Supplementary Material for "Measuring Group Advantage: A Comparative Study of Fair Ranking Metrics"

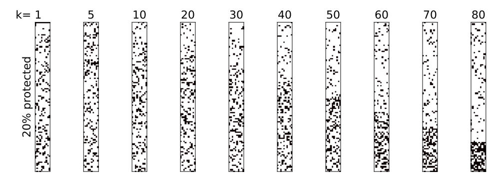
1 Applicability of Evaluation Framework Criteria

In our analysis so far, we consider functions of advantage f which are applied *monotonically* throughout the ranking. However, in the real-world other factors may impact the probability of candidates being assigned to positions. Sample data observed in practice is likely to be noisy and inconsistent. Or bias may be injected adversarially. If we relax our assumptions, many such scenarios where bias may fluctuate throughout the ranking are now considered.

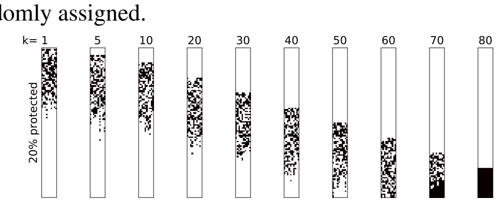
1.1 Alternative Advantage Functions

As a concrete example, consider the Rooney rule for hiring which has been a topic of interest by the fairness community (Celis, Mehrotra, and Vishnoi 2020; Kleinberg and Raghavan 2018). This strategy dictates that at least one candidate from the protected group is included in the top-k positions in the ranking. This is meant as a fairness-correcting intervention to ensure representation of the protected group. However one can also imagine an unfair manipulation using a similar strategy to ensure that a candidate from the advantaged group is always guaranteed the top spot in the ranking.

Figure 1 illustrates versions of these scenarios. Sets of 10 randomly generated rankings are shown for a dataset with 20% protected candidates. In Figure 1a, for different values of k, the rankings are required to assign 10% of the top-k rank positions to the protected group. Below k, the



(a) Top-k positions are assigned 10% to candidates from the protected group, while the rest of the ranking is randomly assigned.



(b) Top-k positions are reserved for candidates from the non-protected group. In the rest of the ranking the protected group is advantaged by $\alpha = 0.5$.

Figure 1: Sets of 10 random rankings with 20% protected candidates generated using alternative advantage functions.

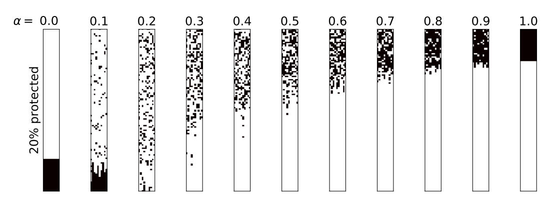
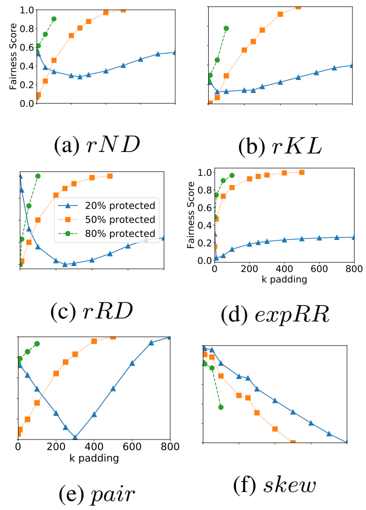


Figure 2: Sets of 10 random rankings with 20% protected candidates and different degrees of advantage.



(a) rND (b) rKL (c) rRD (d) $expRR$ (e) $pair$ (f) $skew$

Figure 3: Fairness metrics applied to rankings where the top-k positions are reserved for candidates from the non-protected group, for different values of k. In the rest of the ranking the protected group is advantaged by $\alpha = 0.5$.

rank positions are assigned randomly. Figure 1b illustrates another scenario where the top-k positions are all reserved for candidates from the non-protected group, and then in the rest of the ranking the protected group is advantaged by $\alpha = 0.5$.

For these rankings, unfairness manifests in different ways than in our previous analysis. In Figure 1a, if k is small then the rankings overall will align with our notion of statistical parity. However if k is very large, then the protected group is disadvantaged. Figure 1b depicts rankings that are unbalanced, however one could imagine that the unfairness at the top and bottom of the ranking may cancel each other out. Comparing these examples to our original rankings in Figure 2 we can see that the advantage of each group is more subtly distributed throughout the rankings in this case.

1.2 Evaluating Metrics under Alternative Advantage Functions

Data Generation. We consider the alternative advantage scenario shown in Figure 1b. Here the k top spots in each ranking are given to candidates from the non-protected group. After this top-k padding, the protected group is then given an advantage of $\alpha = 0.5$ according to the data generation procedure for standard bias.

Observations. In Figure 3 k is varied along the x axis of the charts, showing that when k is small (meaning the protected group is concentrated toward the top of the ranking) the metrics totally disagree on whether this is fair or unfair, in particular when the protected group is the minority. The $pair$ metric indicates very unfair around 0.8 and $expRR$ gives a score close to 0. The majority of the metric values stay relatively flat for the 20% protected case as well, while $pair$ goes through the range of all possible values. At a certain point, the pairwise advantage between the groups balances out and appears fair.

References

Celis, L. E.; Mehrotra, A.; and Vishnoi, N. K. 2020. Interventions for ranking in the presence of implicit bias. In *Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency*, 369–380.

Kleinberg, J.; and Raghavan, M. 2018. Selection Problems in the Presence of Implicit Bias. *Proceedings of the 9th Conference on Innovations in Theoretical Computer Science* .