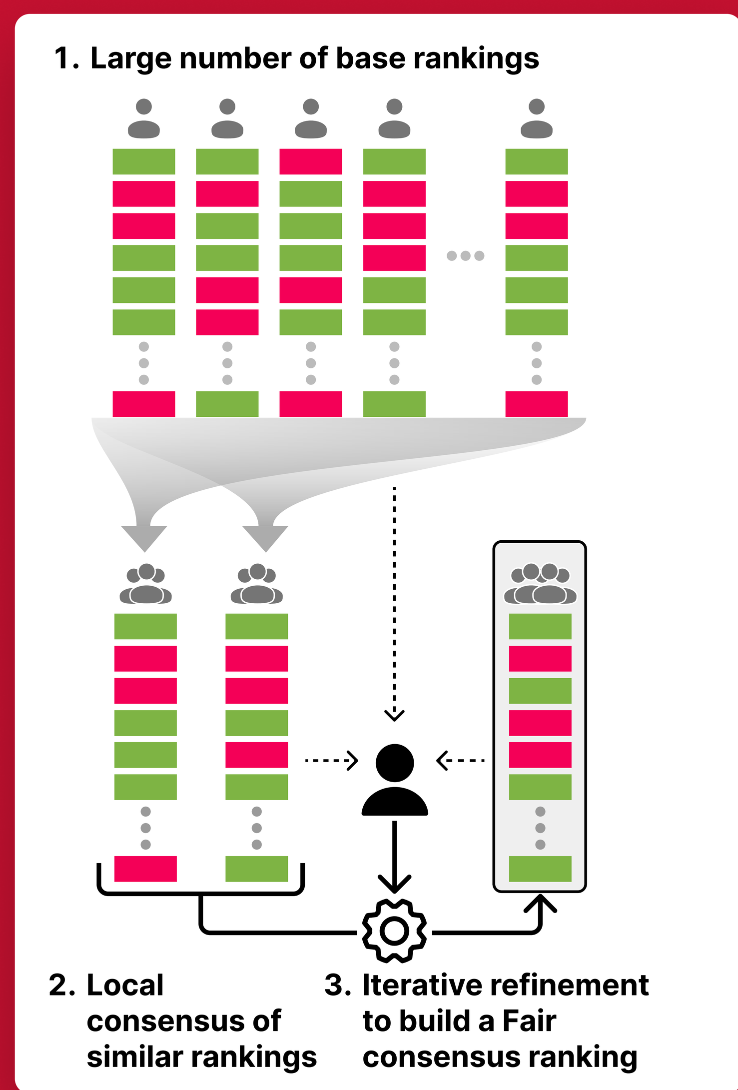
Exploring Fairness across Many Rankings

Hilson Shrestha, Kathleen Cachel, Mallak Alkhathlan, Elke Rundensteiner, **Lane Harrison**



Understand the reasons behind a fair consensus ranking to make informed decision-making

Effectively aggregate and visualize consensus patterns within large-scale ranking data

FairSpace uses a dimensional reduction technique, specifically Multidimensional Scaling (MDS), to visualize the large number of rankings.

1. How can we ensure fairness when people make consequential decisions with rankings?

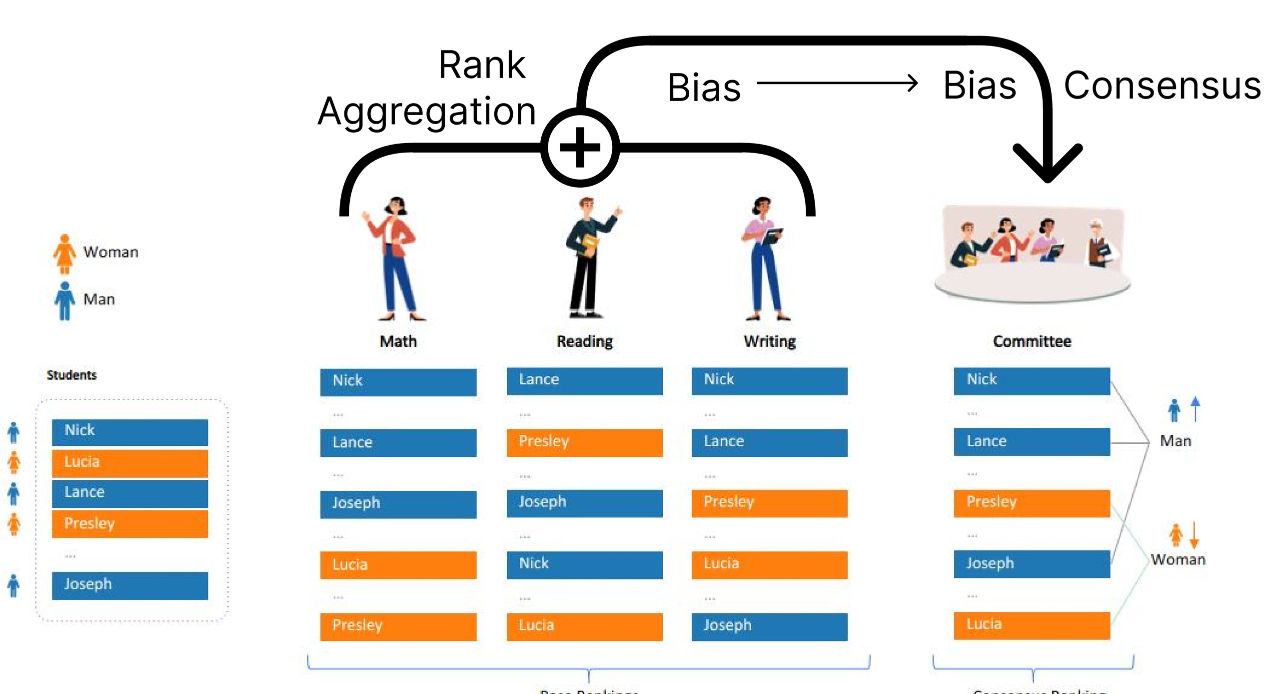
Employee Hiring | Resource Allocation | Scholarships Distribution

People often collaborate with one another, and increasingly with AI systems, when making significant decisions.

2. Challenges

Time | Group Bias | Complexity

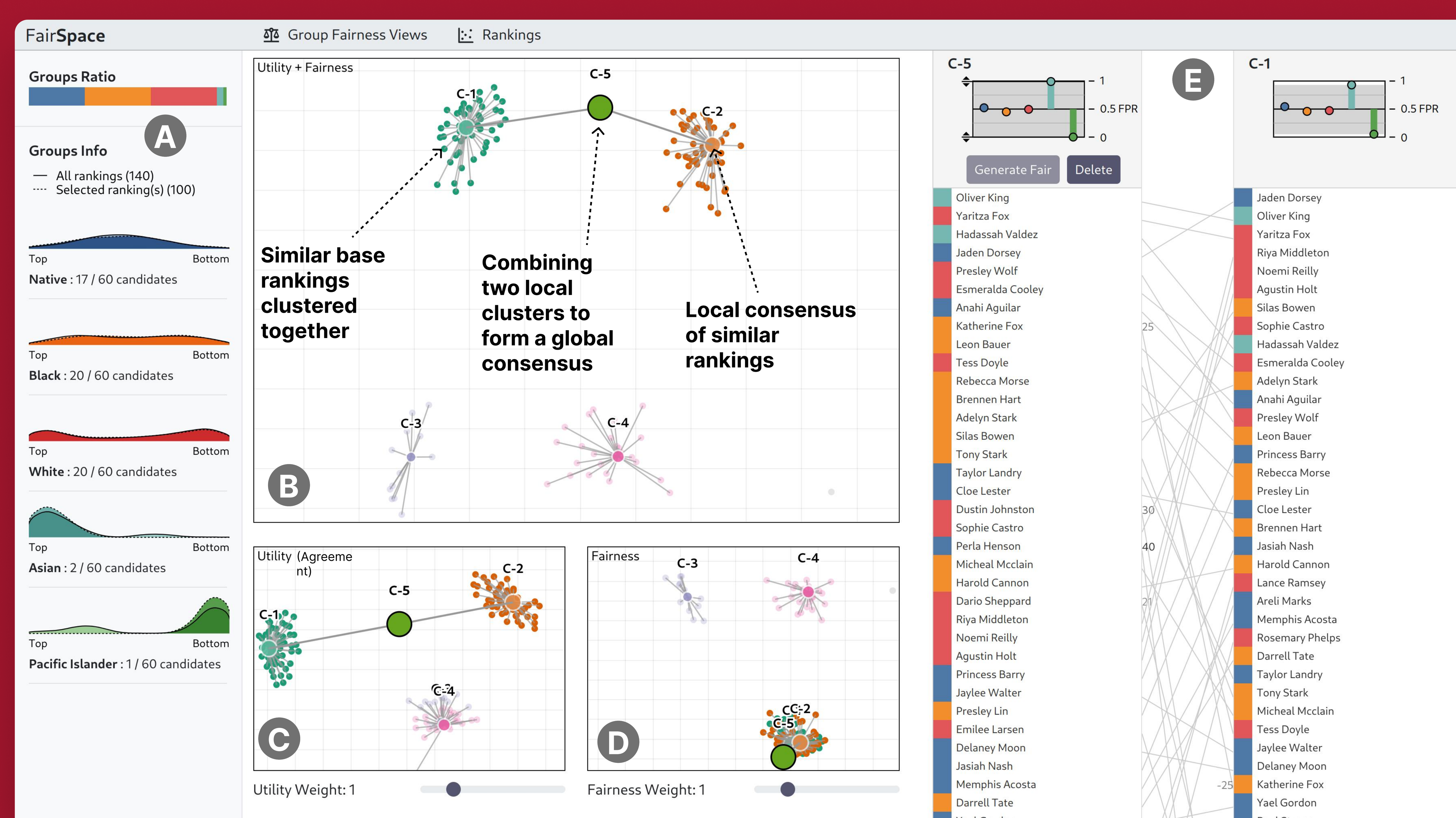
The process of building a consensus ranking is 🕘 time consuming[1] and may surface ⚖ unfair biases in individual or group decision-making:



Integrating large number of individual rankings is even more challenging with additional complexity of maintaining fairness and consensus.

3. Contributions

- Design human-in-the-loop visual analytics systems to enable fair decision making when large number of rankings are involved.
- Enable biases and agreement comparison between and within (dis)similar set of rankings.

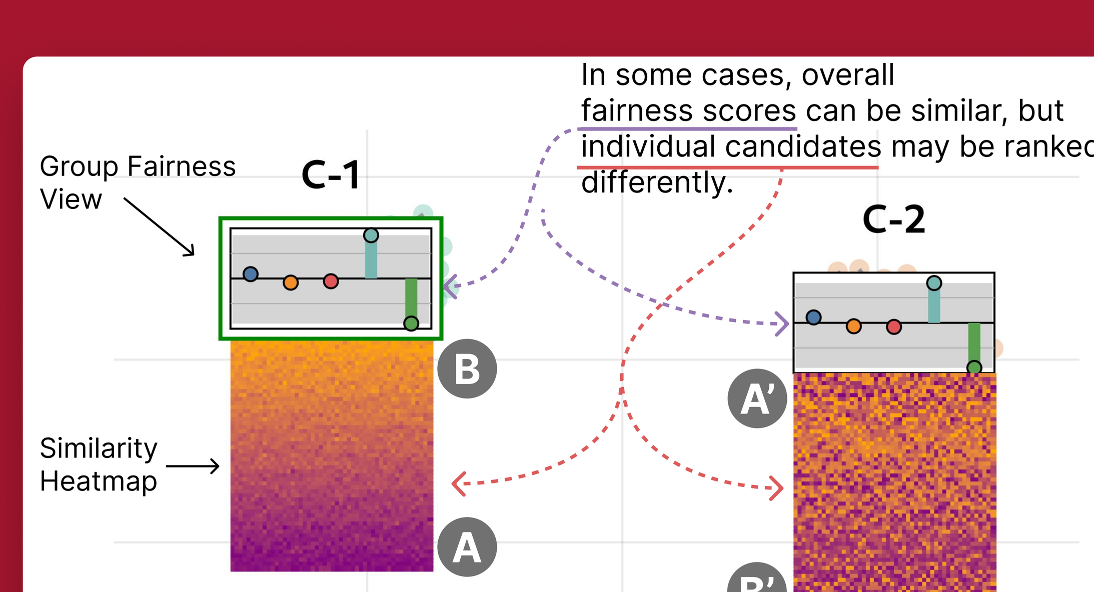


FairSpace is an interactive visualization system designed to explore and analyze large sets of rankings, enabling the creation of fair consensus rankings[2,3].

A) Sidebar providing information of the groups in selected rankings and overall ranking distributions, B,C,D) Cluster Views displaying embedding space of rankings in a devised utility and fairness space, E) A rank comparison view.

FairSpace Supports:

1. Identifying similar rankings and forming local clusters to simplify comparison
2. Comparisons between clusters in terms of fairness and agreement
3. Comparisons of individual rankings with their local cluster
4. Construction of a global consensus through a hierarchical approach
5. Construction of a global fair consensus ranking and analyzing its agreement with local consensuses as well as individual rankings



We design a Fair Divergence View by combining a heat map and Group Fairness View. The heatmap shows the (dis)similarity between rankings, in this case cluster C-1 is selected and its divergence from C-1 is displayed on C-2. Some of the bottom ranked candidates from C-1 (A) are seen to be ranked higher in C-2 (A'), and top ranked candidates from C-1 (B) are ranked at the bottom in C-2 (B').

Future Work

Conduct a user study to validate the system and understand how people might use the system with large datasets

Expand this system to accommodate multiple protected attributes

Provide support for partial/incomplete rankings

[1] Kuhlman, C., & Rundensteiner, E. (2020). Rank aggregation algorithms for fair consensus. Proceedings of the VLDB Endowment, 13(12).

[2] Cachel, K., Rundensteiner, E., & Harrison, L. (2022, May). Mani-rank: Multiple attribute and intersectional group fairness for consensus ranking. In 2022 IEEE 38th International Conference on Data Engineering (ICDE) (pp. 1124-1137). IEEE.

[3] Shrestha, H., Cachel, K., Alkhathlan, M., Rundensteiner, E., & Harrison, L. (2022, October). FairFuse: Interactive Visual Support for Fair Consensus Ranking. In 2022 IEEE Visualization and Visual Analytics (VIS) (pp. 65-69). IEEE.