Addressing **Marketing Bias in Product Recommendations**

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*Work was done while at UC San Diego*
Marketing Bias

• The same product can be marketed using different human images
  • Body Shapes, Genders, Ages, Ethnicity Groups, etc.

• As indicated in many marketing studies, these strategies could affect consumer behavior
A female user wants to buy a boxing product
• A common hypothesis (‘self-congruence’) in marketing
  • A consumer may tend to buy a product because its public impression (‘product image’) is consistent with one’s self-perceptions (‘user identity’)

• Biased interaction dataset
  • consumers’ intrinsic preferences (the target of a RecSys) and marketing preferences (confounding factors) are entangled

• Potential marketing bias could be propagated by ML algorithms
  • Market imbalance can be worsen – even worse recommendation accuracy in the underrepresented market segment
Female user buying a boxing product
• Q1: Does such a marketing bias exist in the input interaction data?
• Q2: How do standard algorithms respond to the biased inputs?
• Q3: How to improve the market fairness of recommendations?
• Q1: Does such a marketing bias exist in the input interaction data?
  • Observational analysis on two collected e-commerce datasets (ModCloth & Amazon Electronics)
Data Collection

• **Modcloth**
  • Clothing website
  • Potential marketing bias
    • The *body shape* (small/large) of the human models in product images

• **Amazon Electronic**
  • Electronic products
  • Potential marketing bias
    • The *gender* (male/female) of the human models in product images

• Users’ rating scores on product items are available on both websites
Q1: Does marketing bias exist in the input data?

Are user identity and product image correlated to each other in the input interactions?

$H_0$: user identity groups ($m$) and product image groups ($n$) are independent in terms of interaction frequency
Q1: Does marketing bias exist in the input data?

$H_0$: user identity groups ($m$) and product image groups ($n$) are independent in terms of interaction frequency

$\chi^2$-test for statistical independence:

$$f_{m,n} - Ef_{m,n}$$
Q1: Does marketing bias exist in the input data?

$H_0$: user identity groups ($m$) and product image groups ($n$) are independent in terms of interaction

**Product image and user identity are correlated with each other**

Large $\chi^2$, small p-value, $H_0$ is rejected
Q1: Does marketing bias exist in the input data?

‘Self-Congruency’ pattern is significant

- People are more likely to consume products represented by someone ‘similar’ to themselves

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**Observed Frequency** \((f)\) — **Expected Frequency** \((Ef)\) > 0

WHEN “user identity” = “product image”

<table>
<thead>
<tr>
<th>User Group</th>
<th>Product Group</th>
<th>Expected Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>Female</td>
<td>Female &amp; Male</td>
<td>+1473</td>
</tr>
<tr>
<td>Male</td>
<td>Female &amp; Male</td>
<td>-1473</td>
</tr>
<tr>
<td>Male</td>
<td>Male</td>
<td>+2354</td>
</tr>
</tbody>
</table>

**Electronics**

\[ \chi^2 = 581.8, p < 0.001 \]
Q2: how do standard recommendation algorithms respond to the biased input data?
Q2: How do standard algorithms respond to the biased inputs?

- Predictive Task
  - Rating Prediction \( s_{u,i} := f(u, i) \rightarrow y_{u,i} \)

- \( \text{diff}_{m,n} = \bar{e}_{(m,n)} - \bar{e}(m,n) \)
  - \( > 0 \): segment \( (m,n) \) is favored by the algorithm (smaller prediction error inside the market segment)

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Q2: How do standard algorithms respond to the biased input data?

- $\text{diff}_{m,n} = \bar{e}_{-1}(m,n) - \bar{e}_{(m,n)}$

- Market segments are sorted based on their sizes in training data
Q2: How do standard algorithms respond to the biased input data?

Real market size \( (f) \) < Expected market size \( (Ef) \)

<table>
<thead>
<tr>
<th>User Group</th>
<th>Electronics (MF)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Female</td>
<td>+1473</td>
</tr>
<tr>
<td>Male</td>
<td>-1473</td>
</tr>
<tr>
<td>Female &amp; Male</td>
<td>+881</td>
</tr>
<tr>
<td>Male</td>
<td>-881</td>
</tr>
<tr>
<td>Male</td>
<td>-2354</td>
</tr>
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</tbody>
</table>

- **Electronics**: the trend correlates to the deviations of the real market size from the expected market size

- Male users buying products w. female model(s)
Q3: how to mitigate such an algorithmic bias and improve the market fairness of recommendations?
Market Fairness of Rating Predictions

• Rating Prediction Fairness
  • Prediction errors across different consumer-product market segments \((m, n)\) are expected to be consistent \((H_0)\)

• \(F\)-test for statistical independence
  • Small between-segment error variation \((V)\)
  • Compared to within-segment error variation \((U)\)
  • Small F-statistic:
    • \(F = \frac{V/(M*N-1)}{U/(|D|-M*N)}\) – deviation of the observed errors from \(H_0\)
    • A metric to evaluate the market fairness of rating predictions with a tractable statistical distribution
Q3: How to improve the market fairness of recommendations?

• Matrix Factorization
  • \( s_{u,i} := f(u, i) = \langle \gamma_u, \gamma_i \rangle \rightarrow y_{u,i} \)
  • MSE-based loss function: 
    \[
    L = \sum (s_{u,i} - y_{u,i})^2
    \]

• Error Correlation Loss
  • \( L^* = \sum (s_{u,i} - y_{u,i})^2 + \alpha L_{\text{corr}} \)
  • \( L_{\text{corr}} \) regularizes the correlation between prediction errors and the distribution of market segments
    • \( L_{\text{corr}} = V/U \), where between-segment error variation: \( V \); within-segment error variation: \( U \);
    • Reflecting the previous fairness metric – F-stat
Q3: How to improve the market fairness of recommendations?

- The proposed framework **MF (corr.error)** provides a superior recommendation fairness without trading-off much recommendation accuracy.
Takeaway & Future

- Marketing bias: a resource of bias for recommendation algorithms
  - Possibly due to the ‘self-congruence’ effect in the training data

- Calibrating prediction errors across different market segments leads to better recommendation fairness
  - Without trading-off much recommendation accuracy

- Encourage RecSys researchers and practitioners to keep investigating this type of bias
  - Better data collection
  - Comprehensive user study
  - Address in algorithms at scale