Fairness of Exposure in Ranking Systems

Ashudeep Singh
PhD Thesis Defense
Cornell University

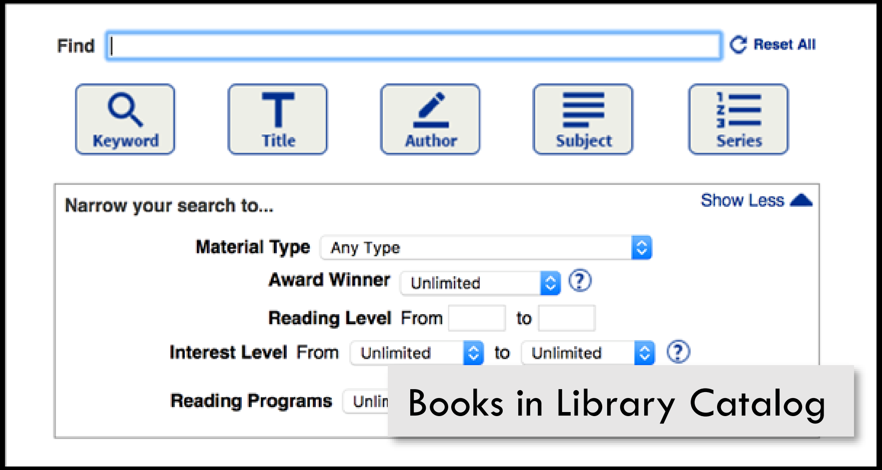
June 25, 2021

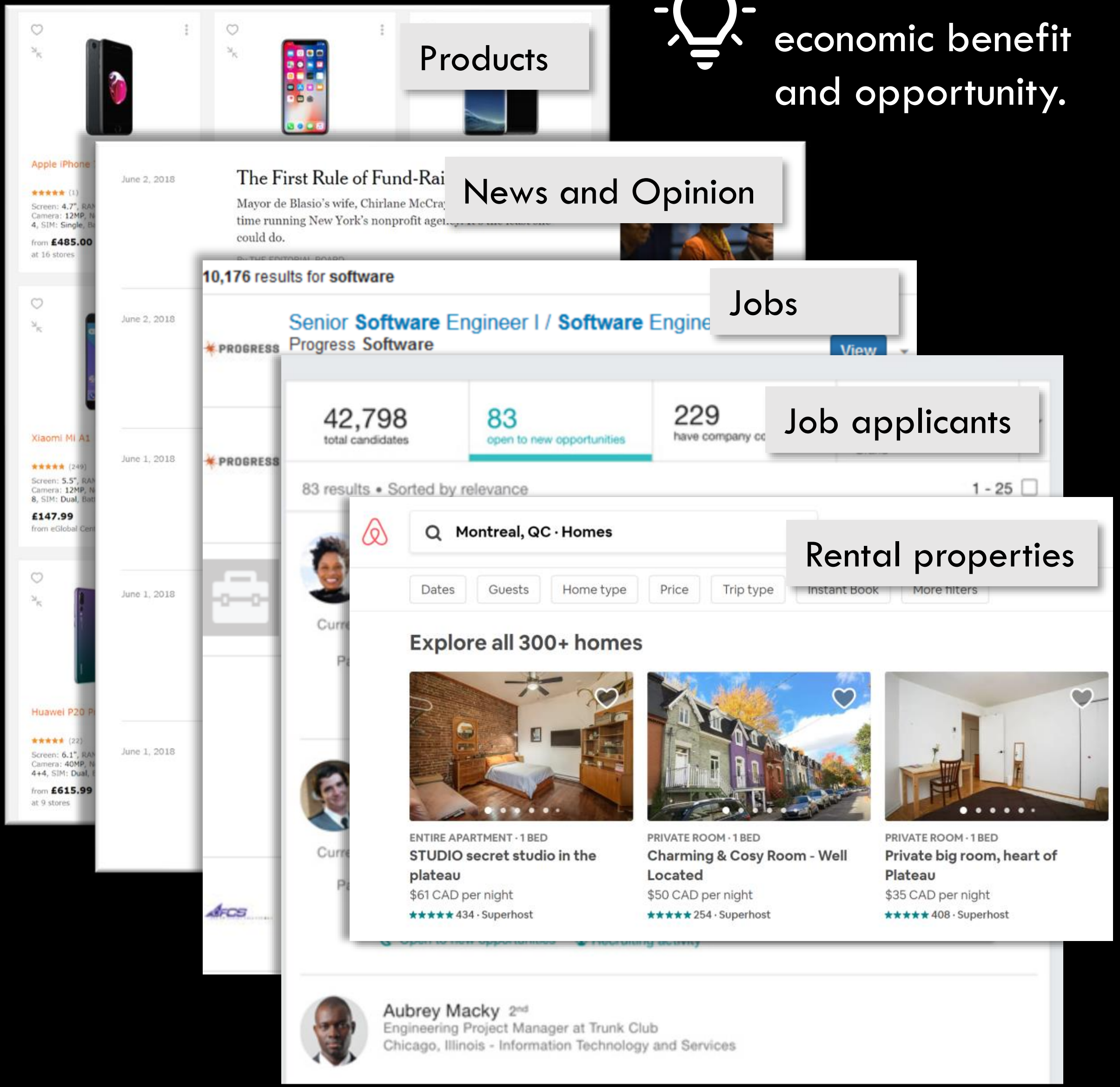
Rankings in Online Platforms

Two-sided markets: Items that transfer economic benefit and opportunity.

1970s

2020s





What is a good ranking?

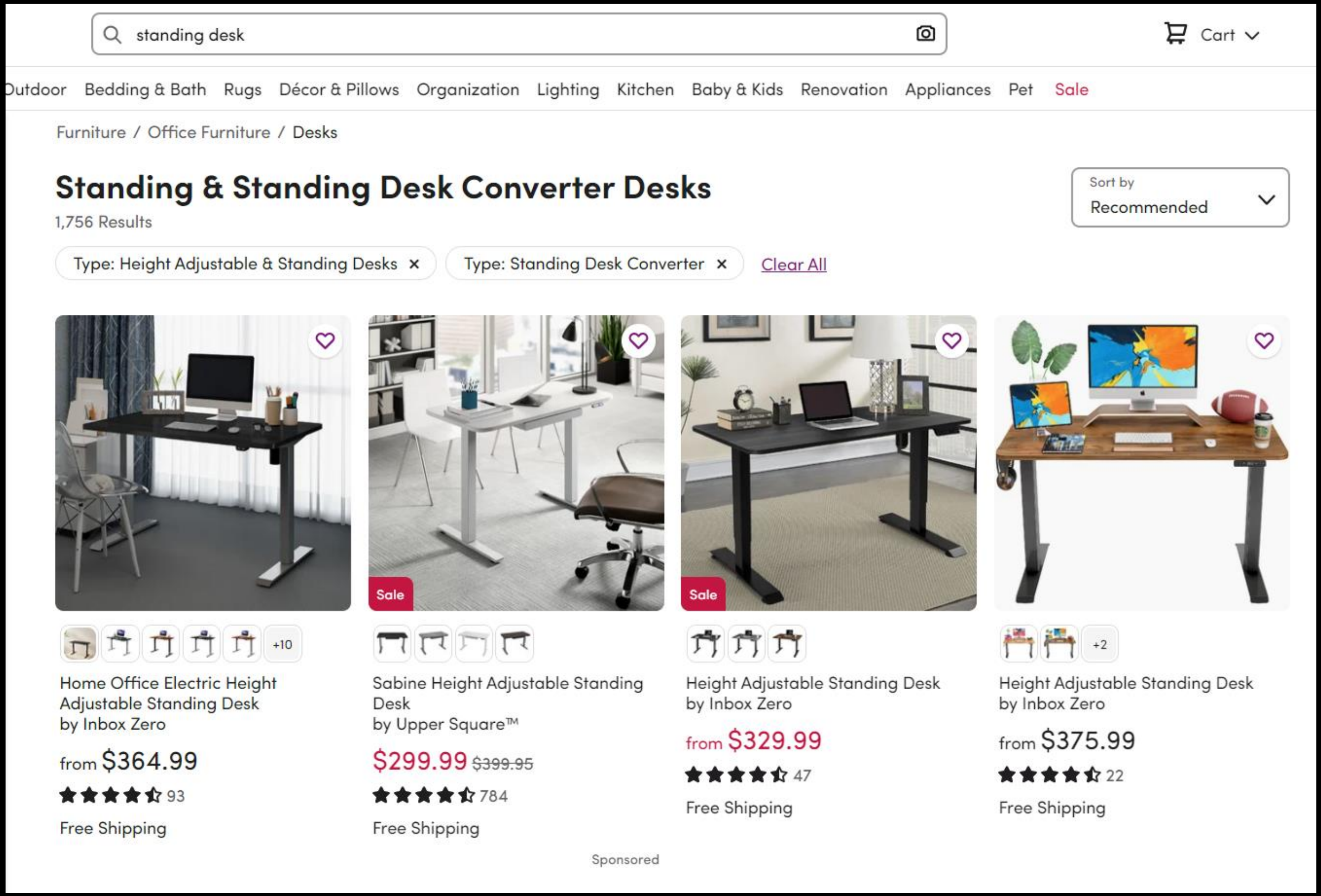
> **Probability Ranking Principle [Robertson, 1977]**
> Ranking items by the probability of relevance to the users maximizes user utility for most measures U
> $$y^* := \operatorname{argmax}_y U(y|x)$$

Utility in Two-sided markets

Example: Online Retail

- Utility to user:
  Customer finds products they want.

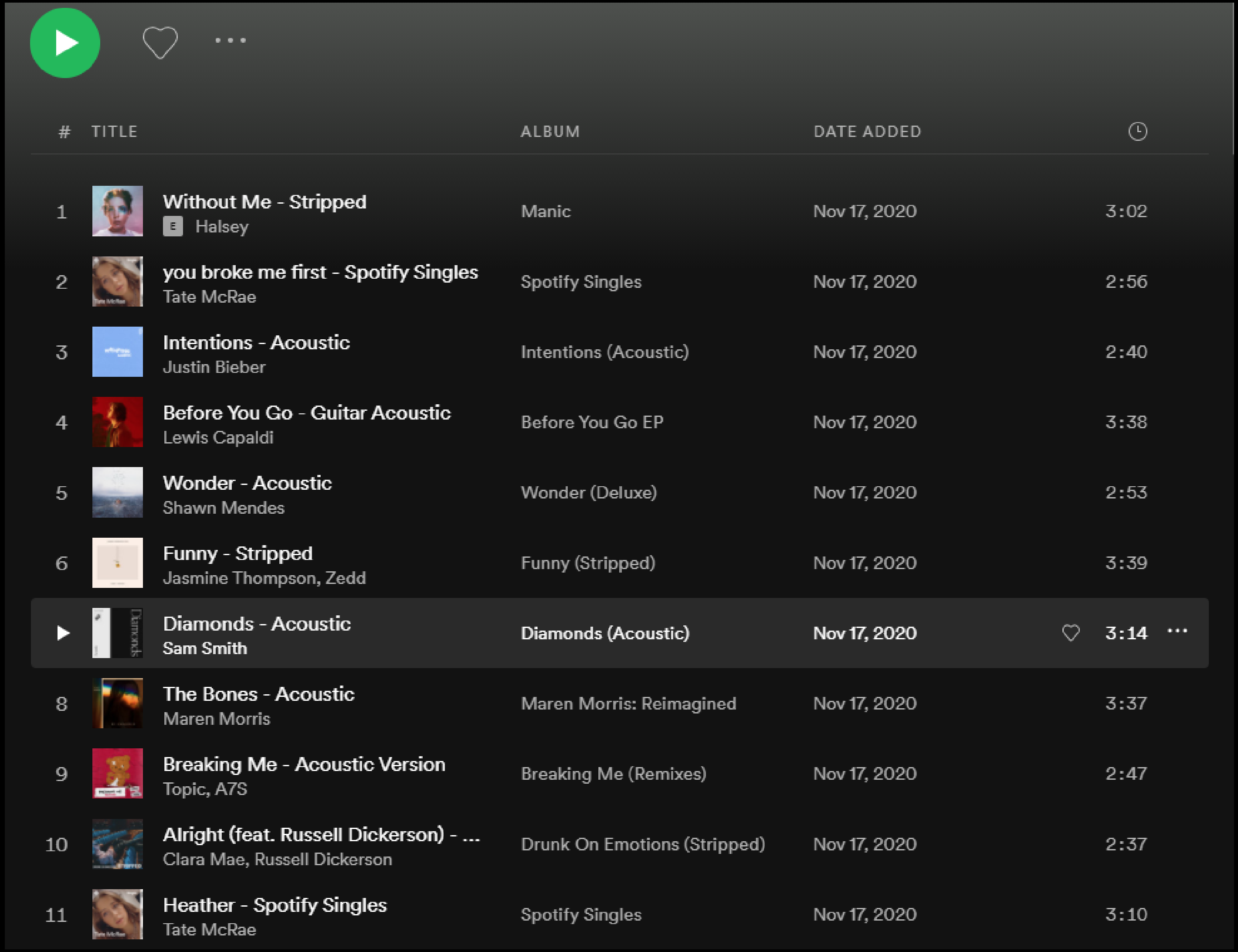
- Utility to items:
  Sellers earn revenue.



Utility in Two-sided markets

Example: Music Streaming

- Utility to user:
  Enjoyment from the music.
- Utility to items:
  Streaming Revenue to the artists.

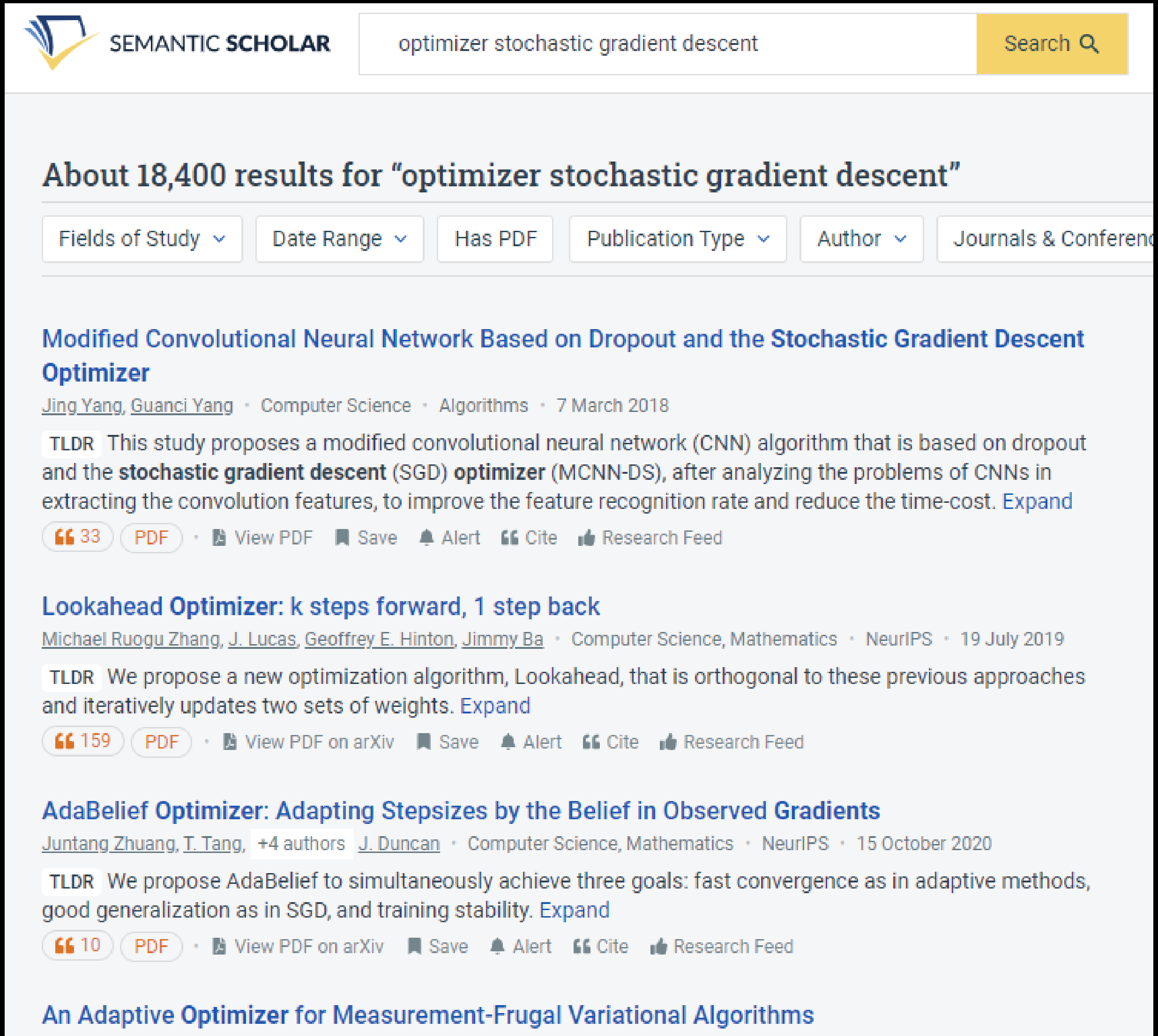


Utility in Two-sided markets

Example: Scholarly work

- Utility to user:
  Readers find relevant articles.

- Utility to items:
  Authors get read, cited, advance their research agenda/career.



Two-sided markets

User Utility

Item Utility

Goals & Challenges

- [KDD'18] [NeurIPS'19] Fairness to Creators/Producers
- [SIGIR'20] Marketplace Dynamics
- Regulations and Legal requirements
- Preventing Filter bubbles
- Tackle manipulation: Spam, SEO, fake reviews, etc.

- Position Bias [NeurIPS'19] [SIGIR'20] [KDD'18]
- Trust Bias
- Selection Bias [ICML'16] [SIGIR'20]
- Uncertainty [In Submission '21]
- Human Inconsistency
- Societal Biases
- Short-term Reward vs Long-term Risk [RecSys FAccTRec'20]

Are conventional methods fair?

- Probability Ranking Principle: Rank items by probability of relevance.
- In two-sided markets, PRP might be inadequate since it does not explicitly consider the item-side utility.
- Examples:
  - Job Candidate Ranking
    - Amplifies existing biases.

Position	x	P(interview)
1	A_1	50.99%
2	A_2	50.98%
3	A_3	50.97%
…	…	…
101	B_1	49.99%
102	B_2	49.98%
103	B_3	49.97%
…	…	…

High Exposure

Position Bias

Low Exposure

Job Candidate Ranking Example

Are conventional methods fair?

- Probability Ranking Principle: Rank items by probability of relevance.
- In two-sided markets, PRP might be inadequate since it does not explicitly consider the item-side utility.
- Examples:
  - Job Candidate Ranking
    - Amplifies existing biases.
  - Music Recommendation
    - Winner-takes-all!

Position	x	$\mathbb{E}$[Rating]
1	A_1	4.99
2	A_2	4.98
3	A_3	4.97
…	…	…
11	A_{11}	4.89
12	A_{12}	4.88
13	A_{13}	4.87
…	…	…

High Exposure

Position Bias

Low Exposure

Music Recommendation Example

Are conventional methods fair?

- Probability Ranking Principle: Rank items by probability of relevance.
- In two-sided markets, PRP might be inadequate since it does not explicitly consider the item-side utility.
- Examples:
    - Job Candidate Ranking
        - Amplifies existing biases.
    - Music Recommendation
        - Winner-takes-all!
    - News Ranking
        - Leads to polarization of the platform.

Position	x	$P(read)$
1	R_1	50.99%
2	R_2	50.98%
3	R_3	50.97%
…	…	…
101	T_1	49.99%
102	T_2	49.98%
103	T_3	49.97%
…	…	…

High Exposure

Position Bias

Low Exposure

News Ranking Example

In online platforms,

Exposure → Opportunity

Hence,

Fairness → Fair Allocation of Exposure

Outline

1. Fair Allocation of Exposure

[**Singh** & Joachims, KDD 2018]

2. Learning-to-Rank with Fairness Constraints

3. Fairness in Dynamic Learning-to-Rank with Biased Feedback

Position-based Model of Exposure

Exposure e_k is the probability a user observes the item at position k.

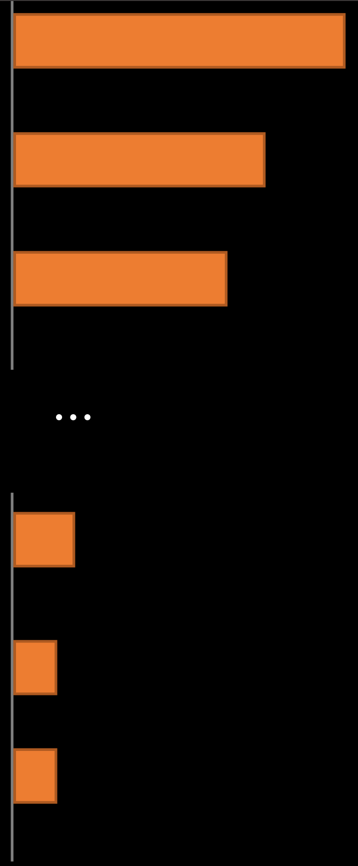
Exposure of a Group (e.g., seller, artist, etc.)

$$Exp(G|y) = \sum_{y(k) \in G} e_k$$

How to estimate?

- Eye tracking [Joachims et al. 2007]
- Intervention studies [Joachims et al. 2017]
- Intervention harvesting [Agarwal et al. 2019]

Rank	**P[user observes rank k]**
1	e_1
2	e_2
3	e_3
…	…
101	e_{101}
102	e_{102}
103	e_{103}
…	…



Fairness of Exposure

Goal: Enable the explicit statement of how exposure is allocated relative to the merit of the items in the group.

$$Exp(G|x) = f_x(Rel(G|x))$$

Disparity$(G) = |Exp(G|x) - f_x(Rel(G|x))|$.

For example: Allocate **exposure proportional to relevance** per group

Group Fairness

Individual Fairness?

$$\text{Exposure} \propto \text{Relevance} \rightarrow \frac{Exp(G_0|x)}{Exp(G_1|x)} = \frac{Rel(G_0|x)}{Rel(G_1|x)}$$

[**Singh** & Joachims, KDD 2018]

Fairness of Exposure

Objective: Given relevance scores, find a ranking that optimizes user utility while satisfying fairness of exposure constraints.

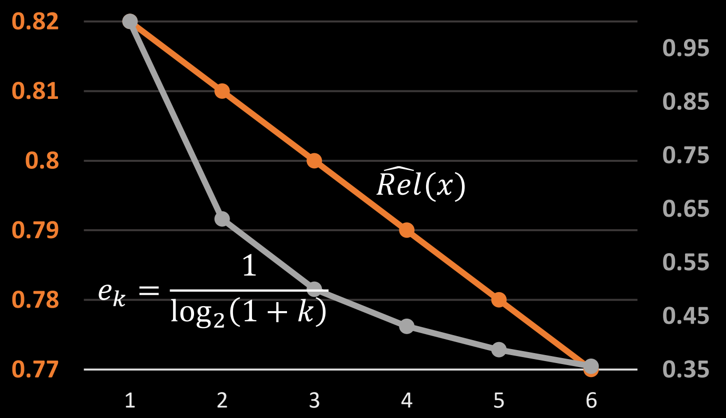
Problem: Rankings are discrete combinatorial objects

- Exponential solution space.

x	$\widehat{Rel}(x)$
A_1	0.82
A_2	0.81
A_3	0.80
B_1	0.79
B_2	0.78
B_3	0.77

$\times$

Exposure@k
e_1
e_2
e_3
e_4
e_5
e_6



[**Singh** & Joachims, KDD 2018]

Key Idea 1: Stochastic Ranking Policies

- Ranking Policy

  $\pi(y|x)$ is the conditional distribution over rankings of items under query x.

- Utility

$$U(\pi|x) = \sum_y U(y|x) \cdot \pi(y|x)$$

- Exposure

$$Exp(i|\pi) = \sum_k e_k \cdot P(rank(i) = k \mid \pi)$$

- Problem: The distribution is over the set of permutations which is still exponential in size.

y_1	y_2	y_3	y_4
A_1	A_1	A_1	B_1
A_2	B_1	A_2	A_1
A_3	A_2	B_1	B_2
B_1	B_2	A_3	A_2
B_2	A_3	B_2	B_3
B_3	B_3	B_3	A_3
0.40	0.40	0.16	0.04

Key Idea 2: Doubly Stochastic Matrices

Represent a Stochastic Ranking π as a Marginal Rank Distribution $\mathbb{P}$.

$$\begin{array}{cc} & \text{Rank} \\ \text{Item} & \begin{pmatrix} \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \mathbb{P}_{i,k} & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \end{pmatrix} \end{array}$$

$\mathbb{P}_{i,k}$ = Probability of item i at position k.

Utility (e.g., DCG, Avg Precision) and Exposure can be expressed as a Linear function of matrix $\mathbb{P}$.

For example, $\text{DCG}(\mathbb{P}) = \sum_i \mu_i \sum_k \frac{\mathbb{P}_{i,k}}{\log(1+k)}$.

Objective: Find $\mathbb{P}$ that optimizes utility U and satisfies exposure constraints.

→ Linear Program

(for a large class of fairness constraints and utility functions)

[**Singh** & Joachims, KDD 2018]

Example: Exposure Proportional to Merit

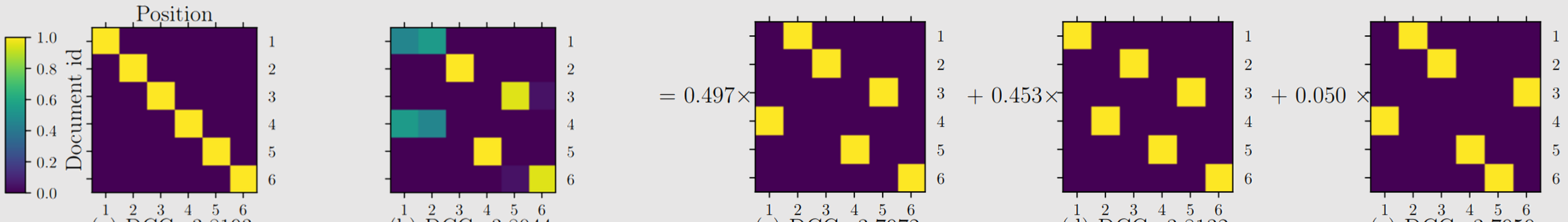
Given relevance scores, find matrix $\mathbb{P}_{\text{fair}}$ that maximizes DCG (i.e., utility) subject to the Proportional Exposure fairness constraint.

How to sample rankings from $\mathbb{P}_{\text{fair}}$ to present to the users?

Birkhoff von Neumann (BvN) decomposition: $\mathbb{P}_{\text{fair}}$ can be decomposed into a distribution over rankings

$$\mathbb{P}_{\text{fair}} = \theta_1 y_1 + \theta_2 y_2 + \cdots + \theta_d y_d.$$

Items	$\hat{h}(x)$		Exposure@k
A_1	0.82		e_1
A_2	0.81		e_2
A_3	0.80		e_3
B_1	0.79		e_4
B_2	0.78		e_5
B_3	0.77		e_6



(a) DCG=3.8193, DTR=1.7483

(b) DCG=3.8044, DTR=1.0000

(c) DCG=3.7972, DTR=0.8179

(d) DCG=3.8132, DTR=1.2815

(e) DCG=3.7959, DTR=0.7879

Without Fairness Constraint

$\mathbb{P}_{\text{fair}}$: Proportional Exposure

Distribution over rankings: BvN decomposition

[**Singh** & Joachims, KDD 2018]

1. Fair Allocation of Exposure

[**Singh** & Joachims, KDD 2018]

Merit-based exposure allocation

- Stochastic Rankings
- Two-stage Approach:
  - Estimate Relevances.
  - Find fair ranking distribution.

Related Work

- Composition-based Fairness notions
  [Yang & Stoyanovich (2017), Zehlike et al. (2017), Celis et al. (2017)]
  - Special case of fairness of exposure.
- Concurrent & Independent work by Biega et al. (2018):
  - Amortized fairness of attention by making exposure proportional to relevance in a sequence of rankings.
  - Individual Fairness.
  - Uses Integer Linear Programming to generate a series of ranking.

1. Fair Allocation of Exposure

[**Singh** & Joachims, KDD 2018]

Merit-based exposure allocation

- Stochastic Rankings
- Two-stage Approach:
  - Estimate Relevances.
  - Find fair ranking distribution.

Applications in the Industry

- LinkedIn Talent Search [Geyik et al. 2019], LinkedIn Network Recommendations [Nandy et al. 2021].
- Spotify Music Recommendations [Mehrotra et al. 2018].
- Google's *production recommender system* [Beutel et al. 2019].
  - Pairwise accuracy fairness: a special case of fairness of exposure.

Outline

1. Fair Allocation of Exposure

[**Singh** & Joachims, KDD 2018]

Merit-based exposure allocation

- Stochastic Rankings
- Two-stage Approach:
  - Estimate Relevances.
  - Find fair ranking distribution.
- Problem: What if the estimation of relevances is biased?

2. Learning-to-Rank with Fairness Constraints

[**Singh** & Joachims, NeurIPS 2019]

Learn an end-to-end ranking model that:

- Generalizes to unseen queries and items.
- Ignores biased features.

3. Fairness in Dynamic Learning-to-Rank with Biased Feedback

Learning-to-Rank

For a query x, rank a candidate set $\mathcal{S}_x = \{d_1, d_2, d_3, \dots\}$ of items

- d_i represented by features $\psi(d_i|x)$, and
- d_i has a merit score (e.g., relevance—whether a user would click it or not).

Ranking Policy π ranks $\mathcal{S}_x$ for a query x.

Learning objective: Find policy π that maximizes expected utility U with small disparity D

$$\pi^* = \mathrm{argmax}_\pi \ \mathbb{E}_x[U(\pi|x)] \text{ s.t. } \mathbb{E}_x[D(\pi|x)] \le \delta.$$

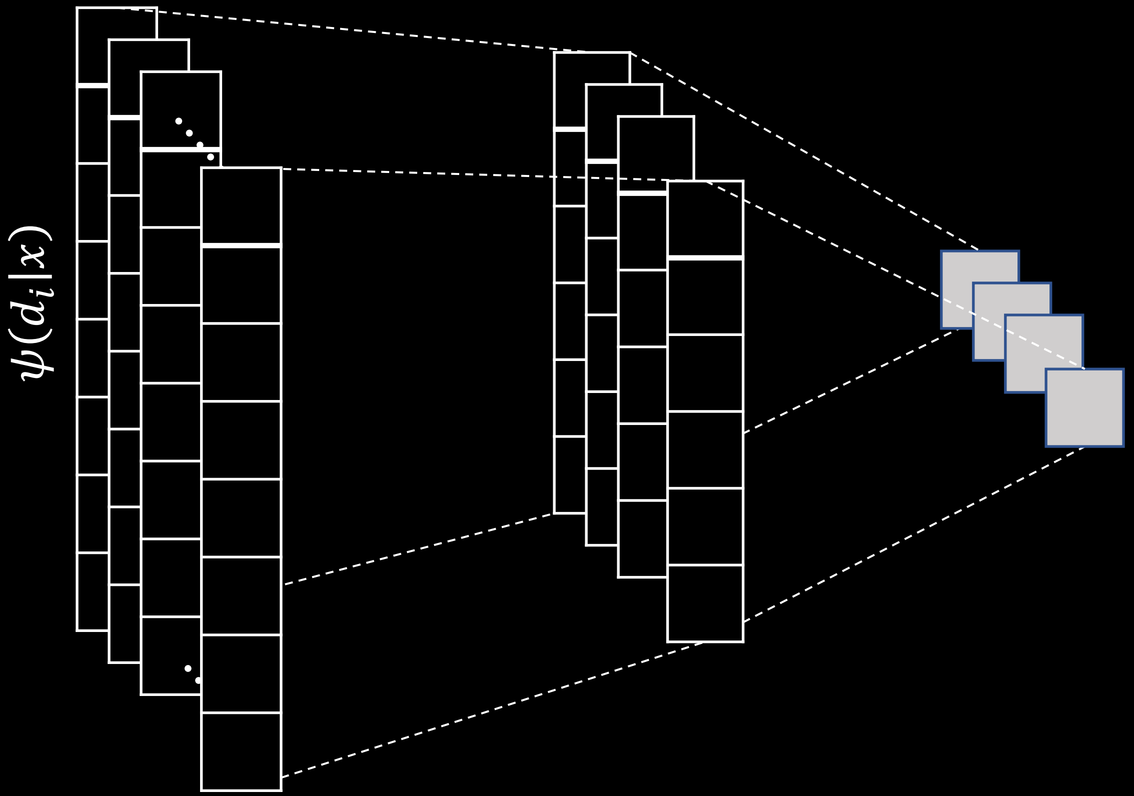
Empirical Risk Minimization with Lagrange multiplier:

$$\pi^* = \mathrm{argmax}_\pi \frac{1}{n} \sum_{i=1}^{n} U(\pi|x_i) - \lambda \cdot D(\pi|x_i)$$

[**Singh** & Joachims, NeurIPS 2019]

Stochastic Ranking Policies: Model

π maps $\mathcal{S}_x$ to a ranking distribution through the feature vectors $\psi(d_j|x)$.



Candidate Set for query $x: \mathcal{S}_x$

$\xrightarrow{\text{Softmax}}$ $[\, p_1 \mid p_2 \mid \ldots \mid p_n \,] \sim y$

Plackett-Luce Sampling

Sample Rankings by sequentially sampling items without replacement.

How do we learn the parameters of the neural network?

[**Singh** & Joachims, NeurIPS 2019]

FAIR-PG-RANK: Policy Gradient for Fair Learning-to-Rank

- Policy Class: Neural Network with Plackett-Luce Sampling π
- Objective: $\pi^* = \operatorname{argmax}_\pi \frac{1}{n} \sum_{i=1}^{n} U(\pi|x_i) - \lambda \cdot D(\pi|x_i)$

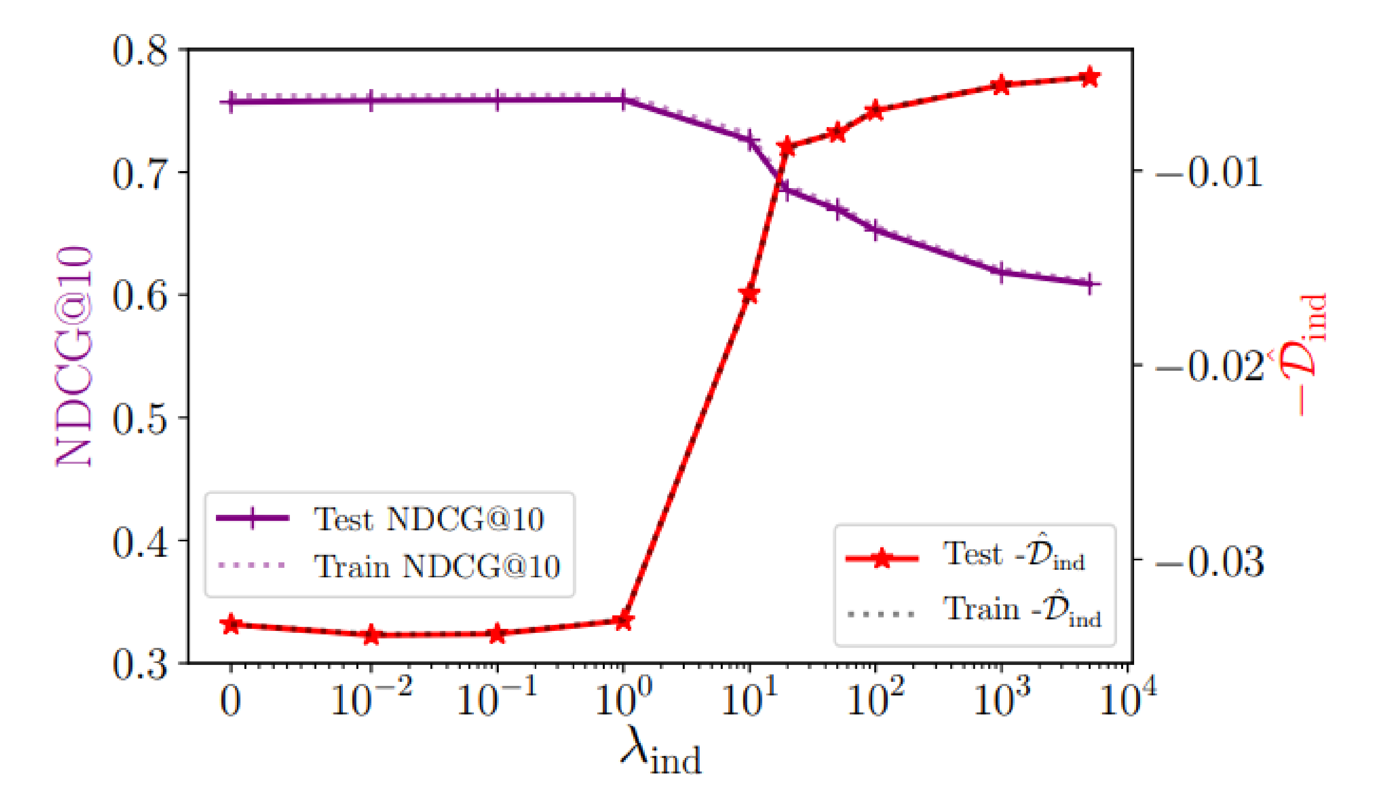
Can optimize an arbitrary U and D metric.

- Training Algorithm:
  - Loss function: REINFORCE loss [Williams'92] with the reward as $U(\pi|x_i) - \lambda \cdot D(\pi|x_i)$.
  - Policy Gradient using Monte-Carlo estimates of gradient.
  - Using Entropy & Variance Regularization.

[**Singh** & Joachims, NeurIPS 2019]

Trade-off between Utility and Disparity

- Data
  - Yahoo! LTR Challenge Dataset
- Fairness Goal
  - Exposure proportional to Relevance
  - Individual Fairness
- Ranking Policy
  - Deep neural network
  - Plackett-Luce sampling



Both Fairness and Utility generalize to test set queries.

[**Singh** & Joachims, NeurIPS 2019]

How does FAIR-PG-RANK handle biased features?

- Two features x_1 and x_2. Relevance $= x_1 + x_2$
- x_2 is biased: informative for G_0 and uninformative for minority G_1.

FAIR-PG-RANK detects biased features.

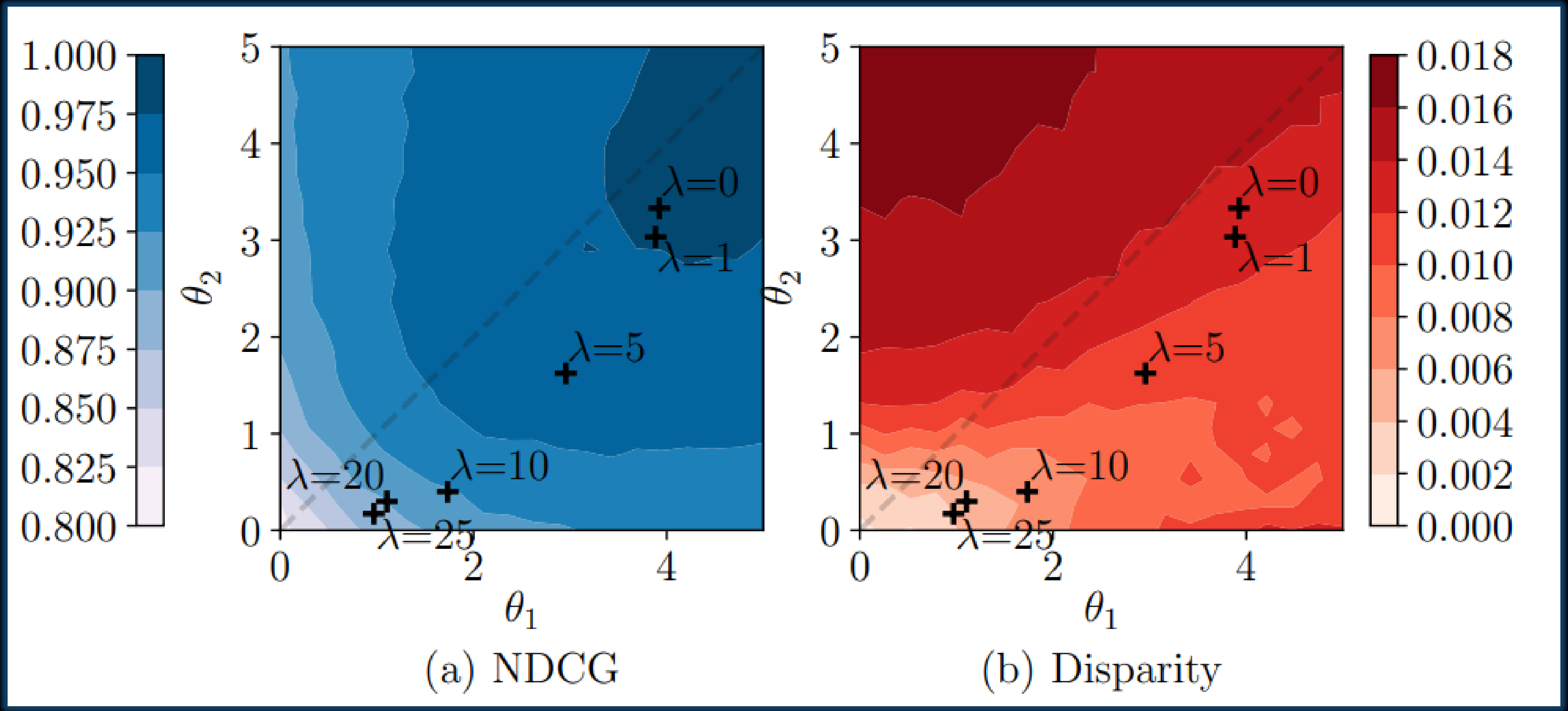


Figure: Visualizing weights of the learned model on two features: one fair, and one biased against the minority group.

[**Singh** & Joachims, NeurIPS 2019]

Outline

1. Fair Allocation of Exposure

[**Singh** & Joachims, KDD 2018]

2. Learning-to-Rank with Fairness Constraints

[**Singh** & Joachims, NeurIPS 2019]

Learn an end-to-end ranking model that:

- Optimizes user utility.
- Generalizes to unseen queries and items.
- Ignores biased features.

Problem: Using clicks instead of ground truth relevance for training.

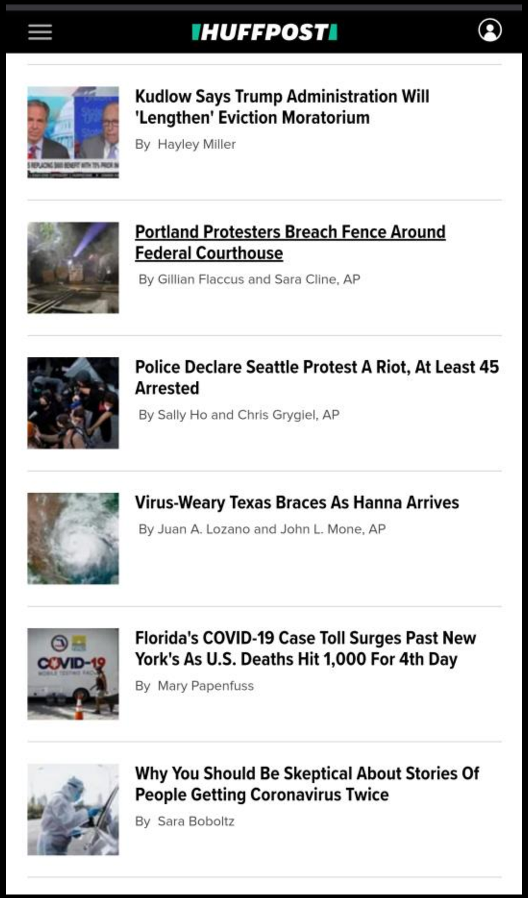
3. Fairness in Dynamic Learning-to-Rank with Biased Feedback

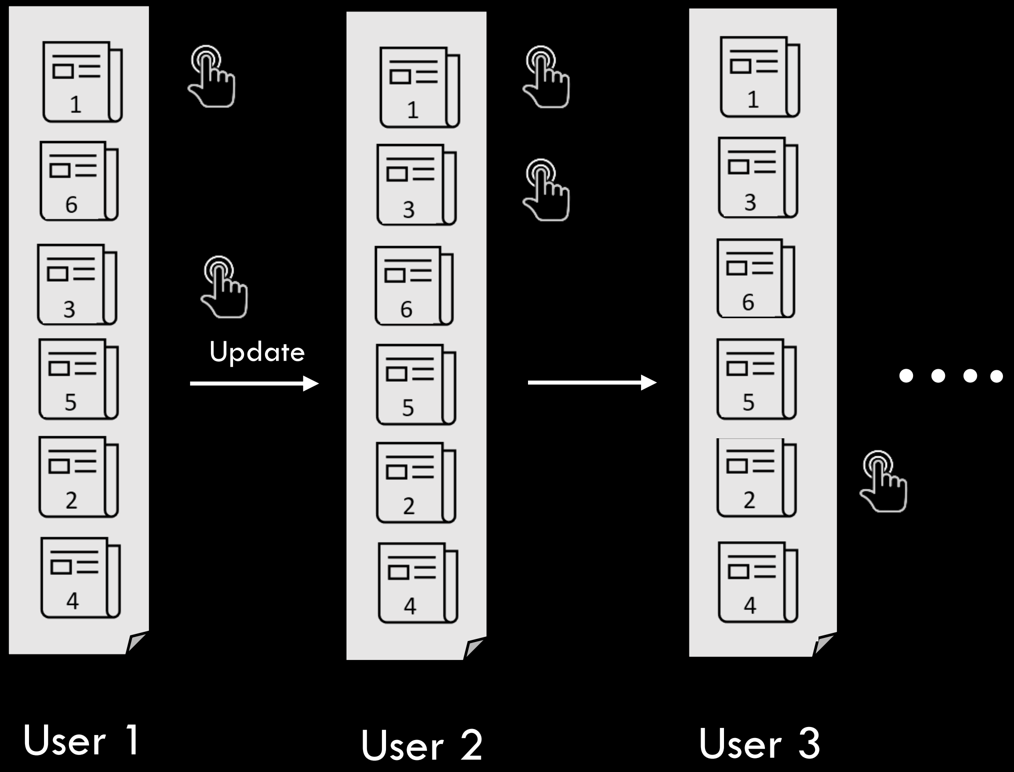
[Morik*, **Singh***, Hong & Joachims, SIGIR 2020 (Best Paper)]

- Partial and biased Click feedback.
- Dynamically adaptive ranking.

Dynamic Learning-to-Rank

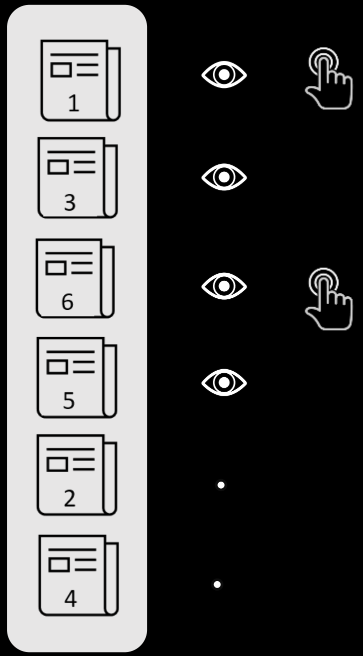
How to train a ranking policy that adapts the ranking to user interactions?





[Morik*, Singh*, Hong & Joachims. SIGIR 2020]

Problem 1: Selection Bias due to position



Position Bias

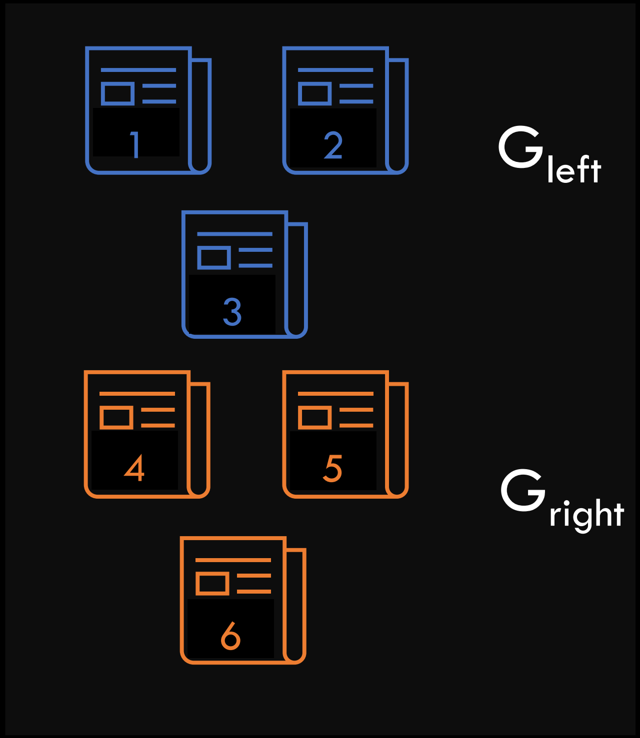
Click count is biased estimator of relevance.

- Lower positions get lower attention.
- Less attention means fewer clicks.

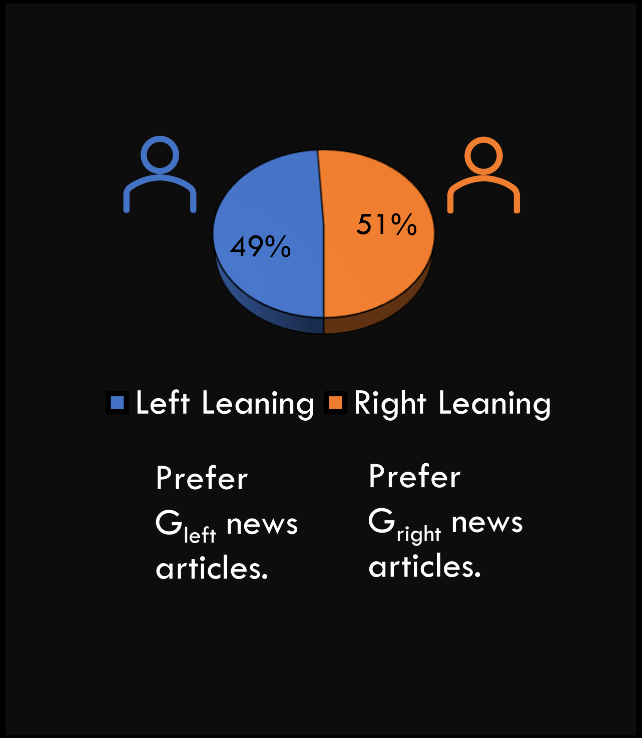
Rich-get-richer dynamic: What starts at the bottom has little opportunity to rise in the ranking.

Problem 2: Exposure Disparity between groups

Item Distribution



User Distribution



Problem: Polarization

Dynamic Learning-to-Rank

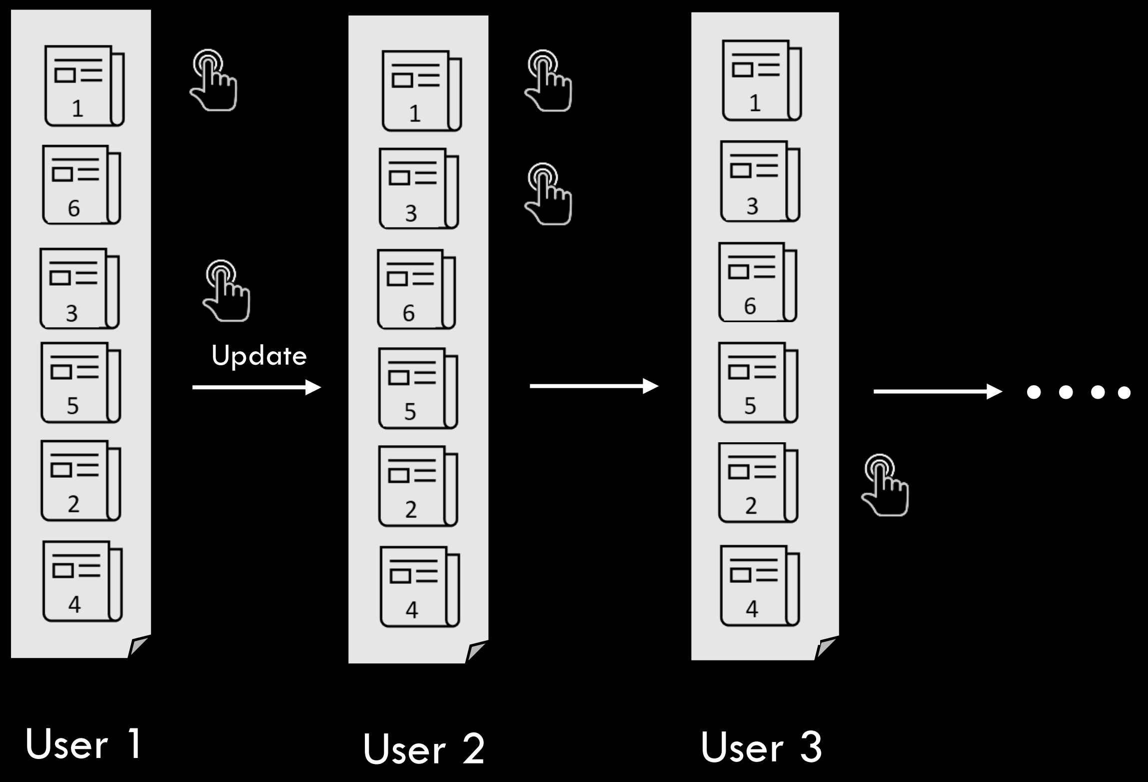
Sequentially present rankings to users to

- Maximize Expected User Utility $\mathbb{E}[U|x]$,
- Ensure Unfairness D_τ goes to 0 with τ,

while learning from **user feedback.**

Problem 1: Selection Bias due to position

Problem 2: Exposure Disparity between groups



[Morik*, Singh*, Hong & Joachims. SIGIR 2020]

Fairness Controller (FairCo) LTR Algorithm

[Morik*, Singh*, Hong & Joachims. SIGIR 2020]

FairCo: Ranking at time τ for query x

$$\sigma_\tau = \mathrm{argsort}_{d \in \mathcal{D}} \left(\hat{R}(d|x) + \lambda \, \mathrm{err}_\tau(d) \right)$$

P-Controller:
Linear feedback control system where correction is proportional to the error.

$\hat{R}(d|x)$: Estimated Conditional Relevance

Problem 1: Selection Bias

$\lambda > 0$

$err_\tau(d) = (\tau - 1) \max_{G_i} (\hat{D}_\tau^E(G_i, G(d)))$

Problem 2: Exposure Disparity

Theorem:

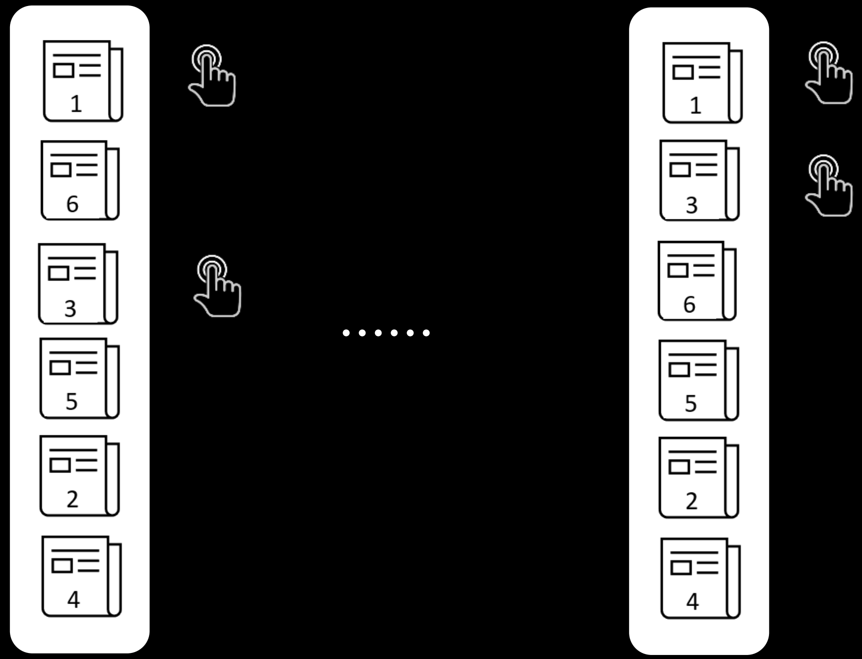
When the problem is well posed, FairCo ensures that $\overline{D_\tau} \rightarrow 0$ as $\tau \rightarrow \infty$ at the rate of $\mathcal{O}\left(\frac{1}{\tau}\right)$.

Estimating Relevances from Clicks

Data

- Query Distribution: $x_j \sim \mathbb{P}(X)$
- Deployed Rankings: $y_{\mathrm{t}} = \pi_t(x_t)$
- Feedback: *clicks*, purchases, plays, reads, etc.

Question: Clicks $\xrightarrow{?}$ Relevance



Average number of clicks is not a consistent estimator of relevance because the feedback is **biased** by:

- Deployed ranker
- User's position bias

Estimating Relevances from Clicks

Question: Clicks $\xrightarrow{?}$ Relevance

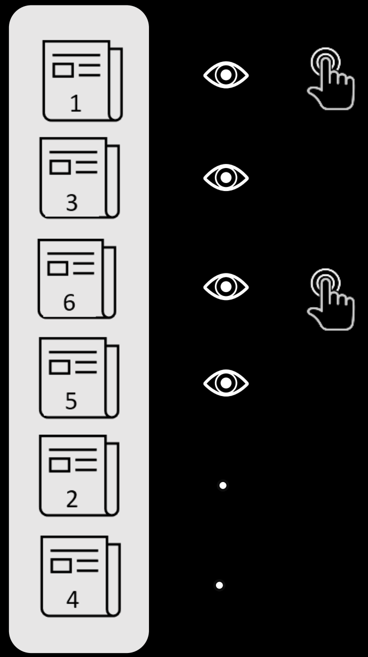
Key Idea: Understand the Observation Mechanism [Joachims et al., 2017].

Assume a Position-based Model:

$$click_i = 1 \leftrightarrow (obs_i = 1) \wedge (rel_i = 1)$$

Problem:

$$click_i = 0 \leftrightarrow (obs_i = 0) \vee (rel_i = 0)$$



Estimating Relevances from Clicks

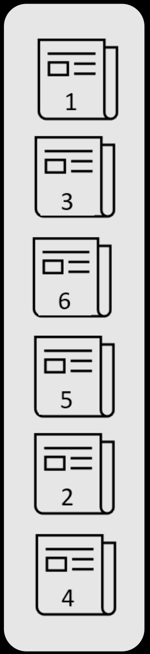
Propensity: $p(d) = P[obs(rank(d)) = 1 \mid y]$

- Can use position-based exposure e_j as an estimate.

Inverse Propensity Score (IPS) Weighting

$$\hat{R}_\tau^{IPS}(d) = \frac{1}{\tau}\sum_{i=1}^{\tau} \frac{click_t(d)}{p_t(d)}.$$

Unbiased estimator of relevance



p
1
0.7
0.5
0.4
0.3
0.2

Estimating Relevances from Clicks

To estimate: $\hat{R}^w(d|\boldsymbol{x_t})$ – Relevance of document d for query $\boldsymbol{x_t}$.

$$\mathcal{L}^c(w) = \sum_{t=1}^{\tau} \sum_{d} \hat{R}^w(d|x_t)^2 + \frac{c_t(d)}{p_t(d)} \left(c_t(d) - 2\,\hat{R}^w(d|x_t)\right)$$

$\hat{R}^w$	Output of a Neural Network with weights w.
$c_t(d)$	Click on d at time t.
$p_t(d)$	Position bias at position of d.

- Train a neural network by minimizing $\mathcal{L}^c(\mathrm{w})$.
- $\mathcal{L}^c(\mathrm{w})$ is unbiased i.e., in expectation, $\mathcal{L}^c(\mathrm{w})$ is equal to a full information squared loss (with no position bias).

[Morik*, Singh*, Hong & Joachims. SIGIR 2020]

Fairness Controller (FairCo) LTR Algorithm

[Morik*, Singh*, Hong & Joachims. SIGIR 2020]

FairCo: Ranking at time τ for query x

$$\sigma_\tau = \text{argsort}_{d \in \mathcal{D}} \left(\hat{R}(d|x) + \lambda \, \text{err}_\tau(d) \right)$$

$\hat{R}(d|x)$: Estimated Conditional Relevance

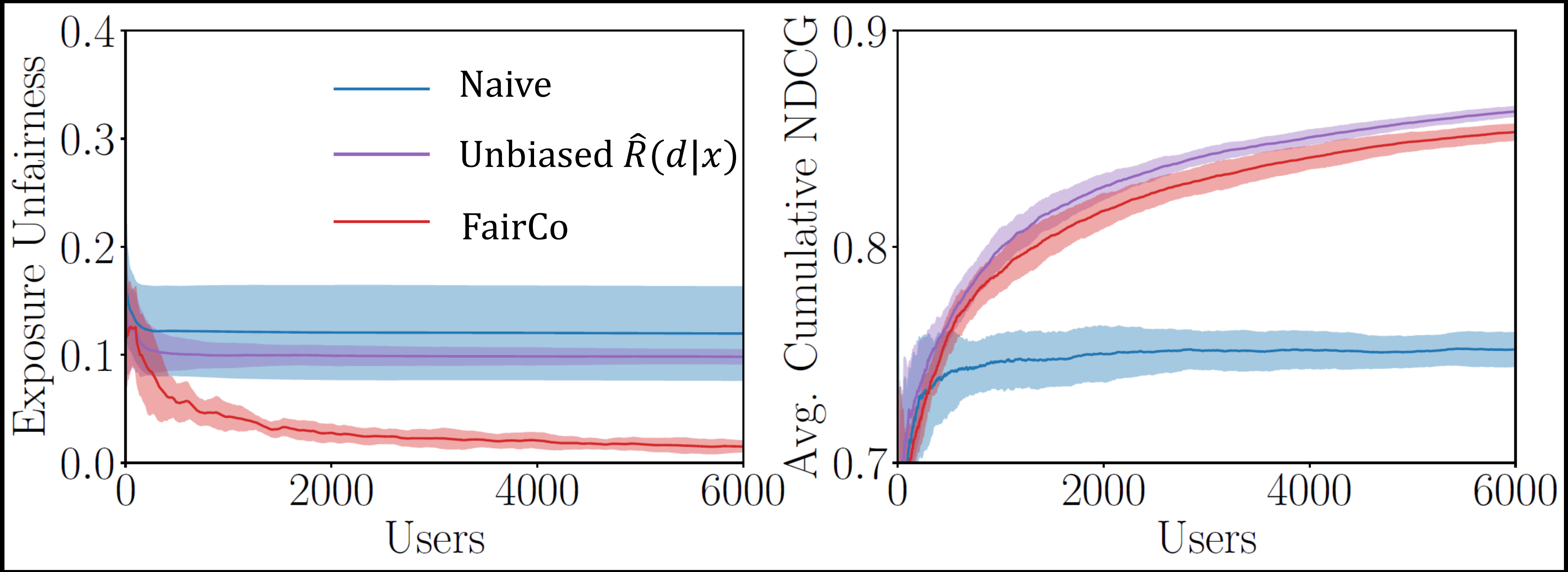
$\lambda > 0$

$$err_\tau(d) = (\tau - 1) \max_{G_i} (\widehat{D}_\tau^E (G_i, G(d)))$$

Problem 1: Selection Bias

Problem 2: Exposure Disparity

Does FairCo ensure fairness with effective personalization?



Personalized Rankings with FairCo achieve high utility (NDCG), while also reducing Unfairness to 0 with τ.

[Morik*, Singh*, Hong & Joachims. SIGIR 2020]

Can FairCo break the Rich-get-richer dynamic?

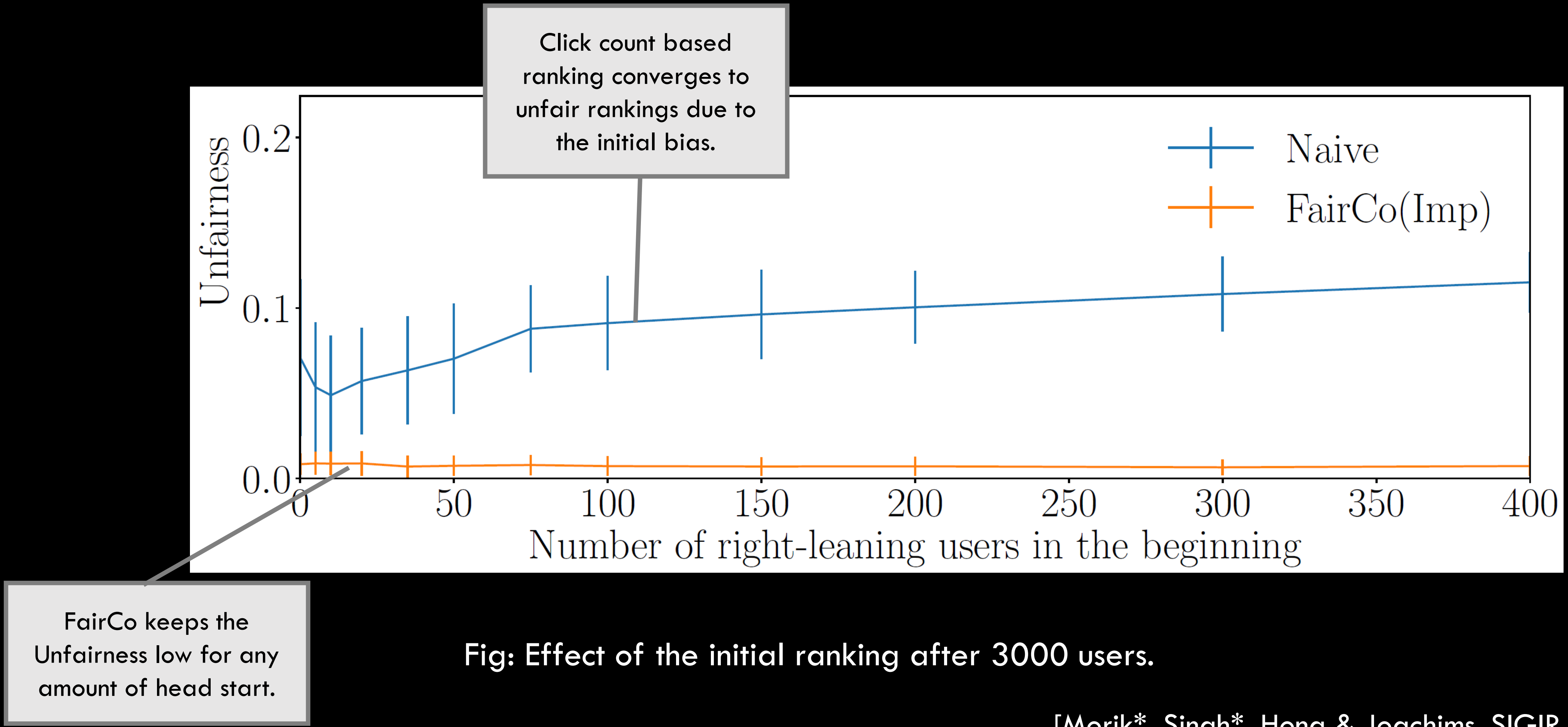
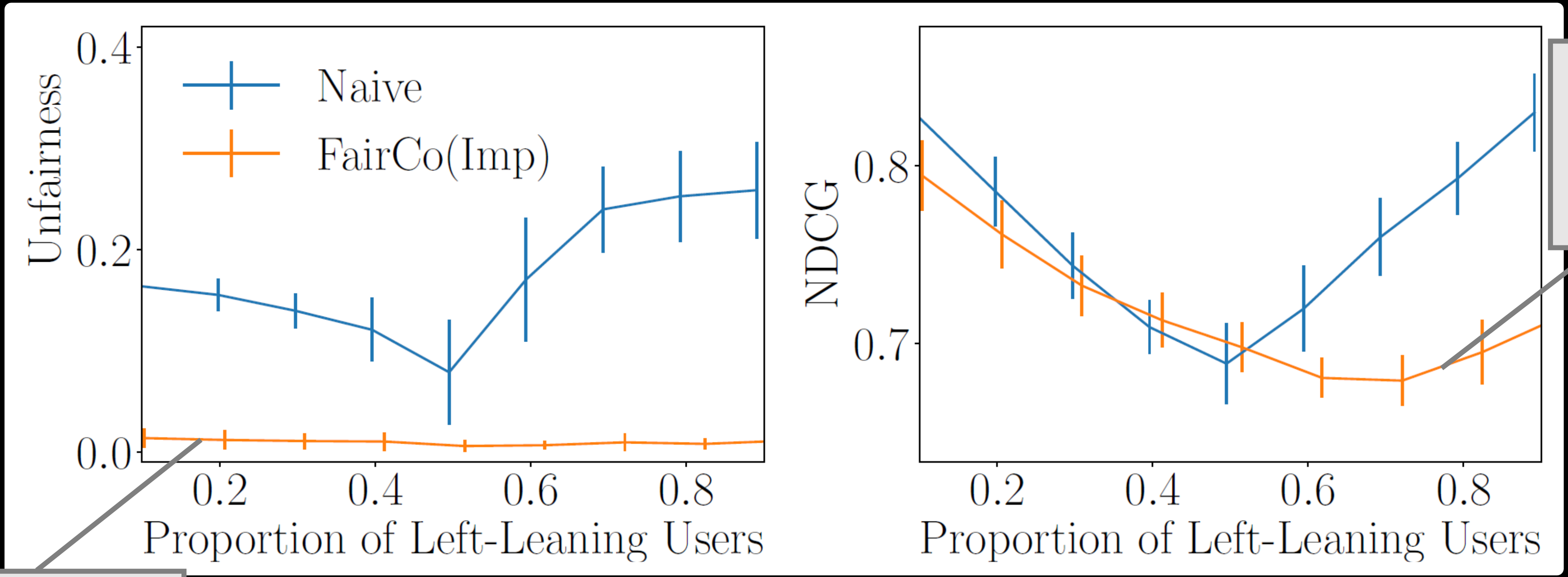


Fig: Effect of the initial ranking after 3000 users.

[Morik*, Singh*, Hong & Joachims. SIGIR 2020]

Can FairCo ensure fairness for Minority user groups?



Trades off utility for fairness when there is an imbalance in user distribution.

FairCo converges to fair ranking for all user distributions.

[Morik*, Singh*, Hong & Joachims. SIGIR 2020]

Outline

1. Exposure-based Fairness for Rankings

[**Singh** & Joachims, KDD 2018]

2. Learning-to-Rank with Fairness Constraints

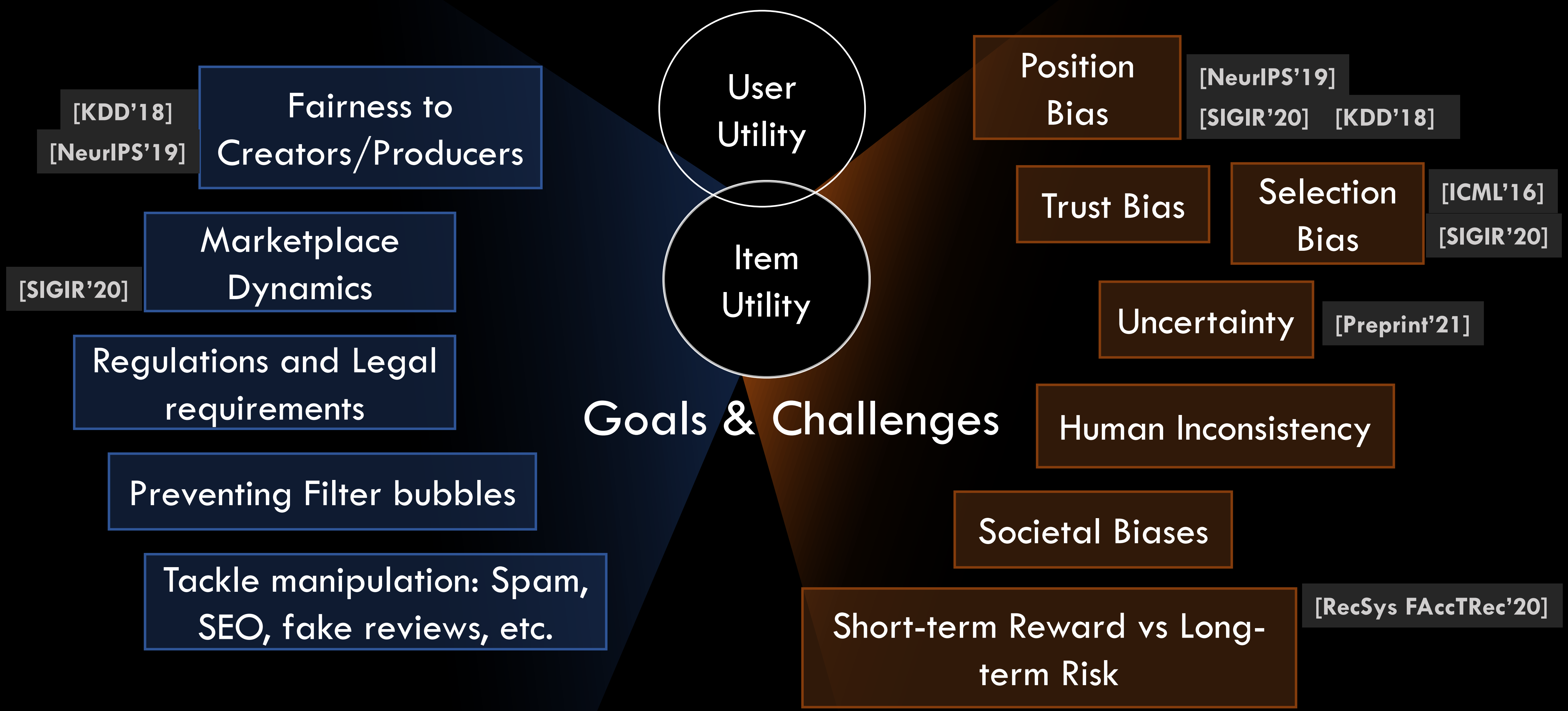
[**Singh** & Joachims, NeurIPS 2019]

3. Fairness in Dynamic Learning-to-Rank with Biased Feedback

[Morik*, **Singh***, Hong & Joachims, SIGIR 2020 (Best Paper)]

1. **Selection bias**: Use unbiased estimators to learn relevance from clicks.
2. **Fairness**: The controller minimizes disparity over time.

Ranking and Recommendations in two-sided markets

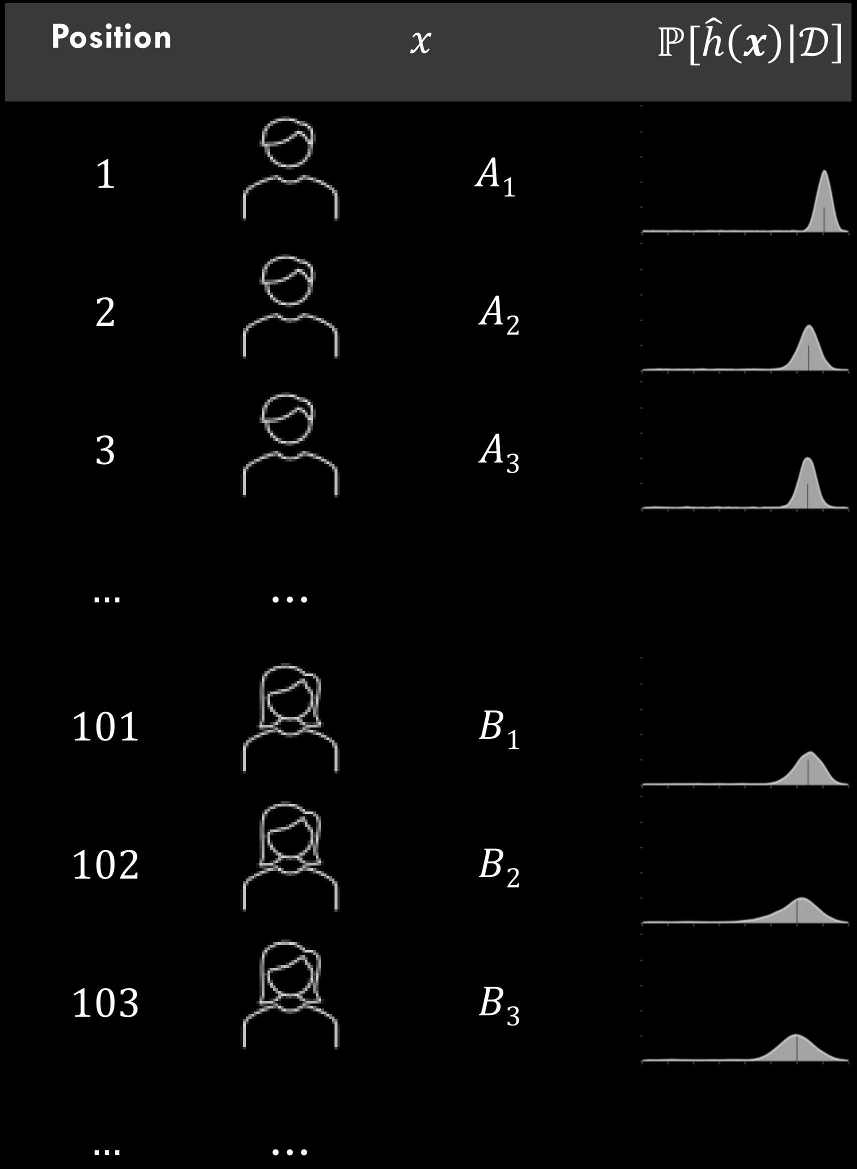


Fairness under Uncertainty in Merit Estimates

- Ranking Policy that *respects* the uncertainty in merits.

- Such a fairness notion incentivizes the system to more equitably evaluate the merits of the items.

[**Singh,** Kempe & Joachims. 2021 *(Under Submission)*]



Ranking and Recommendations in two-sided markets

User Utility

Item Utility

Goals & Challenges

- [KDD'18] [NeurIPS'19] Fairness to Creators/Producers
- [SIGIR'20] Marketplace Dynamics
- Regulations and Legal requirements
- Preventing Filter bubbles
- Tackle manipulation: Spam, SEO, fake reviews, etc.

- Position Bias [NeurIPS'19] [SIGIR'20] [KDD'18]
- Trust Bias
- Selection Bias [ICML'16] [SIGIR'20]
- Uncertainty [Preprint'21]
- Human Inconsistency
- Societal Biases
- Short-term Reward vs Long-term Risk [RecSys FAccTRec'20]

Ranking and Recommendations in two-sided markets

User Utility

[KDD'18]
[NeurIPS'19]
Fairness to Creators/Producers

[SIGIR'20]

Preventing Filter bubbles

Tackle manipulation: Spam, SEO, fake reviews, etc.

Position Bias
[NeurIPS'19]
[SIGIR'20] [KDD'18]

Trust Bias

Selection
[ICML'16]

Societal Biases

Short-term Reward vs Long-term Risk
[RecSys FAccTRec'20]

Search and Recommender systems are the arbiters of exposure in modern two-sided online platforms.

For the long-term well-being, ranking algorithms should be able to consider utility and fairness for both users as well as creators and producers.

Acknowledgements

Thorsten Joachims
(Ph.D. Advisor)

Committee Members: David Mimno, Karthik Sridharan, Solon Barocas

Co-authors and Collaborators





Research Group






Internships

Grants and Gifts

IIS-2008139, IIS-1247637, IIS-1217686, IIS-1615706, IIS-1513692

Acknowledgements

Family and friends

Thank you

Questions and comments.

Slides:
www.ashudeepsingh.com/phd-thesis