Deconfounded Recommendation for Alleviating Bias Amplification

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Speaker: Wenjie Wang
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1. Bias amplification
2. Related work
3. Deconfounded RS
4. Experiments
5. Conclusion
• Bias amplification: over-recommend items in the majority group

- More action movies!

• Bias is continually amplified due to the feedback loop.

(a) An example of bias amplification.

- Problems:
  1. Low-diversity: limit users’ view and narrow down user interests.
  2. Possible reason of Filter bubbles and echo chambers.
  3. Unfairness: unfair to the high-quality items in minority groups.
Related work

1. Fairness
   • Pursue equal exposure opportunities for items of different groups.
   • e.g., discounted cumulative fairness (Yang et al. 2017), and fairness of exposure (Singh et al. 2018).

2. Diversity
   • Decrease the similarity of the recommended items
   • e.g., re-ranking via the intra-list similarity (Ziegler et al. 2005).

3. Calibration
   • Encourage the distribution of recommended item groups to follow that of the browsing history.
   • e.g., calibrated recommendation: re-ranking based on KL-divergence (Steck et al. 2018).
   • Common drawback: inevitably sacrifice recommendation accuracy.

• Yang et al. 2017. Measuring fairness in ranked outputs. In SSDBM.
• Singh et al. 2018. Fairness of exposure in rankings. In KDD.
• Ziegler et al. 2005. Improving recommendation lists through topic diversification. In WWW.
Method

- What is the **root reason** for bias amplification?
- An example of bias amplification.

- 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.
**Method**

- **A Causal View of Bias Amplification**

\[
D: \text{user historical distribution over item groups. Given } N \text{ item groups } \{g_1, \ldots, g_N\}, d_u = [p_u(g_1), \ldots, p_u(g_N)] \in \mathbb{R}^N \text{ is a particular value of } D. \text{ e.g., } d_u = [0.8, 0.2].
\]

- Use \( M \) to describe how much the **user likes different item groups**; decided by \( D \) and \( U \).

- The prediction score \( Y \) is affected by \( U \) and \( M \), implying that:
  - an item \( i \) can have a high prediction score because 1) user’s pure preference over the item \( (U \rightarrow Y) \) or 2) the user shows interest in the item group \( (U \rightarrow M \rightarrow Y) \).

\[
M \text{ is a confounder between } U \text{ and } Y: \text{ opens the backdoor path } (U \leftarrow D \rightarrow M \rightarrow Y).
\]

- **Cause spurious correlation** when estimating the effect of \( U \) on \( Y \): given the item \( i \) in a group \( g \), the more items in group \( g \) the user \( u \) has clicked in the history, the higher the prediction score \( Y \) becomes.

- i.e., the high prediction scores are purely caused by the users’ historical interest in the group instead of the items themselves.
Method

- A Causal View of Bias Amplification

![Diagram showing causal view of bias amplification]

- Impact of the spurious correlation:

1) **Bias amplification**: the items in the majority group, even including the low-quality ones, are easy to have high ranks.

2) **User interest drift.** The user representation heavily relies on the user historical distribution over item groups, e.g., \( d_u = [0.8, 0.2] \). Once users’ future interest in item groups changes (i.e., OOD settings), the recommendations will be dissatisfying.
Method

• **Backdoor Adjustment**

\[ P(Y|U = u, I = i) = \sum_{d \in \mathcal{D}} \sum_{m \in \mathcal{M}} \frac{P(d)P(u|d)P(m|d, u)P(i)P(Y|u, i, m)}{P(u)P(i)} \]  

(1a)

\[ = \sum_{d \in \mathcal{D}} \sum_{m \in \mathcal{M}} P(d|u)P(m|d, u)P(Y|u, i, m) \]  

(1b)

\[ = \sum_{d \in \mathcal{D}} P(d|u)P(Y|u, i, M(d, u)) \]  

(1c)

\[ = P(d_u|u)P(Y|u, i, M(d_u, u)), \]  

(1d)

**Conditional probability**

- **Deconfounded Recommender System (DecRS)**
  - Use backdoor adjustment to achieve \( P(Y|do(U = u), I = i) \) where \( do(U = u) \) can be intuitively seen as cutting off the edge \( D \rightarrow U \) in the causal graph and blocking the effect of \( D \) on \( U \).
  - DecRS estimates the prediction score \( Y \) by considering every possible value \( d \) of \( D \) subject to the prior \( P(d) \), rather than the only \( d_u \) in Eq. (1d).
  - The items in the majority group will not receive high prediction scores purely because of a high click probability in \( d_u \). => **alleviate bias amplification**.

\[
\begin{align*}
P(Y|do(U = u), I = i) & \quad \text{law of total probability & Bayes rule} \\
& = \sum_{d \in \mathcal{D}} P(d)P(Y|do(U = u), i, M(d, do(U = u))) \quad (2a) \\
& = \sum_{d \in \mathcal{D}} P(d)P(Y|do(U = u), i, M(d, do(U = u))) \quad (2b) \\
& = \sum_{d \in \mathcal{D}} P(d)P(Y|U = u, i, M(d, u)), \quad \text{action/observation exchange} \quad (2c)
\end{align*}
\]

Force \( U, I \) to incorporate every \( d \) fairly during training. Cut off the relation between \( D \) and \( U \).
Method

- **Backdoor Adjustment**

\[
P(Y|do(U = u), I = i)
= \sum_{d \in \mathcal{D}} P(d|do(U = u))P(Y|do(U = u), i, M(d, do(U = u)))
\] (2a)

\[
= \sum_{d \in \mathcal{D}} P(d)P(Y|do(U = u), i, M(d, do(U = u)))
\] (2b)

\[
= \sum_{d \in \mathcal{D}} P(d)P(Y|u, i, M(d, u)),
\] (2c)

- **Deconfounded Recommender System (DecRS)**
  - **Challenge:** the sample space of \( \mathcal{D} \) is infinite.
  - **Backdoor Adjustment Approximation:**
    1) Sample users’ historical distributions over item groups in the training data to estimate the distribution of \( \mathcal{D} \);
    Use function \( f(\cdot) \) (FM) to calculate \( P(Y|u, i, M(d, u)) \).
    \[
P(Y|do(U = u), I = i) \approx \sum_{d \in \mathcal{D}} P(d)P(Y|u, i, M(d, u))
    = \sum_{d \in \mathcal{D}} P(d)f(u, i, M(d, u)),
    \] (4)

  2) Approximation of \( E_{\mathcal{D}}[f(\cdot)] \).
    - Expectation of function \( f(\cdot) \) of \( d \) in Eq. 4 is hard to compute because we need to calculate the results of \( f(\cdot) \) for each \( d \).
    - **Jensen’s inequality:** take the sum into the function \( f(\cdot) \).
    \[
P(Y|do(U = u), I = i) \approx f(u, i, M(\sum_{d \in \mathcal{D}} P(d|u, M, d, u))).
    \] (5)
Method

• Inference Strategy
  • Some users might only like several majority groups, i.e., enjoy the over-recommending of majority groups.
  • A user-specific inference strategy to regulate the impact of backdoor adjustment dynamically.
    1) Divide the historical interactions into two parts according to the timestamps.
    2) Calculate the symmetric KL divergence to measure stability.
    3) Use KL divergence to balance $P(Y|U=u, I=i)$ and $P(Y|do(U=u), I=i)$.
  • Users with low KL divergence will rely more on the conditional probability.

\[
\eta_u = KL(d_u^1|d_u^2) + KL(d_u^2|d_u^1) \\
= \sum_{n=1}^{N} P_u^1(g_n) \log \frac{P_u^1(g_n)}{P_u^2(g_n)} + \sum_{n=1}^{N} P_u^2(g_n) \log \frac{P_u^2(g_n)}{P_u^1(g_n)},
\]

\[
Y_{u,i} = (1 - \hat{\eta}_u) \ast Y_{u,i}^{RS} + \hat{\eta}_u \ast Y_{u,i}^{DE}, \quad \hat{\eta}_u = \left(\frac{\eta_u - \eta_{\text{min}}}{\eta_{\text{max}} - \eta_{\text{min}}}\right)^\alpha
\]
To summarize, DecRS has three main differences from the conventional RS:

1) **DecRS models the causal effect** $P(Y|do(U = u), I = i)$ **instead of the conditional probability** $P(Y|U = u, I = i)$.

2) **DecRS equips the recommender models with a backdoor adjustment operator.**

3) **DecRS makes recommendations with a user-specific inference strategy** instead of the simple model prediction (e.g., a forward propagation).
Experimental Settings

- **Datasets**: ML-1M and Amazon-Book.
- **Baselines**:
  1. **Unawareness** (Kusner et al. 2017) removes the features of item groups (e.g., movie genre in ML-1M).
  2. **FairCo** (Morik et al. 2020) introduces one error term to control the exposure fairness across groups.
  3. **Calibration** (Steck et al. 2018) uses a calibration metric $C_{KL}$ to re-rank items.
  4. **Diversity** (Ziegler et al. 2005) aims to decrease the intra-list similarity.
  5. **IPS** (Saito et al. 2020) is a classical causal method to reduce bias.
- **Evaluation Metrics**.
  1. Recall@K and NDCG@K
  2. **A calibration metric** $C_{kl}$ (Steck et al. 2018): quantifies the distribution drift over item groups between the history and the new recommendation list (comprised by the top-20 items). Higher $C_{kl}$ scores suggest a more serious issue of bias amplification.

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- Morik et al. 2020. Controlling Fairness and Bias in Dynamic Learning-to-Rank. In SIGIR.
# Experiments

## Table 3: Overall performance comparison between DecRS and the baselines on ML-1M and Amazon-Book. \%improv. denotes the relative performance improvement achieved by DecRS over FM or NFM. The best results are highlighted in bold.

<table>
<thead>
<tr>
<th>Method</th>
<th>ML-1M</th>
<th>Amazon-Book</th>
<th>NFM</th>
<th>Amazon-Book</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>R@10</td>
<td>R@20</td>
<td>N@10</td>
<td>N@20</td>
</tr>
<tr>
<td>FM/NFM [16, 29]</td>
<td>0.0676</td>
<td>0.1162</td>
<td>0.0566</td>
<td>0.0715</td>
</tr>
<tr>
<td>Unawareness [15]</td>
<td>0.0679</td>
<td>0.1179</td>
<td>0.0575</td>
<td>0.0730</td>
</tr>
<tr>
<td>FairCo [21]</td>
<td>0.0676</td>
<td>0.1165</td>
<td>0.0570</td>
<td>0.0720</td>
</tr>
<tr>
<td>Calibration [32]</td>
<td>0.0647</td>
<td>0.1149</td>
<td>0.0539</td>
<td>0.0695</td>
</tr>
<tr>
<td>Diversity [47]</td>
<td>0.0670</td>
<td>0.1159</td>
<td>0.0555</td>
<td>0.0706</td>
</tr>
<tr>
<td>IPS [30]</td>
<td>0.0663</td>
<td>0.1188</td>
<td>0.0556</td>
<td>0.0718</td>
</tr>
<tr>
<td>DecRS</td>
<td>0.0704</td>
<td>0.1231</td>
<td>0.0578</td>
<td>0.0737</td>
</tr>
<tr>
<td>%improv.</td>
<td>4.14%</td>
<td>5.94%</td>
<td>2.12%</td>
<td>3.08%</td>
</tr>
</tbody>
</table>

## Table 4: Performance comparison across different user groups on ML-1M and Amazon-Book. Each line denotes the performance over the user group with $\eta_u >$ the threshold. We omit the results of threshold > 4 due to the similar trend.

<table>
<thead>
<tr>
<th>Threshold</th>
<th>ML-1M</th>
<th>Amazon-Book</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>FM @20</td>
<td>DecRS %improv.</td>
</tr>
<tr>
<td>0</td>
<td>0.1162</td>
<td>0.1231</td>
</tr>
<tr>
<td>0.5</td>
<td>0.1215</td>
<td>0.1296</td>
</tr>
<tr>
<td>1</td>
<td>0.1303</td>
<td>0.1412</td>
</tr>
<tr>
<td>2</td>
<td>0.1432</td>
<td>0.1646</td>
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<tr>
<td>3</td>
<td>0.1477</td>
<td>0.1637</td>
</tr>
<tr>
<td>4</td>
<td>0.1454</td>
<td>0.1768</td>
</tr>
</tbody>
</table>
Experiments

- Effectiveness of alleviating bias amplification

Figure 4: The performance comparison between the base-lines and DecRS on alleviating bias amplification.
Experiments

- Effectiveness of the inference strategy

Figure 5: Ablation study of DecRS on ML-1M.
• **Conclusion**
  a) Explain that **bias amplification is caused by the confounder** from a causal view.
  b) An approximation operator for **backdoor adjustment** to remove the spurious correlation.
  c) **A user-specific inference strategy** to regulate the impact of backdoor adjustment.

• **Future work**
  a) **New evaluation metric** of alleviating bias amplification.
  b) The **discovery of more fine-grained causal relations** in recommendation models.
  c) Apply DecRS to reduce various **biases caused by imbalanced data distribution**.
  d) Bias amplification is one essential cause of the **filter bubble and echo chambers**. The effect of DecRS on mitigating these issues can be studied.
Thank you!