affect ratings and only one cause) are negligible.



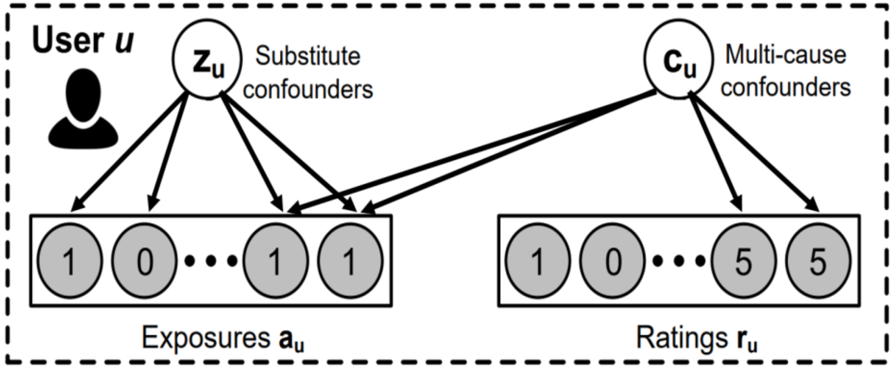
Wang et al. RecSys 2020. Causal inference for recommender system.
Zhu et.al. Arxiv 2022. Deep causal reasoning for recommendations.

Learning Substitutes-based Method

- Learning substitutes to deconfounding:

Key: if Z_u renders the $a_{u,i}$'s conditionally independent then there cannot be another multi-cause confounder

Contradiction: assume $p(a_{u1}, \dots, a_{um} | z_u) = \prod_i p(a_{ui} | z_u)$, if there is a multi-cause confounder, the conditional independence cannot hold.



- Step 1: learning substitutes

Finding a Z_u, such that:

$$p(a_{u1}, \dots, a_{um} | z_u) = \prod_i p(a_{ui} | z_u)$$

Example:

find a generative model:

$$P_\Theta(A_u | Z_u) = \prod_{i=1}^{m} Bern(a_{ui} | \theta(z_u)_i)$$

then:

find $q_\Phi(Z_u | A_u)$ with variation-inference

- Step 2: deconfounded recommender

Control the substitutes to fit recommender model

Example:

$$y_{ui}(a) = \theta_u^\top \beta^i \cdot a + \gamma_u \cdot z_{ui} + \epsilon_{ui}$$

where θ_u and β_i refer user preference and item attributes, respectively.

Wang et al. RecSys 2020. Causal inference for recommender system.
Wang et.al. *J Am Stat Assoc 2019.* The blessings of multiple causes.
Zhu et.al. Arxiv 2022. Deep causal reasoning for recommendations.

Papers for confounding in recommendation

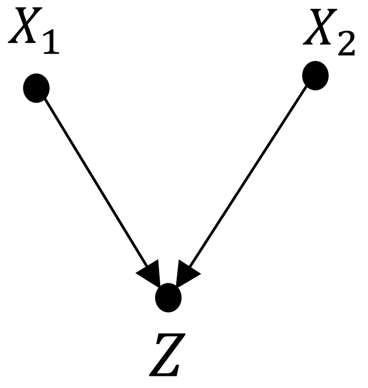
- Zhang, Yang, et al. "Causal intervention for leveraging popularity bias in recommendation." *Proceedings of the 44th International ACM SIGIR Conference on Research and Development in Information Retrieval*. 2021. (Zhang et.al. PDA)
- Wang, Wenjie, et al. "Deconfounded recommendation for alleviating bias amplification." *Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining*. 2021. (wang et.al. DecSR)
- Wang, Xiangmeng, et al. "Causal Disentanglement for Semantics-Aware Intent Learning in Recommendation." IEEE Transactions on Knowledge and Data Engineering (2022). (Wang et.al. CaDSI)
- Gupta, Priyanka, et al. "CauSeR: Causal Session-based Recommendations for Handling Popularity Bias." Proceedings of the 30th ACM International Conference on Information & Knowledge Management. 2021. (Gupta et.al., CauSeR)
- Yang, Xun, et al. "Deconfounded video moment retrieval with causal intervention." *Proceedings of the 44th International ACM SIGIR Conference on Research and Development in Information Retrieval*. 2021. (Yang et.al. DCM)
- Wang, Yixin, et al. "Causal inference for recommender systems." Fourteenth ACM Conference on Recommender Systems. 2020. (Wang et.al. DCF)

Recommendation based on SCM

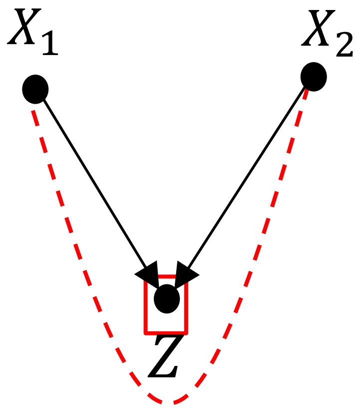
- Dealing with confounding structures in recommendation
  - Confounding in recommendation.
  - Deal with observed confounders.
  - Deal with unobserved confounders.
- Considering colliding structures in recommendation
  - Colliders in recommendation
  - Modeling the colliding effect
- Counterfactual recommendation
  - Counterfactual inference for recommendation
  - Counterfactual data augmentation
  - Counterfactual fairness
  - Counterfactual explanation

Colliders in Recommendation

- Are there colliders in recommendation?
  - There are variables affected by many factors. Such as, the happening of clicking is affected by user preference and the exposure position.
  - Existing work also tries to construct colliders manually.



- To utilize or eliminate colliding effects?
  - Assume that we have known X_2, try to estimate X_1.
  - Condition on Z, X_1 and X_2 could be correlated.
  - That means condition on Z, X_2 would provide us more information to estimate X_1.



In recommendation, we usually face with this case (know X_2 and Z to predict X_1). Thus existing work based on SCM tries to utilize colliding effects to better learn some targets.

DICE: Colliding Effects for Disentangling True Interest

- What are causes of a user-item interaction (click)?

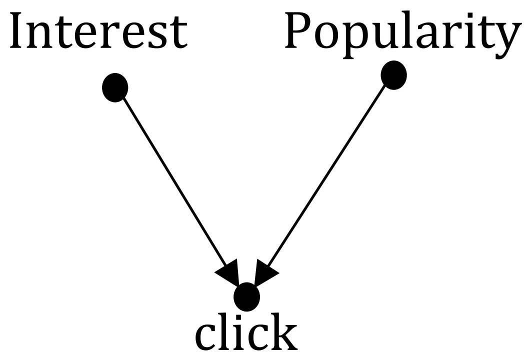
Two main causes:

- Interest
- Conformity

  User tend to follow the mainstream

- Disentangle Interest and Conformity to identify true interest.
- But it is hard because of lacking ground-truth. (An interaction can come from either factor or both factors)

- Colliding effect can come to help:



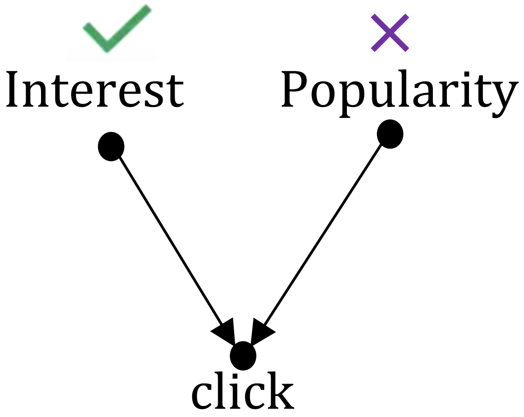
- Interest and Popularity (conformity) are independent
- But, they are correlated given clicks:

  A click on less popular item → High Interest

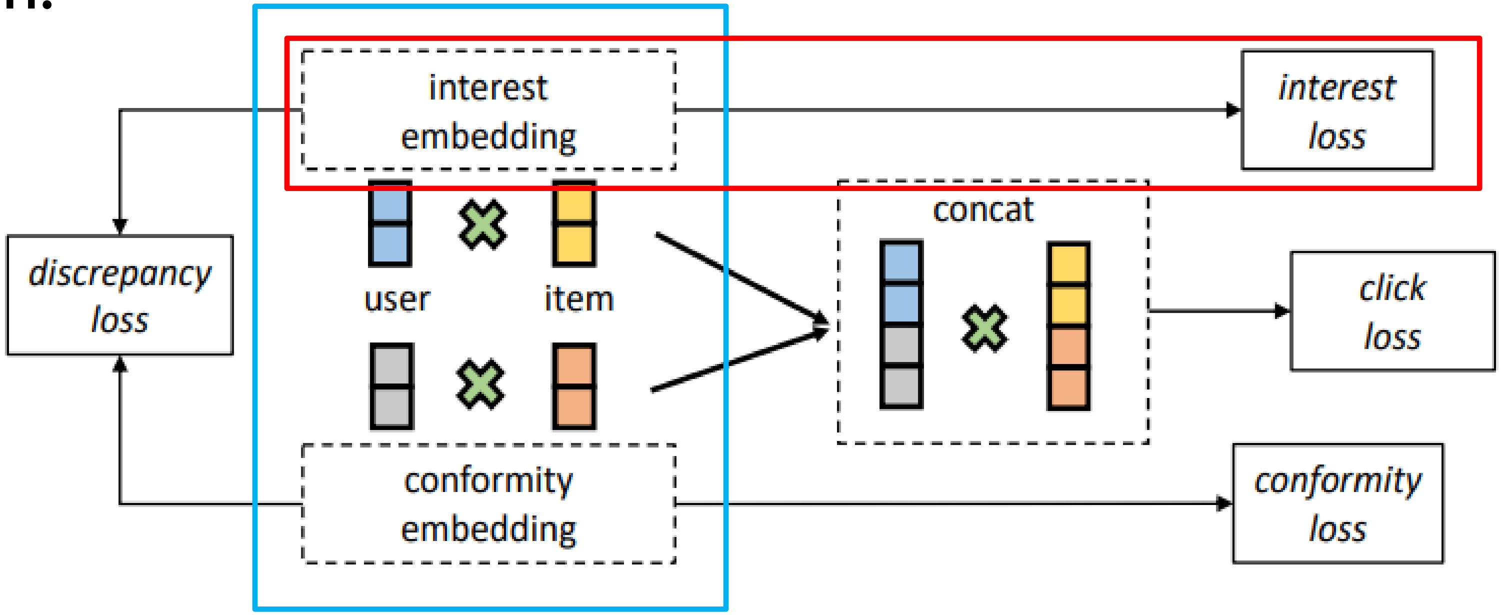
Zheng et al. WWW 2021. Disentangling User Interest and Conformity for Recommendation with Causal Embedding

DICE: Colliding Effects for Disentangling True Interest

- Partial pairwise data identifies true interest:
  - O_1: $\{<u, pos\_item, neg\_item>$, wherein pos_item is less popular than $neg\_item\}$
  - Pairwise cause-specific data (interst-driven): we can ascertain that the interaction is more likely due to user interest



- Solution:



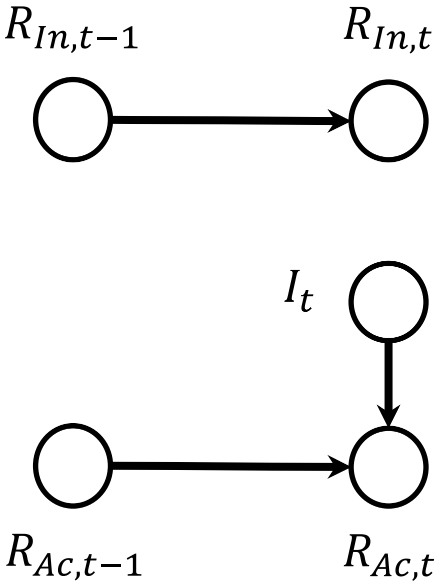
- Key2: learning interest embedding on interest-driven pairwise data (O_1).

- Key1: Split user/item representation into two embeddings

Zheng et al. WWW 2021. Disentangling User Interest and Conformity for Recommendation with Causal Embedding

Colliding Effects for Incremental Training

- Incremental training for recommender system
  - Usually, using the incremental interaction data I_t for efficient retraining.
  - Only updating the representations of **active** user/item corresponding to I_t.
  - Ignoring the representations of **inactive** user/item.



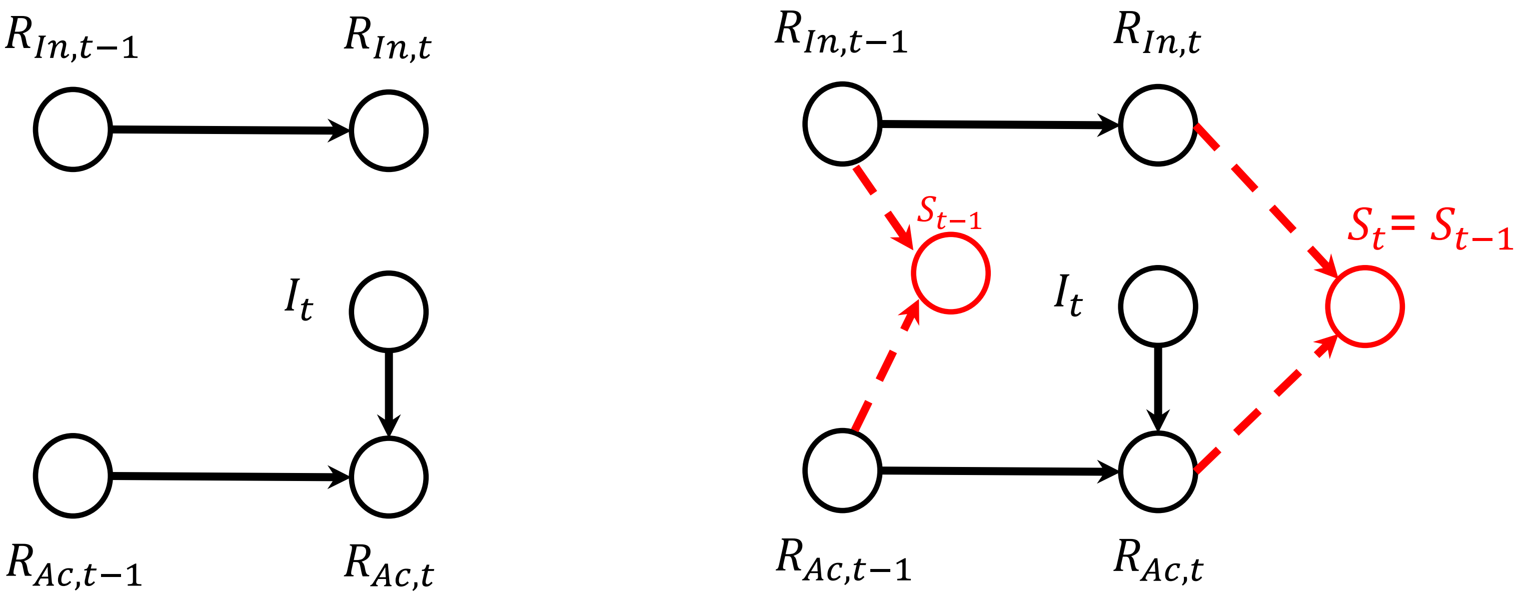
Causal graph of incremental training

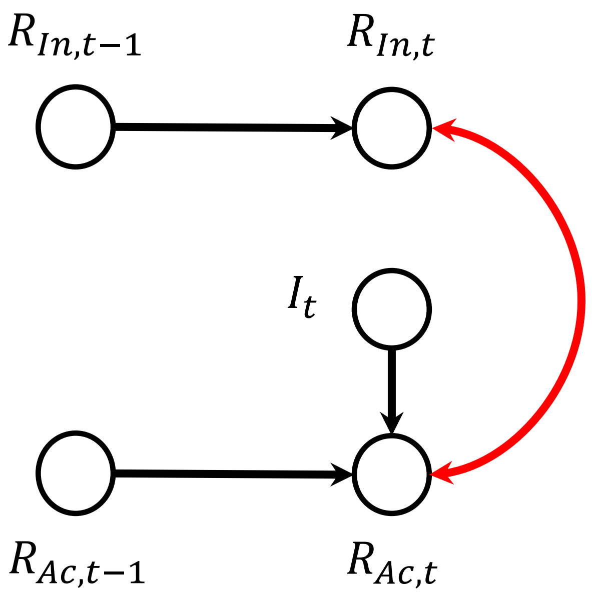
- $R_{In,t-1}$: Representations of inactivate user/item at time *t-1*.
- $R_{In,t}$: Representations of inactivate user/item at time *t*.
- $R_{Ac,t-1}$: Representations of activate user/item at time *t-1*.
- $R_{Ac,t}$: Representations of activate user/item at time *t*.
- I_t: Incremental interaction data collected from time *t-1* to *t*.

Ding, Sihao, et al. "Causal incremental graph convolution for recommender system retraining." IEEE TNNLS (2022).

Colliding Effects for Incremental Training

- Causal incremental training with colliding effects





Building colliding effect

- Creating a collider S_t between $R_{In,t}$ and $R_{Ac,t}$, S_t is the similarity between representations of active and inactivate user/item.
- Restraining $S_t = S_{t-1}$ to open the causal path $I_t \rightarrow R_{Ac,t} \rightarrow R_{In,t}$ with the help of colliding effect.
- Using the incremental data I_t simultaneously update both $R_{Ac,t}$ and $R_{In,t}$.

Ding, Sihao, et al. "Causal incremental graph convolution for recommender system retraining." IEEE TNNLS (2022).

Recommendation based on SCM

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• Counterfactual Recommendation

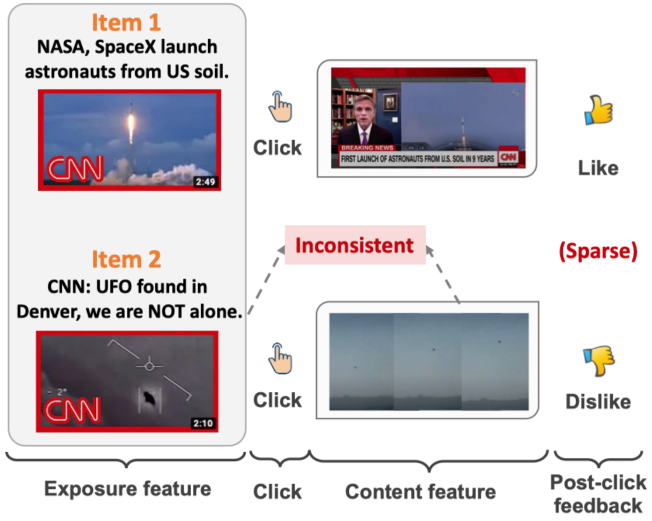
- Counterfactual inference for recommendation
  - Focus on **removing path-specific effects** for debiasing or OOD generalization
  - First estimate the causal effect by comparing a counterfactual world with the factual world, and then mitigate path-specific effects.

- Representative Work
  - Wang, et al. Clicks can be cheating: Counterfactual recommendation for mitigating clickbait issue. In SIGIR 2021.
  - Wei, et al. Model-agnostic counterfactual reasoning for eliminating popularity bias in recommender system. In KDD 2021.
  - Wang, et.al. Causal representation learning for out-of-distribution recommendation. In WWW 2022.
  - Wang, et.al. User-controllable recommendation against filter bubbles. In SIGIR 2022.

• Counterfactual Recommendation

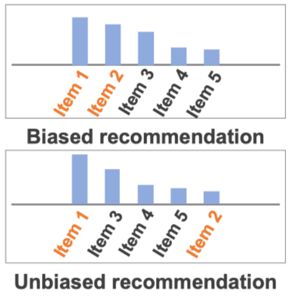
Clickbait Issue

- It is common that a user is "misled" to click an item by the attractive title/cover.
- Consequently, recommender model will recommend items with attractive exposure features but disappointing content features frequently.
- Negative effect:
  - **Unfair** to the items with high-quality video content.
  - Hurt **user's trust and satisfaction**.
- Attractive **exposure features** (e.g., title/cover) and disappointing **content features** (e.g., video).



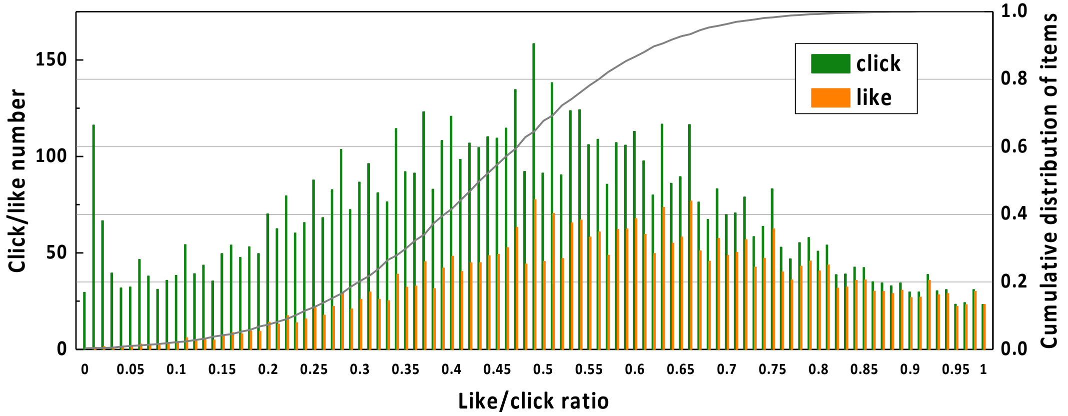
(a) Browsing behaviors of users on Tiktok.

(b) Click/like number of items.



(c) Ranking score of items.

Fig. Statistics of clicks and likes on Tiktok dataset. Partly show the wide existence of clickbait issue.



Wang, et al. "Clicks can be cheating: Counterfactual recommendation for mitigating clickbait issue." *SIGIR 2021.*

• Counterfactual Recommendation

❖ **Causal Graph**

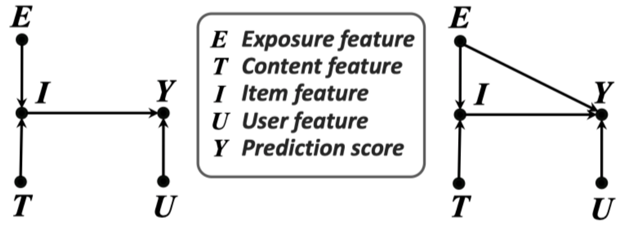
- describe causal relationships
- Exposure features and content features are fused into item features.
- **A direct shortcut** from exposure features to the prediction score: an item can be recommended purely because of its attractive title/cover.
- **Reference situation** denotes that the feature influence is null.

❖ **NDE of exposure features on the prediction score**

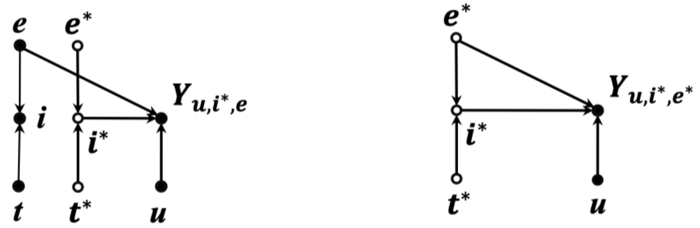
- Estimate natural direct effect (NDE) in a counterfactual world, which **imagines** *what the prediction score would be if the item had only the exposure features.*

❖ **CR inference:**

- Reduce the direct effect of exposure features during inference.

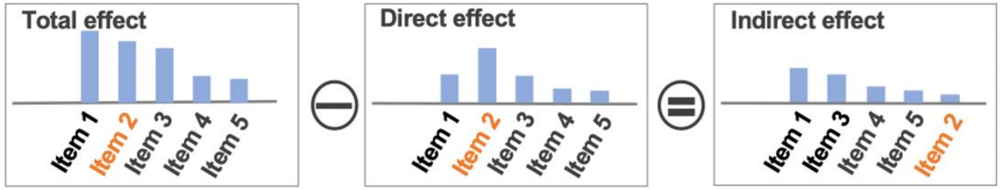


(a) Conventional causal graph (b) The proposed causal graph



(c) Counterfactual world (d) The reference situation

Figure 3: The causal graphs for conventional and counterfactual recommendations. $*$ denotes the reference values.



Wang, et al. "Clicks can be cheating: Counterfactual recommendation for mitigating clickbait issue." *SIGIR 2021.*

• Counterfactual Recommendation

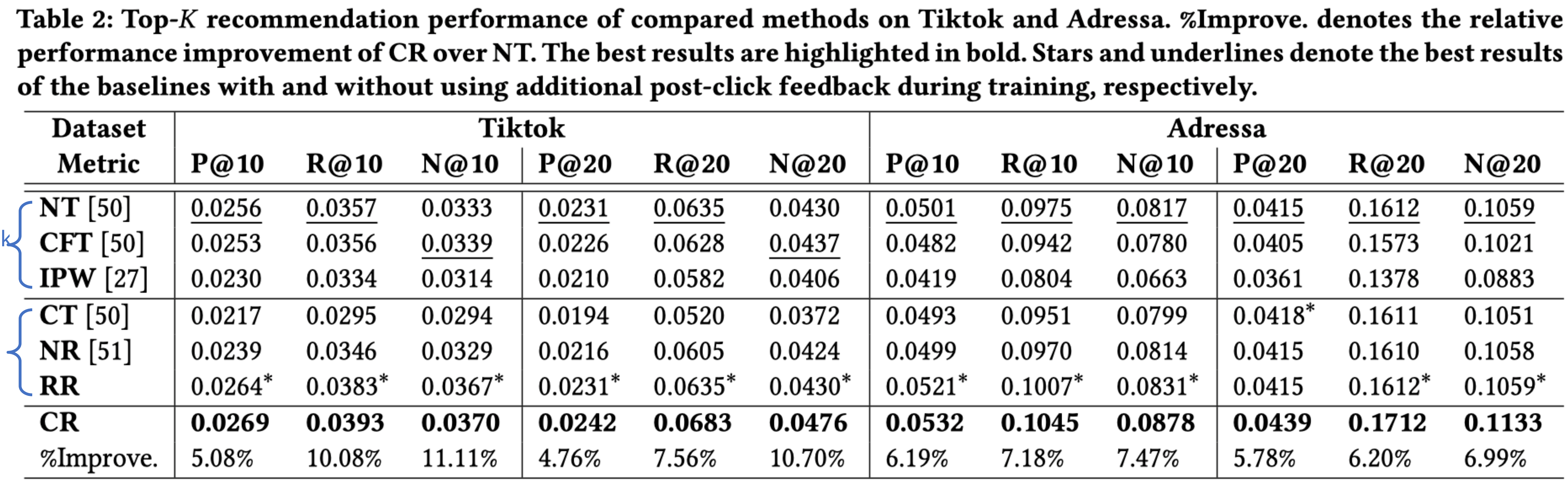


Table 2: Top-K recommendation performance of compared methods on Tiktok and Adressa. %Improve. denotes the relative performance improvement of CR over NT. The best results are highlighted in bold. Stars and underlines denote the best results of the baselines with and without using additional post-click feedback during training, respectively.

w/o post-click feedback

w/ post-click feedback

Dataset	Tiktok						Adressa					
Metric	P@10	R@10	N@10	P@20	R@20	N@20	P@10	R@10	N@10	P@20	R@20	N@20
NT [50]	$\underline{0.0256}$	$\underline{0.0357}$	0.0333	$\underline{0.0231}$	$\underline{0.0635}$	0.0430	$\underline{0.0501}$	$\underline{0.0975}$	$\underline{0.0817}$	$\underline{0.0415}$	$\underline{0.1612}$	$\underline{0.1059}$
CFT [50]	0.0253	0.0356	$\underline{0.0339}$	0.0226	0.0628	$\underline{0.0437}$	0.0482	0.0942	0.0780	0.0405	0.1573	0.1021
IPW [27]	0.0230	0.0334	0.0314	0.0210	0.0582	0.0406	0.0419	0.0804	0.0663	0.0361	0.1378	0.0883
CT [50]	0.0217	0.0295	0.0294	0.0194	0.0520	0.0372	0.0493	0.0951	0.0799	0.0418*	0.1611	0.1051
NR [51]	0.0239	0.0346	0.0329	0.0216	0.0605	0.0424	0.0499	0.0970	0.0814	0.0415	0.1610	0.1058
RR	0.0264*	0.0383*	0.0367*	0.0231*	0.0635*	0.0430*	0.0521*	0.1007*	0.0831*	0.0415	0.1612*	0.1059*
CR	**0.0269**	**0.0393**	**0.0370**	**0.0242**	**0.0683**	**0.0476**	**0.0532**	**0.1045**	**0.0878**	**0.0439**	**0.1712**	**0.1133**
%Improve.	5.08%	10.08%	11.11%	4.76%	7.56%	10.70%	6.19%	7.18%	7.47%	5.78%	6.20%	6.99%

Evaluation: evaluate the performance by post-click feedback (e.g., rating).

Observations:

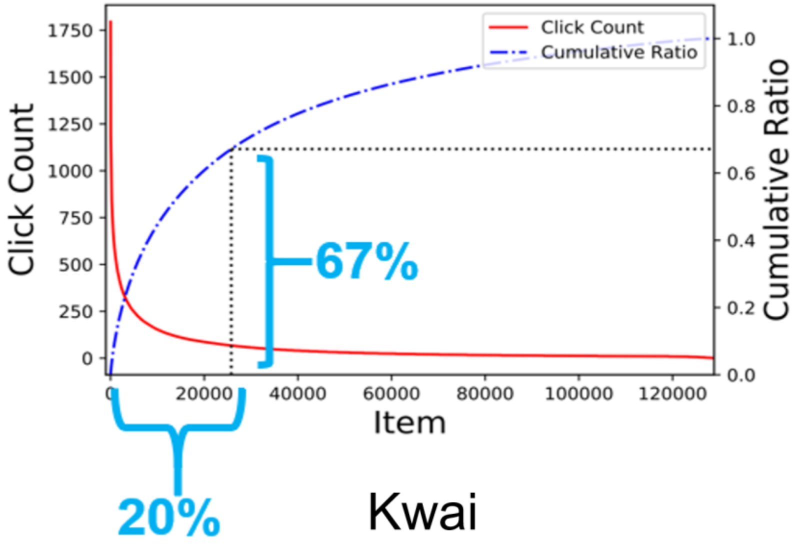
- CFT and IPW perform worse than NT.
- Post-click feedback could be helpful based on the performance of RR.
- Proposed CR inference significantly recommends more satisfying items by mitigating clickbait issue.

Wang, et al. "Clicks can be cheating: Counterfactual recommendation for mitigating clickbait issue." *SIGIR 2021.*

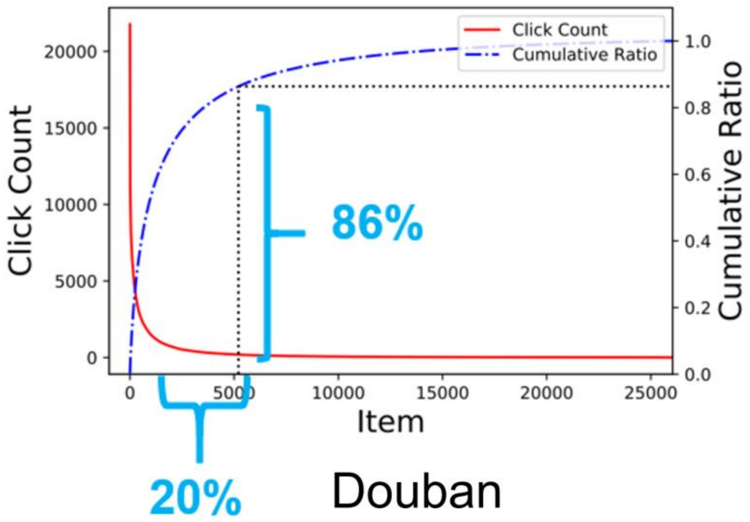
• Counterfactual Recommendation

Popularity Bias in Recsys

- Popularity bias ≠ Uneven popularity distribution
  - The popular items are recommended even more frequently than their popularity would warrant, amplifying long-tail effects.
  - Favor a few popular items while not giving deserved attention to the majority of others.
- From data perspective:



Kwai



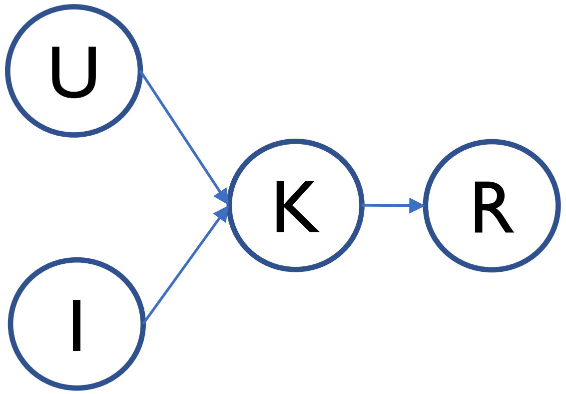
Douban

Long-tail distribution

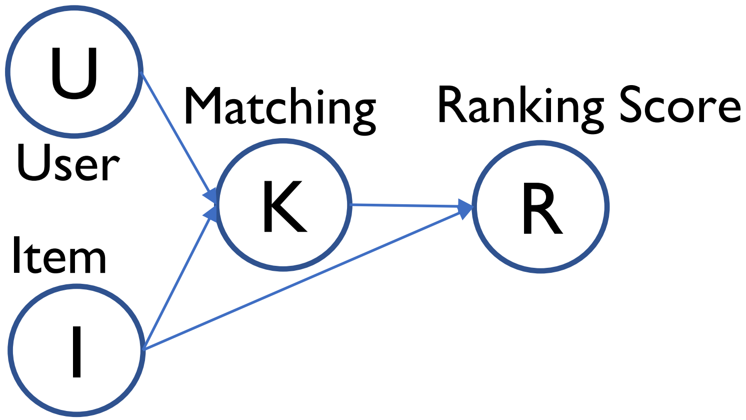
Wei et al. Model-Agnostic Counterfactual Reasoning for Eliminating Popularity Bias in Recommender System. In KDD 2021.

Counterfactual Recommendation

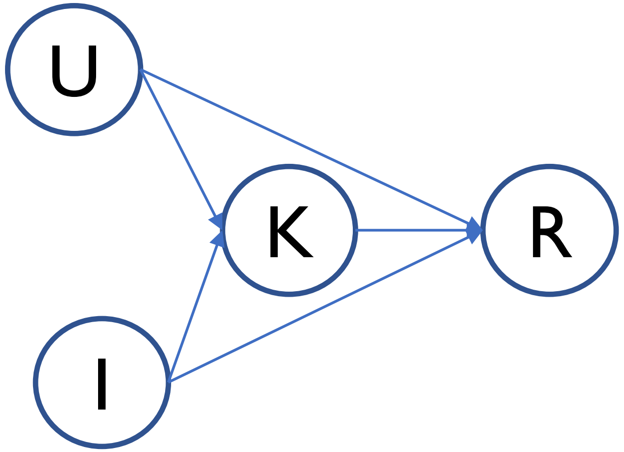
- Causal View of Popularity Bias



Common Recommender
User-Item Matching



Popularity bias modeling:
Incorporating item popularity



User-specific modeling:
Incorporating item popularity & user activity

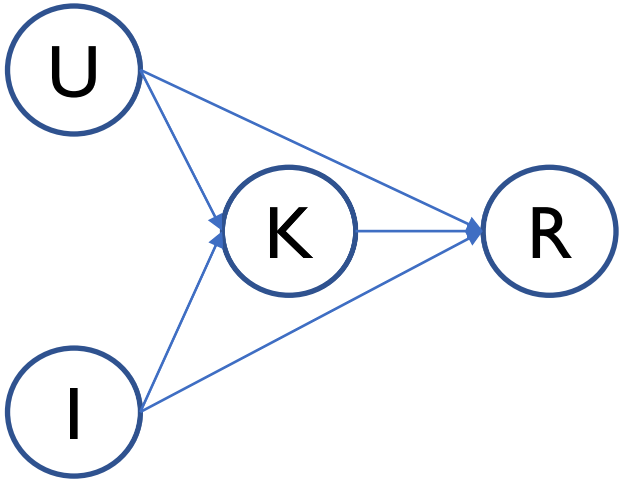
- Edge I→R captures popularity bias.
- Edge U→R captures the user sensitive to popularity.

- Solution Idea:
  - Train a recommender based on the causal graph via a multi-task learning
  - Perform counterfactual inference to eliminate popularity bias (*Question to answer: what would the prediction be if there were only popularity bias?*)

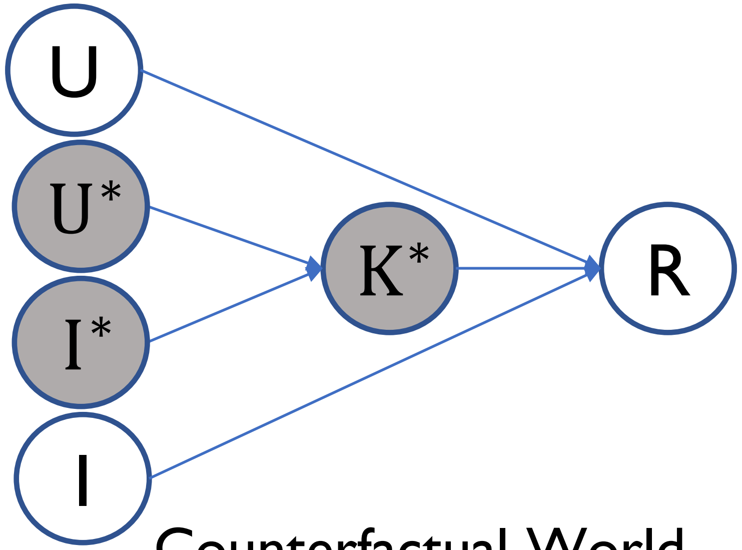
Wei et al. Model-Agnostic Counterfactual Reasoning for Eliminating Popularity Bias in Recommender System. In KDD 2021.

• Counterfactual Recommendation

- **Counterfactual Inference to Remove Bias**
- *Question: what the prediction would be if there were no bias?*



Factual World
(original prediction)



Counterfactual World
(block matching to capture bias)

$$TIE = TE - NDE = \underbrace{Y(U=u, I=i, K=K_{u,i})}_{\text{Factual world}} - \underbrace{Y(U=u, I=i, K=K_{u^*,i^*})}_{\text{Counterfactual world}}$$

Inference with TIE $= \hat{y}_k \times \sigma(\hat{y}_i) \times \sigma(\hat{y}_u)$ - $c \times \sigma(\hat{y}_i) \times \sigma(\hat{y}_u)$

Wei et al. Model-Agnostic Counterfactual Reasoning for Eliminating Popularity Bias in Recommender System. In KDD 2021.

• Counterfactual Recommendation

- Evaluate MACR framework on two base models: MF and LightGCN.
- Testing data is intervened to be uniform.

MF-based

data Method	**Adressa**		**Yelp2018**	
	Recall	NDCG	Recall	NDCG
MF	0.0853	0.0341	0.0060	0.0094
ExpoMF	0.0896	0.0365	0.0060	0.0093
MF_causE	0.0835	0.0365	0.0051	0.0083
MF_BS	0.0900	0.0377	0.0061	0.0098
MF_reg	0.0659	0.0332	0.0050	0.0081
MF_IPS	**0.0964**	**0.0392**	**0.0062**	**0.0100**
MACR	0.1090	0.0495	0.0264	0.0192

LightGCN-based

data Method	**Adressa**		**Yelp2018**	
	Recall	NDCG	Recall	NDCG
Lgcn	0.0977	0.0395	0.0044	0.0086
Lgcn_causE	0.0823	0.0374	0.0050	0.0088
Lgcn_BS	0.1085	0.0469	**0.0048**	**0.0088**
Lgcn_reg	**0.0979**	**0.0390**	0.0042	0.0083
Lgcn_IPS	0.1070	0.0468	0.0054	0.0090
MACR	0.1273	0.0525	0.0312	0.0177

Wei et al. Model-Agnostic Counterfactual Reasoning for Eliminating Popularity Bias in Recommender System. In KDD 2021.

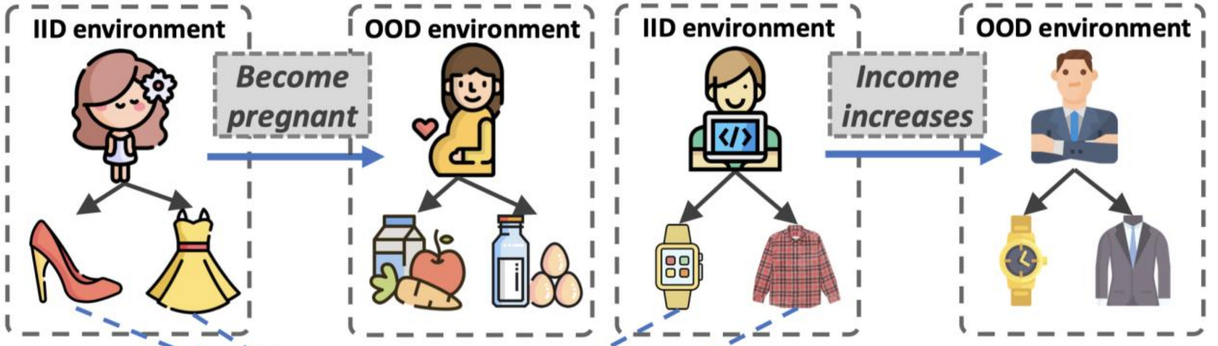
• Counterfactual Recommendation

Counterfactual inference for OOD recommendation

- Recommender learns user preference from historical interactions.
- However, user representation learning is usually based on the IID assumption between the training and testing interactions.
- OOD recommendation: $P(Y=1|U,I) = P(Y=1|U,I,E=1)P(E=1|U,I)$
  1) Shift of $P(Y=1|U,I,E=1)$: change of user preference.
  2) Shift of $P(E=1|U,I)$: change of recommendation policy (e.g., biased policy).

U: user; I: item
Y: user interaction
E: exposure

- Focus on the shift of $P(Y=1|U,I,E=1)$: change of user preference.
  - Observed features, e.g., *consumption level, location, age.*
  - Unobserved features, e.g., *changed mood, context factors.*



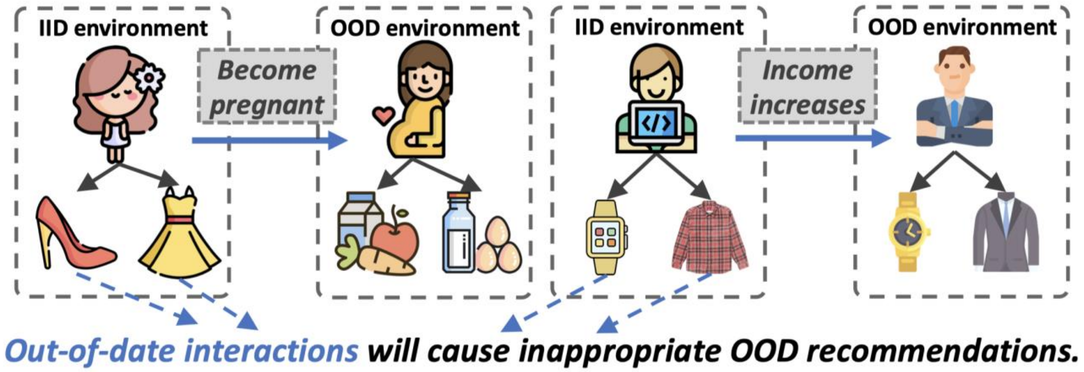
***Out-of-date interactions* will cause inappropriate OOD recommendations.**

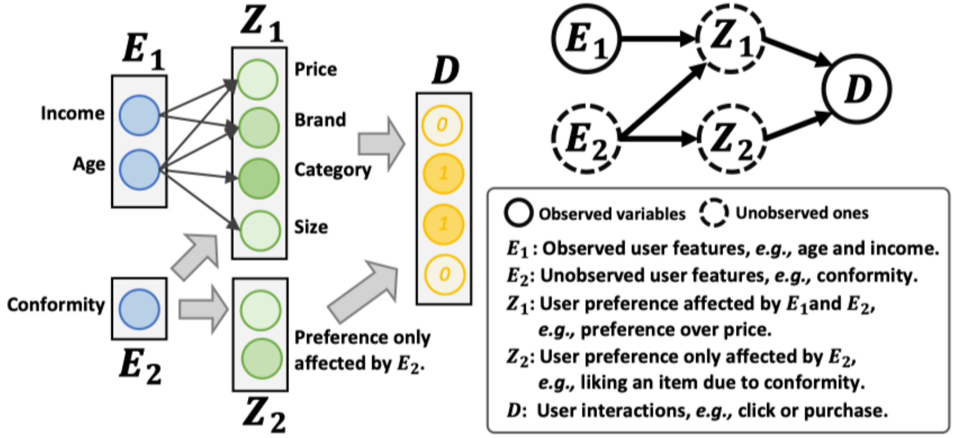
Wang, et al. “Causal Representation Learning for Out-of-Distribution Recommendation.” In WWW 2022.

• Counterfactual Recommendation

Causal OOD recommendation framework

- Propose **OOD objective** for user representation learning.
  - Strong OOD generalization without new interactions.
- Two key considerations:
  1) Figure out the **mechanism** how feature shifts affect user preference.
  2) Mitigate the effect of **out-of-date interactions**.
- Consideration 1: use causal graph to inspect interaction generation procedure.
- Formulation of OOD recommendation: $P(D|do(E_1 = \boldsymbol{e'}_1), E_2)$.



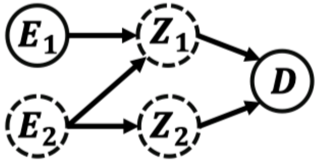


Wang, et al. "Causal Representation Learning for Out-of-Distribution Recommendation." In WWW 2022.

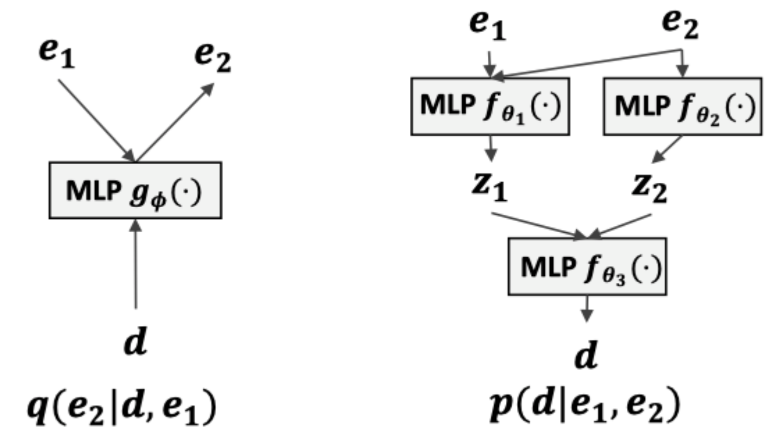
• Counterfactual Recommendation

Causal OOD recommendation framework

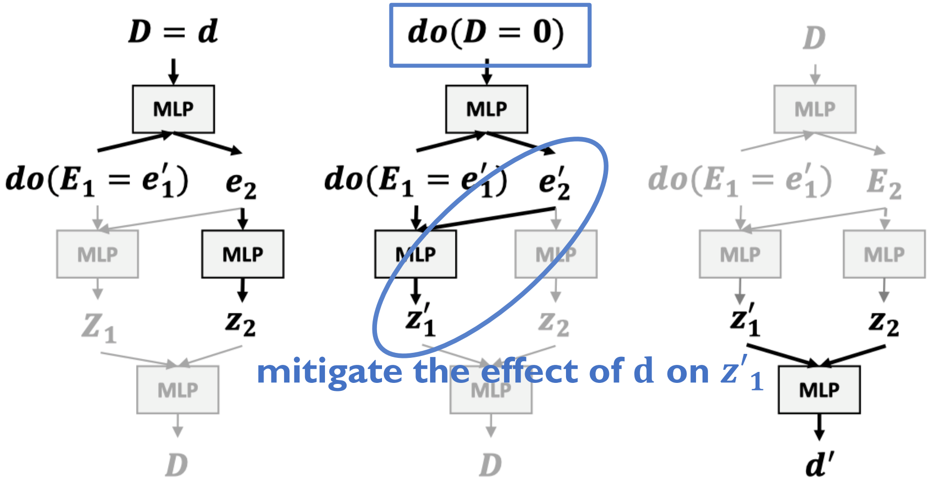
- Leverage VAE framework to model the interaction generation process
  1) Encoder: predict the unobserved user features E_2.
  2) Decoder: model the causal relations $(E_1, E_2) \rightarrow (Z_1, Z_2) \rightarrow D$.



- Consideration 2: mitigate the effect of out-of-date interactions.
  - Z_1 is updated due to $do(E_1 = \boldsymbol{e}_1')$, but Z_1 is still affected by out-of-date $\boldsymbol{d}$ because $\boldsymbol{d}$ affects $\boldsymbol{e}_2$.
    → User counterfactual inference to mitigate the effect of $\boldsymbol{d}$ on Z_1.



(a) Encoder Network. (b) Decoder Network.

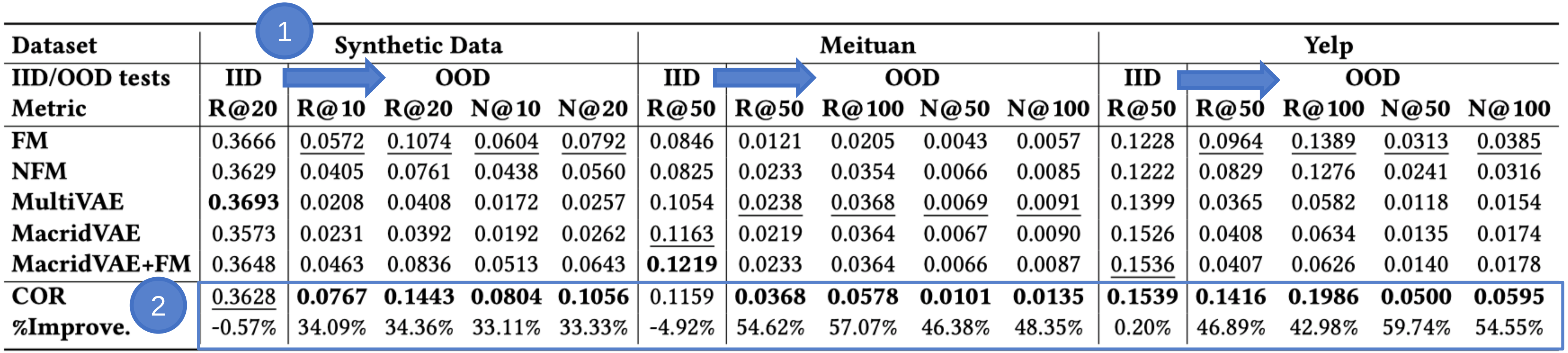


(a) Abduction. (b) Action. (c) Prediction.

Wang, et al. "Causal Representation Learning for Out-of-Distribution Recommendation." In WWW 2022.

• Counterfactual Recommendation

Table. The comparison of OOD generalization performance **without using OOD interactions**.



Dataset	**Synthetic Data**					**Meituan**					**Yelp**				
IID/OOD tests	**IID**	**OOD**				**IID**	**OOD**				**IID**	**OOD**			
Metric	**R@20**	**R@10**	**R@20**	**N@10**	**N@20**	**R@50**	**R@50**	**R@100**	**N@50**	**N@100**	**R@50**	**R@50**	**R@100**	**N@50**	**N@100**
FM	0.3666	0.0572	0.1074	0.0604	0.0792	0.0846	0.0121	0.0205	0.0043	0.0057	0.1228	0.0964	0.1389	0.0313	0.0385
NFM	0.3629	0.0405	0.0761	0.0438	0.0560	0.0825	0.0233	0.0354	0.0066	0.0085	0.1222	0.0829	0.1276	0.0241	0.0316
MultiVAE	**0.3693**	0.0208	0.0408	0.0172	0.0257	0.1054	0.0238	0.0368	0.0069	0.0091	0.1399	0.0365	0.0582	0.0118	0.0154
MacridVAE	0.3573	0.0231	0.0392	0.0192	0.0262	0.1163	0.0219	0.0364	0.0067	0.0090	0.1526	0.0408	0.0634	0.0135	0.0174
MacridVAE+FM	0.3648	0.0463	0.0836	0.0513	0.0643	**0.1219**	0.0233	0.0364	0.0066	0.0087	0.1536	0.0407	0.0626	0.0140	0.0178
COR	0.3628	**0.0767**	**0.1443**	**0.0804**	**0.1056**	0.1159	**0.0368**	**0.0578**	**0.0101**	**0.0135**	**0.1539**	**0.1416**	**0.1986**	**0.0500**	**0.0595**
%Improve.	-0.57%	34.09%	34.36%	33.11%	33.33%	-4.92%	54.62%	57.07%	46.38%	48.35%	0.20%	46.89%	42.98%	59.74%	54.55%

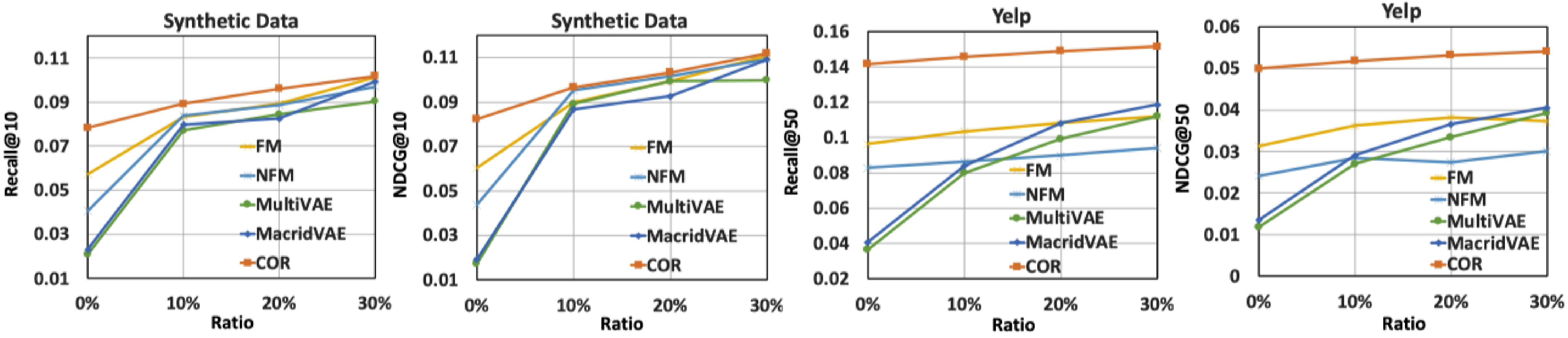
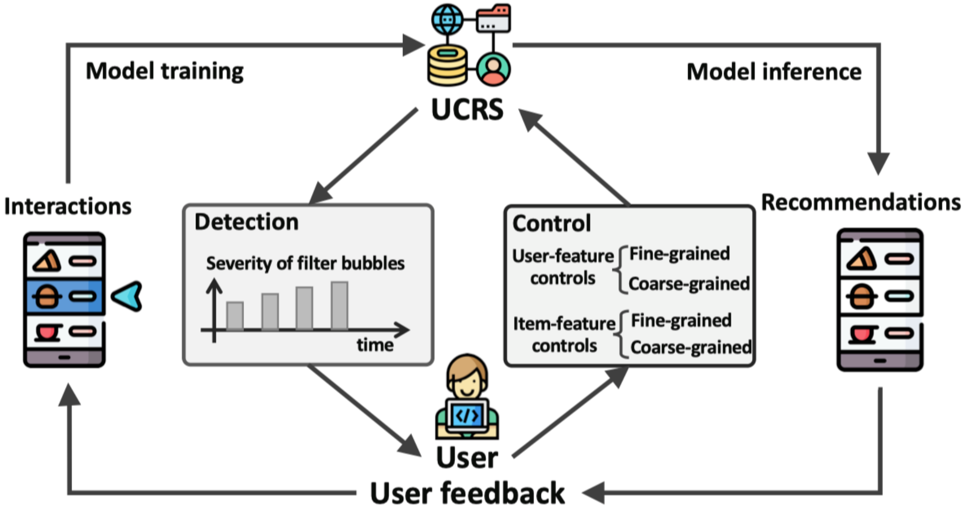


Figure. Fast adaptation performance *w.r.t.* different proportions of new interactions collected from the OOD environment.

Wang, et al. “Causal Representation Learning for Out-of-Distribution Recommendation.” In WWW 2022.

• Counterfactual Recommendation

- Counterfactual inference for mitigating filter bubbles
  - **Filter bubbles** in recommendation: continually recommending many **homogeneous items**, isolating users from diverse contents.
  - Solution: let users control the filter bubbles by directly adjusting recommendations.
  - Two-level user controls regarding either a user or item feature.
    - Fine-grained level: increase the items *w.r.t.* a specified user or item feature.
      - For example, "more items liked by young users".
    - Coarse-grained level: no need to specify the target user/item group.
      - For example, "no bubble *w.r.t.* my age"
  - A counterfactual imagination
    - Real-time response to user controls.
    - Need to reduce the effect of historical user representations.
    - **Counterfactual inference.**



Wang, et al. User-controllable recommendation against filter bubbles. In SIGIR 2022.

Recommendation based on SCM

- Dealing with confounding structures in recommendation
    - Confounding in recommendation.
    - Deal with observed confounders.
    - Deal with unobserved confounders.
- Considering colliding structures in recommendation
    - Colliders in recommendation
    - Modeling the colliding effect
- Counterfactual recommendation
    - Counterfactual inference for recommendation
    - Counterfactual data augmentation
    - Counterfactual fairness
    - Counterfactual explanation

• Counterfactual Recommendation

- Counterfactual data augmentation for alleviating data sparsity
  - Generate counterfactual interaction sequences for sequential recommendation.
  - Simulate the recommendation process and generate counterfactual samples, including recommendations and user feedback.
- Representative work
  - Zhang, et al. “Causerec: Counterfactual user sequence synthesis for sequential recommendation.” In SIGIR 2021.
  - Wang, et al. "Counterfactual data-augmented sequential recommendation." In SIGIR 2021.
  - Yang, Mengyue, et al. "Top-N Recommendation with Counterfactual User Preference Simulation." In CIKM 2021.

• Counterfactual Recommendation

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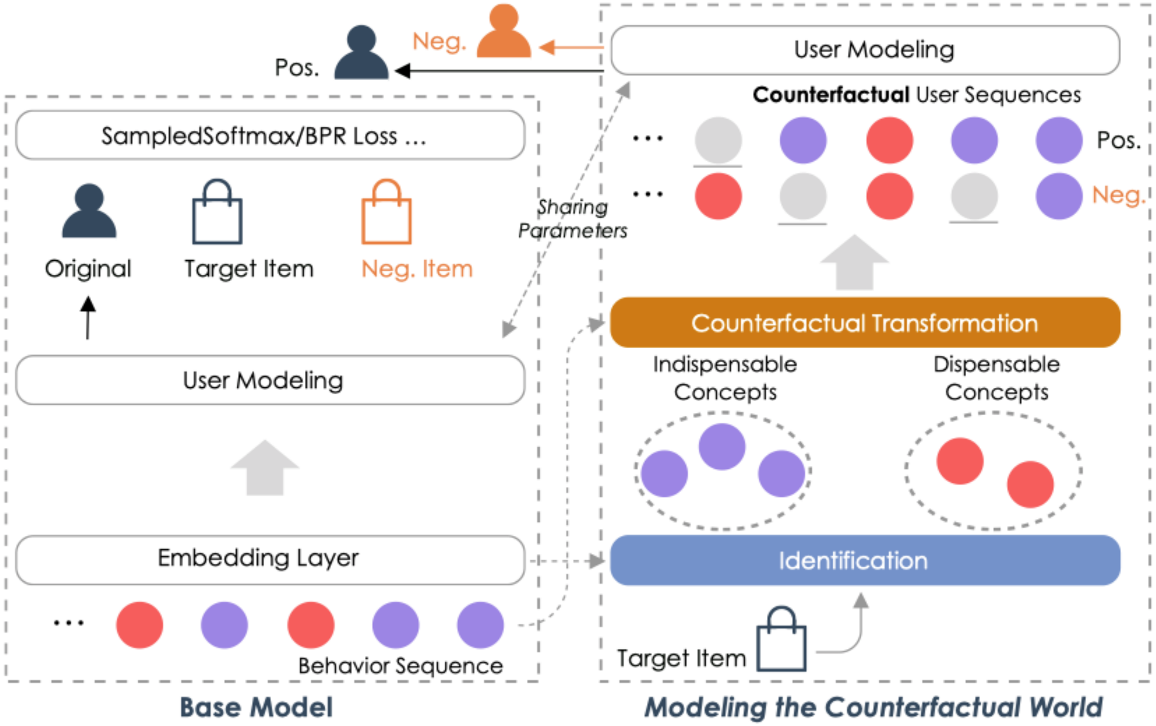
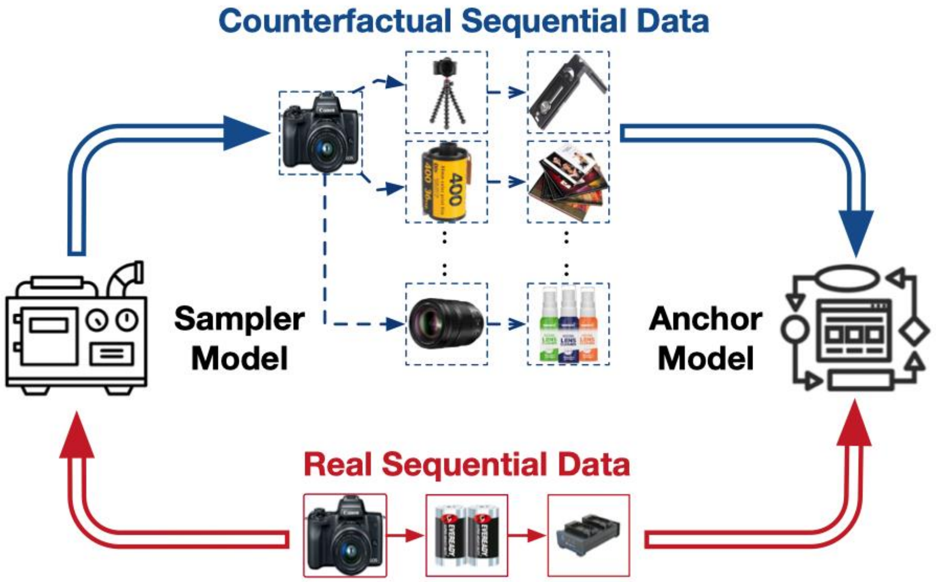


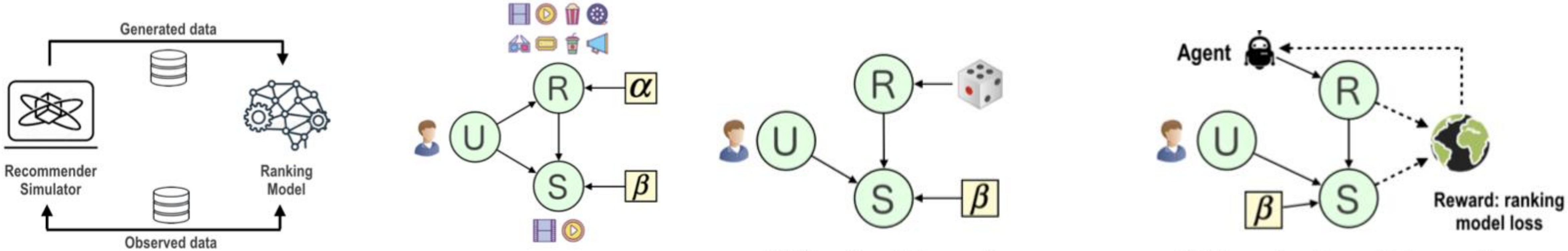
Zhang, et al. "Causerec: Counterfactual user sequence synthesis for sequential recommendation." In SIGIR 2021.



Wang, et al. "Counterfactual data-augmented sequential recommendation." In SIGIR 2021.

• Counterfactual Recommendation

- Counterfactual data augmentation
  - Simulate the recommendation process and generate counterfactual samples, including recommendations and user feedback.
    1) Learn SCM from observed data to simulate the recommendation process.
    2) Conduct intervention on the recommendation list (R) to generate counterfactual samples.
    3) Use observed and generated data to train the ranking model.



(a) Illustration of our framework (b) Recommendation as a SCM (c) Random Intervention (d) Learning-based Intervention

Yang, et al. “Top-N Recommendation with Counterfactual User Preference Simulation.” In CIKM 2021.

Recommendation based on SCM

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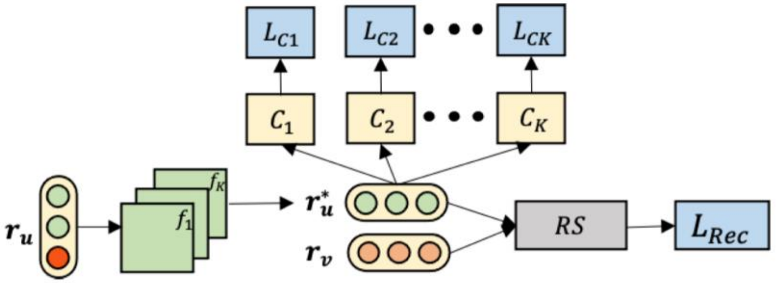
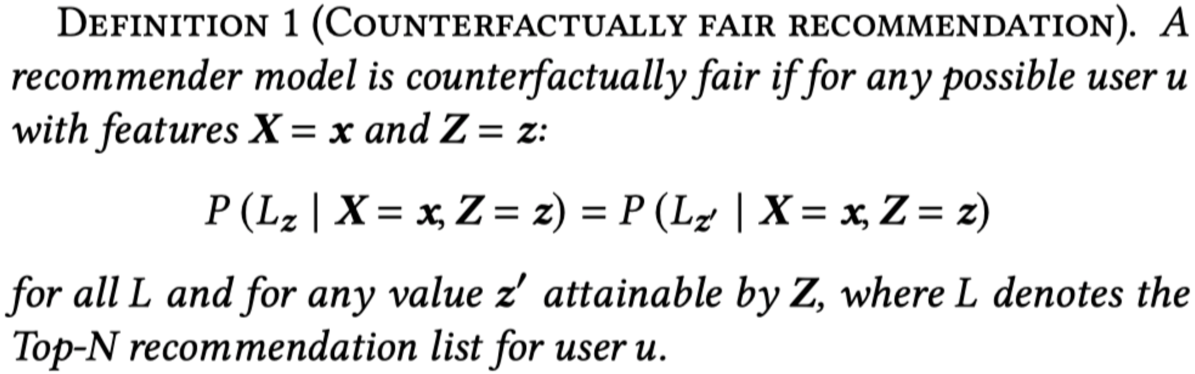
  - Counterfactual inference for recommendation
  - Counterfactual data argumentation
  - Counterfactual fairness
  - Counterfactual explanation

• Counterfactual Recommendation

• Counterfactual fairness

- Pursue fair recommendation for the users with different **sensitive attributes** (*e.g.*, age and gender).
- Counterfactual fair recommendation.
- Use **adversarial learning** to remove the sensitive information from user embedding (r_u).

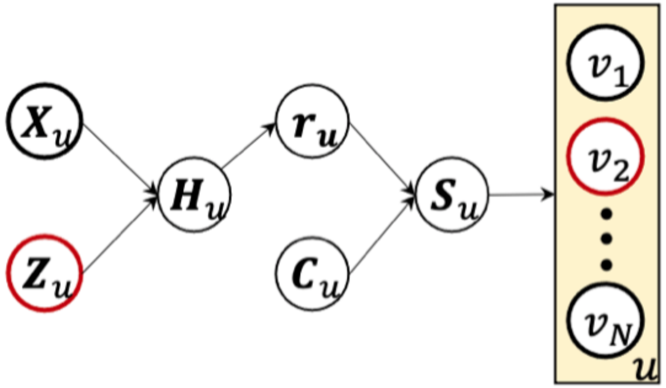




DEFINITION 1 (COUNTERFACTUALLY FAIR RECOMMENDATION). *A recommender model is counterfactually fair if for any possible user u with features* $\boldsymbol{X} = \boldsymbol{x}$ *and* $\boldsymbol{Z} = \boldsymbol{z}$*:*

$$P\left(L_{\boldsymbol{z}} \mid \boldsymbol{X} = \boldsymbol{x}, \boldsymbol{Z} = \boldsymbol{z}\right) = P\left(L_{\boldsymbol{z}'} \mid \boldsymbol{X} = \boldsymbol{x}, \boldsymbol{Z} = \boldsymbol{z}\right)$$

for all L and for any value $\boldsymbol{z}'$ *attainable by* $\boldsymbol{Z}$*, where L denotes the Top-N recommendation list for user u.*



- X_u and Z_u are insensitive and sensitive features of the user u, respectively.
- H_u is the user interaction history.
- r_u is the user embedding.
- C_u is the candidate item set for u.
- S_u are the predicted scores over the candidate items.

Li, et al. “Towards personalized fairness based on causal notion.” In SIGIR 2021.

Recommendation based on SCM

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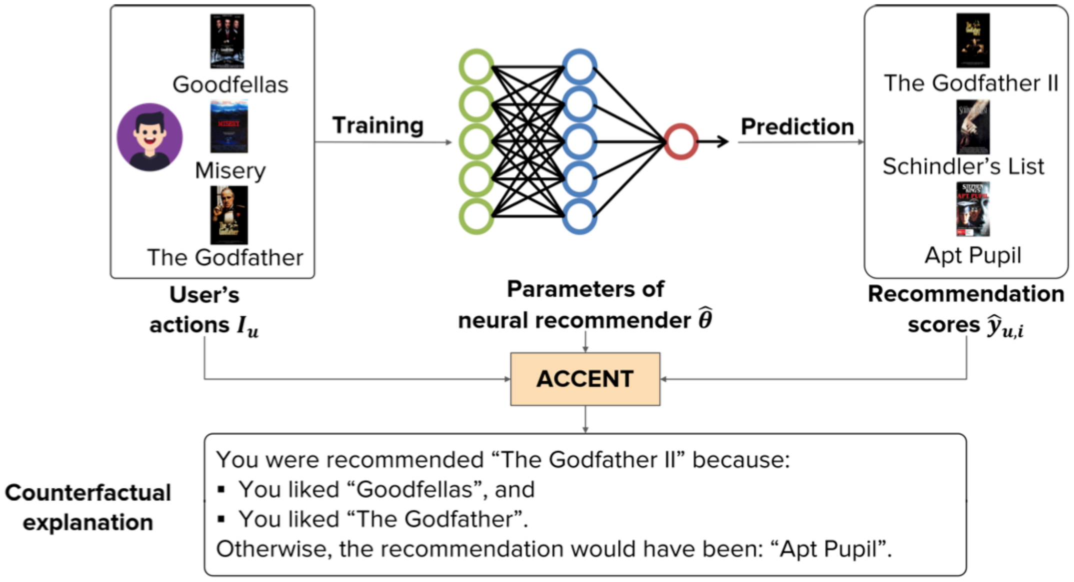
- Counterfactual recommendation
  - Counterfactual inference for recommendation
  - Counterfactual data argumentation
  - Counterfactual fairness
  - Counterfactual explanation

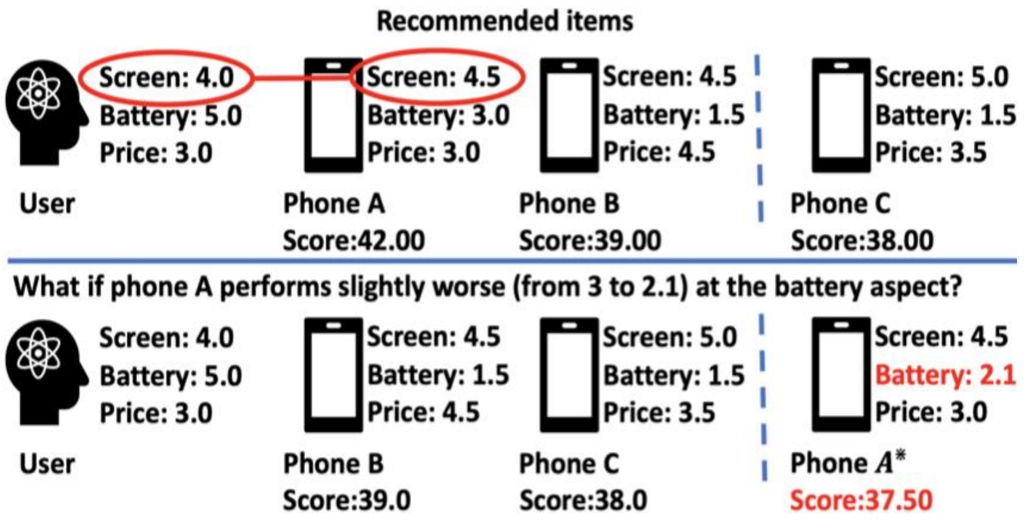
• Counterfactual Recommendation

- Counterfactual explanation
  - Generate explanation by counterfactual thinking.
  - Find the minimal changes that lead to a different recommendation.
  - Identify the most critical features causing the recommendations.



You were recommended "The Godfather II" because:
- You liked "Goodfellas", and
- You liked "The Godfather".

Otherwise, the recommendation would have been: "Apt Pupil".



What if phone A performs slightly worse (from 3 to 2.1) at the battery aspect?

Tran, et al. "Counterfactual Explanations for Neural Recommenders." In SIGIR 2021.

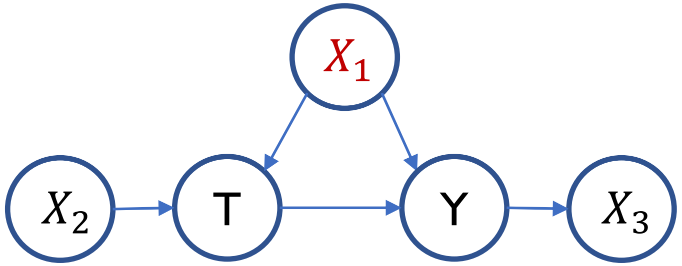
Tan, et al. "Counterfactual explainable recommendation." In CIKM 2021.

Papers for Counterfactual Recommendation

- Wang, et al. Clicks can be cheating: Counterfactual recommendation for mitigating clickbait issue. In SIGIR 2021.
- Wei, et al. Model-agnostic counterfactual reasoning for eliminating popularity bias in recommender system. In KDD 2021.
- Wang, et.al. Causal representation learning for out-of-distribution recommendation. In WWW 2022.
- Wang, et.al. User-controllable recommendation against filter bubbles. In SIGIR 2022.
- Zhang, et al. “Causerec: Counterfactual user sequence synthesis for sequential recommendation.” In SIGIR 2021.
- Wang, et al. "Counterfactual data-augmented sequential recommendation." In SIGIR 2021.
- Yang, Mengyue, et al. "Top-N Recommendation with Counterfactual User Preference Simulation." In CIKM 2021.
- Li, et al. “Towards personalized fairness based on causal notion.” In SIGIR 2021.
- Tran, et al. “Counterfactual Explanations for Neural Recommenders.” In SIGIR 2021.
- Tan, et al. “Counterfactual explainable recommendation.” In CIKM 2021.

Comparisons between PO and SCM

- Connections
  - logically equivalent: most theorem and assumptions can be equally translated.
- SCM
  - Intuitive: use causal graph to explicitly describe causal relationships.
  - Need more knowledge and assumptions on the causal graph.
- PO
  - Easy to capture some assumptions that can not be naturally represented by DAGs, such as the identification of the Local Average Treatment Effect (LATE).



An intuitive example:

- To estimate the causal effect of T on Y, SCM might first assume the relationships between X_1, X_2, X_3, T, and Y, and then SCM can control X_1.
- PO might directly control X_1, X_2, and X_3 without knowing the fine-grained causal relationships.

Outline

- Introduction
- Potential outcome framework for recommendation
- Structural causal model-based recommendation
- Comparison
- Open problems, future directions and conclusions

Summary of Current Causal Recommendation

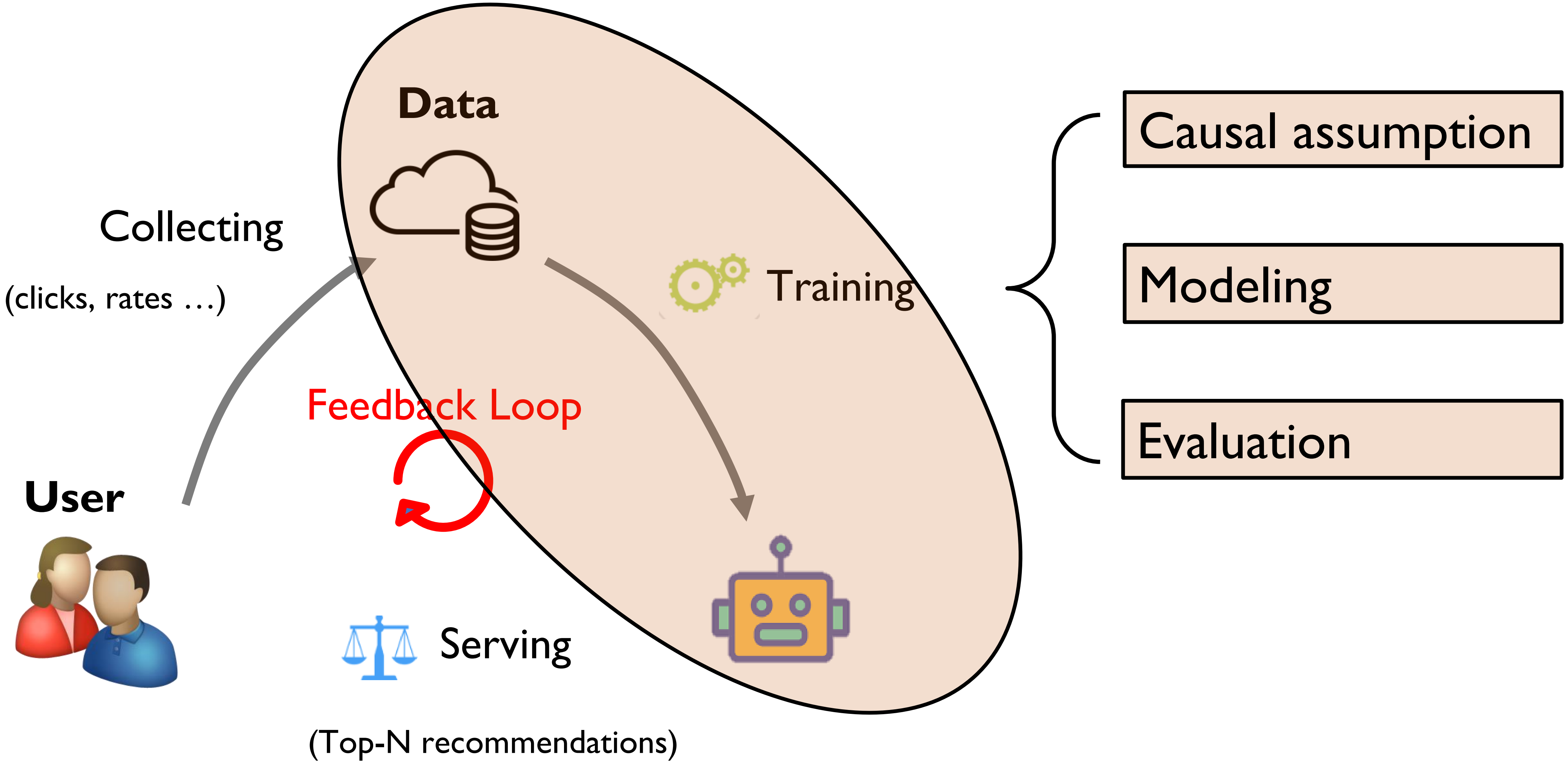
- Causal recommendation → Better Recommendation
  - Debias
  - Fairness
  - Generalization
  - … (*Many other researches, we apologize for not covering all! Kindly let us know about your work and suggestions: fulifeng93@gmail.com*)

- Try causal perspective to solve your recommendation problem

- Two frameworks: PO and SCM-based methods
  - Causal graph is the key of the SCM-based methods.
  - Propensity scores are usually choice in PO-based methods.
  - SCM based methods may need more causal assumptions.

- How to choose between PO and SCM? Requirements

Open Problems and Future Directions



Data

Collecting

(clicks, rates …)

Training

Feedback Loop

User

Serving

(Top-N recommendations)

Causal assumption

Modeling

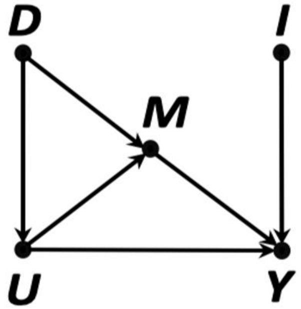
Evaluation

Causal Assumption

- PO & SCM requires assumptions
  - Existing PO-based methods need to choose covariates to satisfy the exchangeability assumption.
  - Existing SCM-based methods need to manually draw the casual graph.

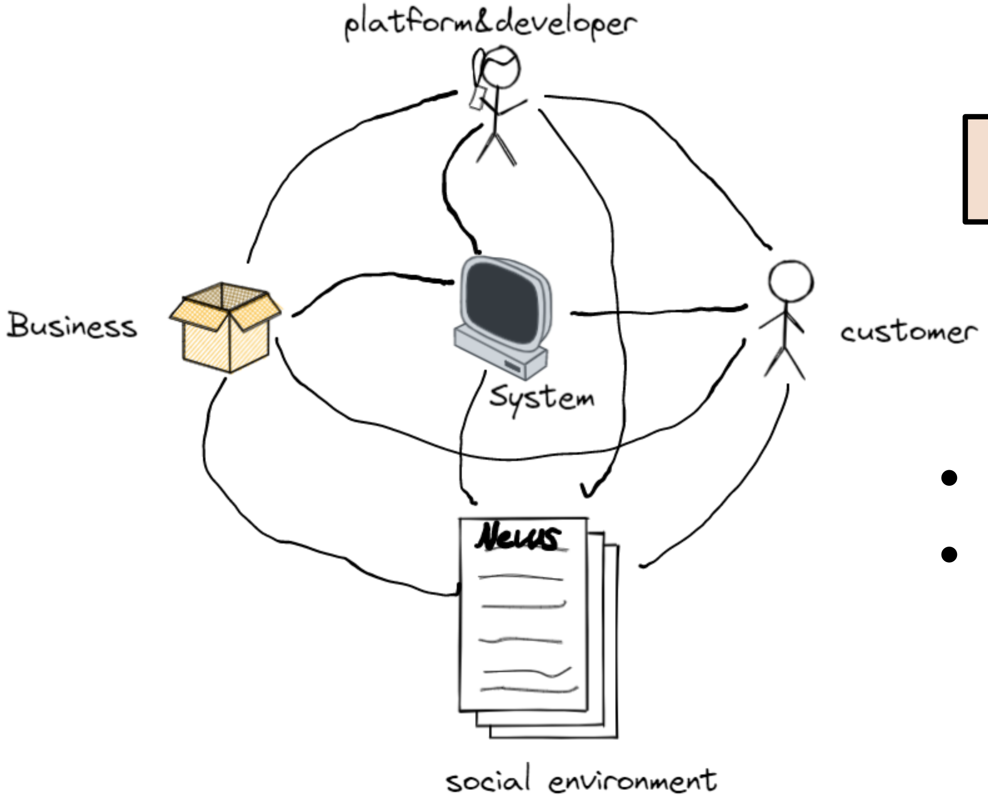
$P(Y^a \perp A|L)$

POM assumption



SCM assumption

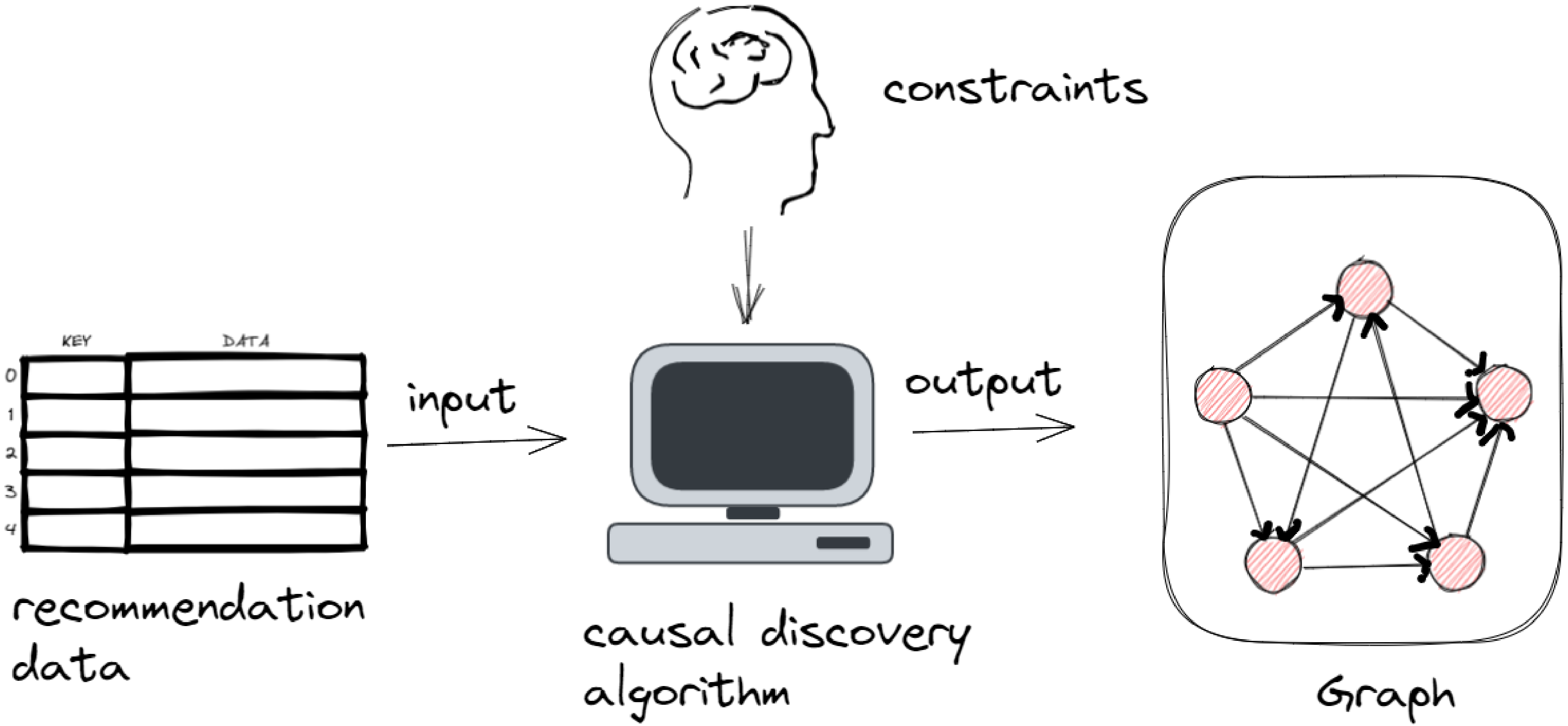
How to obtain proper causal assumptions?



- Recommender system is a complex environment.
- Prior knowledge are insufficient.

Causal Assumption

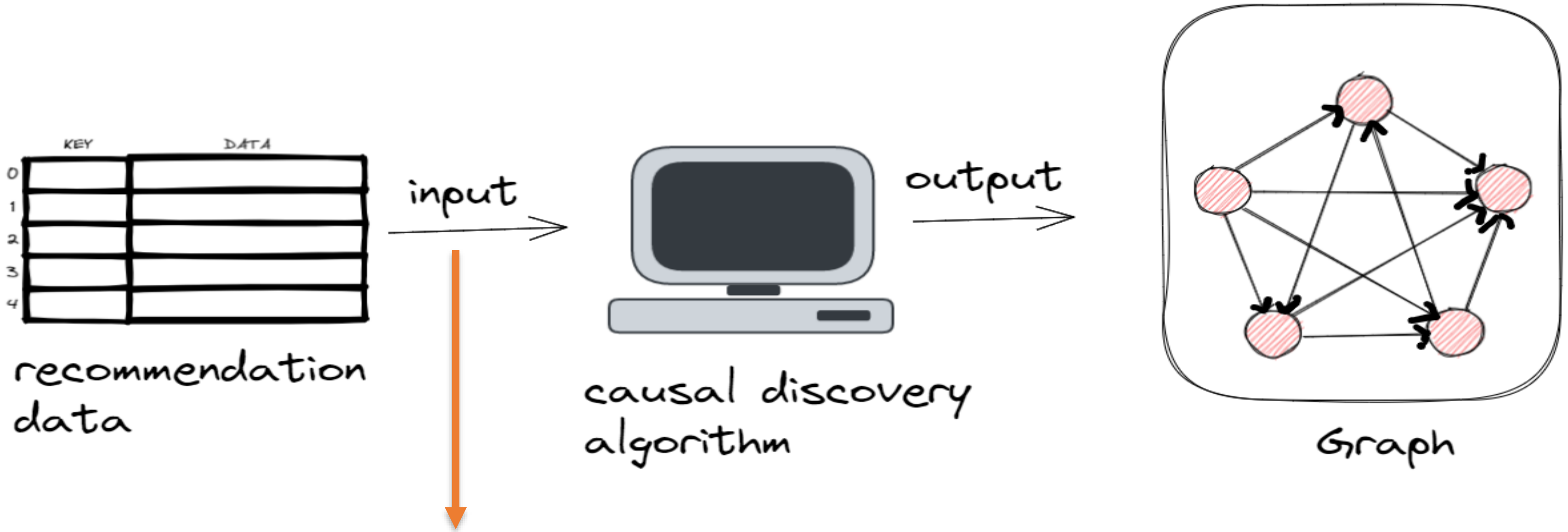
- Future direction: causal discovery in recommendation



Automatic discovery of cause graphs with causal discovery algorithms

Causal assumption

- Future direction: causal discovery in recommendation
  - Challenges for applying casual discovery algorithms in recommendation

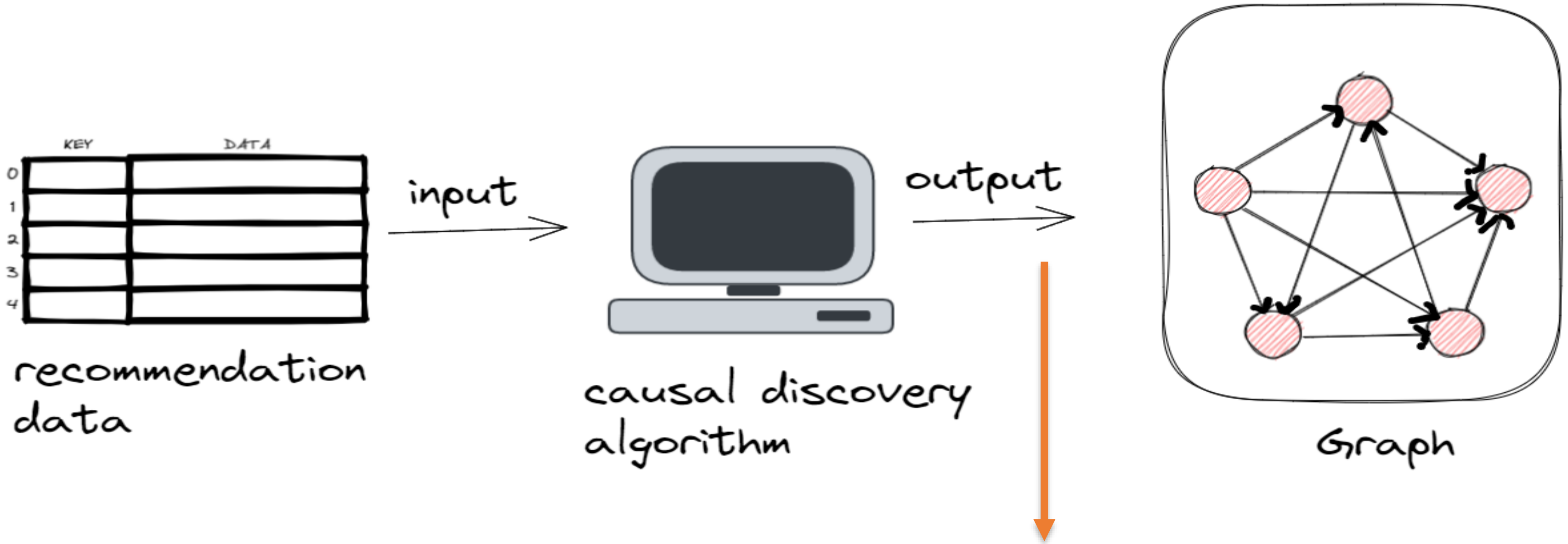


- Normal causal discovery algorithm only deals with few variables
- Challenge 1:

  High-dimensional inputs; hidden variables.

Causal Assumption

- Future direction: causal discovery in recommendation
  - Challenges for applying casual discover algorithms to recommendation

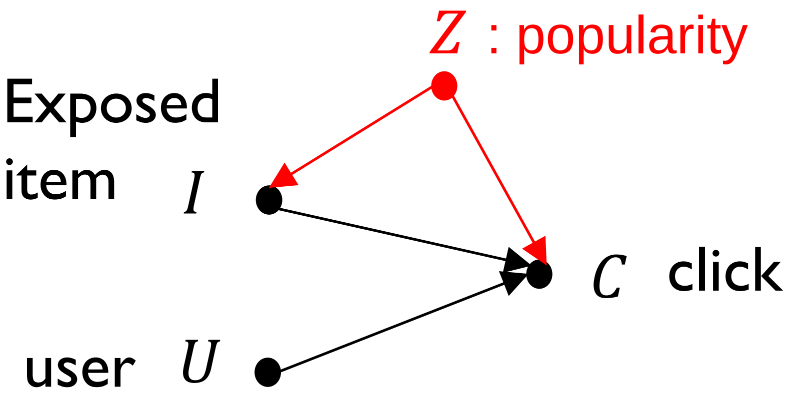


- The output usually is a set of causal graphs instead of only one graph.
- Challenge 2:

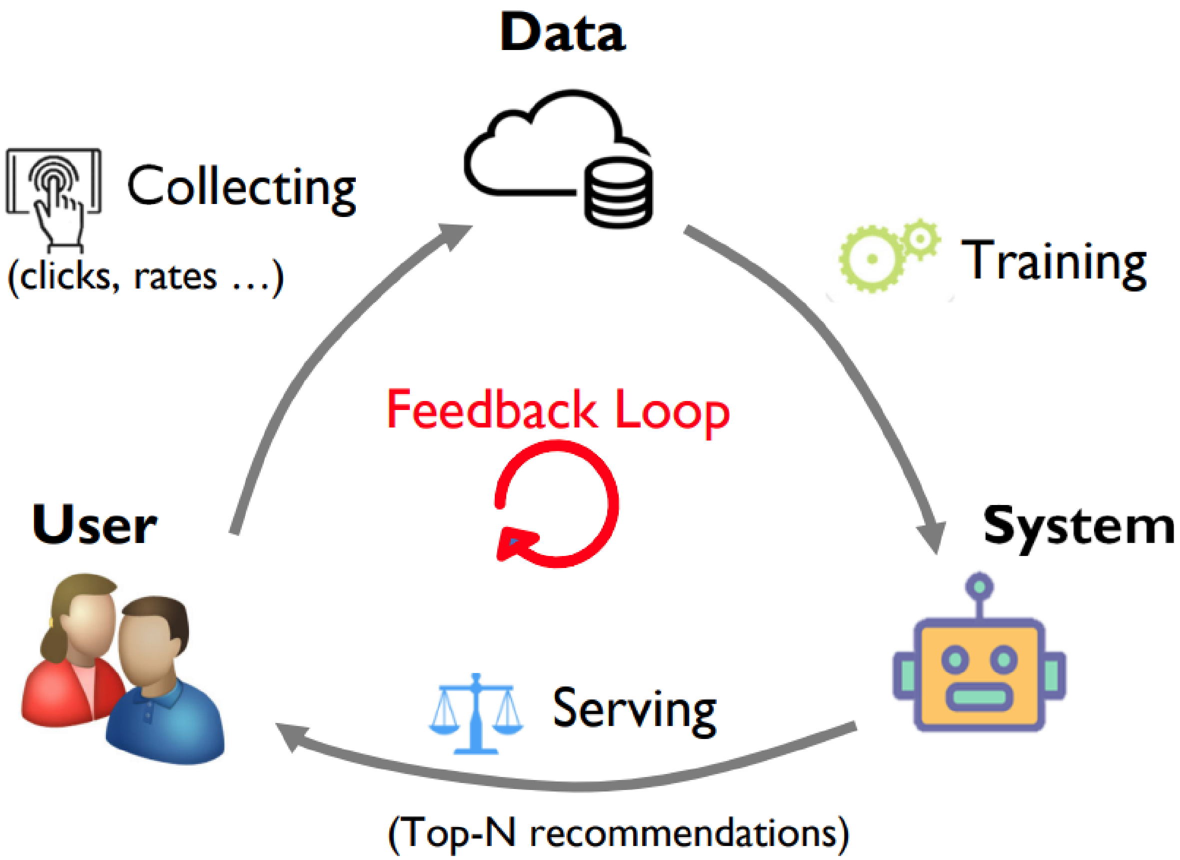
  Unreliable graphs in the graph set.

Causal Modeling

- Existing work focuses on one training step



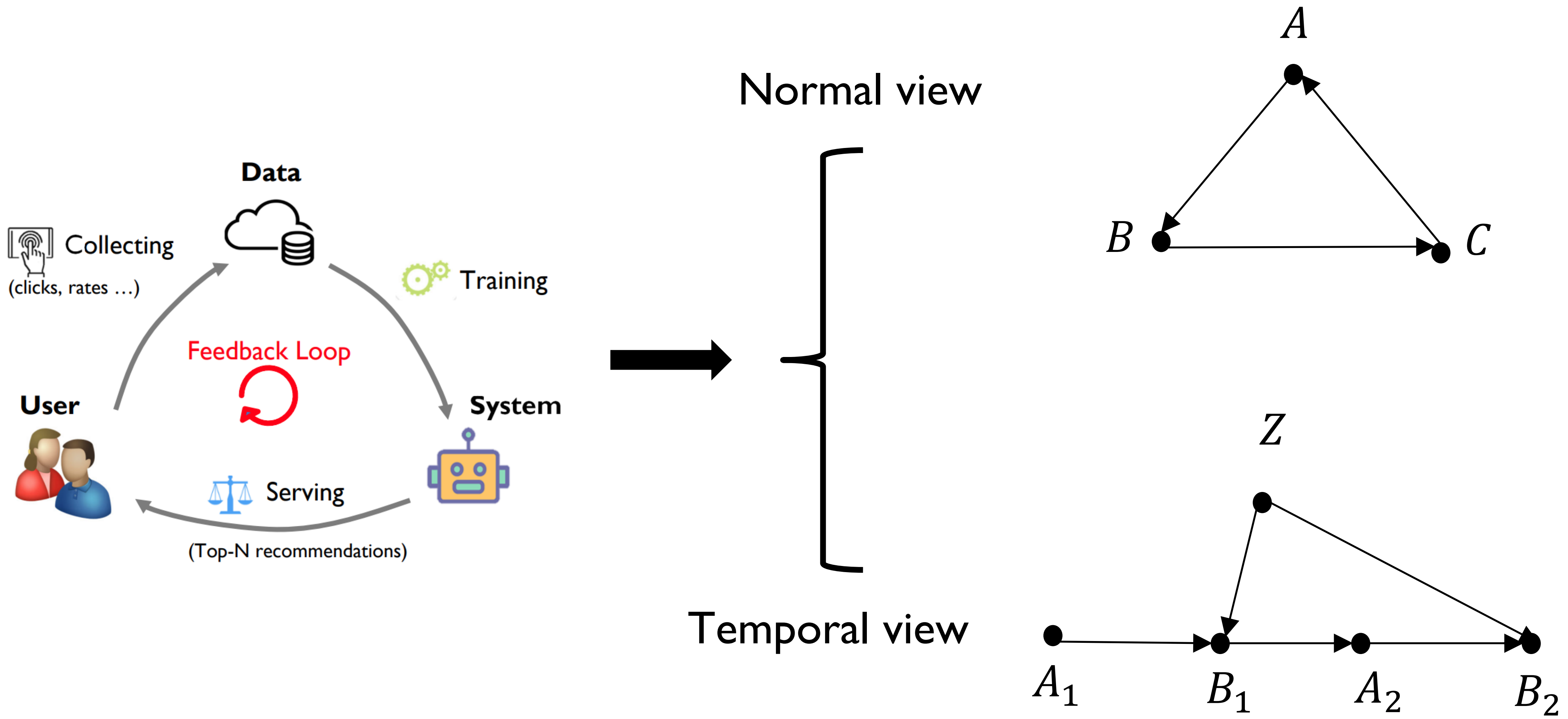
Popularity also influences the collecting step



How to model the causal effect of feedback loop?

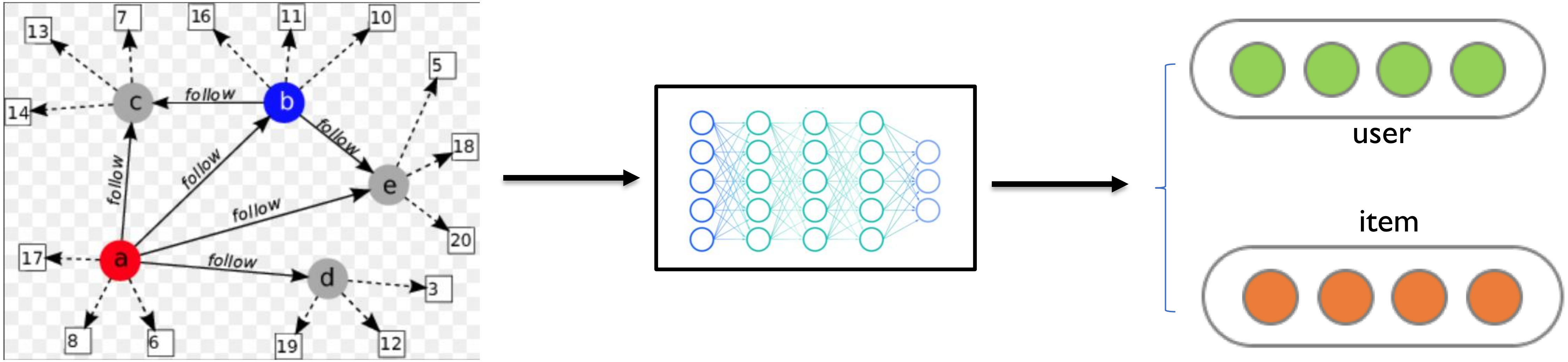
Causal Modeling

- Future direction: Temporal causal modeling



Causal Modeling

- Existing work relies on latent representation



Recommendation data

Neural network

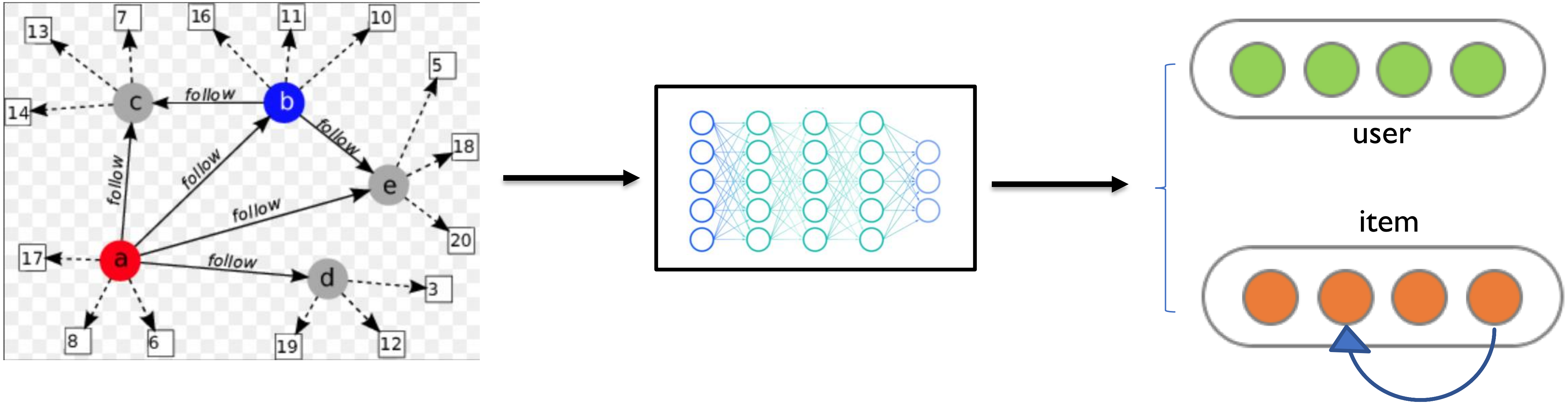
representation

- The key of many recommender models is to learn user/item representations
- But, rare work focus on injecting causation into representations

How to learn causal representation?

Causal Modeling

- Future direction: causal representation learning



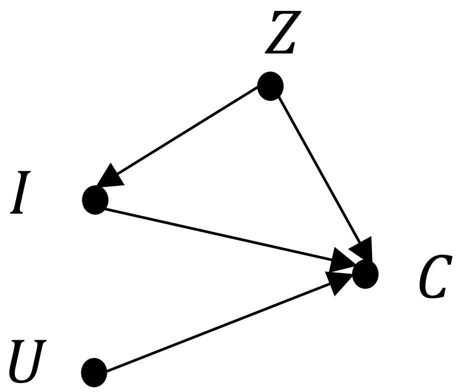
- Challenges:
  - \- Grounding
  - \- Modularity

$$P(x_1, x_2, \dots, x_n) = P(x_1|pa_1)P(x_2|pa_2)\cdots p(x_n|pa_n)$$

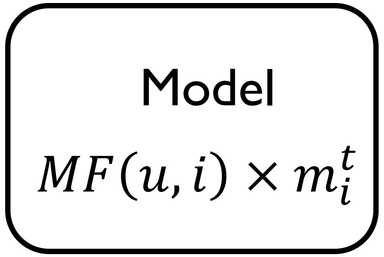
- $\mathrm{P}(x_i|pa_i)$ and $P(x_j|pa_j)$ are independent.

Causal Modeling

- Existing work requires many manual operations



P(*C*|do(*U*),do(*I*)) = $\sum_{z} P(C|U,I,Z)P(Z)$



$MF(u,i) \times m_i^t$

① Manually define causal assumption, e.g., casual graph

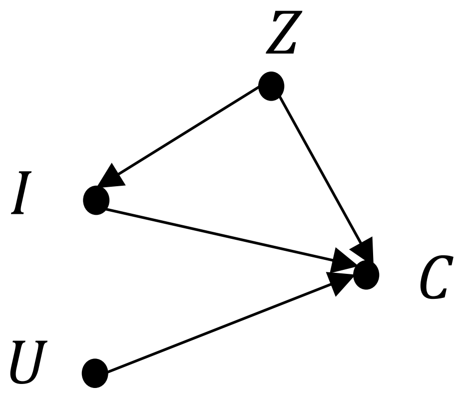
② Manually identify estimation goal according to ①

③ Manually design recommender model based on ②

How to reduce the cost of human-efforts?

Causal Modeling

- Future direction: Auto-causal recommendation



$$P(C|\mathrm{do}(U),\mathrm{do}(I)) = \sum_z P(C|U,I,Z)P(Z)$$

Model

$$MF(u,i) \times m_i^t$$

① Manually define causal assumption

Causal discovery

② Manually identify estimation goal according to ①

Query/target causal understanding + automated causal inference

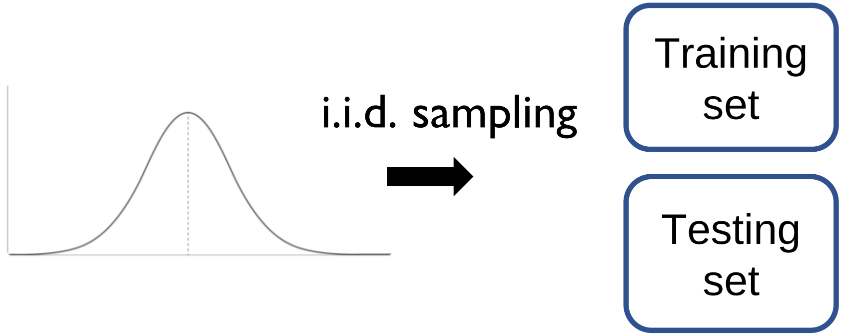
③ Manually design recommender model based on ②

Causal model automated searching

Evaluation

- One thousand papers, one thousand evaluation protocols

Normal setting is hard to show the superiority of the causal recommendation. Lack the standard evaluation setting.



Normal setting

OOD setting: debiasing, temporal setting
Small random exposure data
Different labels for training and testing

Existing strategies

What are the standards for causal recommendation evaluation?

- Future direction: benchmark

New benchmark dataset for causal recommendation, standardize the evaluation setting.

Evaluation

- Future direction: causality-aware evaluation metrics

Example 1 -- the effect of recommending operation

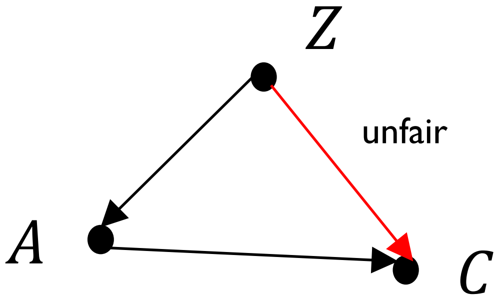
A and B are both matched to user preference, but recommending B can bring more gains.

Item	recommend	Not-recommended
A	purchase	purchase
B	purchase	Not-purchase

Masahiro Sato et.al. Unbiased Learning for the Causal Effect of Recommendation. In RecSys 2020.

Example 2 --- path-specific fairness

Z affects C via two paths: $Z \rightarrow A \rightarrow C$ and $Z \rightarrow C$
Only $Z \rightarrow C$ is unfair.



THANKS

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