AutoDebias: Learning to Debias for Recommendation

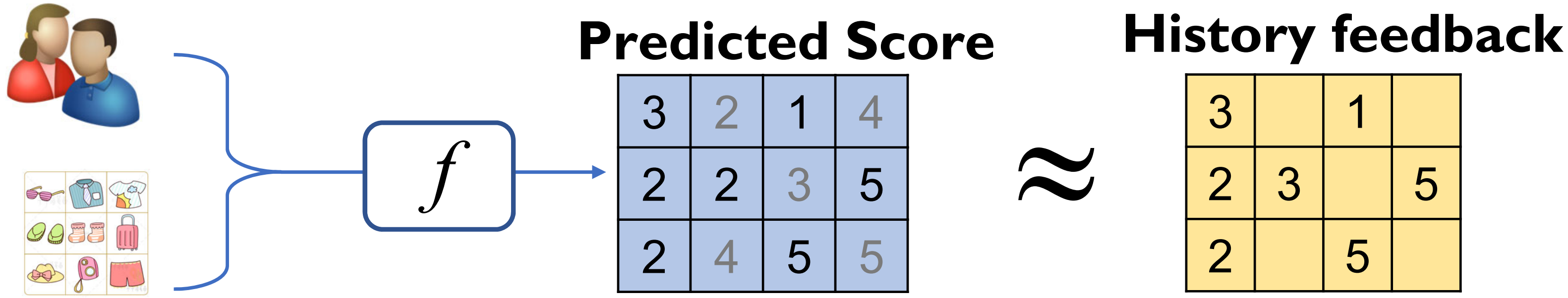
Jiawei Chen, Hande Dong, Yang Qiu, Xiangnan He,
Xin Xin, Liang Chen, Guli Lin, Keping Yang
cjwustc@ustc.edu.cn

• Outline

- ❑ Background
  - ❑Bias Issue in Recommender System
  - ❑Recent debiasing strategies
- ❑ Proposed Method: AutoDebias
  - ❑A uniform learning framework for various biases
- ❑ Experiments
- ❑ Conclusion and Future Work

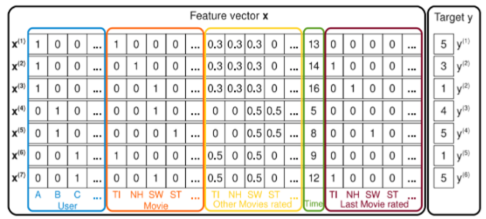
• Mainstream Models: Fitting Historical Data

• Minimizing the difference between historical feedback and model prediction



➢ Collaborative filtering

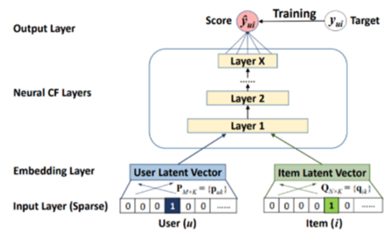
- Matrix factorization & factorization machines



Factorization Machines

➢ Deep learning approaches

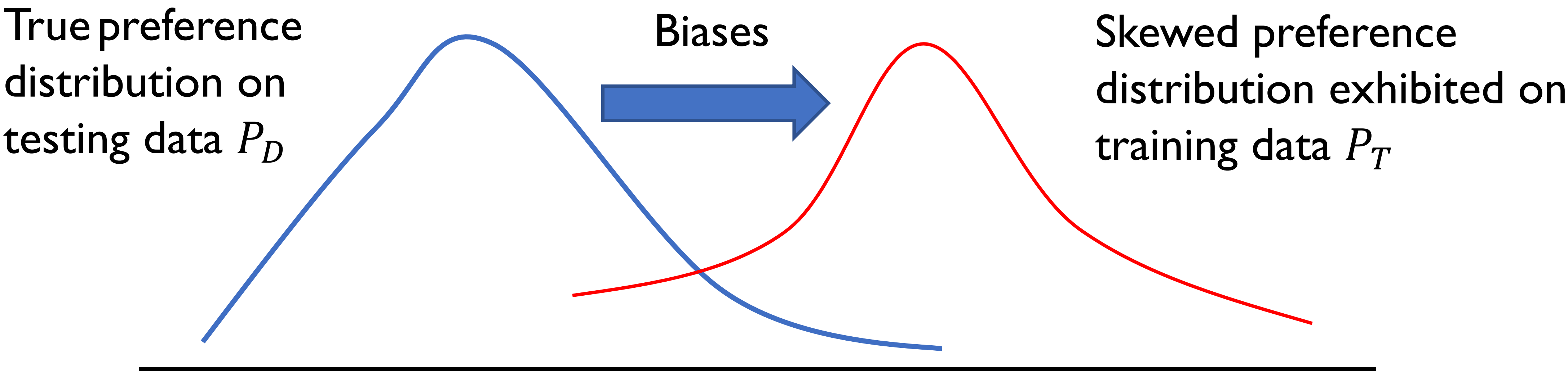
- Neural factorization machines & graph neural networks



Neural Collaborative Filtering

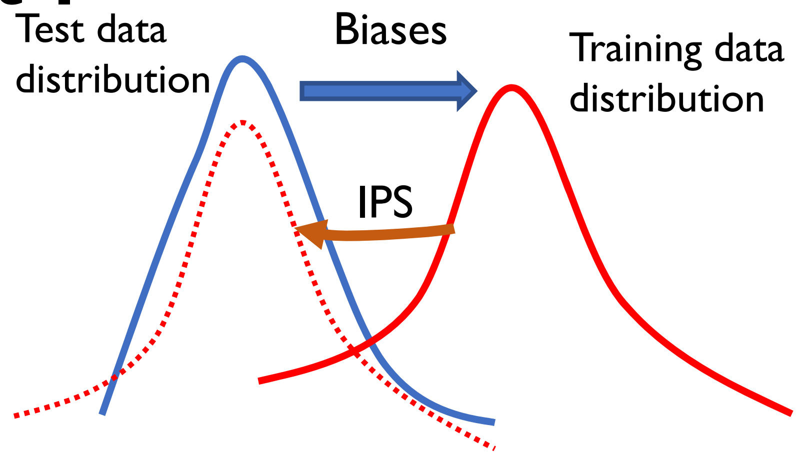
• Bias is Common in RS

- The data is observational rather than experimental.
  - Affected by user self-selection (selection bias), exposure mechanism of the system (exposure bias), public opinion(conformity bias), and the display position (position bias).



- Training data deviates from reflecting user true preference.
- Blindly fitting user history behavior data would yield unexpected results.

• Existing Debiasing Strategy: Part I



- Inverse Propensity Score (IPS):
  - adjust data distribution by sample reweighting:

$$L_{ips} = \frac{1}{|U| \cdot |I|} \sum_{(u,i) \in D_T} \frac{1}{\boxed{ps(u,i)}} \delta(r_{ui}, \hat{f}_{ui})$$

- Data Imputation:
  - assigns pseudo-labels for missing data

$$L_{IM} = \frac{1}{|U| \cdot |I|} \Big(\sum_{(u,i) \in D_T} \delta(r_{ui}, \hat{f}_{ui}) + \sum_{(u,i) \notin D_T} \delta(m_{ui}, \hat{f}_{ui}) \Big)$$

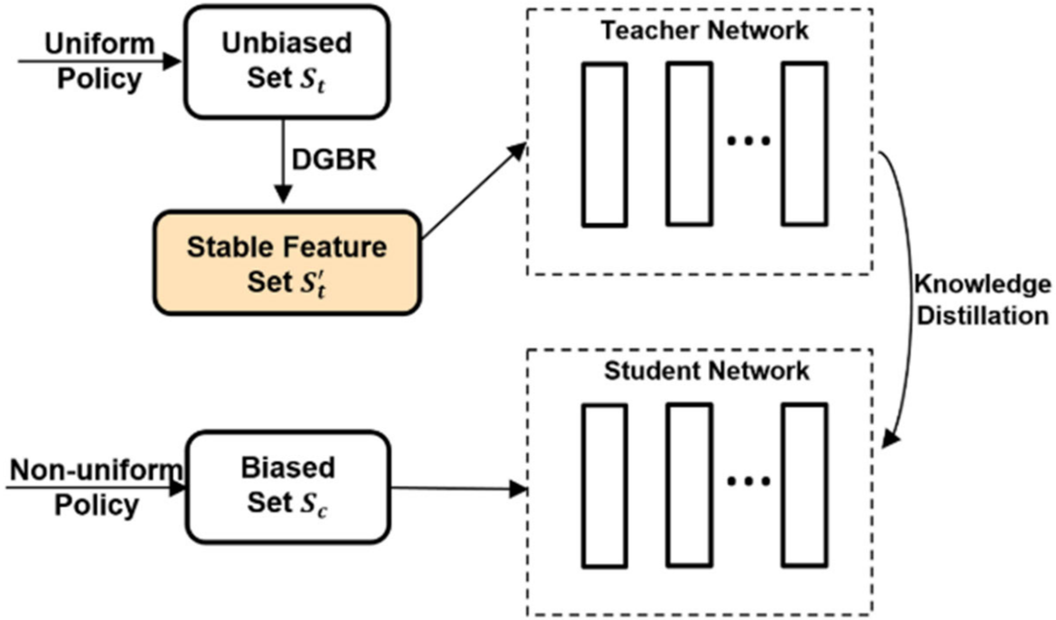
Schnabel, Tobias, et al. "Recommendations as treatments: Debiasing learning and evaluation." international conference on machine learning. PMLR, 2016.
H. Steck, "Training and testing of recommender systems on data missing not at random," in KDD, 2010, pp. 713–722.

• Existing Debiasing Strategy: Part 2

- Generative Modeling:
  - assumes the generation process of data and reduces the biases accordingly.

Knowledge Distillation:

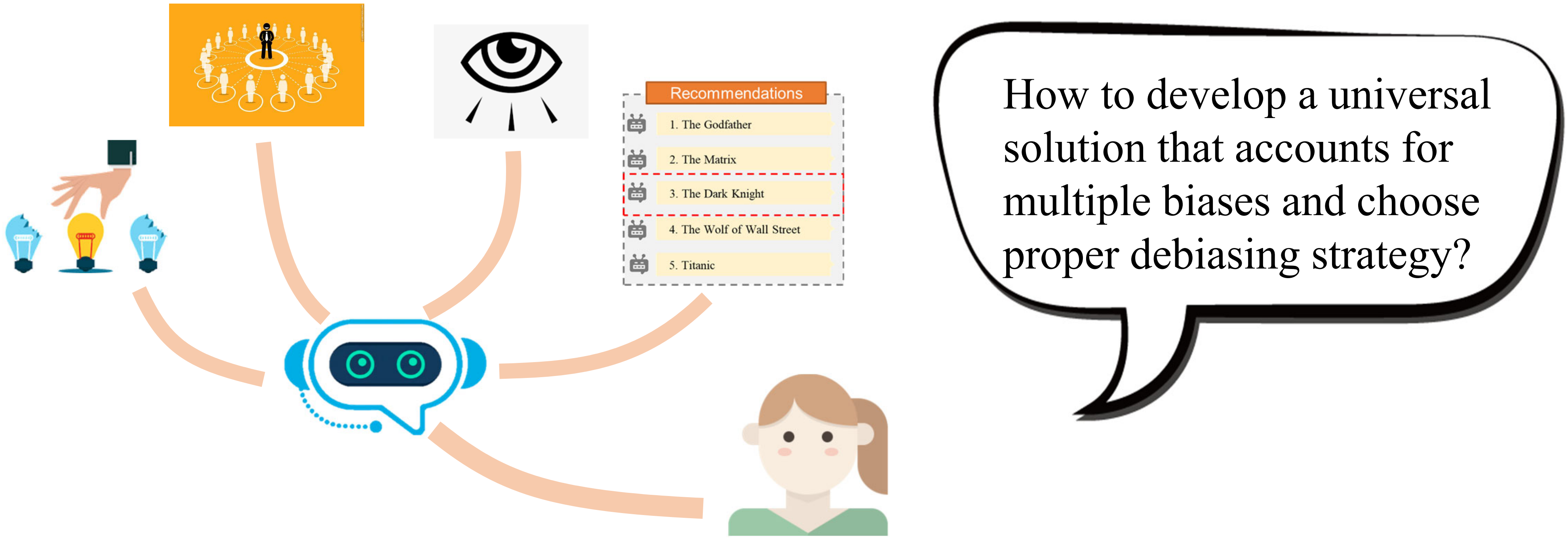
- trains a separate teacher model on the uniform data to guide the normal model training



J. M. Hern´andez-Lobato, N. Houlsby, and Z. Ghahramani, "Probabilistic matrix factorization with non-random missing data." in ICML, 2014, pp. 1512–1520.
Liu, Dugang, et al. "A general knowledge distillation framework for counterfactual recommendation via uniform data." In SIGIR 2020.

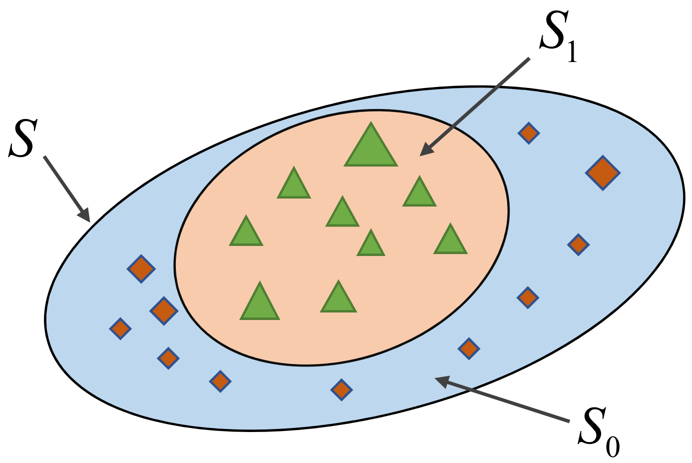
• Shortcomings of Existing Debiasing Strategy

- **Lack of Universality**: These methods are designed for addressing one or two biases of a specific scenario.
- **Lack of Adaptivity**: The effectiveness of these methods depends on proper debiasing configurations.



• AutoDebias: A Universal Learning Framework

- Just leveraging propensity score is insufficient:



$S : \{(u,i,r) : p_U(u,i,r) > 0\}$

$S_0 : \{(u,i,r) : p_U(u,i,r) > 0, p_T(u,i,r) = 0\}$

$S_1 : \{(u,i,r) : p_U(u,i,r) > 0, p_T(u,i,r) > 0\}$

▲ : Training data

◆ : Imputed data

  - Due to the data bias, training data distribution P_T may only provide the partial data knowledge of the region S (S_0 is not included)
  - IPS cannot handle this situation
- Imputing pseudo-data to the region S_0:

$$L_T = \sum_{(u,i)\in D_T} w_{ui}^{(1)}\, \delta(r_{ui}, \hat{y}_{ui}) + \boxed{\sum_{u\in U, i\in I} w_{ui}^{(2)}\, \delta(m_{ui}, \hat{y}_{ui})}$$

• AutoDebias: Adaptive learning algorithm

- How to specify proper debiasing parameters $\phi \equiv \{w_{ui}^{(1)}, w_{ui}^{(2)}, m_{ui}\}$?
  - Heuristic:  inaccurate, rely human expertise.

- We propose to learn from uniform data:
  - Uniform data provides signal on the effectiveness of debiasing
  - Meta learning mechanism:
    - Base learner: optimize rec model with fixed ϕ

$$\theta^*(\phi) = \underset{\theta}{\operatorname{argmin}} \sum_{(u,i)\in D_T} w_{ui}^{(1)}\, \delta(y_{ui}, \hat{y}_{ui}(\theta)) + \sum_{u\in U, i\in I} w_{ui}^{(2)}\, \delta(m_{ui}, \hat{y}_{ui}(\theta))$$

    - Meta learner: optimize debiasing parameters on uniform data

$$\phi^* = \underset{\phi}{\operatorname{argmin}} \sum_{(u,i)\in D_U} \delta(y_{ui}, \hat{y}_{ui}(\theta^*))$$

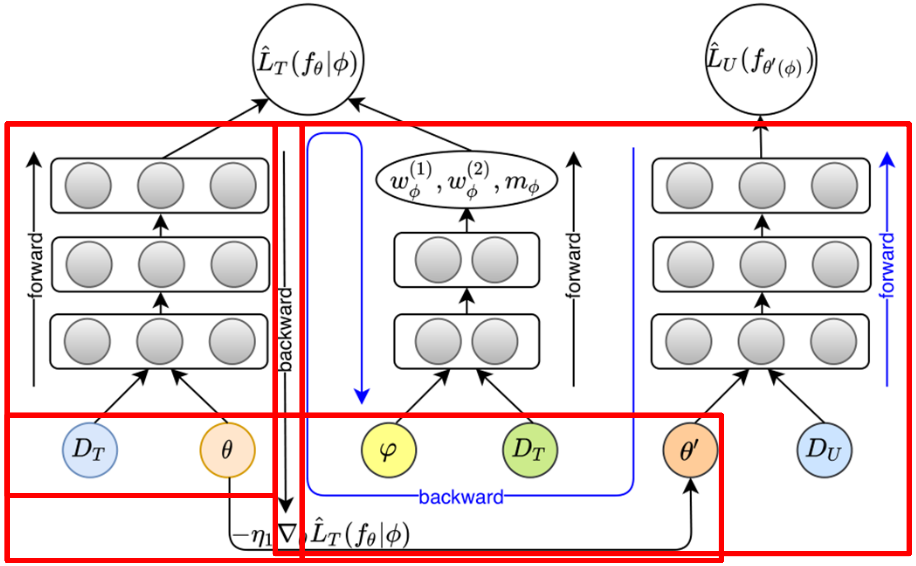
• Work#1: AutoDebias: Method

- Two challenges:
  - Overfitting: small uniform data but many debiasing parameters ϕ
    - Solution: Introduce a small meta model to generate ϕ, e.g., linear model

$$w_{ui}^{(1)} = \exp\left(\varphi_1^T[\mathbf{x}_u \circ \mathbf{x}_i \circ \mathbf{e}_{y_{ui}}]\right), \quad w_{ui}^{(2)} = \exp\left(\varphi_2^T[\mathbf{x}_u \circ \mathbf{x}_i \circ \mathbf{e}_{O_{ui}}]\right), \quad m_{ui} = \sigma\left(\varphi_3^T[\mathbf{e}_{y_{ui}} \circ \mathbf{e}_{O_{ui}}]\right)$$

  - Inefficiency: obtaining optimal ϕ involves nested loops of optimization
    - Solution: Update recsys model and debiasing parameters alternately in a loop

- Step 1: Make a tentative update of θ to θ' with current ϕ
- Step 2: Test θ' on uniform data, which gives feedback to update ϕ
- Step 3: Update θ actually with updated ϕ



• Work#1: AutoDebias: Experiments

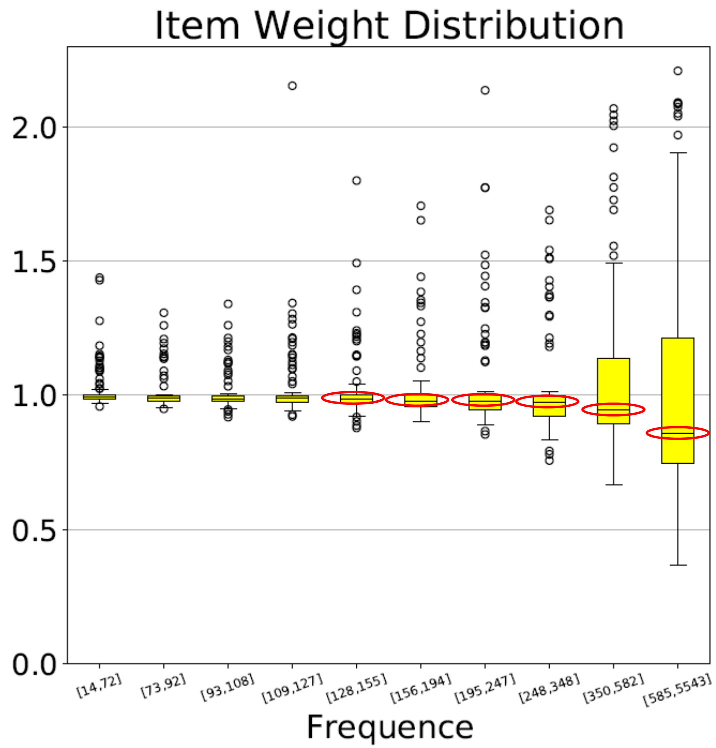
- Evaluate AutoDebias on two Yahoo!R3 and Coat (random exposure)

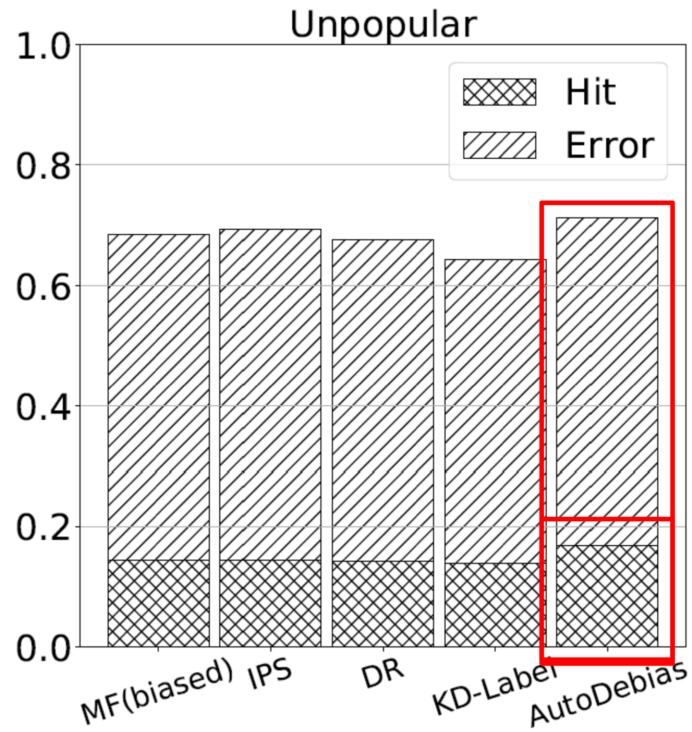
Methods	On Yahoo!R3		On Coat	
	AUC	NDCG@5	AUC	NDCG@5
MF(biased)	0.727	0.550	0.747	0.500
MF(uniform)	0.573	0.449	0.580	0.358
MF(combine)	0.730	0.554	0.750	0.504
IPS	0.723	0.549	0.759	0.509
DR	0.723	0.552	0.765	0.521
CausE	0.731	0.551	0.762	0.500
KD-Label	0.740	0.580	0.748	0.504
AutoDebias-w1	0.733	0.573	0.762	0.510
AutoDebias	**0.741**	**0.645**	**0.766**	**0.522**

- AutoDebias outperforms state-of-the-arts methods
- AutoDebias>AutoDebias-w1: Introducing imputation strategy is effectiveness
- AutoDebias-w1>IPS: learning debiasing parameters from uniform data is superior over heuristic design

• Work#1: AutoDebias: Experiments

- Distribution of the learned debiasing weights $w_{ui}^{(1)}$ with item popularity





- Adaptively down-weigh the contribution of popular items
  - item popularity ↑, average of $w_{ui}^{(1)}$ ↓
- Addressing popularity bias
  - Improves recommendation opportunity and precision of unpopular items

• Conclusion

- Importance to eliminate biases
  - Data-driven methods cannot handle biases
- Limitations of exist methods: lacking university and adaptivity
- Universal debiasing objective function:

$$L_T(f|\phi) = \sum_{(u,i)\in D_T} w_{ui}^{(1)}\,\delta(r_{ui}, \hat{f}_{ui}) + \sum_{u\in U, i\in I} w_{ui}^{(2)}\,\delta(m_{ui}, \hat{f}_{ui})$$

- Meta-learning algorithm for automatic debiasing:
  - optimize debiasing parameters on uniform data

- Future Work
  - Explore more sophisticate meta model
  - Biases is dynamic instead of static

THANK YOU!

cjwustc@ustc.edu.cn