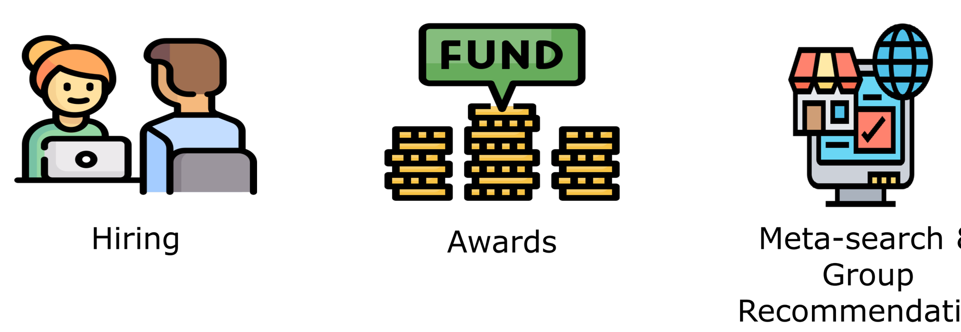
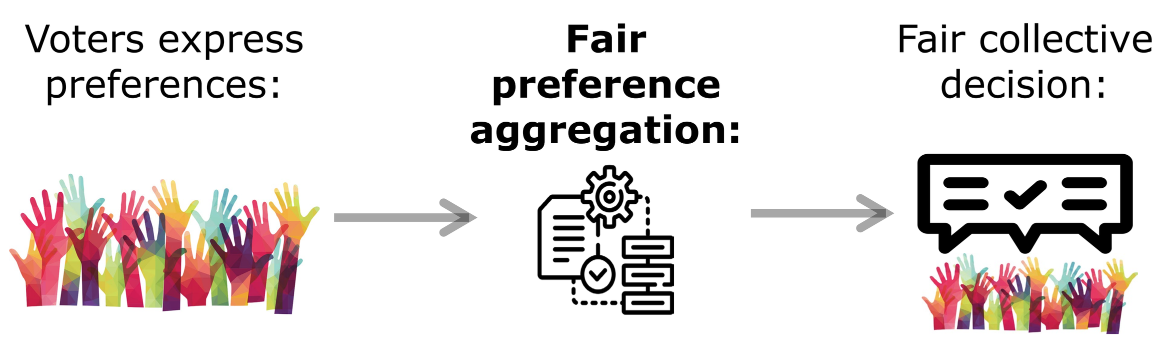
# Ranked Candidate Fairness in Preference Aggregation

## Preference Aggregation Domains & Applications

Social Choice & Information Retrieval.




## Fair Preference Aggregation




1. Unbiased (fair) decisions for ranked candidates
2. Represent voter preferences as much as possible

## Intersectional Fair Preference Aggregation [1]

Pairwise fair ranking metrics for multi-group attributes and intersectional groups.

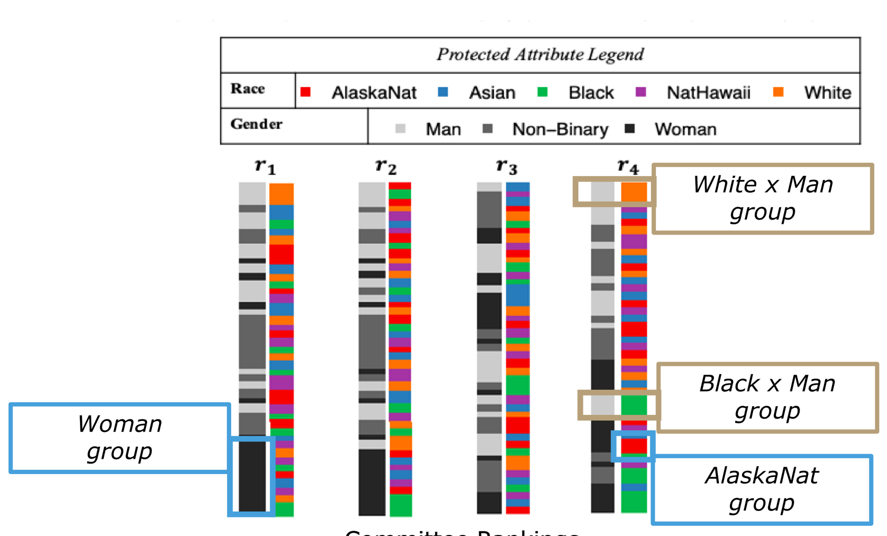
MANI-RANK problem - Multi-attribute and intersectional fair consensus rankings.

Design PFair-Kemeny to solve MANI-RANK.

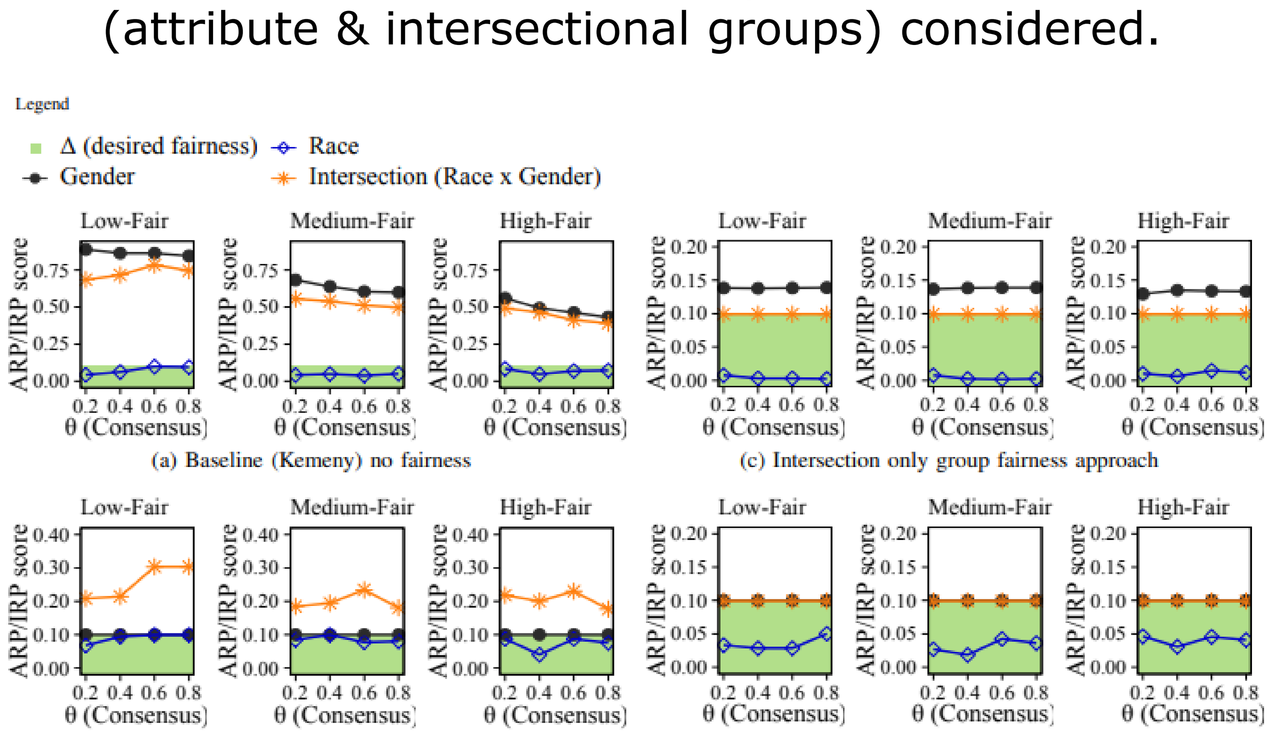
**MANI-RANK fairness:**

$$ARP_{p^k}(\pi) \leq \Delta \ (\forall\ p^k \in \mathcal{P})$$ multi-group pairwise fairness

$$IRP(\pi) \leq \Delta$$ intersectional pairwise fairness



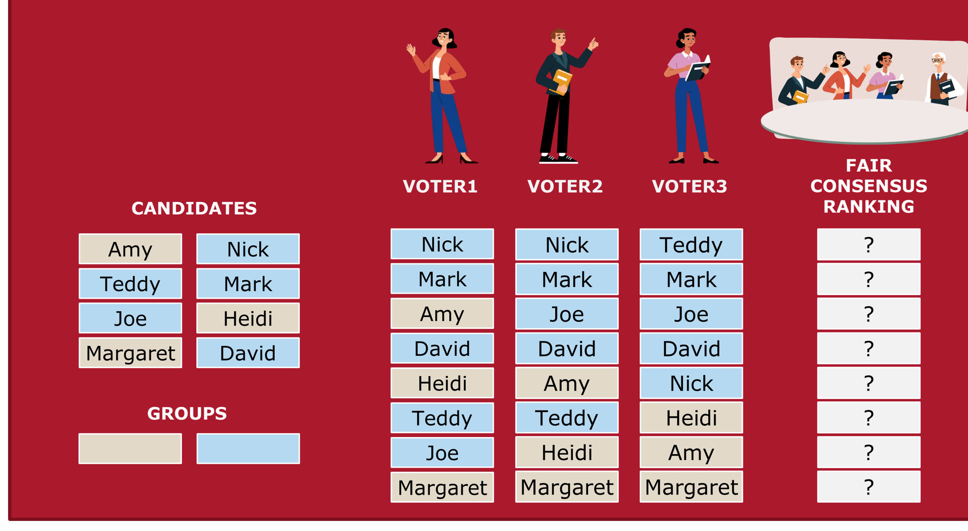

Intersectional Fairness only arises when all (attribute & intersectional groups) considered.




## References

[1] Cachel, Kathleen, Elke A. Rundensteiner and Lane Harrison. "MANI-Rank: Multiple Attribute and Intersectional Group Fairness for Consensus Ranking." *IEEE ICDE* (2022).
[2] Shrestha, Hilson, Kathleen Cachel, Mallak Alkhathlan, Elke A. Rundensteiner and Lane Harrison. "Help or Hinder? Evaluating the Impact of Fairness Metrics and Algorithms in Visualizations for Consensus Ranking." *ACM FAccT*(2023).
[3] Cachel, Kathleen and Elke A. Rundensteiner. "Fairer Together: Mitigating Disparate Exposure in Kemeny Rank Aggregation." *Proceedings of the 2023 ACM FAccT* (2023).
[4] Singh, Ashudeep and Thorsten Joachims. "Fairness of Exposure in Rankings." *ACM SIGKDD* (2018).

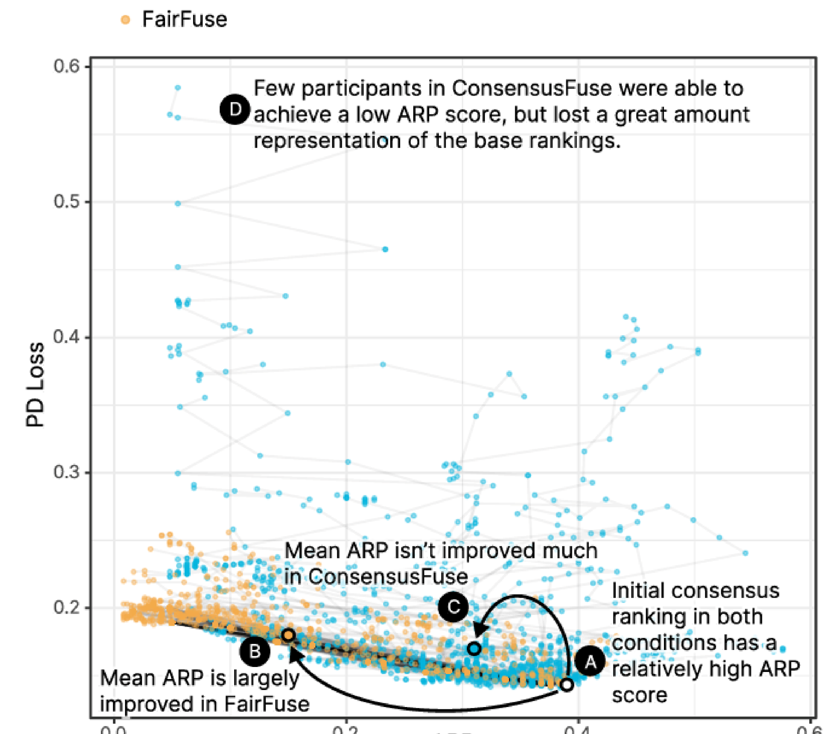
How can voters make collective decisions over candidates in such a manner that is unbiased (fair) towards marginalized groups of candidates?




## Effects of Interactive Fair Preference Aggregation [2]

FairFuse interactive consensus ranking system.

We compare two visualization systems for fair consensus ranking, with task-based evaluation results highlighting the value and challenges of visualizing fairness metrics & algorithms.


Good visualizations can help users navigate complexity.

Visually displaying metrics can lead to an increase credence in and over-reliance of fairness metrics.

## Acknowledgements

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## Fair Exposure Preference Aggregation [3]

Introduction of Fair Exposure Kemeny Rank Aggregation.

**Fair-Exp KAP:** Find ranking $r$ such that

1. *Exposure Ratio*$(r) \geq \gamma$

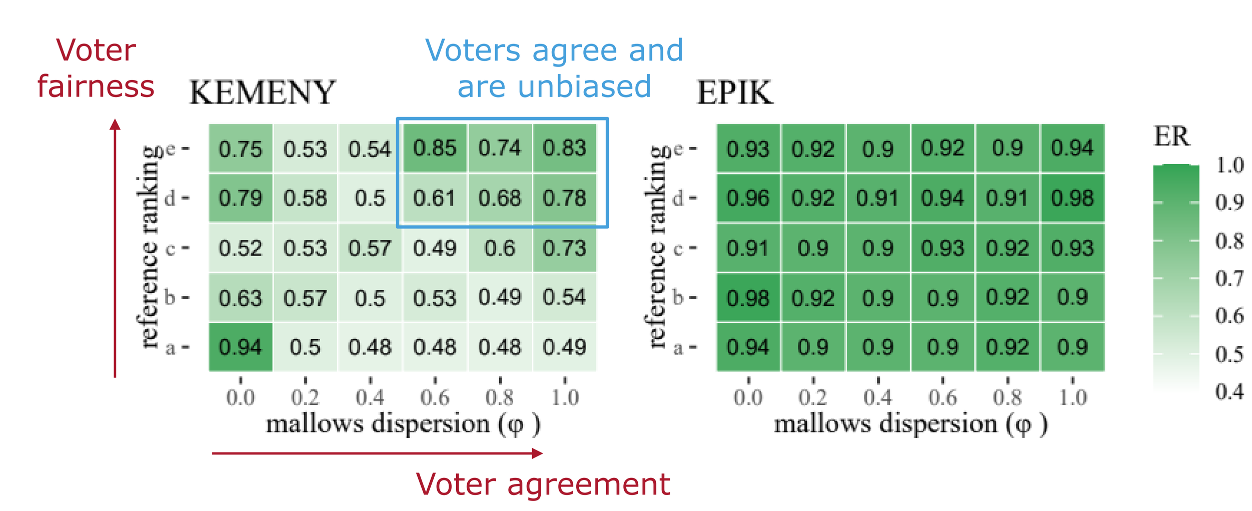
Candidate fairness sensitive to position bias.
Using fairness of exposure from Singh et al. [4].

2. Maximize *Consensus Accuracy*$(r \mid prefs)$

Combines and maximizes preference representation.
Using Kendall-tau (Kemeny) distance.

Introduce two fairness-tunable methods EPIK (Exposure Parity in Kemeny) & EPIRA (Exposure Parity in Rank Aggregation).

Experimentally find while Kemeny is fair in certain instances only EPIK is always fair.




Methods with alternate fairness goals can introduce unfairness (disparate exposure).

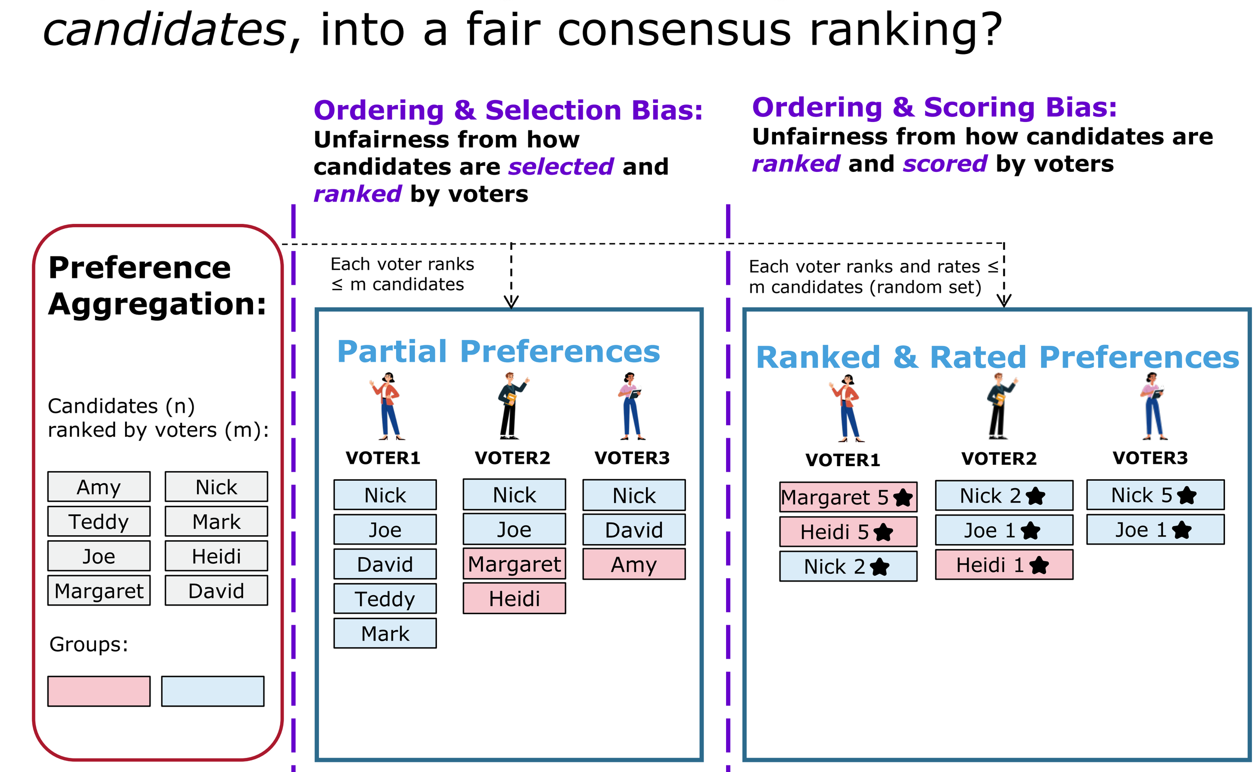
| Dataset | Metric | KEMENY | EPIK $\gamma = .95$ | EPIRA $\gamma = .95$ | PFAIR-KEM $\delta = .1$ | RAPF | PRE-FE $\gamma = .95$ |
|---|---|---|---|---|---|---|---|
| *AGH 2003* | consensus accuracy (CA) | 0.7536 | 0.6897 | 0.6714 | 0.7456 | 0.7190 | 0.7536 |
| | group A avg. exposure | 0.4343 | 0.4796 | 0.4680 | 0.4305 | 0.4329 | 0.4343 |
| | group B avg. exposure | 0.5496 | 0.4590 | 0.4821 | 0.5572 | 0.5524 | 0.5496 |
| | exposure ratio (ER) | 0.7902 | 0.9572 | **0.9707** | 0.7725 | 0.7836 | 0.7902 |

Paper includes 6 additional datasets.

## Work in Progress

How can we combine *incomplete voter preferences* into a suitable consensus mitigating both discriminatory bias in voter rankings and in the selection of who is ranked?

How can we combine voter preferences, expressed as *rankings and ratings of candidates*, into a fair consensus ranking?

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