

# Comparing Fair Ranking Metrics

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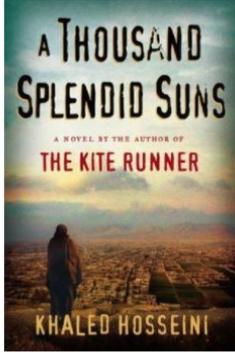
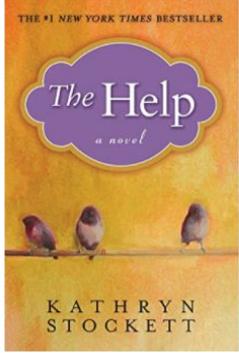
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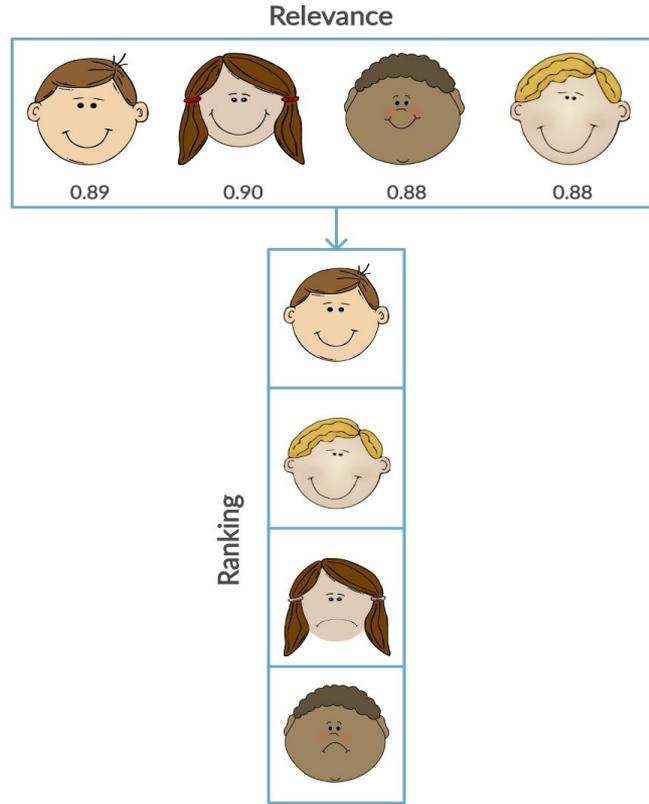
Trending Now



# Motivation



Bias in ranking

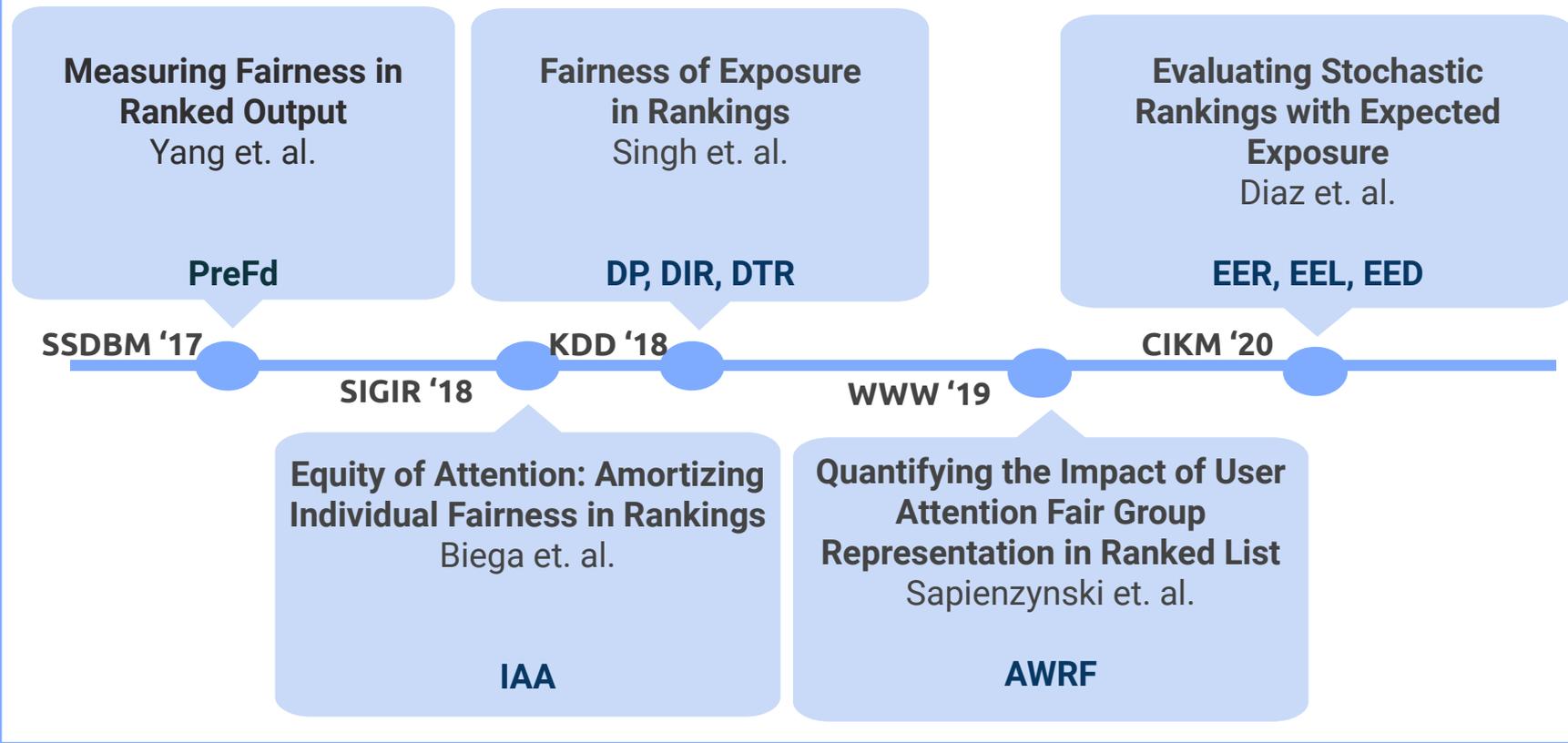


Disparate exposure

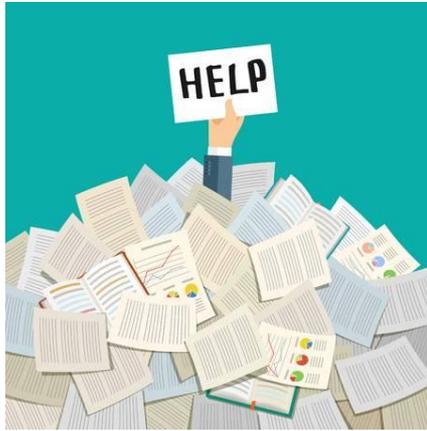


Several metrics to measure (un)fairness

# Fair Ranking Metrics Resources



## Why the problem is a problem!



Several metrics to  
measure (un)fairness



Finding the suitable  
metric

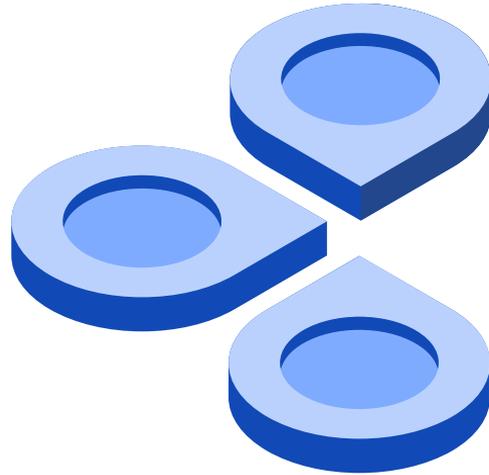


Differences among  
the metrics

# Contribution

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Describe and compare exposure and rank-fairness metrics in **unified** framework



Identify gaps between their original presentation and the practicalities of applying them to recommender systems

Direct comparison of their outcomes with the same data and experimental setting

# Fairness Positioning



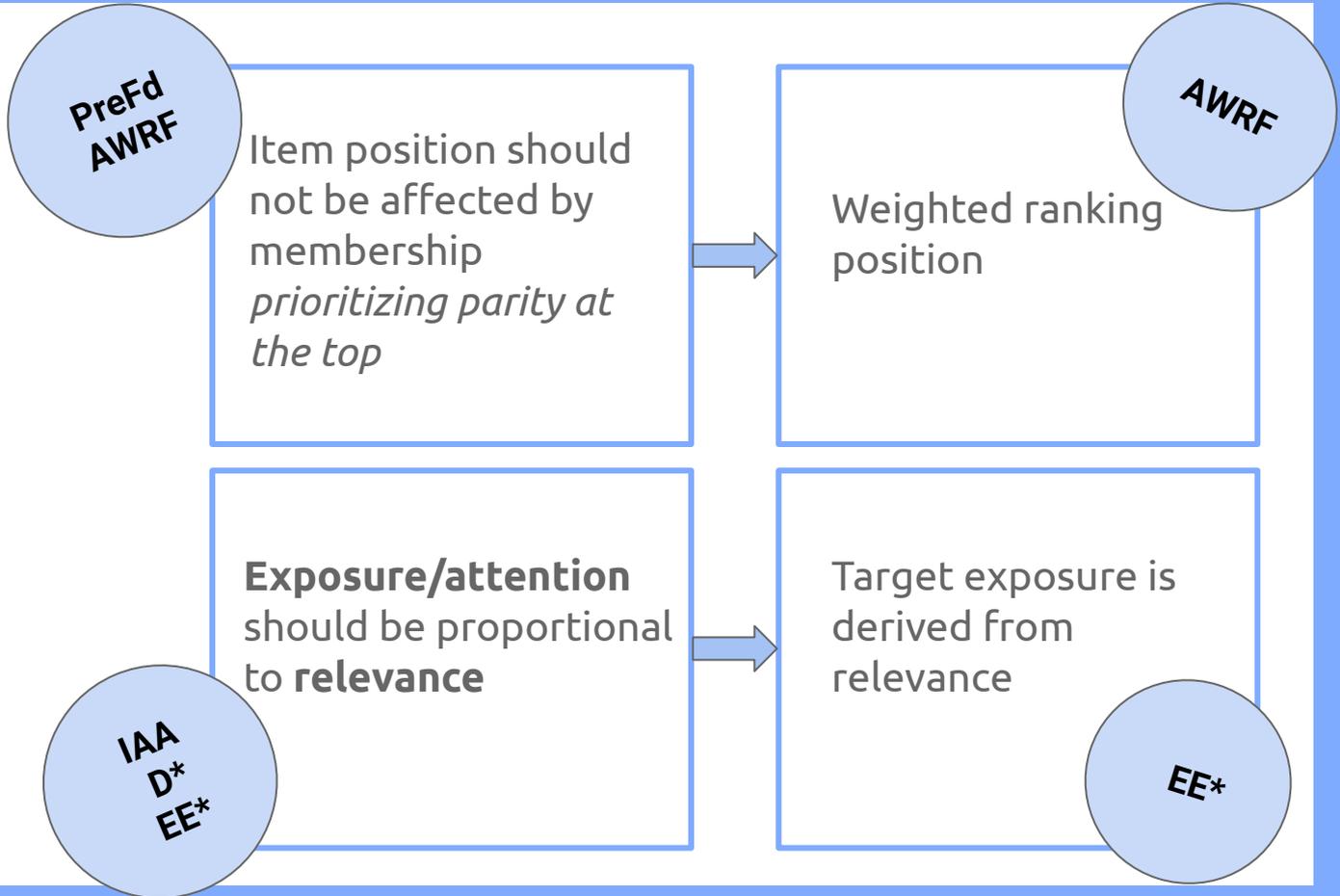
**Provider fairness**



**Group fairness**

# Fairness Definition

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# Classification of Fair Ranking Metrics

## Single-List Metric

PreFd  
AWRF

## Distribution and Sequence Metrics

IAA  
D\*  
EE\*

# Summary of Fair Ranking Metrics

Metric(s)	Goal	Weighting	Relevance	Binary
PreFd	Each prefix representative of whole ranking	✗	✗	Dep on d
AWRF	Weighted representation matches population	Geometric	✗	✗
DP	Exposure equal across groups	Logarithmic	✗	✓
DTR	Exposure proportional to relevance	Logarithmic	✓	✓
DIR	Discounted gain proportional to relevance	Logarithmic	✓	✓
IAA	Exposure proportional to predicted relevance	Geometric	Predicted	✗
EEL, EER	Exposure matches ideal (from relevance)	Cascade, Geom	✓	✗
EED	Exposure well-distributed	Cascade, Geom	✗	✗

# Experimental Setup

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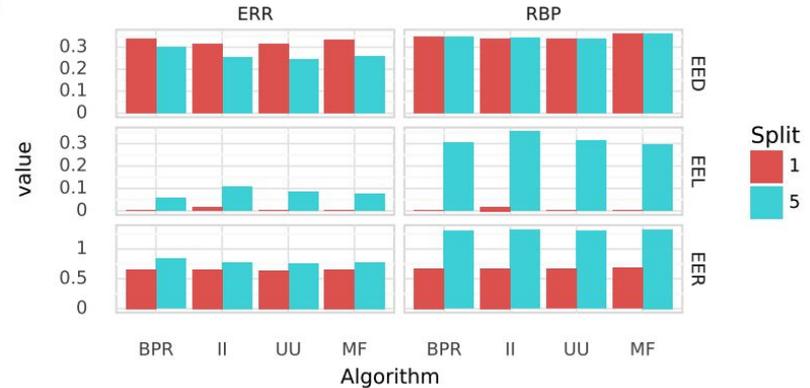
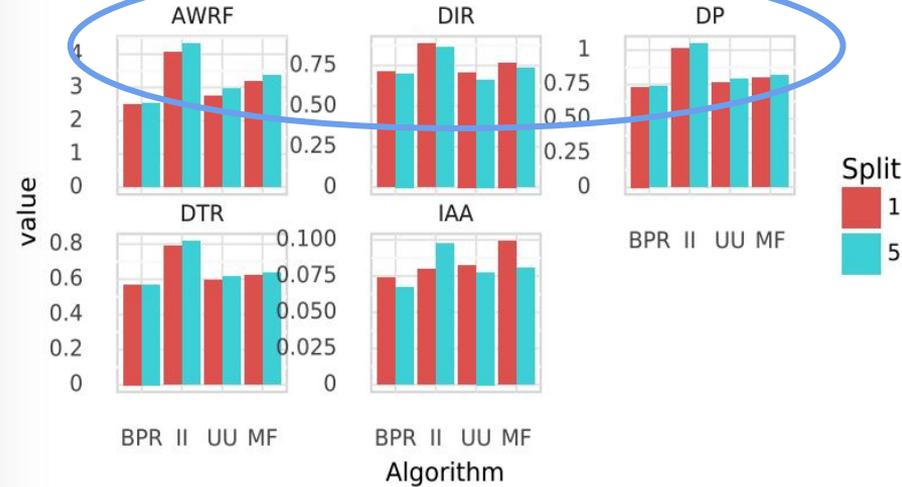
- Dataset
  - GoodReads book data (implicit feedback)
- Sensitive Attribute
  - Gender of author
- Recommendation Algorithms
  - user-based CF (UU)
  - item based CF (II)
  - matrix factorization (MF) and
  - Bayesian Personalized Ranking (BPR)

Two samples of 5000 users

- Split 1: each user rated at least **5** books, **1** held out
- Split 5: each user rated at least **10** books; **5** held out

# Comparative Analysis

- Algorithms did not show significant differences on most metrics (exception: II)
- Size of relevance set has more effect on  $EE^*$  than the choice of user model
- No clear agreement



# Conclusion

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## Summary

- Unified the metrics under one framework
- Metrics are surprisingly similar
- Direct comparison did not provide conclusive result
- Missing pieces in implementing on real data

**Request for Feedback!!!**



## Future Work

- Missing labels
- Missing Relevance
- Sensitivity analysis
- More metrics
- More datasets



# Fair Ranking Metrics

<b>PreFd</b> Prefix Fairness Family	<b>AWRF</b> Attention-Weighted Rank Fairness	<b>IAA</b> Inequity of Amortized Attention
<b>DP</b> Demographic Parity	<b>DTR</b> Disparate Treatment Ratio	<b>DIR</b> Disparate Impact Ratio
<b>EEL</b> Expected Exposure Loss	<b>EER</b> Expected Exposure Relevance	<b>EED</b> Expected Exposure Disparity