How Fair is Fairness-aware Representative Ranking?

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ABSTRACT

It has been observed in several works that the ranking of candidates based on their score can be biased for candidates belonging to the minority community. In recent works, the fairness-aware representative ranking was proposed for computing fairness-aware re-ranking of results. The proposed algorithm achieves the desired distribution of top-ranked results with respect to one or more protected attributes. In this work, we highlight the bias in fairness-aware representative ranking for an individual and for a group if the group is sub-active on the platform. We define individual unfairness and group unfairness from two different perspectives. We further propose methods to generate ideal individual and group fair representative ranking if the universal representation ratio is known. The paper is concluded with open challenges and further directions.

CCS CONCEPTS

• **Information systems** → **Learning to rank**; *Information retrieval diversity*.

KEYWORDS

Fairness, Representative Ranking, Bias

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1 INTRODUCTION

The ranking problem is encountered in many different applications, including ordering job candidates, providing results for search queries, providing suggestions and recommendations [4, 6, 16]. There are several works that have highlighted the bias in placing the elements in top- k returned results [12, 19, 20]. It is important to understand the limitations of these methods and update the models to achieve fair outcomes for sensitive scenarios as they have been applied to everyday applications [7–9]. There are several works on

proposing fairness-aware ranking methods, including [1, 2, 4, 5, 18–20]. The recent works have investigated both notions of fairness, (i) individual fairness [3, 8, 11], and (ii) group fairness [13–15].

Geyik et al. [10] proposed fairness-aware representative ranking (FRR) maintains the ratio of candidates for each category in top- k elements based on their ratio in the eligible candidates so that each group will get a fair number of resources. They verified the proposed method by applying FRR on LinkedIn Talent Search and observed three-times improvement in the fairness without affecting the quality of the results. However, there is one big concern with the proposed method is what representation ratio for each group of candidates based on protected attributes should be maintained? We show that the deserving candidates of a group miss out on the opportunities by getting ranked lower in the returned list if the universal representation ratio of the candidates is not known.

Example. Let's assume that for a search query r , the set of eligible candidates in Universe is represented by U and the set of eligible candidates on a platform $\mathbb{L}$ is represented by L . For a protected attribute A having two values the candidates are divided into two groups G_1 and G_2 . The elements belonging to group G_1 are $\{b_1, b_2, b_3, b_4, b_5, b_6, b_7, b_8, b_9, b_{10}\}$, and the ranking of candidates is $b_1 > b_2 > b_3 > b_4 > b_5 > \dots > b_{10}$, therefore candidate b_1 has the highest ranking 1. The candidates belonging to group G_2 are $\{g_1, g_2, g_3, g_4, g_5\}$ and their ranking is $g_1 > g_2 > g_3 > g_4 > g_5$. Now, we assume that all candidates of group G_1 joins the platform $\mathbb{L}$, and group G_2 is sub-active (or less active) on platform $\mathbb{L}$, therefore, only two candidates (g_1, g_2) join the platform $\mathbb{L}$ as shown in Figure 1. Both set U and L will apply fair representative ranking by maintaining the ratio of candidates for each protected group when top- k candidates are requested; The fair representative ranking is explained in detail in Section 2.1. In this example, set U will maintain the ratio $(G_1 : G_2) = (10 : 5)$ and set L will maintain the ratio $(G_1 : G_2) = (10 : 2)$.

If an employer requests top-6 candidates for search query r :

- U will return: $(b_1 > g_1 > b_2 > b_3 > g_2 > b_4)$.
- L will return: $(b_1 > b_2 > b_3 > g_1 > b_4 > b_5)$.

You can observe that even though g_2 deserves the opportunity and is active on platform $\mathbb{L}$, the candidate has not been selected in top-6 when the FRR was applied on the platform $\mathbb{L}$. The main reason for this unfairness is that the *representative ranking on platform $\mathbb{L}$ (LRR)* maintained the candidates' ratio for protected attributes based on L and did not consider the universal representation ratio. Therefore, the eligible candidates miss the opportunity if other members belonging to that group either do not join or are sub-active on the platform.

This paper presents how the existing approach of fairness representative ranking is inadequate to generate a fair ranking given

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Figure 1: Example for displaying the unfairness in representative ranking for a sub-active group.

the protected attributes. We also present the definitions of unfairness that should be considered while proposing a fairness-aware ranking method. We discuss how the system should be extended to mitigate bias in ranking problems if the complete information is unknown. We discuss open challenges associated with the problem while applying fair representative ranking and further directions that might be considered for solving these challenges.

2 PREREQUISITE

Fair Representative Ranking. The FRR method works as follows. (i) Partition the set of qualified candidates into different groups based on protected attribute values. For example, in the case of gender, the candidates will be divided into two groups, males and females. (ii) Rank the candidates in each group according to their scores. (iii) To generate representative ranking, merge these groups in such a way that the proportion of each group in the ranked list for every index of the list is similar to their corresponding proportions in the set of qualified candidates.

Terminologies. The protected attribute are represented as $A = \{a_1, a_2, a_3, \dots, a_l\}$. For a candidate, its protected attribute is denoted by $A(c_i)$. For the given protected attributes A , the qualified candidates can be divided into n groups ($G_1, G_2, \dots, G_n$). The fraction of eligible candidates for each protected value in U is $\{p_{a_1}, p_{a_2}, \dots, p_{a_l}\}$. $\tau_{U,r,A}$ represents the representative ranking of candidates from set U for the search query r , based on protected attribute A . $\tau_{U,r,A}^k$ denotes top k elements in the ranking. $\tau_{U,r,A}$ and $\tau_{L,r,A}$ are also referred as URR and LRR, respectively.

3 FAIRNESS DEFINITIONS

3.1 Benefited Candidate

DEFINITION 1. For the given set L , skill set r , protected attribute A , and top- k selected candidates, a candidate c_i is benefited candidate if $c_i \in \tau_{L,r,A}^k$.

3.2 Individual Unfairness

DEFINITION 2. For the given set U and L , search query r , and protected attribute A , if top- k candidates are selected from L , the individual unfairness for a candidate c_i is defined as, $IUF(c_i) = 1$, if $(c_i \notin \tau_{L,r,A}^k \text{ and } c_i \in \tau_{U,r,A}^k)$, and 0, otherwise.

3.3 Favored Candidate

DEFINITION 3. For the given set U and L , search query r , and protected attribute A , if top- k candidates are selected from L , a candidate c_i is favored candidate if, $c_i \in \tau_{L,r,A}^k$ and $c_i \notin \tau_{U,r,A}^k$.

3.4 Group Unfairness

DEFINITION 4. In top- k selected candidates, group G_i has been treated unfairly by platform L , if $|\{c_i | c_i \in G_i \text{ and } c_i \in \tau_{L,r,A}^k\}| < |\{c_i | c_i \in G_i \text{ and } c_i \in \tau_{U,r,A}^k\}|$.

3.5 Favored Group

DEFINITION 5. In top- k selected candidates, group G_i is favored by platform L , if $|\{c_i | c_i \in G_i \text{ and } c_i \in \tau_{L,r,A}^k\}| > |\{c_i | c_i \in G_i \text{ and } c_i \in \tau_{U,r,A}^k\}|$.

3.6 Relation of different Definitions

3.6.1 Individual Unfairness v.s. Favored Candidate.

PROPOSITION 1. In top- k selected candidates, if a candidate c_i from group G_i is treated unfairly as defined in Definition 2, then a candidate from any other group will be favored as defined in Definition 3.

PROOF. We prove it using proof of contradiction. Let's assume there are two groups and a candidate c_i from group G_1 is treated unfairly and no candidate of group G_2 is favored. In top- k elements, URR will return $\text{round}(p_{a_1} * k)$ candidates from group G_1 and $\text{round}(p_{a_2} * k)$ candidates from group G_2 , where $\text{round}(p_{a_1} * k) + \text{round}(p_{a_2} * k) = k$.

Now, if the candidate c_i Group G_1 is treated unfairly then $c_i \notin \tau_{L,r,A}^k$ and $\tau_{L,r,A}^k(c_i) > k$, so the place of c_i candidate in top- k candidates will be vacant. Therefore, the platform L will return $\text{round}(p_{a_1} * k) - 1$ candidates from group G_1 and $\text{round}(p_{a_2} * k)$ candidates from group G_2 as no candidate from group G_2 is favored. Now, the total number of returned candidates by platform L is $\text{round}(p_{a_1} * k) - 1 + \text{round}(p_{a_2} * k) = k - 1$. That is a contradiction as top- k elements were selected by L . Therefore, by the proof of contradiction, an element from group G_2 will be favored. $\square$

3.6.2 Favored Candidate v.s. Individual Unfairness. Intuitively it seems, If a candidate from group G_i is favored, then a candidate from any other group G_j will be treated individually unfairly as the total number of selected candidates are k . However, this is **not always true**.

PROOF. We prove it using the proof of construction. Let's assume, in the example (Figure 1), only g_2 and g_4 joins the platform L . Now ($G_1 : G_2 = 10 : 2$), so, the new representative ranking in set L is: $b_1 > b_2 > b_3 > g_2 > b_4 > b_5 > b_6 > b_7 > b_8 > g_4 > b_9 > b_{10}$. If top-6 candidates are selected,

- U will return: $b_1 > g_1 > b_2 > b_3 > g_2 > b_4$

- L will return: $b_1 > b_2 > b_3 > g_2 > b_4 > b_5$

As you can see that the candidate b_5 is favored but no candidate of group G_2 is treated unfairly. Hence proved. $\square$

3.6.3 Individual Unfairness v.s. Group Unfairness.

LEMMA 1. If there is individual unfairness (as defined in Definition 2) for a candidate c_i and $c_i \in G_i$, it implies the group unfairness (as defined in Definition 4) for group G_i .

3.6.4 Favored Group v.s. Group Unfairness.

LEMMA 2. If there exists a group G_i that is favored group, then it implies that there will also exist a group G_j that suffers through group unfairness.

Algorithm 1: *Ideal – IFRR*($\tau_{U,r,A}, L$)

Input : $\tau_{U,r,A}$: universal representative ranking, L : set of users on platform $\mathbb{L}$

Output: $IFRR^L$: Individual fair representative ranking on $\mathbb{L}$

```

1  $IFRR^L = []$ 
2 for  $k$  in  $range(1, len(\tau_{U,r,A}))$  do
3   if  $\tau_{U,r,A}[k] \in L$  then
4      $\text{append } \tau_{U,r,A}[k]$  to  $IFRR^L$ 
5 return  $IFRR^L$ 

```

3.6.5 Individual Fairness v.s. Group Fairness. This is important to understand how individual and group fairness are correlated so that the appropriate solutions can be designed.

LEMMA 3. *The individual fairness-aware solution does not imply group fairness.*

PROOF. Let's assume, in top- k candidates, the number of chosen candidates by URR from groups $(G_1, \dots, G_i, \dots, G_2)$ are $(l_{G_1}^U, \dots, l_{G_i}^U, \dots, l_{G_2}^U)$, respectively, and the candidates in set H ($H = \{c_i | c_i \in G_i \text{ and } c_i \in \tau_{U,r,A}^k\}$) does not join the platform $\mathbb{L}$.

In this case, even if no candidate of G_i is chosen by an algorithm in top- k candidates, the algorithm is still providing an individual-fair solution as there is no individual unfairness as per Definition 2; however, it is not a group-fair solution, as $l_{G_i}^U$ candidates from group G_i should have been chosen in top- k for adhering the group fairness as per the Definition 4. Hence proved. $\square$

LEMMA 4. *Group fairness-aware solution will imply individual aware-fairness.*

Refer to [17] for the proof.

4 FAIR REPRESENTATIVE RANKING

In this section, we discuss what is an ideal solution for ideal fair representative ranking on a platform $\mathbb{L}$ if some candidates do not join it.

4.1 Individual Fair Representative Ranking

A ranking is fair for an individual c_i if $c_i \in \tau_{U,r,A}^k$ then $c_i \in \tau_{L,r,A}^k$. IFRR for platform $\mathbb{L}$ can be generated by projecting URR on the candidates of set L . It is denoted by $IFRR^L$, and the algorithm is given in Algo 1. In the algorithm, $range(1, n)$ function iterates from 1 to n and $len(\tau_{U,r,A})$ function returns the length of the given list. In steps 2 to 4, we iterate over each candidate c_i of the URR, and if the candidate belongs to set L ($c_i \in L$), it is added to $IFRR^L$.

4.2 Group Fair Representative Ranking

A ranking solution is group fair representative ranking (GFRR) if no group G_i satisfies the condition of group unfairness as defined in Definition 4. For each index k , an ideal-GFRR solution will maintain the group fairness for each group G_i until all the elements of that group are exhausted. Therefore, a ranking is fair for a group G_i having protected value a_i in A , if $|c_i \text{ s.t. } c_i \in \tau_{L,r,A}^k \text{ and } A(c_i) = a_i| = \min(|c_i \text{ s.t. } c_i \in \tau_{U,r,A}^k \text{ and } A(c_i) = a_i|, |c_i \text{ s.t. } c_i \in L \text{ and } A(c_i) = a_i|)$.

Algorithm 2: *Ideal – GFRR*($\tau_{U,r,A}, L, A$)

Input : $\tau_{U,r,A}$: universal representative ranking, L : set of users on platform $\mathbb{L}$, A : set of protected attribute

Output: $GFRR^L$: Group fair representative ranking on $\mathbb{L}$

```

1  $GFRR^L = []$ 
2  $IFRR^L = \text{Ideal} - IFRR^L(\tau_{U,r,A}, L)$ 
3 for  $k$  in  $range(1, len(\tau_{U,r,A}))$  do
4    $a = \text{getAttribute}(\tau_{U,r,A}[k])$ 
5    $c = \text{getNext}(IFRR^L, a)$ 
6   if  $c \neq \text{'NA'}$  then
7      $\text{remove } c$  from  $IFRR^L$ 
8      $\text{append } c$  to  $GFRR^L$ 
9 return  $GFRR^L$ 

```

It is denoted by $GFRR^L$, and the method is explained in Algorithm 2. For each index k of URR, if the candidate $\tau_{U,r,A}[k]$ is in set L , it is added to $GFRR^L$; otherwise, the next eligible candidate of this protected group is added to $GFRR^L$. The $\text{getAttribute}(c)$ function returns the protected attribute of candidate c , $\text{getNext}(R, a)$ function returns the first element of ranked list R having protected attribute a , if there is no remaining element having this attribute, it returns 'NA'.

5 PROBLEM STATEMENT

If the URR is known, then $IFRR^L$ and $GFRR^L$ can be generated using Algorithm 1 and 2; however, it is unknown in most real-world applications. For example, for a given skill set s , how many males and females candidates are eligible (the universal representation ratio) might not be known to any given platform $\mathbb{L}$.

Problem Statement. Given set L containing eligible candidates for a search query r , protected attribute set A , and the number of selected candidates k , propose methods to generate optimal IFRR and GFRR.

The proposed solutions should maintain IFRR or GFRR based on the representation ratio of different classes of protected attributes. Therefore, the solutions are categorized into two following classes: (i) If universal representation ratio is known: In this work, we will propose solutions and possible approaches to generate optimal IFRR and GFRR solutions, and (ii) If universal representation ratio is unknown: Here, we first design methods to estimate the universal representation ratio and then the solutions proposed for the first category can be applied. These solutions are not covered here.

6 THE PROPOSED SOLUTIONS

In this section, first, we discuss a method to generate an optimal solution for GFRR. The solution to generate optimal IFRR is not straight forward as IFRR ranking is highly dependent on the kind of missing data; we will discuss these complexities and possible IFRR solution in the next subsection.

6.1 Generate GFRR

The method to generate GFRR will maintain the given ratio of candidates based on protected attribute classes for each index k .

Figure 2: Average Rank Difference versus active fraction of group G_g for group G_g .

The method is inspired from [10], and the generated GFRR ranking is represented by $\widehat{GFRR}^L$. The generated solution will be an Ideal-GFRR; as both $\widehat{GFRR}^L$ and $GFRR^L$ rankings maintain the representation ratio for each index k .

6.2 Generate IFRR

The solutions to generate IFRR need more information, even if the universal representation ratio is known. We will explain it with the help of an example. Let's assume, in the universal set U there are two groups (G_1, G_2) and for search query r , in group G_1 , there are four eligible candidates (b_1, b_2, b_3, b_4) and in group G_2 , there are four eligible candidates (g_1, g_2, g_3, g_4). We assume that in each group the rank of $c_i > c_j$ if $i < j$. So, IFRR on set U is ($g_1, b_1, g_2, b_2, g_3, b_3, g_4, b_4$) if group G_2 is prioritized. Let's assume that four candidates from group G_1 and two candidates from group G_2 joins the platform L , therefore $L = \{b_1, b_2, b_3, b_4, g'_1, g'_2\}$. Now, the question is: if the universal representation ratio is known as (0.5:0.5), how to generate an individual fair representative ranking. It is not straight forward as we do not know which two out of four members of group G_2 have joined L . Let's further understand with case scenarios. In case 1: If g'_1 is g_1 and g'_2 is g_2 , then the Ideal-IFRR will be ($g_1, b_1, g_2, b_2, b_3, b_4$). In case 2: If g'_1 is g_1 and g'_2 is g_4 , then the Ideal-IFRR will be ($g_1, b_1, b_2, b_3, g_4, b_4$). Therefore, an IFRR solution also require the knowledge of missing data or the knowledge of what kind of candidates have joined L .

The information of what kind of candidates have joined the platform L can either be gathered by surveys or by using statistical methods. The surveys can help in knowing what is the probability of a candidate joining L and what is its correlation with the candidate's characteristics. For example, if we know that the higher-ranked people are more likely to join a platform L , then one estimated IFRR solution for the above-discussed example is: ($g'_1, b_1, g'_2, b_2, b_3, b_4$) as shown in case 1. In another approach, the statistical methods can be used to estimate the actual distribution using the partial available information. In this work, we provide a solution for the case when the candidates from a given group G_i are missing uniformly at random. In the proposed solution, for each ranking place reserved for a sub-active group, its candidate will be placed with the probability equal to the fraction of active people of this group. The method is represented by $\widehat{IFRR}^L$.

7 SIMULATION RESULTS

Datasets. The experimental results are shown on synthetic datasets so that the impact of different activeness can be better studied and

Figure 3: Average Skew ratio versus active fraction of group G_g for top-10000 ranking for group G_g .

various values of protected attributes can be considered. The data has a protected attribute having 3 values $A = \{g, b, u\}$ and so the candidates are categorized into three groups G_g, G_b, G_u . A real-world example of this situation is gender classes having 'male', 'female', and 'unknown' values. For a search query r , in each group, there are 10000 eligible candidates, and their scores are assigned uniformly at random from (0,1). We assume that group G_g is less active on the platform L , and the ratio of active members ranges from 0.1 to 0.9; and all candidates of G_b and G_u join L .

Metrics. *Rank Difference* is used to capture the individual unfairness for ranking R_1 v.s. ranking R_2 . It is computed as, $RankDiff(c_i) = R_1(c_i) - R_2(c_i)$.

Skew ratio measures group unfairness and denotes the extent to which the top-k elements for a given search query and for a given sub-group differ from the desired proportion. It is computed as,

$$Skew_{R_1, R_2}^{a_i} = \log_e \left(\frac{|\{c_i \text{ s.t. } c_i \in R_1^k \text{ and } A(c_i) = a_i\}|}{|\{c_i \text{ s.t. } c_i \in R_2^k \text{ and } A(c_i) = a_i\}|} \right).$$

Discussion. Figure 2 shows the rank-difference of LRR and the proposed IFRR with Ideal-individual fairness representative ranking. The results show that the performance of LRR is poor for the activeness ratio from 0.4 if the candidates join u.a.r. However, detailed solutions will be proposed further. Figure 3 shows the skewness of LRR versus ideal-group fairness representative ranking, and the proposed method performs as good as the ideal method as both maintain the representation ratio.

8 CONCLUSION

In this paper, we discussed how a fairness-aware ranking method might be unfair due to the unavailability of universal information. We proposed individual and group fairness definitions that should be considered while verifying the fairness of the proposed representative ranking if some groups are less active. We further discussed the correlation and dependencies of the proposed definitions. We proposed methods to generate IFRR and GFRR if the universal representation ratio is known. The experiments show preliminary results for unfairness increases in LRR as the group becomes less active and the improvements achieved by proposed methods.

The main challenge in real-life applications is to identify the universal representation ratio based on the given protected attribute. In this work, we highlighted two approaches to solve this (i) perform a survey to understand the existing distribution, (ii) apply statistical methods to estimate the exact distribution based on the available score-ranking information of the candidates belonging to different protected attributes based groups. These solutions will be discussed in future work.

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