Fairness of Exposure in Rankings

Presenters: Madhumita Sakthi
Pratyush Kar

Problem Statement

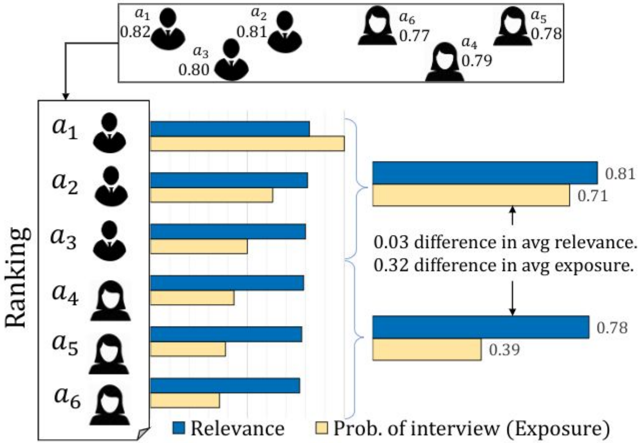
- Address the responsibility of ranking systems
  - To users
  - The items being ranked
- The framework helps in formulation of fairness constraints on ranking in terms of exposure allocation
- The algorithm helps in finding rankings that maximize the utility for the user
- Fairness constraints: demographic parity, disparate treatment and disparate impact

Probability Ranking Principle

- Ideal ranking should order items in decreasing order of probability of relevance
- This maximizes utility of the retrieval system to the user
- This principle asserts that relevance has a probabilistic interpretation
- Documents are ranked by $P(rel|d,q)$
    - Rel is the event of document d being relevant to query q

Scenario 1 : Fairly Allocating economic opportunity

- A web service connects employers(users) to employees(items)
- A standard exposure drop-off of *1/log(1+j)*, where *j* is the position
- Female applicants have 30% less exposure



Fairly Representing a Distribution of Results

- Disproportionate number of males vs. females
- PRP doesn't produce results that represent the relevance distribution in an unbiased way
- Distribute exposure proportional to relevance even if there is a drop in utility

Giving Speakers Fair Access to Willing Listeners

- Ranking systems play an increasing role as a medium for speech
- It is creating a connection between bias and fairness in rankings and principles behind freedom of speech
- Search engines should have no editorial policies other than that their results are **comprehensive, impartial, and solely ranked by relevance**
- Explore other relevance-based ranking with equitable distribution of exposure

Fairness in Rankings

- Statistical parity based measures that compute the difference in the distribution of different groups for different prefixes of the ranking (top-10, top-20 and so on)
  - Averaged differences using DCG measure is used as a regularization term
- ‘Fair Top-k ranking’ that optimizes utility with constraints
  - In-group **monotonicity for utility** (i.e. more relevant items above less relevant within the group)
  - A fairness constraint that the proportion of protected group items in every prefix of the top-k ranking is above a minimum threshold

Fairness in Rankings conti..

- Constrained maximum weight matching algorithm
  - the maximum number of items with each sensitive attribute allowed in the top positions
- The task of designing fair scoring functions that satisfy desirable fairness constraints
- **Parity constraints** restricting the fraction of items with each attribute in the ranking

Information Diversity in Retrieval

- Both the PRP and diversified ranking maximize utility for the **user alone**
- **Extrinsic diversity** , the utility measure accounts for uncertainty(Jaguar) and diminishing returns from multiple relevant results
- **Intrinsic diversity**, the utility measure considers rankings as portfolios and reflects redundancy (diversity for overview)
- **Exploration diversity**, the aim is to maximize utility to the user in the long term through more effective learning

Mathematical Formulation

- Consider a given query *q*
- We want to present ranking *r* of a set of documents $\mathcal{D}$

$$\mathcal{D} = \{d_1, d_2, \ldots, d_n\}$$

$$r = \text{argmax}_r \quad U(r|q)$$

$$\text{s.t. } r \text{ is fair}$$

- where *U(r|q)* denotes the utility of ranking *r* given query *q*

Utility of Ranking

- Utility of ranking is usually derived from the relevance of the individual items
- Depends on two application-dependent functions
  - *v(rank(d|r))* – models the attention a document gets at a particular rank
  - *λ(rel(d|u,q))* – maps relevance of a document to its utility

$$\mathrm{U}(r|q) = \sum_{u \in \mathcal{U}} P(u|q) \sum_{d \in \mathcal{D}} v(\mathrm{rank}(d|r))\lambda(\mathrm{rel}(d|u,q)),$$

Probabilistic Rankings

- Evaluating all possible rankings would be exponential in $|\mathcal{D}|$
- Consider a probabilistic ranking *R*

$$
\begin{aligned}
\mathrm{U}(R|q) &= \sum_{r} R(r) \sum_{u \in \mathcal{U}} P(u|q) \sum_{d \in \mathcal{D}} v(\mathrm{rank}(d|r)) \lambda(\mathrm{rel}(d|u,q)) \\
&= \sum_{r} R(r) \sum_{d \in \mathcal{D}} v(\mathrm{rank}(d|r))\, u(d|q)
\end{aligned}
$$

- Still exponential, consider a doubly-stochastic matrix *P*
- $P_{i,j}$ is the probability of document d_i at rank j

$$U(P|q) = \sum_{d_i \in \mathcal{D}} \sum_{j=1}^{N} P_{i,j} u(d_i|q) v(j) = \mathbf{u}^T \mathbf{P} \mathbf{v}$$

Optimizing Fair Rankings

$$
\begin{aligned}
\mathbf{P} = \operatorname{argmax}_{\mathbf{P}} \ & \mathbf{u}^T \mathbf{P} \mathbf{v} && \text{(expected utility)} \\
\text{s.t.} \ & \mathbb{1}^T \mathbf{P} = \mathbb{1}^T && \text{(sum of probabilities for each position)} \\
& \mathbf{P} \mathbb{1} = \mathbb{1} && \text{(sum of probabilities for each document)} \\
& 0 \leq \mathbf{P}_{i,j} \leq 1 && \text{(valid probability)} \\
& \mathbf{P} \text{ is fair} \qquad \mathbf{f}^T \mathbf{P} \mathbf{g} = h. && \text{(fairness constraints)}
\end{aligned}
$$

- Computing *R* from *P* can be achieved via BvN decomposition

$$P = \theta_1 P_1 + \theta_2 P_2 + \ldots + \theta_n P_n$$

$$\text{where } 0 \leq \theta_i \leq 1, \quad \sum_i \theta_i = 1$$

Constructing Group Fairness Constraints

- The goal is to allocate exposure fairly between groups G_k

$$\text{Exposure}(d_i|\mathbf{P}) = \sum_{j=1}^{N} \mathbf{P}_{i,j}\mathbf{v}_j$$

- Toy dataset (job seeker)
  - 6 applicants with probabilities of relevance to an employer of u = (0.81,0.80,0.79,0.78,0.77,0.76)T
- News recommendation dataset
  - subset the Yow news recommendation dataset
  - The ‘relevant’ field is used as the measure of relevance for our task.
  - Since the relevance is given as a rating from 1 to 5, we divide it by 5 and add a small amount of Gaussian noise (ε = 0.05) to break ties.

Demographic Parity Constraint

- Average exposure of the documents in each groups is equal
- Constraint may lead to a big loss in utility in cases when the two groups are very different in terms of relevance distribution

$$\text{Exposure}(G_k|\mathbf{P}) = \frac{1}{|G_k|} \sum_{d_i \in G_k} \text{Exposure}(d_i|\mathbf{P}),$$

this can be expressed as the following constraint in our framework:

$$\text{Exposure}(G_0|\mathbf{P}) = \text{Exposure}(G_1|\mathbf{P}) \tag{4}$$

$$\Leftrightarrow \frac{1}{|G_0|} \sum_{d_i \in G_0} \sum_{j=1}^{N} \mathbf{P}_{i,j}\mathbf{v}_j = \frac{1}{|G_1|} \sum_{d_i \in G_1} \sum_{j=1}^{N} \mathbf{P}_{i,j}\mathbf{v}_j \tag{5}$$

$$\Leftrightarrow \sum_{d_i \in \mathcal{D}} \sum_{j=1}^{N} \left(\frac{\mathbb{1}_{d_i \in G_0}}{|G_0|} - \frac{\mathbb{1}_{d_i \in G_1}}{|G_1|} \right) \mathbf{P}_{i,j}\mathbf{v}_j = 0 \tag{6}$$

$$\Leftrightarrow \mathbf{f}^T P\mathbf{v} = 0 \qquad \left(\text{with } \mathbf{f}_i = \frac{\mathbb{1}_{d_i \in G_0}}{|G_0|} - \frac{\mathbb{1}_{d_i \in G_1}}{|G_1|}\right)$$

Demographic Parity Constraint – Experiment

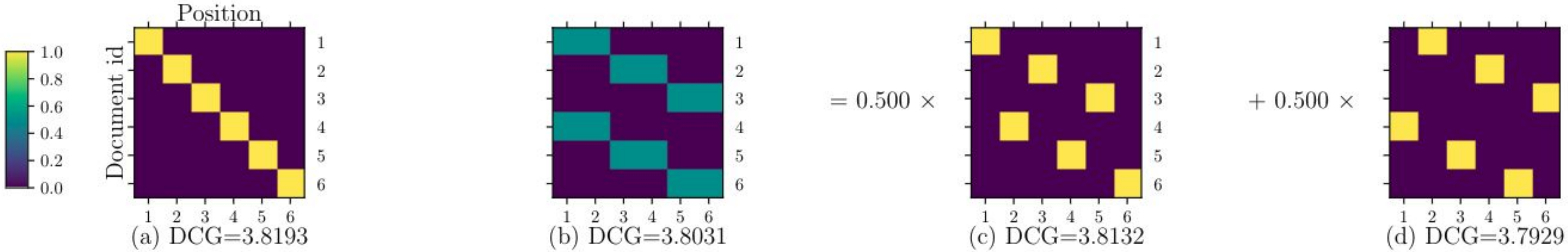


Figure 3: Job seeker example with demographic parity constraint. (a) Optimal unfair ranking that maximizes DCG. (b) Optimal fair ranking under demographic parity. (c) and (d) are the BvN decomposition of the fair ranking.

Disparate Treatment Constraint

- Exposure received by each group is proportional to its average utility

$$\frac{\text{Exposure}(G_0|\mathbf{P})}{\text{U}(G_0|q)} = \frac{\text{Exposure}(G_1|\mathbf{P})}{\text{U}(G_1|q)}$$

$$\Leftrightarrow \frac{\frac{1}{|G_0|}\sum_{d_i \in G_0}\sum_{j=1}^{N}\mathbf{P}_{i,j}\mathbf{v}_j}{\text{U}(G_0|q)} = \frac{\frac{1}{|G_1|}\sum_{d_i \in G_1}\sum_{j=1}^{N}\mathbf{P}_{i,j}\mathbf{v}_j}{\text{U}(G_1|q)} \qquad (7)$$

$$\Leftrightarrow \sum_{i=1}^{N}\sum_{j=1}^{N}\left(\frac{\mathbb{1}_{d_i \in G_0}}{|G_0|\text{U}(G_0|q)} - \frac{\mathbb{1}_{d_i \in G_1}}{|G_1|\text{U}(G_1|q)}\right)\mathbf{P}_{i,j}\mathbf{v}_j = 0 \qquad (8)$$

$$\Leftrightarrow \mathbf{f}^T P\mathbf{v} = 0 \qquad \left(\text{with } \mathbf{f}_i = \left(\frac{\mathbb{1}_{d_i \in G_0}}{|G_0|\text{U}(G_0|q)} - \frac{\mathbb{1}_{d_i \in G_1}}{|G_1|\text{U}(G_1|q)}\right)\right)$$

- Disparate Treatment Ratio (DTR)

$$\text{DTR}(G_0, G_1|\mathbf{P}, q) = \frac{\text{Exposure}(G_0|\mathbf{P})/\text{U}(G_0|q)}{\text{Exposure}(G_1|\mathbf{P})/\text{U}(G_1|q)}$$

Disparate Treatment Constraint – Experiment

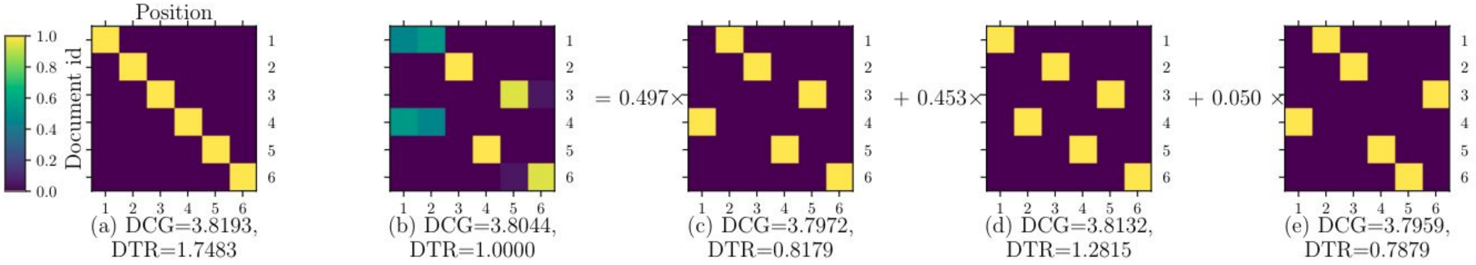


Figure 5: Job seeker example with disparate treatment constraint. (a) Optimal unfair ranking. (b) Fair ranking under disparate treatment constraint. (c), (d), (e) are the BvN decomposition of the fair ranking.

Disparate Impact Constraint

- Expected click-through rate (CTR) is proportional to the average utility for each group

$$\mathrm{CTR}(G_k|\mathbf{P}) = \frac{1}{|G_k|}\sum_{i\in G_k}\sum_{j=1}^{N}\mathbf{P}_{i,j}\mathbf{u}_i\mathbf{v}_j.$$

$$\frac{\mathrm{CTR}(G_0|\mathbf{P})}{\mathrm{U}(G_0|q)} = \frac{\mathrm{CTR}(G_1|\mathbf{P})}{\mathrm{U}(G_1|q)} \tag{9}$$

$$\Leftrightarrow \frac{\frac{1}{|G_0|}\sum_{i\in G_0}\sum_{j=1}^{N}\mathbf{P}_{i,j}\mathbf{u}_i\mathbf{v}_j}{\mathrm{U}(G_0|q)} = \frac{\frac{1}{|G_1|}\sum_{i\in G_1}\sum_{j=1}^{N}\mathbf{P}_{i,j}\mathbf{u}_i\mathbf{v}_j}{\mathrm{U}(G_1|q)} \tag{10}$$

- Disparate Impact Ratio (DIR)

$$\mathrm{DIR}(G_0, G_1|\mathbf{P}, q) = \frac{\mathrm{CTR}(G_0|\mathbf{P})/\mathrm{U}(G_0|q)}{\mathrm{CTR}(G_1|\mathbf{P})/\mathrm{U}(G_1|q)}$$

Disparate Impact Constraint – Experiment

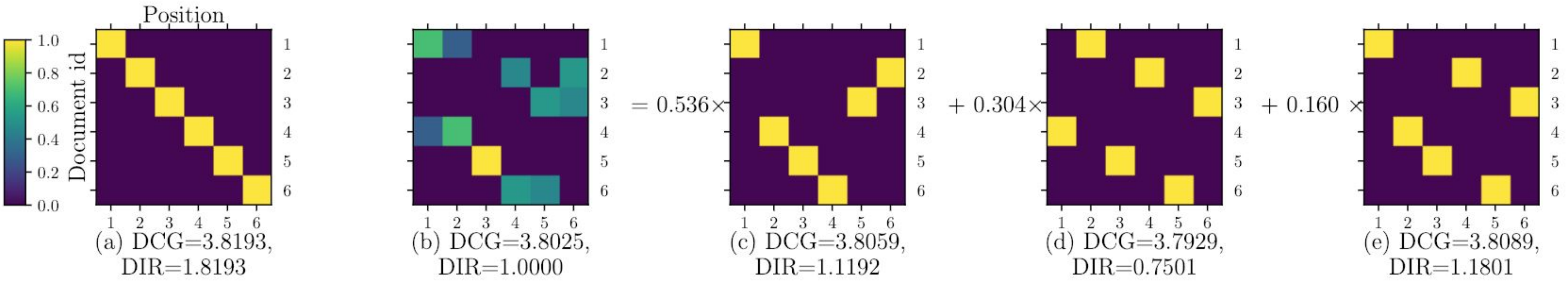


Figure 7: Job seeker example with disparate impact constraint. (a) Optimal unfair ranking. (b) Fair ranking under disparate impact constraint. (c), (d), (e) are the BvN decomposition of the fair ranking.

Questions?