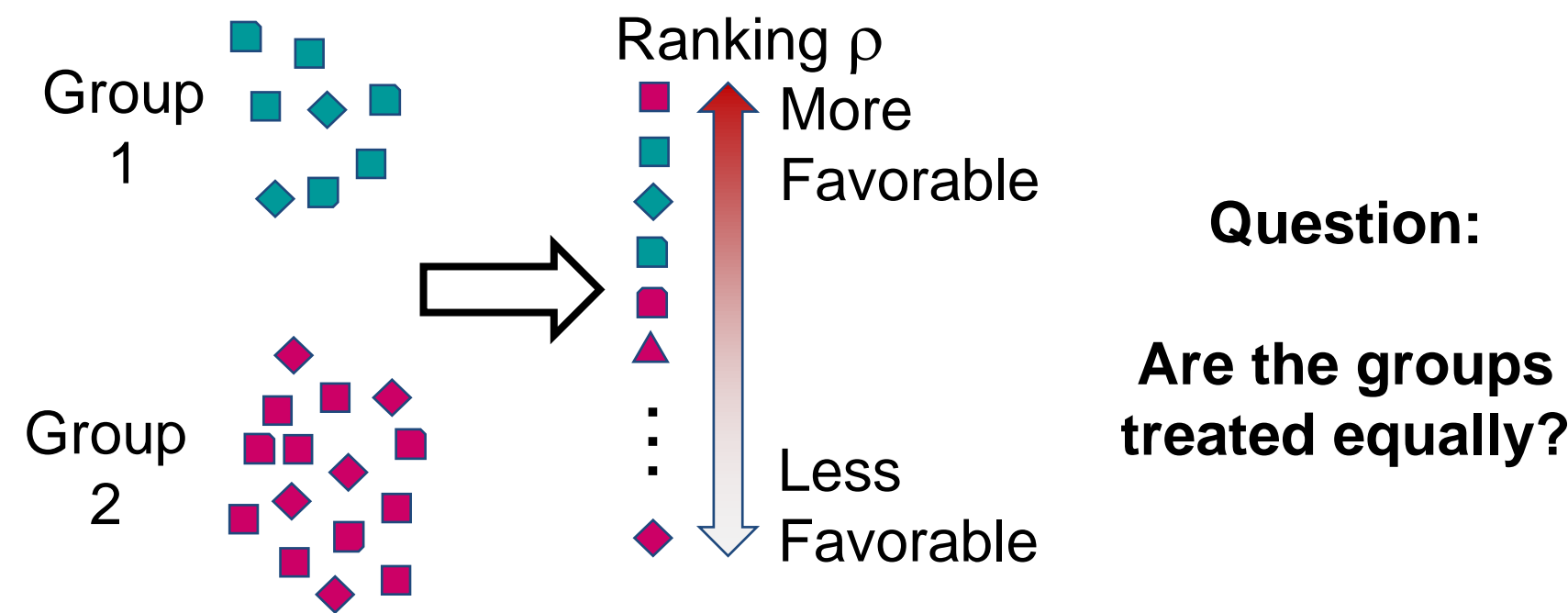


Measuring Group Advantage: A Comparative Study of Fair Ranking Metrics

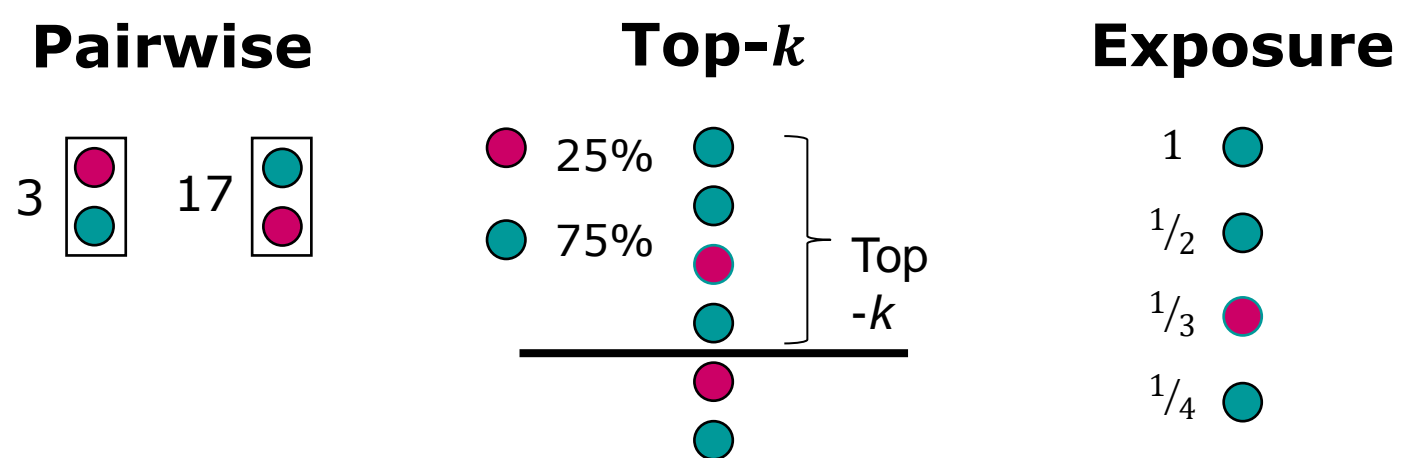
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FAIR RANKINGS



STATISTICAL PARITY METRICS

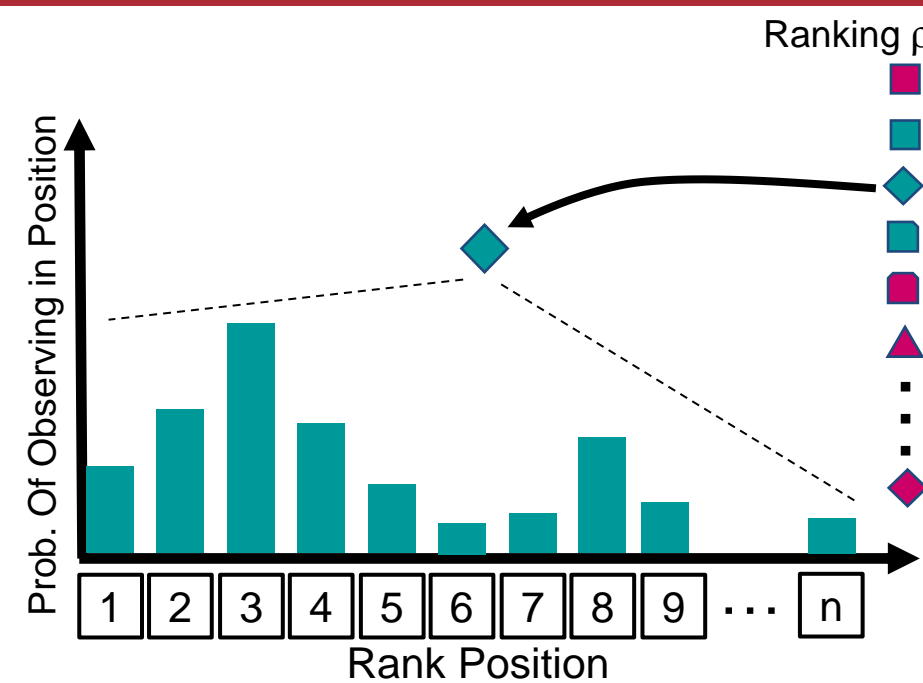
Three major kinds of statistical parity fairness metrics:



Our work is the first comprehensive comparison of these three metric types

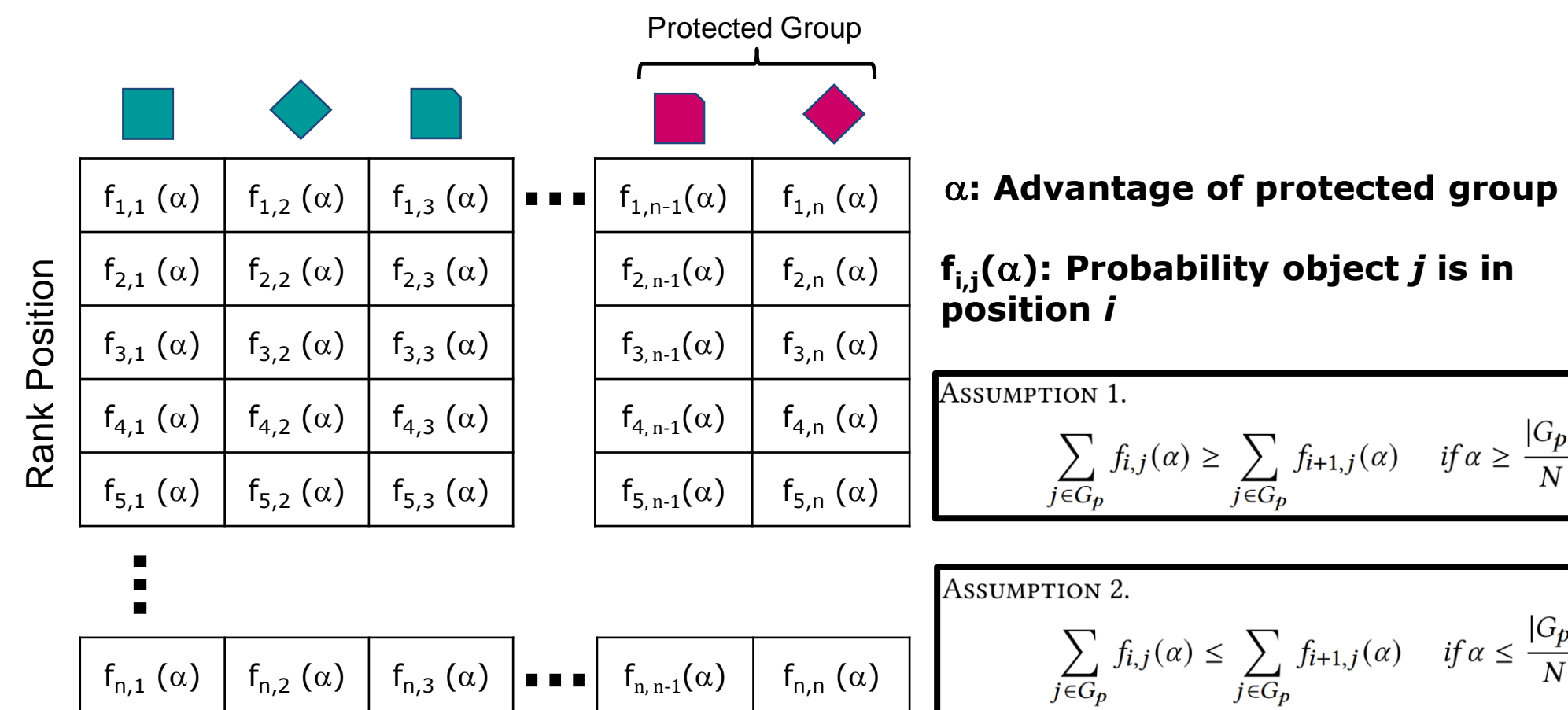
STOCHASTIC RANKING

- Item has probability of being in any rank position
- Models many real-world ranking scenarios
 - Multiple rankers
 - Unbiased click feedback in IR
- Statistical parity metrics evaluated on expectations of stochastic rankings



RANKING MATRIX FRAMEWORK

- Propose unified ranking matrix framework for metric evaluation and comparison
 - Columns = candidates
 - Rows = rank positions
- i,j -th cell represents probability candidate j is in position i
 - Probability represented by function $f_{i,j}: [0,1] \rightarrow [0,1]$
- Function of *advantage* α
 - $\alpha = 0$ implies total disadvantage, $\alpha = 1$ total advantage
 - Advantage with respect to "protected group"
 - One group designated as the protected group
- Assumptions: Probability that protected group monotonically increasing/decreasing if α greater/less than group proportion



THEORETICAL ANALYSIS

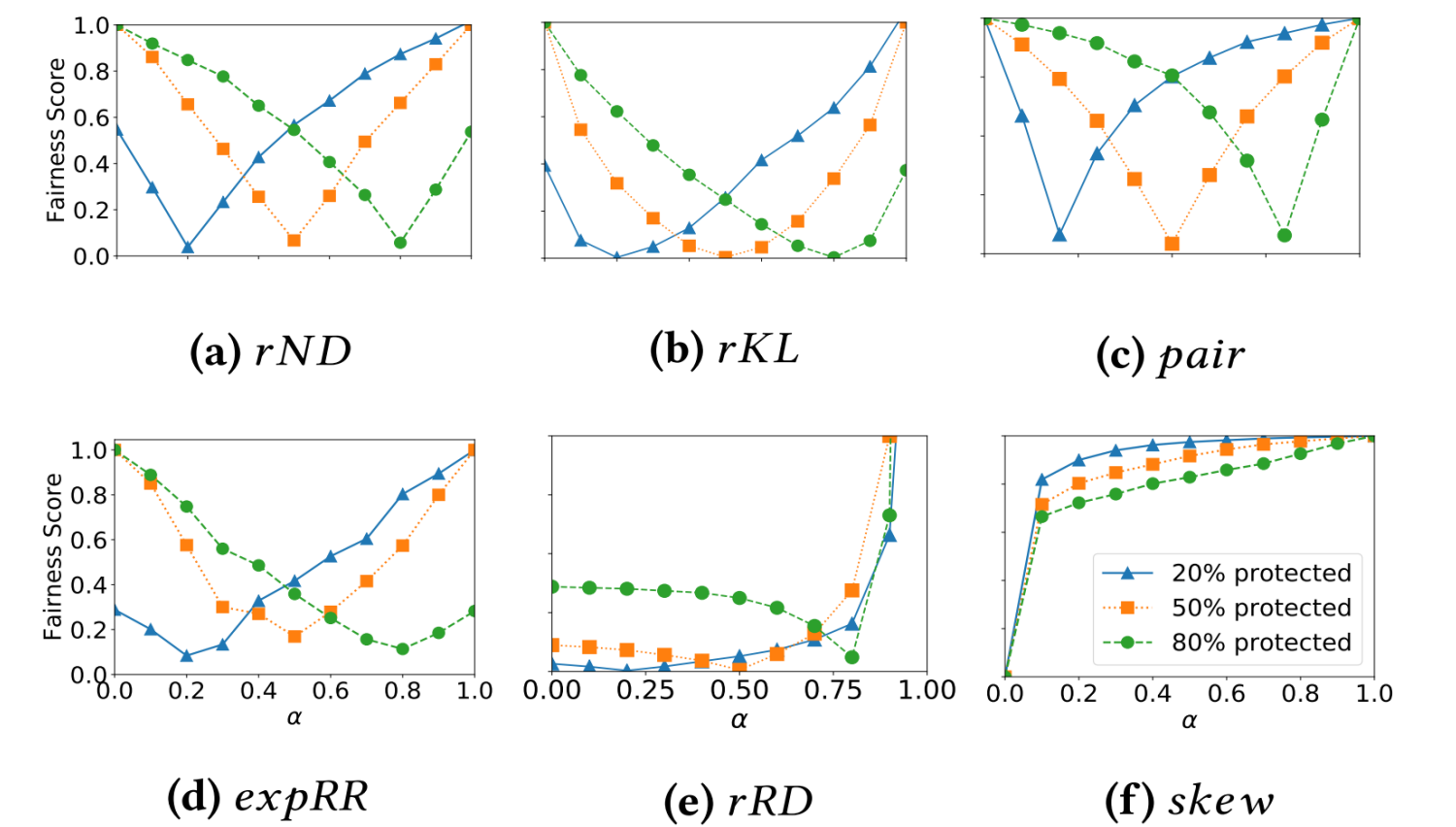
- We compare the standard statistical parity metrics:
 - rND , rRD , $skew$, rKL , $expRR$, $pair$
- Surprising result: All metrics besides skew behave the same when Assumption 1+2 are met
 - Proof intuition: Metrics have same minima and signs of derivatives are equal everywhere
- Optimizing for one metric optimizes for all
- We propose test to determine if theoretical assumptions hold for real data
 - Statistical equivalence to monotonic function

THEOREM 1. Given a ranking ρ with a protected group of candidates G_p and associated advantage α , if Assumptions 1 and 2 hold, then the rND , rRD , rKL , $expRR$, and $pair$ metrics share the same minima.

THEOREM 2. Given a ranking ρ with a protected group of candidates G_p and associated advantage α , if Assumptions 1 and 2 hold, then signs of the derivative with respect to α of the rND , rKL , rRD , and $expRR$ metrics are the same.

EXPERIMENTAL RESULTS

- Simulated rankings with different group sizes
- Results match analysis: all but skew have same minima/slopes
- Key difference:** $pair$ treats absolute (dis)advantage equally regardless of group size, others won't flag complete disadvantage minority
 - Crucial, as fairness evaluation might be most needed for small minority groups



- Code for experiments, including cases where rankings do not conform to our assumptions, available at: https://github.com/waltergerych/AIES_2021_Measuring_Group_Advantage

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REFERENCES

- Caitlin Kuhlman, MaryAnn VanValkenburg, and Elke Rundensteiner. 2019. FARE: Diagnostics for fair ranking using pairwise error metrics. WWW.
- Harikrishna Narasimhan, Andy Cotter, Maya Gupta, and Serena Lutong Wang. 2020. Pairwise Fairness for Ranking and Regression. AAAI.
- Meike Zehlike, Francesco Bonchi, Carlos Castillo, Sara Hajian, Mohamed Megahed, and Ricardo Baeza-Yates. 2017. Fa* ir: A fair top-k ranking algorithm. CIKM.
- Ke Yang and Julia Stoyanovich. 2017. Measuring fairness in ranked outputs. SSDBM.
- Sahin Cem Geyik, Stuart Ambler, and Krishnamurthy Kenthapadi. 2019. Fairness-aware ranking in search & recommendation systems with application to LinkedIn talent search. KDD.
- Ashudeep Singh and Thorsten Joachims. 2018. Fairness of Exposure in Rankings. KDD.
- Asia J Biega, Krishna P Gummadi, and Gerhard Weikum. 2018. Equity of attention: Amortizing individual fairness in rankings. SIGIR.