Unbiased Implicit Recommendation and Propensity Estimation via Combinational Joint Learning

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Introduction

RecSys learned by biased implicit feedback (missing not at random) will provide biased recommendation results. Previous works address this issue by inverse propensity scoring, but rely on a heuristic propensity estimation, which leads to compromised performance.

Contributions:
• Propose a new combinational joint learning model to learn user-item relevance and propensity simultaneously to provide unbiased recommendation results.
• Extensive experiments on two public datasets demonstrate the effectiveness of the proposed model in terms of estimation accuracy for both user-item relevance and propensity.

Propensity Estimation

• Power-law function of item popularity in existing works:

\[ \theta_{ui} = \left( \sum_{i \in \mathcal{I}} Y_{ui} / \text{max}_{i \in \mathcal{I}} (\sum_{i \in \mathcal{I}} Y_{ui}) \right)^{\gamma} \]

which is not an unbiased estimation of the exposure probability: item popularity only considers the observed positive user-item interactions, but item exposure is determined by both observed positive interactions and unobserved negative feedback.

• Uniased propensity estimation by Inverse Relevance Scoring:

\[ L_{IPS} = \sum_{(u,i) \in \mathcal{D}} \frac{Y_{ui}}{\sum_{i \in \mathcal{I}} \tilde{Y}_{ui} (\tilde{Y}_{ui} + 1)} \frac{(1 - \tilde{Y}_{ui})}{(1 - \tilde{Y}_{ui})} \]

where \( Y_{ui} \) is the probability of item \( i \) being relevant to user \( u \); and \( \tilde{Y}_{ui} \) is the predicted propensity, modeled as \( \tilde{Y}_{ui} = (\omega \cdot w + (1 - \omega) \cdot K_i)^c \), with \( w = f_w(Q_i) \), \( a = f_a(Q_i) \), \( e = f_e(Q_i) \), and \( K_i = \sum_{u \in \mathcal{U}} \max_{i \in \mathcal{I}} (\sum_{i \in \mathcal{I}} Y_{ui}) \).

Combinational Joint Learning

\[ \phi_c = \{ \rho_c, Q_c \} \]

where \( \rho_c \) and \( Q_c \) are the corresponding residual sub-models for \( D_c \).

Algorithm 1: Training algorithm.

1. \[ \rho_c = \{ \rho_1, \rho_2, \ldots, \rho_C \} \]
2. for \( (u,i) \in \mathcal{D}_c \), do
3. \[ \text{Calculate } \rho_{u,i} \text{ and } Q_{u,i} \text{ on } \mathcal{D}_c \]
4. Update \( \{ \rho_c, \ldots, \rho_C \} \) with \( \mathcal{L}_{CJM} \)
5.  with \( \{ \rho_c, \ldots, \rho_C \} \) fixed.
6. Update \( \{ \rho_c, \ldots, \rho_C \} \) with \( \mathcal{L}_{CJM} \) calculated by \( \{ \rho_1, \ldots, \rho_C \} \) fixed.
7. Update \( \{ \rho_c, \ldots, \rho_C \} \) with \( \mathcal{L}_{CJM} \) calculated by \( \{ \rho_1, \ldots, \rho_C \} \) fixed.
8. until converge.

Effectiveness of Estimated Propensity

• Baselines can perform better with the learned propensity from the proposed combinational joint learning method than with the power-law function propensity estimation.

Table 1. Recommendation performance comparison, where best baselines are marked by underlines.

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<thead>
<tr>
<th>Point-wise models</th>
<th>Pair-wise models</th>
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<tr>
<td>MF</td>
<td>MF</td>
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<tr>
<td>RMSE</td>
<td>CE</td>
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<tr>
<td>Yahoo</td>
<td>DCG</td>
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</tbody>
</table>

Effectiveness of Estimated Propensity

• Performance of CJMF improves rapidly then converges as \( C \) increases, reaching a peak level when \( C \geq 5 \)
• Without the residual component, the proposed model is less effective than the complete version of the proposed model.

Fig. 1. Comparing unbiased models with item popularity as propensity and with estimated propensity from proposed models.

Fig. 2. DCG@3 of CJMF and CJMF without residual components on the Yahoo dataset, with varying \( C \).