

Towards **User-oriented** privacy for recommender system data: A **personalization**-based approach to gender **obfuscation** for user profiles

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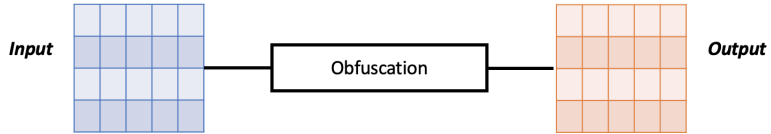
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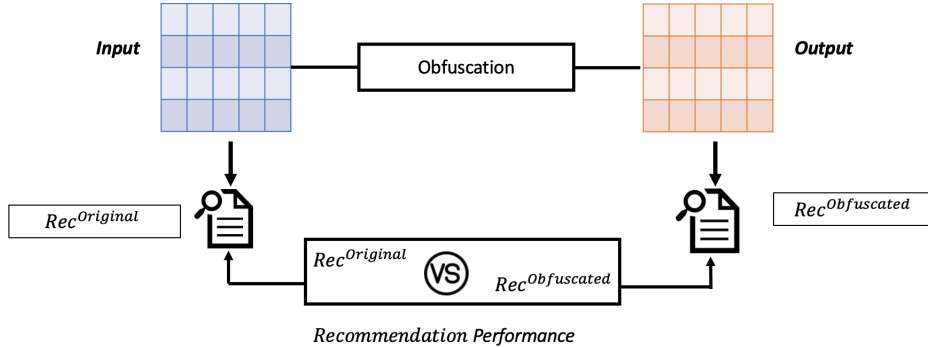
Framework

		<i>Items</i>						
		i_1	i_2	i_3	i_4	i_5	i_6	i_7
<i>Users</i>	u_1	5	0	5	0	3	0	0
	u_2	4	0	3	0	5	0	1
	u_3	2	5	0	4	0	0	3
	u_4	5	0	4	0	0	4	0
	u_5	0	0	1	4	3	0	2

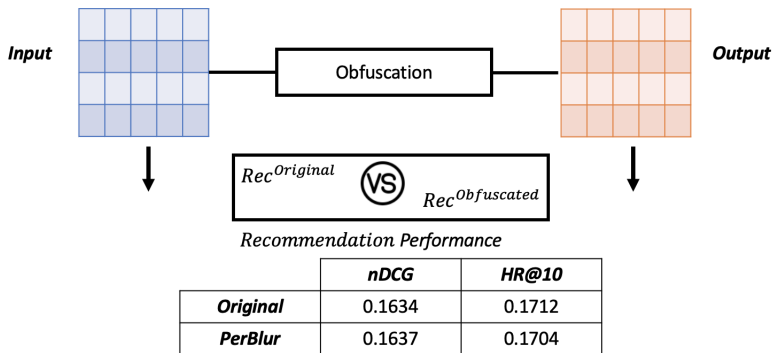
Framework



Framework

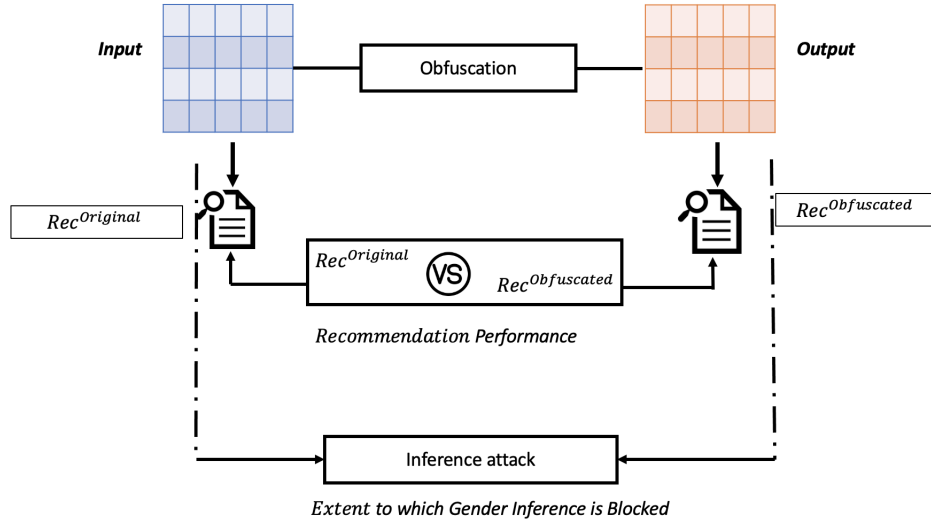


Framework

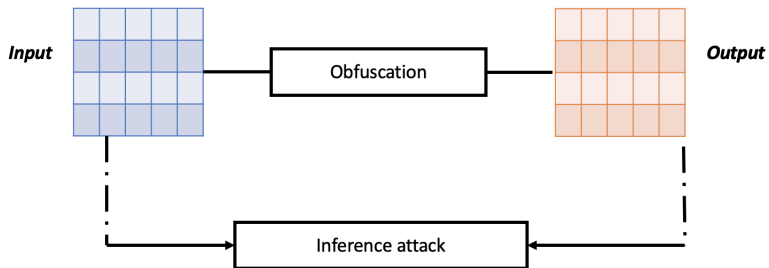


In the table: we used ML1M data set. **PerBlur** is created with *addition* from the **personalized** lists of indicative items.

Framework



Framework



Extent to which Gender Inference is Blocked

	Extra ratings			
	0%	1%	2%	5%
PerBlur	0.87	0.66	0.53	0.26

In the table: we used ML1M data set. **PerBlur** is created with *addition* from the **personalized** lists of indicative items. Logistic regression classifier.

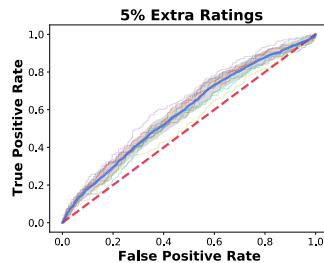
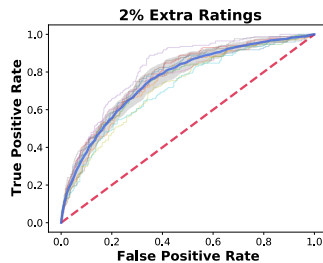
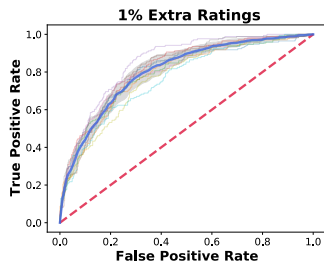
Take home message

- A simple, yet effective **personalized**-based approach to gender **obfuscation** for user profiles
- A recommender system trained on the obfuscated data is able to reach performance **comparable** to what is attained when trained on the original data
- A classifier can **no longer** reliably predict the gender of users
- The ability to recommend **diverse** items.

PerBlur - Personalized Blurring

- PerBlur creates the *personalized lists* of indicative items by intersecting:
 - Two lists of indicative items: L_m and L_f
 - A personalized list of items ranked in order of the probability that the user will have rated them.
- *Standard PerBlur*
 - Obfuscation by **adding** extra items from the personalized lists of indicative items
 - Level of obfuscation.
- *PerBlur with removal*
 - Similar to *Standard PerBlur* but we also **remove** certain items.

Gender inference



Gender inference

- Obfuscation inhibits the inference of the gender
- PerBlur requires less obfuscation
- Transferability

	<i>Personalization</i>	<i>Logistic regression</i>				<i>SVM</i>			
		<i>0%</i>	<i>1%</i>	<i>2%</i>	<i>5%</i>	<i>0%</i>	<i>1%</i>	<i>2%</i>	<i>5%</i>
<i>BlurMe</i>	<i>None</i>	0.87	0.76	0.69	0.48	0.82	0.74	0.67	0.42
<i>PerBlur</i>	<i>Personalized</i>	0.87	0.66	0.53	0.26	0.82	0.61	0.46	0.16

In the table: we report the AUC scores on MLIM data set. **BlurMe** is created with *addition* from L_m or L_f . **PerBlur** is created with *addition* from the **personalized** lists of indicative items.

Recommendation performance

	<i>nDCG</i>	<i>HR@10</i>
<i>Original</i>	0.1634	0.1712
<i>BlurMe</i>	0.1536	0.1633
<i>PerBlur</i>	0.1637	0.1704

- The recommendation performance comes close to what is achieved on original data
- PerBlur, thanks to its **personalization**, approaches the original performance more closely and more consistently than BlurMe

In the table: we used BPRMF algorithm on ML1M data set. **BlurMe** is created with *addition* from L_m or L_f . **PerBlur** is created with *addition* from the **personalized** lists of indicative items.

Achieving diverse results

- The proportion of correctly recommended items that are stereotypical for gender
- Three different cutoff levels (10, 20, 50)

	Obfuscation Strategy		Gender-stereotypical items					
	Personalization	Removal	top10F	top10M	top20F	top20M	top50F	top50M
Original	<i>None</i>	<i>None</i>	0.0020	0.0045	0.0038	0.0069	0.0082	0.0128
PerBlur	<i>Personalized</i>	<i>Greedy</i>	0.0003	0.0005	0.0014	0.0020	0.0051	0.0073

- PerBlur is effective in lowering the proportion of TopN gender-stereotypical items

In the table: we used ML1M data set. **PerBlur** is created with *addition* from the **personalized** lists of indicative items and *removal* from L_m or L_f .

Outlook and future work

- 1 Data obfuscation for recommender systems
- 2 Step toward **data sharing** without privacy concerns
- 3 From privacy to **fairness** and **diversity**
- 4 From **partially** to **fully** synthetic data

Thank You

References



Manel Slokom, Martha Larson and Alan Hanjalic (2021)

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Under review.



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