Causal Intervention for Leveraging Popularity Bias in Recommendation

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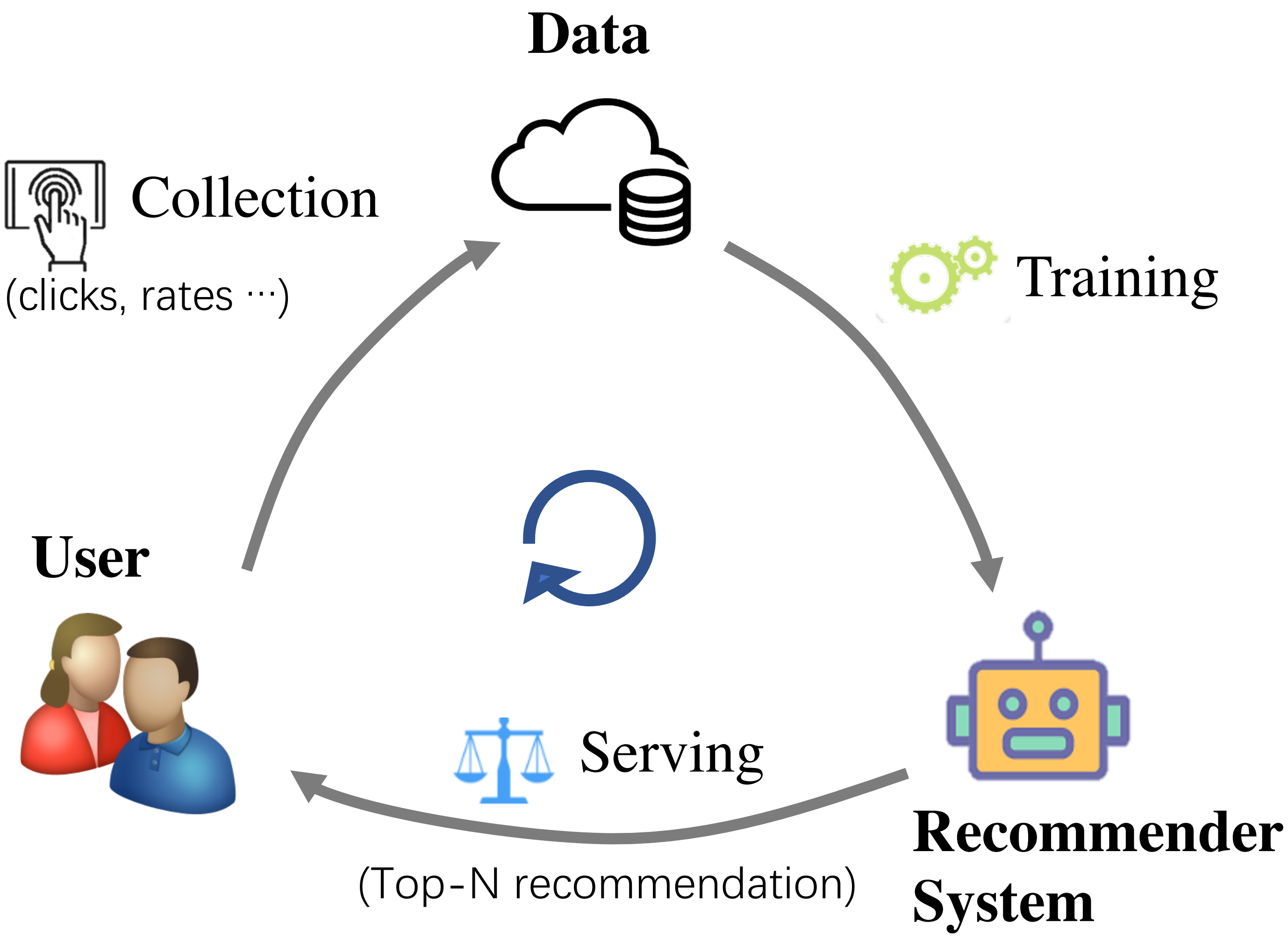
Recommender System

- Working flow of RS
  - Training: RS are trained or updated on observed user-item interaction data.
  - Serving: RS infers user preference over items and gives recommendation lists.
  - Collecting: User new actions are merged into the training data.
- Forming a feedback loop



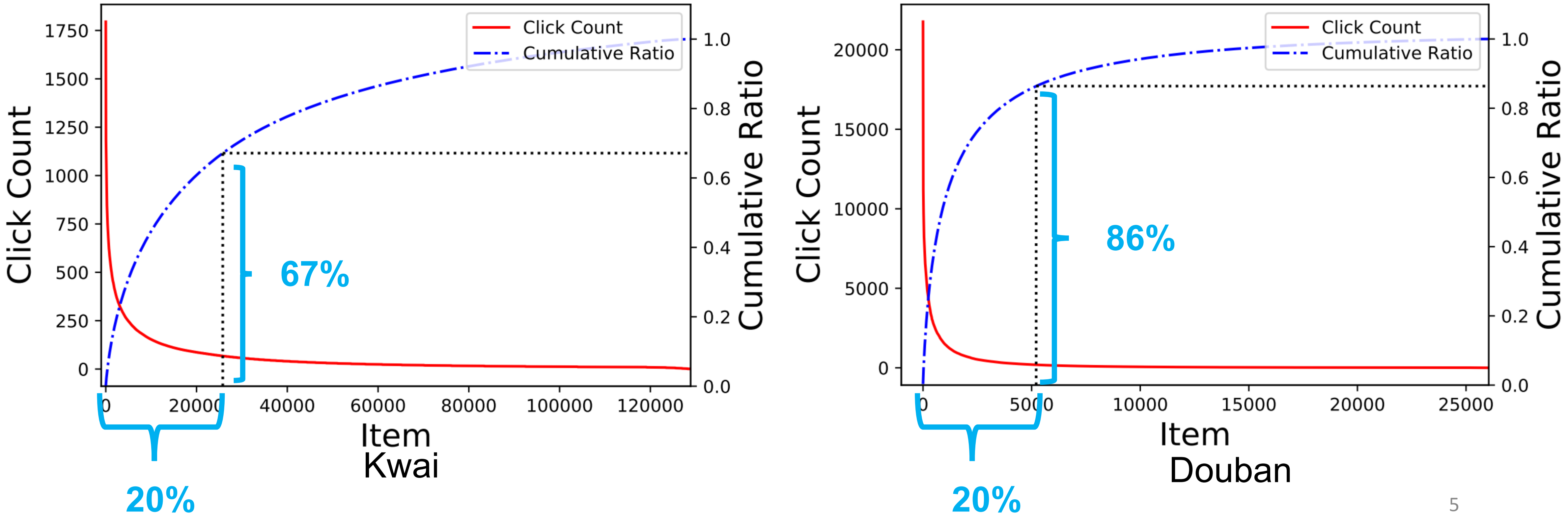
Popularity Bias

- Definitions [1]:
  - Popularity bias refers to the problem where the recommendation algorithm **favors a few popular items** while not giving deserved attention to the majority of other items.
  - Popularity bias is a well-known phenomenon in recommender systems where popular items are recommended even more frequently than their popularity would warrant, **amplifying** long-tail effects already present in many recommendation domains.

[1] Abdollahpouri, Himan. *Popularity Bias in Recommendation: A Multi-stakeholder Perspective*. Diss. University of Colorado, 2020.

Source of Popularity Bias

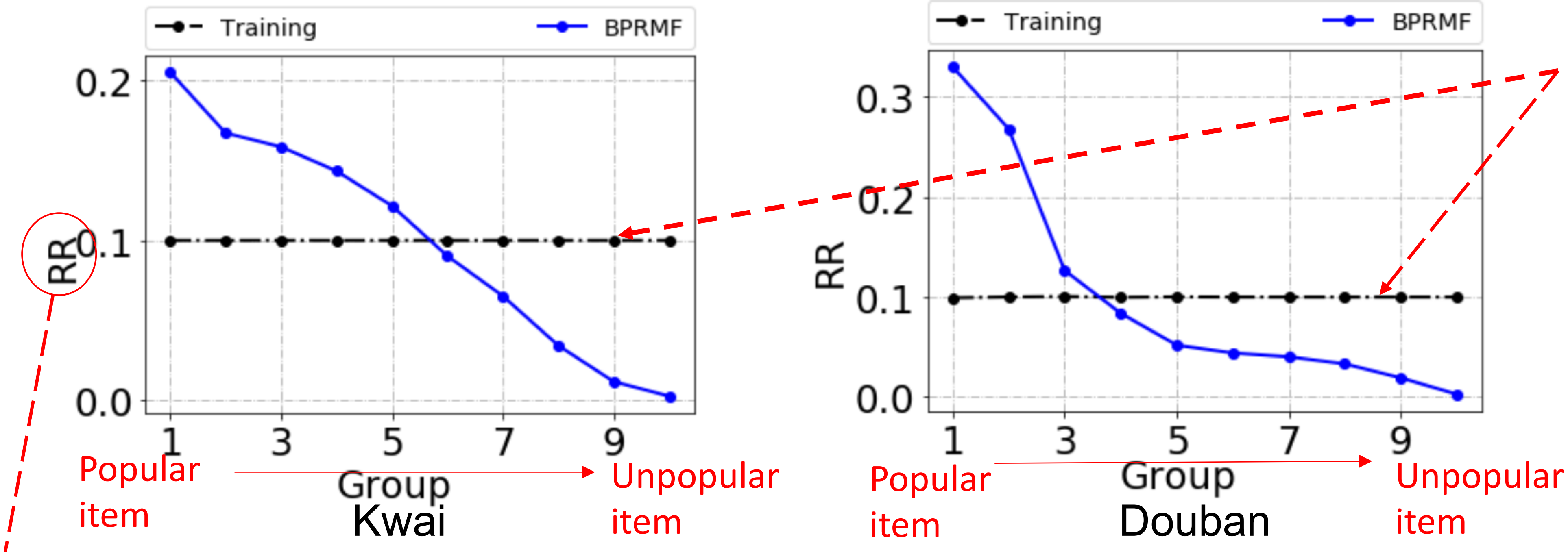
- The Underlying Data
  - Few popular items which take up the majority of rating interactions while the majority of the items receive small attention from the users.



Source of Popularity Bias

- Algorithmic Bias
  - Not only inherit bias from data, but also amplify the bias.

    —— the rich get richer and the poor get poorer

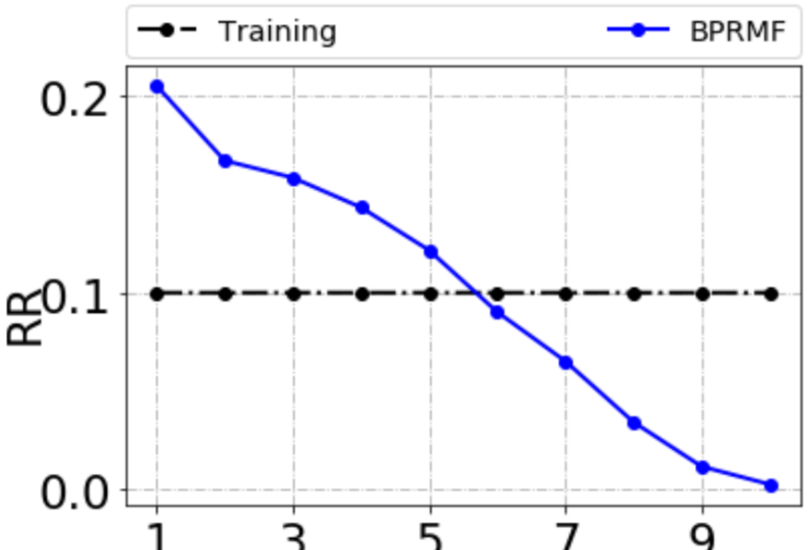


Each group has the same number of interactions in the training set

Recommendation Rate

Impacts of Popularity Bias

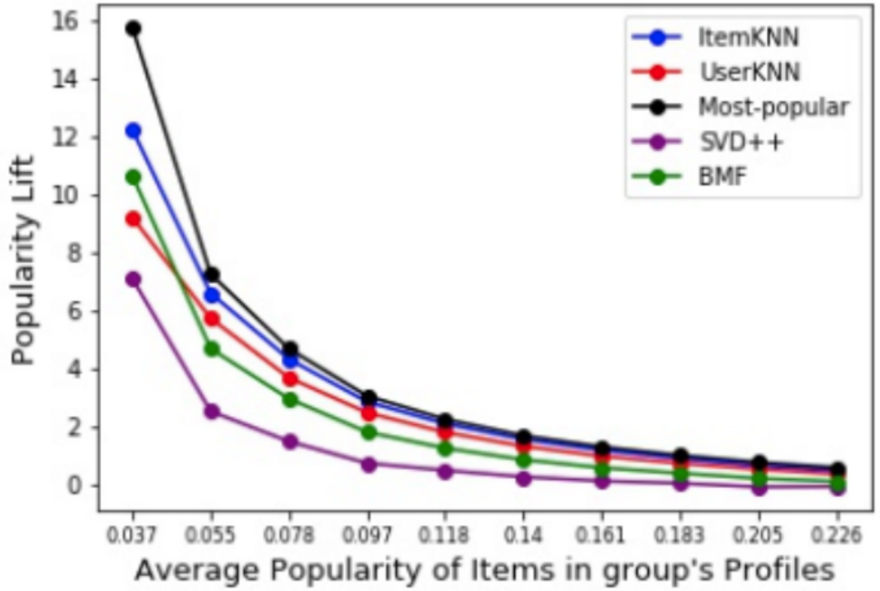
➢ Item-side



popular → unpopular

Kwai

User-side [1]



(a) MovieLens

Like popular items

Matthew effect; Amplified interests for popular items; Unfairness for both users and items

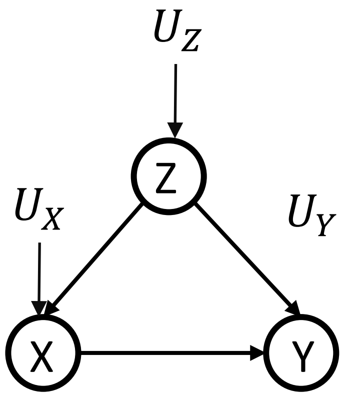
[1]. Abdollahpouri, Himan, et al. "The Connection Between Popularity Bias, Calibration, and Fairness in Recommendation." Fourteenth ACM Conference on Recommender Systems. 2020.

Causal Inference

➢ Basic Concepts in Causal Theory [1]

☐ Causal Graph:

Graphical models used to encode assumptions about the data-generating process.

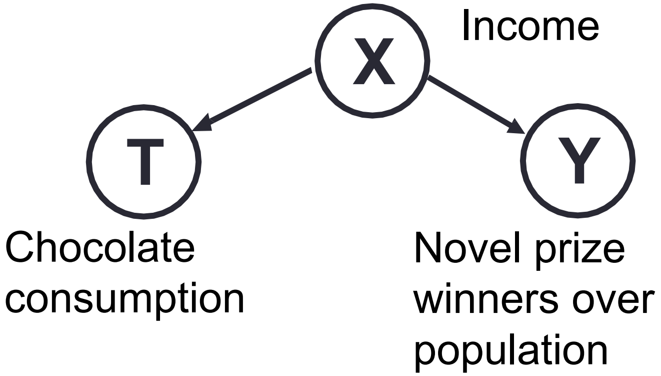


☐ Causal Effect

To what extent, the change on X changes the value of Y

X: treatment variable

Y: response variable



[1]. Pearl, Judea, Madelyn Glymour, and Nicholas P. Jewell. *Causal inference in statistics: A primer*. John Wiley & Sons, 2016.

Causal Inference

- Basic Concepts in Causal Theory [1]
  - Causal Effect:

    P(Y| do(X=x)) – P(Y | do(X=x_{ref}))

    measures the expected increase in Y as the treatment changes from $X = x$ to X=x_{ref}

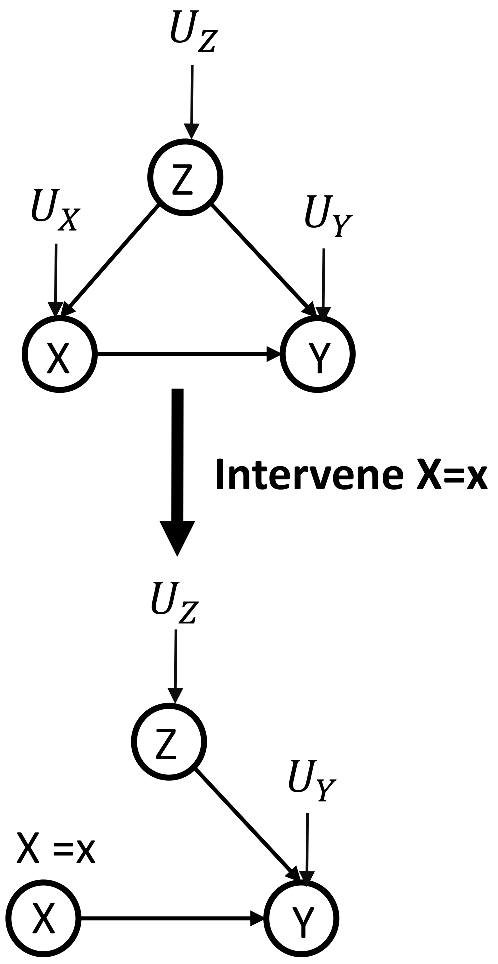
    Post-intervention probability: P(Y| do(X=x))

  - Intervention on X [term: do(X=x)]

    Study specific causal relationships between X and the target variable.

    Randomized controlled trial.

    In graph: Cut off the paths that point into X



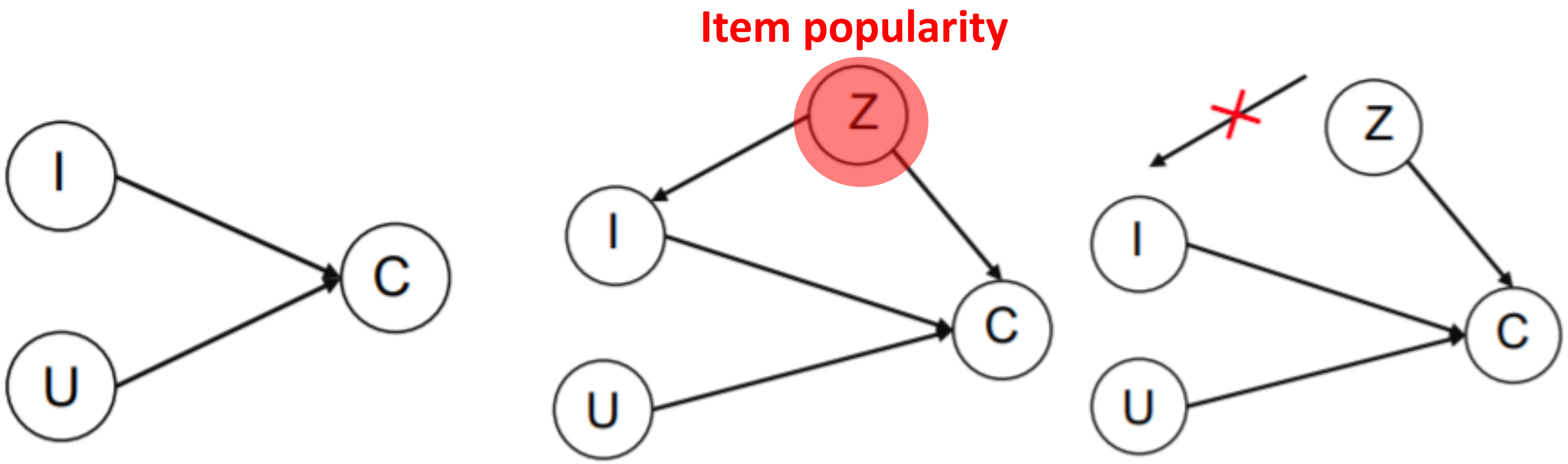
[1]. Pearl, Judea, Madelyn Glymour, and Nicholas P. Jewell. *Causal inference in statistics: A primer*. John Wiley & Sons, 2016.

Causal Intervention for Popularity Bias

➢ De-confounding —— Popularity De-confounding(PD) and Adjusting (PDA)

Key: item popularity is a confounder, both bad and good effect of popularity exist.

Leverage popularity bias instead of blindly removing.



(a) Causal graph of traditional methods. (b) Causal graph that considers item popularity. (c) We cut off $Z \rightarrow I$ for model training

We estimate the user-item matching as $P\,(C|do\,(U\,,\,I))$ based on figure (c)

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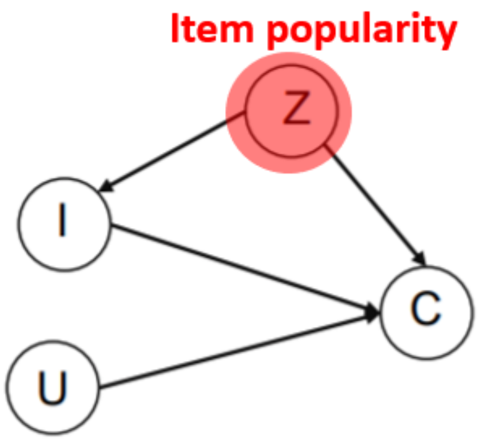
Causal Intervention for Popularity Bias

➢ PD --- Popularity De-confounding



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

vs
Correlation:
$P(C|U,I) = \sum_Z P(C|U,I,Z)P(Z|U,I)$

☐ **De-confounding --- estimate $\boldsymbol{P(C|do(U,I))}$:**

- **Step 1**. estimate P(C|U,I,Z)
  - $P_\Theta(c=1|u,i,m_i^t) = ELU'(f_\Theta(u,i)) \times (m_i^t)^\gamma$
  - m_i^t the popularity of item i in timestamp t
  - $f_\Theta(u,i)$: user-item matching, such as MF
  - Learning this component from data

- **Step 2**. computing $P(\mathrm{C|do(U,I)})$
  - $\sum_Z P(C|U,I,Z)P(Z) \propto ELU'(f_\Theta(u,i))$
  - ranking with this term

✓ In pursuit of real interests instead of even state!
Higher popularity because of better quality.

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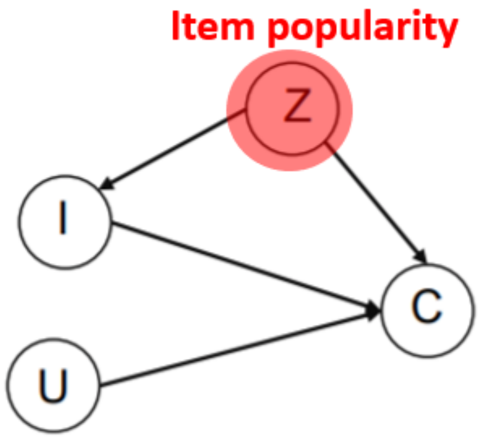
Causal Intervention for Popularity Bias

➢ PDA --- Popularity De-confounding and Adjusting

- We have estimated $P(C|do(U,I))$, which does not chase the even state but the real interests.
- Is it enough?
  - No… In some time, we need inject some desired popularity.
  - Such as we can recommend more item that will be popular if we can know the trends of popularity.



Introducing popularity bias by intervention:

$P\big(C\big|do(U,I),do(Z=\tilde{Z})\big)$ = P(C|U,I, $\tilde{Z}$)

P(C|U,I, $\tilde{Z}$) = $ELU'\big(f_\Theta(u,i)\big)\times\big(\tilde{Z}_i\big)^\gamma$

$\tilde{Z}$: predicted by the trends of item popularity.

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Causal Intervention for Popularity Bias

➢ Experimental Setting

■ Datasets:

Dataset	#User	#Item	#Interaction	#Sparsity	#type
Kwai	37,663	128,879	7,658,510	0.158%	Click
Douban	47,890	26,047	7,174,218	0.575%	Review
Tencent	80,339	27,070	1,816,046	0.084%	Like

■ Data Splitting:

Temporal splitting --- split each into 10 time stages according to timestamp.
0-8th stages: training, 9th stage: validation & testing.

■ Evaluation Setting:

PD: directly test
PDA: Most recent stages can be utilized to predict future popularity.

■ Baselines:

PD: MostPop, BPRMF, xQuad(2019FLAIRS), BPR-PC(2021WSDM), DICE(2021WWW)

PDA: MostRecent(2020SIGIR), BPRMF(t)-pop(2017RecTemp@ RecSys), BPRMF-A, DICE-A

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➢ Results for PD

Dataset	Methods	Top 20					Top 50				
		Recall	Precision	HR	NDCG	RI	Recall	Precision	HR	NDCG	RI
Kwai	MostPop	0.0014	0.0019	0.0341	0.0030	632.4%	0.0040	0.0021	0.0802	0.0036	480.9%
	BPRMF	0.0054	0.0057	0.0943	0.0067	146.3%	0.0125	0.0053	0.1866	0.0089	121.0%
	xQuad	0.0054	0.0057	0.0948	0.0068	145.0%	0.0125	0.0053	0.1867	0.0090	120.3%
	BPR-PC	0.0070	0.0056	0.0992	0.0072	125.0%	0.0137	0.0046	0.1813	0.0092	123.7%
	DICE	0.0053	0.0056	0.0957	0.0067	147.8%	0.0130	0.0052	0.1872	0.0090	119.0%
	PD	**0.0143**	**0.0138**	**0.2018**	**0.0177**	-	**0.0293**	**0.0118**	**0.3397**	**0.0218**	-
Douban	MostPop	0.0218	0.0297	0.2373	0.0349	75.4%	0.0490	0.0256	0.3737	0.0406	55.9%
	BPRMF	0.0274	0.0336	0.2888	0.0405	47.0%	0.0581	0.0291	0.4280	0.0475	34.3%
	xQuad	0.0274	0.0336	0.2895	0.0391	48.3%	0.0581	0.0291	0.4281	0.0473	34.4%
	BPR-PC	0.0282	0.0307	0.2863	0.0381	51.6%	0.0582	0.0271	0.4260	0.0457	38.0%
	DICE	0.0273	0.0336	0.2845	0.0421	46.2%	0.0513	0.0273	0.4000	0.0460	44.5%
	PD	**0.0453**	**0.0454**	**0.3970**	**0.0607**	-	**0.0843**	**0.0362**	**0.5271**	**0.0686**	-
Tencent	MostPop	0.0145	0.0043	0.0684	0.0093	340.8%	0.0282	0.0035	0.1181	0.0135	345.8%
	BPRMF	0.0553	0.0153	0.2005	0.0328	27.1%	0.1130	0.0129	0.3303	0.0497	25.3%
	xQuad	0.0552	0.0153	0.2007	0.0326	27.3%	0.1130	0.0129	0.3302	0.0497	25.3%
	BPR-PC	0.0556	0.0153	0.2018	0.0331	26.5%	0.1141	0.0128	0.3322	0.0500	24.9%
	DICE	0.0516	0.0149	0.1948	0.0312	32.8%	0.1010	0.0132	0.3312	0.0486	29.0%
	PD	**0.0715**	**0.0195**	**0.2421**	**0.0429**	-	**0.1436**	**0.0165**	**0.3875**	**0.0641**	-

The power of de-confounded estimation !!

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Causal Intervention for Popularity Bias

➢ PD —— Recommendation Analysis.

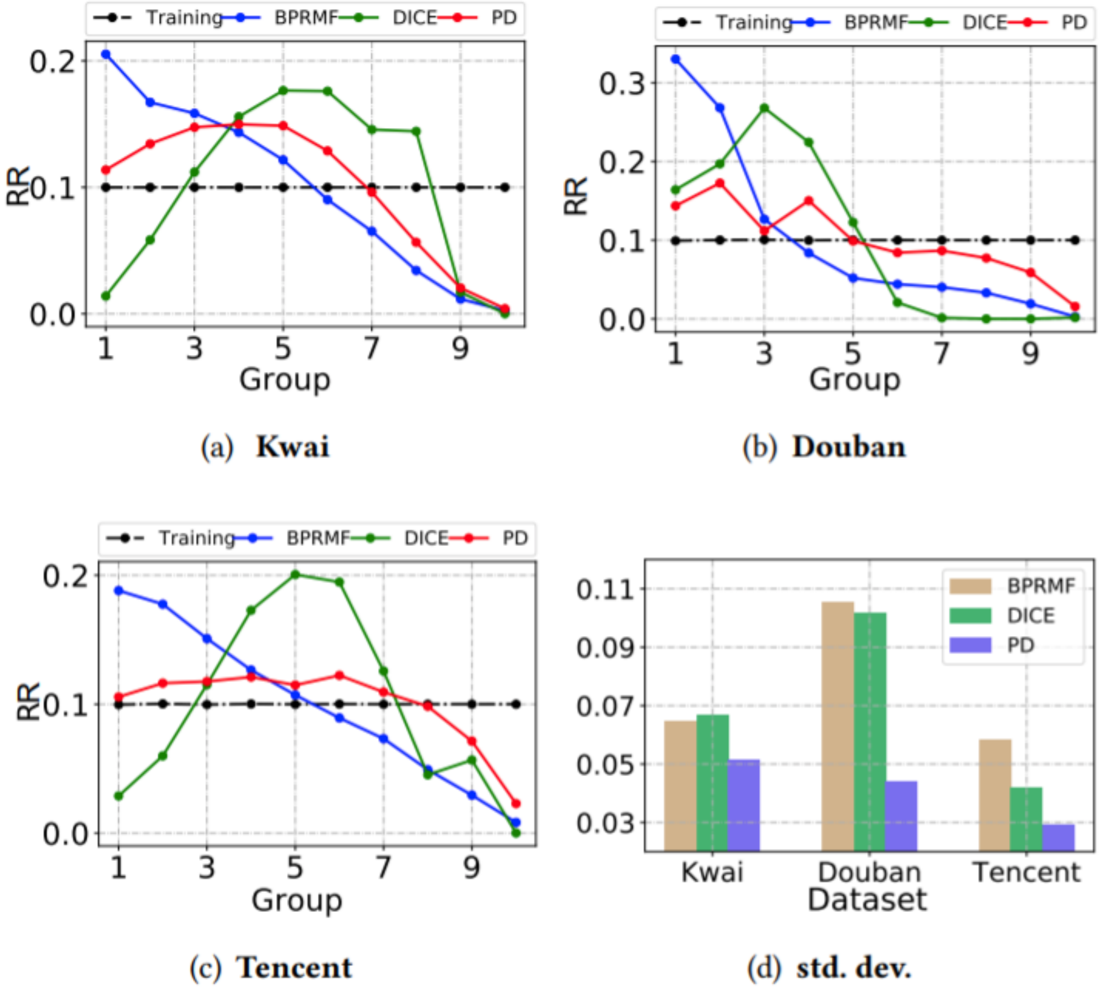

Figure 4: Recommendation rate(RR) over item groups.

- Less amplification for most popular groups compared with BPRMF
- Do not **over-suppress** the most popular groups compared with DICE
- More flat lines and standard deviations over different groups
  --- **relative fair recommendation opportunities** for different group (refer to training set)
- Better performance
  --- remove bad effect but keep good effect of popularity bias

Causal Intervention for Popularity Bias

➢ Results for PDA

Table 2: Top-K recommendation performance with popularity adjusting on Kwai, Douban, and Tencent Datasets.

Datasets		Kwai				Douban				Tencent			
Methods		top 20		top 50		top 20		top 50		top 20		top 50	
		Recall	NDCG	Recall	NDCG	Recall	NDCG	Recall	NDCG	Recall	NDCG	Recall	NDCG
MostRecent		0.0074	0.0096	0.0139	0.011	0.0398	0.0582	0.0711	0.0615	0.0360	0.0222	0.0849	0.0359
BPRMF(t)-pop		0.0188	0.0241	0.0372	0.0286	0.0495	0.0682	<u>0.0929</u>	0.0760	0.1150	0.0726	0.2082	0.1001
BPRMF-A	(a)	0.0191	0.0249	0.0372	0.0292	0.0482	0.0666	0.0898	0.0744	0.1021	0.0676	0.1805	0.0905
	(b)	0.0201	0.0265	0.0387	0.0306	0.0486	0.0667	0.0901	0.0746	0.1072	0.0719	0.1886	0.0953
DICE-A	(a)	0.0242	0.0315	0.0454	0.0363	0.0494	0.0681	0.0890	0.0736	0.1227	0.0807	0.2161	0.1081
	(b)	0.0245	0.0323	0.0462	0.0370	0.0494	0.0680	0.0882	0.0734	0.1249	0.0839	0.2209	0.1116
PDA	(a)	<u>0.0279</u>	<u>0.0352</u>	<u>0.0531</u>	<u>0.0413</u>	<u>0.0564</u>	**0.0746**	**0.1066**	**0.0845**	<u>0.1357</u>	<u>0.0873</u>	<u>0.2378</u>	<u>0.1173</u>
	(b)	**0.0288**	**0.3364**	**0.054**	**0.0429**	**0.0565**	<u>0.0745</u>	**0.1066**	<u>0.0843</u>	**0.1398**	**0.0912**	**0.2418**	**0.1210**

- Introducing desired popularity bias can improve the recommendation performance.
- Our method achieves the best performance.

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THANK YOU

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