Measuring and Mitigating Item Under-Recommendation Bias in Personalized Ranking Systems

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Recommenders – essential conduits
Algorithmic bias in recommenders
Item groups are under-recommended

Due to i) the imbalanced distribution of feedback for different item groups; ii) the unawareness of bias in recommendation algorithm; Items from some groups will be under-recommended compared to other popular item groups.
Item groups are under-recommended

Example: when recommend jobs to users, **non-profit jobs** are under-recommended compared with **high-paying jobs**.

Imbalanced distribution of feedback for item groups.

Model without awareness of bias.

Non-profit jobs are under-recommended.
Previous works

• Measure the bias on predicted scores of item groups.

• Measure the bias based on the concept of statistical parity.

• No bias: $P(score|group1) = P(score|group2) = \cdots = P(score|groupA)$
Previous works

- Measure the bias based on predicted scores of item groups.
- Predicted score is the intermedia step towards the rankings, thus, unbiased scores do not necessarily lead to unbiased recommendation.

- Measure the bias based on the concept of statistical parity.

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 Statistical Parity is too strict for scenarios where there is no sensitive attributes for items (like books or movies).

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• Measure the bias based on the concept of statistical parity.
  • Statistical Parity is too strict for scenarios where there is no sensitive attributes for items (like books or movies).

  ➢ No bias: \( P(\text{score} | \text{group1}) = P(\text{score} | \text{group2}) = \cdots = P(\text{score} | \text{groupA}) \)
  ➢ Therefore, bias measurements based on ranking and other bias concepts are in need.
Contributions

• Propose the ranking-based statistical parity (RSP) measurement;
• Propose the ranking-based equal opportunity (REO) measurement;
• Propose the Debiased Personalized Ranking (DPR) model;
• Empirically demonstrate that the fundamental recommendation model – Bayesian Personalized Ranking (BPR) – is vulnerable to the under-recommendation bias, and show the effectiveness of the proposed DPR.
Ranking-based Statistical Parity (RSP)

\[ P(score|\text{group1}) = P(score|\text{group2}) = \cdots = P(score|\text{groupA}) \]

Predicted scores are intermediate steps towards rankings, which serve as the final recommendation results. Thus, **unbiased predicted scores ≠ unbiased rankings**
Ranking-based Statistical Parity (RSP)

RSP measures the recommendation probability (probability to be ranked in top-k) difference across different item groups.

\[ P(\text{topk}|\text{group1}) = P(\text{topk}|\text{group2}) = \cdots = P(\text{topk}|\text{groupA}) \]
RSP is especially important when the item groups are determined by sensitive attributes (for example, gender or race when people are recommended) because low recommendation probability for specific sensitive groups will result in social unfairness issues.

\[
P(topk|group1) = P(topk|group2) = \cdots = P(topk|groupA)
\]
Example: Recommend job candidates to companies

\[ P(\text{recommend}|\hat{\Phi}) = 0.6 \]

\[ P(\text{recommend}|\hat{\Psi}) = 0.2 \]

Unfair for female candidates.
Ranking-based Equal Opportunity (REO)

For a **more general RecSys**, we do not require statistical parity, but want the RecSys to be driven by **user preference** and the user has the same chance to see items from different groups as long as she likes them (the **same true positive rate** across item groups).
Ranking-based Equal Opportunity (REO)

REO measures the true positive rate difference across item groups.

\[ P(\text{topk}|\text{group1 & liked}) = \cdots = P(\text{topk}|\text{groupA & liked}) \]
Example: Recommend movies to users

\[ p(\text{recommend}|\text{horror & liked}) = 0.3 \]

\[ p(\text{recommend}|\text{sci-fi & liked}) = 0.9 \]

For a long time, horror movies will get fewer and fewer feedback, which is harmful for both horror movie lovers and movies providers.
Data-driven study - MovieLens

BPR generates RSP and REO based bias

Results by Bayesian Personalized Ranking (BPR)
Debiased Personalized Ranking (DPR) Model

To mitigate RSP based bias:
• Decouple the predicted score with group attribute;
• Normalize the score distribution for each user to align predict score with ranking position.
Debiased Personalized Ranking (DPR) Model

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- **Decouple the predicted score with group attribute;**
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\[
\begin{align*}
(u, i, j) \rightarrow & \quad \text{BPR} \\
\hat{y}_{u,i} \rightarrow & \quad \text{Discriminator} \\
& \quad \text{maximize} \\
& \quad \mathcal{L}_{Adv}(\hat{g}_i) + \mathcal{L}_{Adv}(\hat{g}_j) \\
& \quad \text{minimize} \\
& \quad \mathcal{L}_{BPR}(\hat{y}_{u,i}, \hat{y}_{u,j})
\end{align*}
\]
Debiased Personalized Ranking (DPR) Model

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![Diagram of DPR Model]

- \((u, i, j)\) for \(u \in U\), \(i \in I_u^+\), \(j \in I \setminus I_u^+\)
- Maximize: \(L_{Adv}(\hat{g}_i) + L_{Adv}(\hat{g}_j)\)
- Minimize: \(L_{BPR}(\hat{y}_{u,i}, \hat{y}_{u,j})\)
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```latex
\begin{align*}
(u, i, j)_{u \in U, i \in I_u^+, j \in I \setminus I_u^+} & \rightarrow \text{BPR} \rightarrow \hat{y}_{u,i} \rightarrow \text{Discriminator} \rightarrow \hat{g}_i, \hat{g}_j \\
& \text{maximize} \quad \mathcal{L}_{Adv}(\hat{g}_i) + \mathcal{L}_{Adv}(\hat{g}_j) \\
& \text{minimize} \quad \mathcal{L}_{BPR}(\hat{y}_{u,i}, \hat{y}_{u,j})
\end{align*}
```
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\text{maximize} & & & \text{minimize} \\
L_{Adv}(\hat{g}_i) + L_{Adv}(\hat{g}_j) & \rightarrow \hat{g}_i & \hat{g}_j
\end{align*}
\]

\[
L_{BPR}(\hat{y}_{u,i}, \hat{y}_{u,j})
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![Diagram of the DPR model](image.png)
Debiased Personalized Ranking (DPR) Model

To mitigate RSP based bias:

- **Decouple the predicted score with group attribute**;
- Normalize the score distribution for each user to align predict score with ranking position.

$$\min_{\Theta} \max_{\Psi} \sum_{u \in U} \sum_{i \in I_u^+} \sum_{j \in I \setminus I_u^+} \left( \mathcal{L}_{BPR}(u, i, j) + \alpha (\mathcal{L}_{Adv}(i) + \mathcal{L}_{Adv}(j)) \right) + \beta \mathcal{L}_{KL}$$
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Play a minimax game between the BPR component (with parameter set $\Theta$) and the adversarial component (with parameter set $\Psi$).
Debiased Personalized Ranking (DPR) Model

To mitigate RSP based bias:

- **Decouple the predicted score with group attribute;**
  - Normalize the score distribution for each user to align predict score with ranking position.

\[
\min_{\Theta} \max_{\Psi} \sum_{u \in U} \sum_{i \in I_u^+ \atop j \in \bar{I}_u^+} \left( \mathcal{L}_{BPR}(u, i, j) + \alpha(\mathcal{L}_{Adv}(i) + \mathcal{L}_{Adv}(j)) \right) + \beta \mathcal{L}_{KL}
\]

Conventional BPR loss for a user \( u \) with one positive item \( i \) and one negative item \( j \):

\[
\mathcal{L}_{BPR}(u, i, j) = -\ln \sigma(\hat{y}_{ui} - \hat{y}_{uj}) + \frac{\lambda}{2} \| \Theta \|_F^2
\]
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\[
\min_{\Theta} \max_{\Psi} \sum_{u \in U} \sum_{i \in I_u^+} \sum_{j \in I \setminus I_u^+} (\mathcal{L}_{BPR}(u, i, j) + \alpha(\mathcal{L}_{Adv}(i) + \mathcal{L}_{Adv}(j))) + \beta \mathcal{L}_{KL}
\]

The adversarial component takes predicted score as input and predict the group of the given item. Train the adversarial component by

\[
\max_{\Psi} \sum_{a=1}^{A} (g_{i,a} \log \hat{g}_{i,a} + (1 - g_{i,a}) \log (1 - \hat{g}_{i,a}))
\]
Debiased Personalized Ranking (DPR) Model

To mitigate RSP based bias:
• Decouple the predicted score with group attribute;
  ➢ Normalize the score distribution for each user to align predict score with ranking position.

\[
\min_{\Theta} \max_{\Psi} \sum_{u \in \mathcal{U}} \left( \sum_{i \in \mathcal{I}_u^+} \sum_{j \in \mathcal{I} \setminus \mathcal{I}_u^+} (L_{BPR}(u, i, j) + \alpha(L_{Adv}(i) + L_{Adv}(j))) + \beta L_{KL} \right)
\]

Minimize the KL divergence between the score distribution of each user and the standard normal distribution to normalize score distribution for users:

\[
L_{KL} = \sum_{u \in \mathcal{U}} D_{KL}(q_\Theta(u) || N(0, 1))
\]
Debiased Personalized Ranking (DPR) Model

To mitigate REO based bias:
• Decouple the group attribute with the predicted score for positive user-item pair;
• Normalize the score distribution for each user to align predict score with ranking position.

\[
\min_{\Theta} \max_{\Psi} \sum_{u \in U} \sum_{i \in I_u^+} \sum_{j \in I \setminus I_u^+} (\mathcal{L}_{BPR}(u, i, j) + \alpha \mathcal{L}_{Adv}(i)) + \beta \mathcal{L}_{KL}
\]

Only input scores for positive user-item pairs to the adversarial component.
Experiments – visualize debiased results by the proposed DPR
Experiments – compare with baselines
Experiments – compare with baselines

the proposed model
SOTA baselines

BPR
DPR
FATR
Reg

ML1M-2
F1@k
0.200
0.150
0.100
0.050
0.000
top5
top10
top15
0.000
0.050
0.100
0.150
RSP@k
0.600
0.400
0.200
0.000
top5
top10
top15
0.000
0.100
0.200
0.300
REO@k
0.400
0.300
0.200
0.100
0.000
top5
top10
top15
Experiments – compare with baselines

Proposed model preserves high recommendation quality, and enhance RSP and REO fairness effectively!
Experiments – compare with baselines

Proposed model preserves high recommendation quality, and enhance RSP and REO fairness effectively!
Experiments – more in the paper

More experimental details and results can be found in the paper, including:

• Detailed experiment setup;
• Experiments on other datasets;
• Experiments for ablation study;
• Experiments for hyper-parameter study;
• Experiments with multi-group datasets;
Conclusions

• Propose two **ranking-based** under-recommendation bias **metrics**;

• Propose an **adversarial learning based model** which can mitigate the two studied recommendation bias;

• Experiments show the existence of bias in widely used BPR model, and show the **effectiveness** of the proposed debiasing model.
Thank You!

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