ALGORITHMIC SEARCH FOR FAIR AND SUCCESSFUL COLLABORATIVE TEAMS

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INTRODUCTION

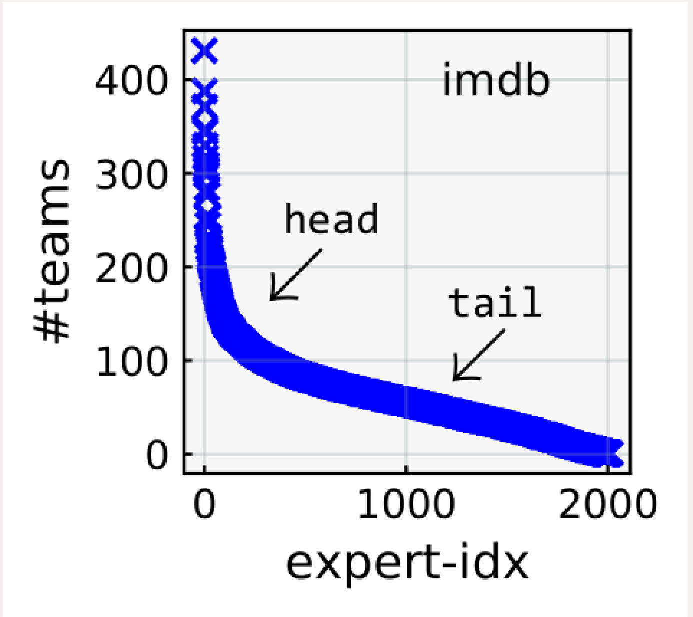
Team formation aims to automate forming teams of experts who can successfully solve difficult tasks which have firsthand effects on creating an organizational performance. Forming a successful team is challenging due to the immense number of candidates with diverse backgrounds and personality traits. Fairness breeds innovation and increases teams' success by enabling a stronger sense of community, reducing conflict, and stimulating more creative thinking. However, there is little to no fairness-aware algorithmic method that considers fairness in team formation.

OBJECTIVE

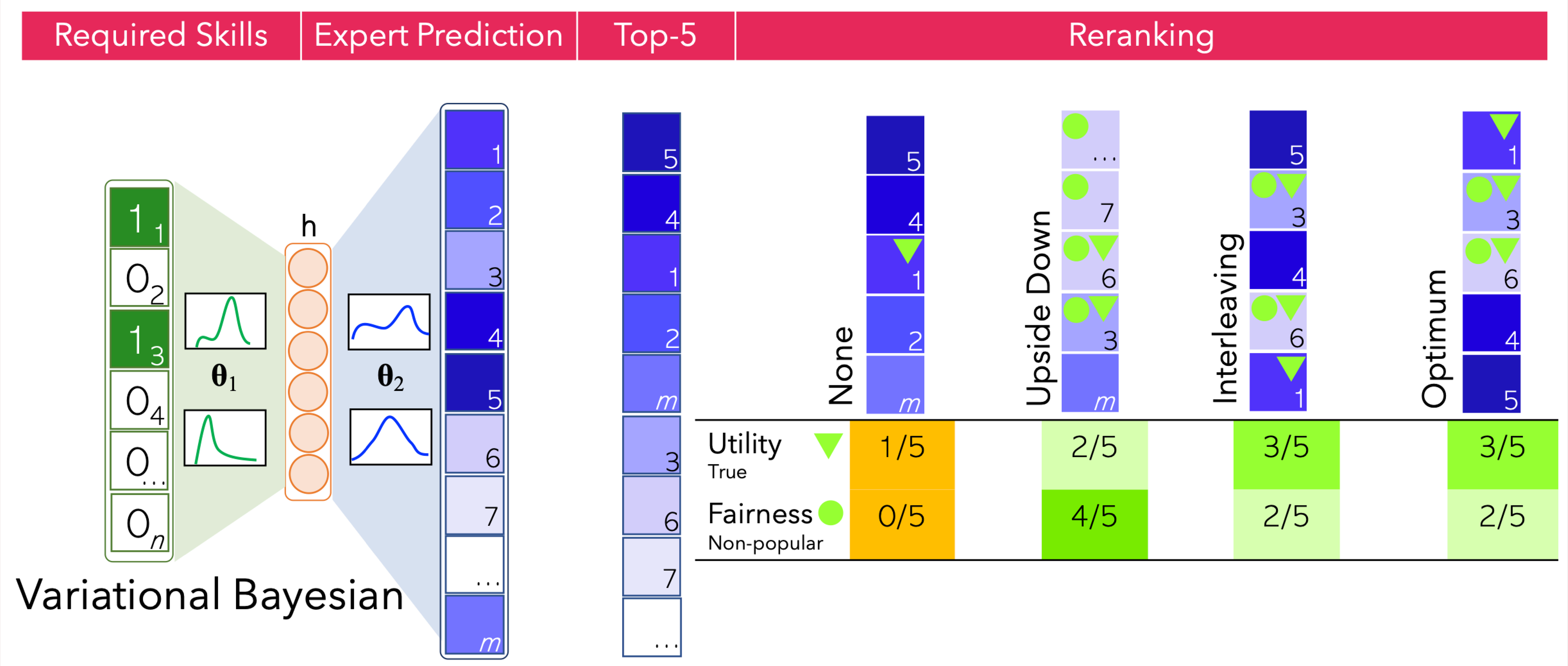
Q1: Do state-of-the-art neural team formation models produce fair teams of experts in terms of popularity bias?

Q2: Do state-of-the-art deterministic greedy re-ranking algorithms improve the fairness of neural team formation models while maintaining their accuracy?

POPULARITY LABELING:



METHODOLOGY:



IMDB DATASET:

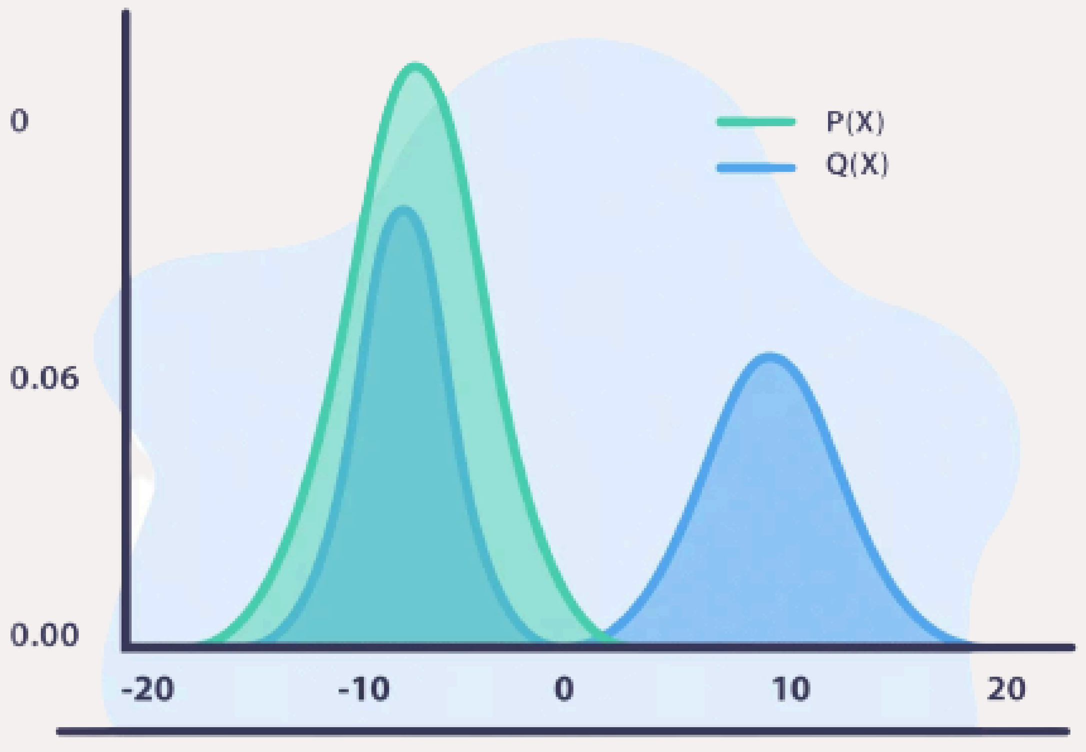
	imdb raw	imdb filtered
#movies	507,034	32,059
#unique casts and crews	876,981	2,011
#unique genres	28	23
average #casts and crews per team	1.88	3.98
average #genres per team	1.54	1.76
average #movie per cast and crew	1.09	62.45
average #genre per cast and crew	1.59	10.85
#team w/ single cast and crew	322,918	0
#team w/ single genre	315,503	15,180

NORMALIZED DISCOUNTED CUMULATIVE KL-DIVERGENCE

Q(x) : distribution of popularity in a team

P(x): desired distribution of popularity

$$KL(Q||P) = -\sum_{x} \mathrm{P}(x) * \log\left(\frac{Q(x)}{P(x)}\right)$$



Kullback–Leibler Divergence

FUTURE REMARKS

- Experimenting on learning-to-rank models
- Including additional fairness metrics
- Including new datasets

FANI-LAB/ADILA