Fair Ranking with Biased Data

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Ranking in Online Systems

Ranking function $\pi$ that ranks items for context $x$. 
What is the ideal ranking?

Goal: Maximize utility of rankings to the users.

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1960
1994
2020

Goal: ???
Two-Sided Market

Online Retail

- Utility to Users:
  Customers find products they want

- Utility to Items:
  Sellers get revenue
Two-Sided Market

Music Streaming

• Utility to Users:
  Customers find music they enjoy

• Utility to Items:
  Artists get streaming revenue
Two-Sided Market

Research Papers

• Utility to Users:
  Readers find relevant articles

• Utility to Items:
  Writers get their voice out (and tenure)
Maximizing Utility to Users

Probability Ranking Principle [Robertson, 1977]:
• Rank documents by probability of relevance $\to y^*$
• For virtually any measure $U$ of ranking quality

$$y^* := \arg\max_y [U(y|x)]$$
Dynamics of Utility Maximization

Probability Ranking Principle:

• Rank documents by probability of relevance \( y^* \) [Robertson, 1977]

• For virtually any measure \( U \) of ranking quality
  \[ y^* := \arg\max_y [U(y|x)] \]

• Are rankings fair/desirable?

<table>
<thead>
<tr>
<th>Rank</th>
<th>Item</th>
<th>( P(\text{read}) )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Times 1</td>
<td>50.99</td>
</tr>
<tr>
<td>2</td>
<td>Times 2</td>
<td>50.98</td>
</tr>
<tr>
<td>3</td>
<td>Times 3</td>
<td>50.97</td>
</tr>
<tr>
<td></td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>100</td>
<td>Review 1</td>
<td>49.99</td>
</tr>
<tr>
<td>101</td>
<td>Review 2</td>
<td>49.98</td>
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<tr>
<td>102</td>
<td>Review 3</td>
<td>49.97</td>
</tr>
<tr>
<td></td>
<td>...</td>
<td>...</td>
</tr>
</tbody>
</table>
Fairness of Exposure

Fair ranking policy $\pi$ allocates exposure to items based on merit.

**Endogenous Factors**
How to allocate exposure based on merit in order to
- be fair to the items
- satisfy legal requirements
- shape market dynamics (e.g. superstar economics, spam, polarization)

**Exogenous Factors**
How to estimate merit without biases like
- position bias
- trust bias
- uncertainty bias
- stereotypes
Position-Based Exposure Model

Definition:

Exposure $e_j$ is the probability a user observes the item at position $j$.

$$
\text{Exp}(G|x,y) = \sum_{j \in G} e_j
$$

How to estimate?

• Eye tracking [Joachims et al. 2007]
• Intervention studies [Joachims et al. 2017]
• Intervention harvesting [Agarwal et al. 2019] [Fang et al. 2019]
Fairness Disparity

Goal: $\text{Exp}(G|x, y) = f(\text{Rel}(G|x))$

Example: Make exposure proportional to relevance (per group)

$$\frac{\text{Exp}(G_0|x, y)}{\text{Exp}(G_1|x, y)} = \frac{\text{Rel}(G_0|x)}{\text{Rel}(G_1|x)}$$

Disparity: $D(y|x) = |\text{Exp}(G|x, y) - f(\text{Rel}(G|x))|$
Learning Fair Ranking Policies

Goal: Policy $\pi$ that maximizes expected utility $U$ with small disparity $D$.

$$\pi^* = \arg\max_\pi E_x [U(\pi|x)] \quad \text{s.t.} \quad E_x [D(\pi|x)] \leq \delta$$

Learning: Empirical Risk Minimization

$$\hat{\pi} = \arg\max_\pi \frac{1}{n} \sum_{i=1}^n U(\pi|x_i) \quad \text{s.t.} \quad \frac{1}{n} \sum_{i=1}^n D(\pi|x_i) \leq \delta$$

$\rightarrow$ Lagrange multiplier

$$\hat{\pi} = \arg\max_\pi \frac{1}{n} \sum_{i=1}^n U(\pi|x_i) - \lambda \frac{1}{n} \sum_{i=1}^n D(\pi|x_i)$$

[Singh & Joachims, 2019]
Stochastic Ranking Policies

• Policy:
  \( \pi(y|x) \) is conditional distribution over rankings.

• Utility:
  \( U(\pi|x) = \sum_y U(y|x)\pi(y|x) \)

• Exposure:
  \( \text{Exp}(G|x, \pi) = \sum_{j \in G} \sum_y e_{\text{rank}(j|y)}\pi(y|x) \)

\[ \begin{array}{cccc}
  y_1 & y_2 & y_3 & y_4 \\
  A & B & A & B \\
  B & A & C & C \\
  C & C & B & A \\
  D & D & D & G \\
  E & E & E & F \\
  F & F & F & E \\
  G & G & G & D \\
\end{array} \]

0.52 0.23 0.20 0.05

[Singh & Joachims, 2018]
Policy Training

Training objective:

$$\hat{\pi} = \arg\max_{\pi} \frac{1}{n} \sum_{i=1}^{n} U(\pi|x_i) - \lambda \frac{1}{n} \sum_{i=1}^{n} D(\pi|x_i)$$

Policy class:

- Plackett-Luce $\pi_w(y|x) = PL(s_1, \ldots, s_k)$ with per-item scoring model $s_j = s(y_j|x, w)$

Training algorithm:

- Policy gradient with Monte-Carlo estimates of gradient.
- Entropy regularization.
- Variance reduction.

[Singh & Joachims, 2019]
Experiment

Data
- Yahoo LTR Challenge

Fairness
- Proportional exposure
- Individual fairness

Ranking policy
- Plackett-Luce
- Deep network scorer

→ Generalizes to be fair on test data.

[Singh & Joachims, 2019]
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Interaction Feedback

Data

- Query distribution: $x_j \sim P(X)$
- Deployed ranker: $\tilde{y}_j \sim \pi_0(y|x_j)$
- Feedback: clicks, purchases, plays, reads

\[ \rightarrow \text{Feedback is biased!} \]
Modeling Position Bias

• Assume:
  – Click implies observed and relevant:

  \[(\text{click}_i = 1) \leftrightarrow (\text{obs}_i = 1) \land (\text{rel}_i = 1)\]

• Problem:
  – No click can mean not relevant OR not observed

  \[(\text{click}_i = 0) \leftrightarrow (\text{obs}_i = 0) \lor (\text{rel}_i = 0)\]

→ Understand observation mechanism
Inverse Propensity Score Estimators

- **Observation Propensities**
  - \( Q(\text{obs}_j = 1|x, \bar{y}) \)
  - Random variable \( \text{obs}_j \in \{0,1\} \) indicates whether relevance label \( \text{rel}_j \) is observed.
  - Can use position-based exposure \( Q(\text{obs}_j = 1|x, \bar{y}) = e_j \)

- **Inverse Propensity Score (IPS) Weighting**
  - Utility: \( \hat{U}(y|x) = \sum_j g(\text{rank}(j|y)) \frac{\text{click}(j|x)}{e_j} \) (e.g. DCG)
  - Relevance: \( \hat{\text{Rel}}(G|x) = \sum_{j \in G} \frac{\text{click}(j|x)}{e_j} \)
  - Unbiased! In expectation independent of past rankings.

<table>
<thead>
<tr>
<th>Presented</th>
<th>( \bar{y} )</th>
<th>( Q )</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td></td>
<td>1.0</td>
</tr>
<tr>
<td>B</td>
<td></td>
<td>0.8</td>
</tr>
<tr>
<td>C</td>
<td></td>
<td>0.5</td>
</tr>
<tr>
<td>D</td>
<td></td>
<td>0.2</td>
</tr>
<tr>
<td>E</td>
<td></td>
<td>0.2</td>
</tr>
<tr>
<td>F</td>
<td></td>
<td>0.2</td>
</tr>
</tbody>
</table>

[Joachims et al., 2017] [Yadav et al., 2020]
Fair Policy Training

Training objective:

\[
\hat{\pi} = \arg\max_{\pi} \frac{1}{n} \sum_{i=1}^{n} \hat{U}(\pi | x_i) - \lambda \frac{1}{n} \sum_{i=1}^{n} \hat{D}(\pi | x_i)
\]

Utility

- Unbiased \( \hat{U}(y|x) \) gives unbiased \( \hat{U}(\pi | x_i) \)

Disparity

- Average relevance \( \hat{Rel}(G) = \sum_x \hat{Rel}(G|x) \)
- Amortized group disparity (similar to [Biega et al., 2018])

\[
\hat{D}(y|x) = \hat{Rel}(G_1)Exp(G_0|x) - \hat{Rel}(G_0)Exp(G_1|x)
\]

[Yadav et al., 2020]
Experiment

Data
- Microsoft LTR Corpus

Fairness
- Amortized proportional exposure
- Group fairness

Ranking policy
- Plackett-Luce
- Linear scorer

[Yadav et al., 2020]
Comparison

• Group blind
  – Fairness through unawareness

• Post processing
  – IPS regression
  – Biega et al. fairness

• Fair-PG-Rank
  – Method from before

[Yadav et al., 2020]
## Fairness of Exposure

A fair ranking policy $\pi$ allocates exposure to items based on merit.

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<thead>
<tr>
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<th>Exogenous Factors</th>
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| How to allocate exposure based on merit in order to  
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  - trust bias  
  - uncertainty bias  
  - stereotypes |
Matching Markets

<table>
<thead>
<tr>
<th>Employer</th>
<th>Preference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Z</td>
<td>A &gt; D &gt; ...</td>
</tr>
<tr>
<td>Y</td>
<td>C &gt; A &gt; ...</td>
</tr>
<tr>
<td>X</td>
<td>E &gt; C &gt; ...</td>
</tr>
<tr>
<td>W</td>
<td>A &gt; B &gt; ...</td>
</tr>
<tr>
<td>V</td>
<td>A &gt; D &gt; ...</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
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</table>

<table>
<thead>
<tr>
<th>Applicant</th>
<th>Preference</th>
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<tbody>
<tr>
<td>A</td>
<td>X &gt; Z &gt; ...</td>
</tr>
<tr>
<td>B</td>
<td>W &gt; V &gt; ...</td>
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<td>C</td>
<td>Y &gt; X &gt; ...</td>
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<tr>
<td>D</td>
<td>Y &gt; Z &gt; ...</td>
</tr>
<tr>
<td>E</td>
<td>V &gt; Z &gt; ...</td>
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<tr>
<td>...</td>
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</tbody>
</table>

→ Multi-sided Preferences, Fairness, and Social Welfare.

[Tu et al., 2014] [Hopcroft et al., 2011]
Simulation Experiment

Effect on Market

Two-sided market with $|J| = 50$ and $|C| = 100$

- Social welfare based
- Relevance based

Effect on Individuals

Two-sided market (random)

Individual utility difference

[Su et al., 2021]
Research Agenda for Ranking

• Fairness to items
• Fairness to user groups
• Market-level objectives
• Long-term dynamics
• Transparency
• Privacy

http://www.joachims.org