AutoDebias: Learning to Debias for Recommendation

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• 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
  
  ![Diagram](image)

  **Predicted Score**
  
<table>
<thead>
<tr>
<th>3</th>
<th>2</th>
<th>1</th>
<th>4</th>
</tr>
</thead>
<tbody>
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<td>2</td>
<td>2</td>
<td>3</td>
<td>5</td>
</tr>
<tr>
<td>2</td>
<td>4</td>
<td>5</td>
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</table>

  **History feedback**
  
<table>
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<td>2</td>
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<td>5</td>
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</tbody>
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  ➢ **Collaborative filtering**
  
  - Matrix factorization & factorization machines
  
  ➢ **Deep learning approaches**
  
  - Neural factorization machines & graph neural networks
• 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:
  \[
  L_{ips} = \frac{1}{|U| \cdot |I|} \sum_{(u,i) \in D_T} \frac{1}{ps(u,i)} \delta(r_{ui}, \hat{f}_{ui})
  \]

• Data Imputation:
  - assigns pseudo-labels for missing data
  \[
  L_{IM} = \frac{1}{|U| \cdot |I|} \left( \sum_{(u,i) \in D_T} \delta(r_{ui}, \hat{f}_{ui}) + \sum_{(u,i) \notin D_T} \delta(m_{ui}, \hat{f}_{ui}) \right)
  \]

• **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


• **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.

How to develop a universal solution that accounts for multiple biases and choose proper debiasing strategy?
**AutoDebias: A Universal Learning Framework**

- Just leveraging **propensity score** is insufficient:

\[
S : \{(u,i,r) : p_U(u,i,r) > 0\}
\]
\[
S_0 : \{(u,i,r) : p_U(u,i,r) > 0, p_T(u,i,r) = 0\}
\]
\[
S_1 : \{(u,i,r) : p_U(u,i,r) > 0, p_T(u,i,r) > 0\}
\]

- 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 \( S_0 \):

\[
L_T = \sum_{(u,i) \in D_T} w_{ui}^{(1)} \delta(r_{ui}, \hat{y}_{ui}) + \sum_{u \in U, i \in I} w_{ui}^{(2)} \delta(m_{ui}, \hat{y}_{ui})
\]
• 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 $\phi$
      $$\theta^*(\phi) = \arg\min_{\theta} \sum_{(u,i) \in D_T} w_{ui}^{(1)} \delta(y_{ui}, \hat{y}_{ui}(\theta)) + \sum_{u \in U, i \in I} w_{ui}^{(2)} \delta(m_{ui}, \hat{y}_{ui}(\theta))$$
    • Meta learner: optimize debiasing parameters on uniform data
      $$\phi^* = \arg\min_{\phi} \sum_{(u,i) \in D_U} \delta(y_{ui}, \hat{y}_{ui}(\theta^*))$$
Work#1: AutoDebias: Method

Two challenges:

- **Overfitting**: small uniform data but many debiasing parameters \( \phi \)
  - Solution: Introduce a small meta model to generate \( \phi \), e.g., linear model
    \[
    w_{ui}^{(1)} = \exp(\varphi_1^T [x_u x_i e_{y_{ui}}]), \quad w_{ui}^{(2)} = \exp(\varphi_2^T [x_u x_i e_{o_{ui}}]), \quad m_{ui} = \sigma(\varphi_3^T [e_{y_{ui}} e_{o_{ui}}])
    \]

- **Inefficiency**: obtaining optimal \( \phi \) involves nested loops of optimization
  - Solution: Update recsys model and debiasing parameters alternately in a loop

---

- Step 1: Make a tentative update of \( \theta \) to \( \theta' \) with current \( \phi \)
- Step 2: Test \( \theta' \) on uniform data, which gives feedback to update \( \phi \)
- Step 3: Update \( \theta \) actually with updated \( \phi \)
• **Work#1: AutoDebias: Experiments**

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

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

• 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

  ![Item Weight Distribution](image)

  • 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!

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