Multi-grouping Robust Fair Ranking

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ABSTRACT

Rankings are at the core of countless modern applications and thus play a major role in various decision making scenarios. When such rankings are produced by data-informed, machine learning-based algorithms, the potentially harmful biases contained in the data and algorithms are likely to be reproduced and even exacerbated. This motivated recent research to investigate a methodology for fair ranking, as a way to correct the aforementioned biases. Current approaches to fair ranking consider that the protected groups, i.e., the partition of the population potentially impacted by the biases, are known. However, in a realistic scenario, this assumption might not hold as different biases may lead to different partitioning into protected groups. Only accounting for one such partition (i.e., grouping) would still lead to potential unfairness with respect to the other possible groupings. Therefore, in this paper, we study the problem of designing fair ranking algorithms without knowing in advance the groupings that will be used later to assess their fairness. The approach that we follow is to rely on a carefully chosen set of groupings when deriving the ranked lists, and we empirically investigate which selection strategies are the most effective. An efficient two-step greedy brute-force method is also proposed to embed our strategy. As benchmark for this study, we adopted the dataset and setting composing the TREC 2019 Fair Ranking track.

KEYWORDS

Fair Ranking, Multi-grouping Fair Ranking, Grouping Robustness

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1 INTRODUCTION

Recently, algorithmic fairness has taken on a crucial role in machine learning. Its importance is also manifest for search and recommendation tasks, where data and algorithm biases can be potentially amplified if no particular measure is adopted. As far as fairness is concerned, ranking tasks have their own peculiarities, which preclude the well-studied methods used in fair classification and regression to be directly used. Indeed, the ranking process by nature and by definition could not directly ensure that similar individuals will be handled in the same way; moreover, fairness should sometimes be considered relatively (e.g. pairwise) and not absolutely.

Most fair ranking approaches [4, 5, 7, 8] focus on group fairness and assume that the partition into protected groups is known. However, norms, regulations, associations of consumers, etc. are often assessing fairness *a posteriori* with their own definition of protected groups. The main research question of this paper is to ensure robustness with respect to these possible unknown definitions when designing fair ranking algorithms. Several approaches could be imagined: for instance, simply introducing diversity in the ranking, using standard diversity-focused IR technique; an alternative strategy would be to ensure fairness at the individual level, as done in [2, 6]. In this paper, we adopt a slightly different viewpoint, by relying on some set of groupings when elaborating the ranking strategy, even if these groupings are different from the target groupings used at evaluation time. How to choose this set of groupings (possibly of size 1) to be robust with respect to unknown and potentially multiple groupings is our key research question.

More precisely, we adopt a post-processing approach as in [3–5, 7, 8] assuming the availability of an accurate relevance probability for each item; we then simply re-rank a relatively small set of candidate items. This is in contrast to pre-processing approaches, which transforms the training data before building a ranking model, or to 'in-processing' approaches, which incorporate fairness into a Learning-to-Rank algorithm either as an extra constraint or directly in the objective function [6]. We consider the 'amortized' setting, where amortization occurs both over time (the same query being repeated multiple times) and over queries (the same producers or groups appearing in multiple queries at the same time). We also wish to be agnostic with respect to particular definitions of exposure and utility and be as general as possible. This precludes the use of techniques such as Linear Programming methods [3, 5], because they impose constraints on the form of the exposure model (the exposure should only depend on the position in the list) and on the way merit and exposure are aggregated at the group level. As solving this general problem is NP-complete, we have to rely on some approximate solver to remain scalable. In this paper, we present an efficient method that mixes brute-force and greedy selection in a two-stage process and show its effectiveness.

In summary, the contributions of the paper are the following:[1]

- We introduce the problem of Multi-grouping Robust Fair Ranking (MRFR), which defines fairness with respect to several unknown groupings.
- We propose a simple but effective two-step greedy brute-force approach, SGBR, to optimize our fair ranking metric.
- We empirically investigate different grouping selection strategies to address the problem of unknown target groupings.

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[1] Code available at https://github.com/tthonet/MRFR

2 PRELIMINARY

We consider a system which returns a ranked list of *items* upon the submission of a *query* by a user. An item is associated to a set of *producers* and a producer is member of several *protected groups*, each belonging to a different *grouping* (i.e., a partition of producers). A grouping is equivalent to one sensitive attribute for which every producer is attributed a categorical value (her group). For example, in the TREC 2019 Fair Ranking track [2] (TREC-FR), items are scientific papers, producers are the authors of those articles, and protected groups are authors with low, medium, high, and very high h-index, thus constituting the h-index grouping. In layman's terms, the task of Multi-grouping Robust Fair Ranking consists in finding a system which returns a ranked list of items that are both relevant to the query and fair, on average over all the submitted queries, with respect to the producers' unknown protected groups.

2.1 Notations and Problem Definition

Let $\mathcal{I}$ denote the set of items and $\mathcal{P}$ the set of producers. Each item $i \in \mathcal{I}$ is attached to a set of producers $\mathcal{P}_i \subset \mathcal{P}$. We define as $\mathcal{Q}$ the set of unique queries which occur in a sequence of searches $\mathcal{S}$ performed by the users of the system. Each query $q \in \mathcal{Q}$ is associated with a set of items $\mathcal{I}_q \subset \mathcal{I}$ to rank and a set of searches $\mathcal{S}_q$ issued for this query. Conversely, each search $s \in \mathcal{S}$ pertains to a query denoted as $q_s \in \mathcal{Q}$. The items $i \in \mathcal{I}_q$ are given a relevance score $\mathrm{rel}(i;q) \in [0,1]$ with respect to query q, which is supposed to be known.[2] Additionally, let $\mathfrak{G}$ define the set of all groupings considered in the fairness to be enforced. Given a grouping $\mathcal{G} \in \mathfrak{G}$, we denote as $g \in \mathcal{G}$ a protected group, which corresponds to a set of producers (i.e., $g \subset \mathcal{P}$). Each producer $p \in \mathcal{P}$ is assumed to be a member of exactly one group $g \in \mathcal{G}$ for every grouping $\mathcal{G} \in \mathfrak{G}$; however this membership information is considered *unknown*.[3]

Given a measure $\mathrm{U}(\Pi;\mathcal{S})$ of the amortized utility (assessed in terms of relevance) of some rankings Π returned for some searches $\mathcal{S}$ and a measure $\Delta(\Pi;\mathcal{S},\mathcal{G})$ of the amortized unfairness of rankings Π for searches $\mathcal{S}$ w.r.t. a grouping $\mathcal{G}$ of the producers, we define the problem of *Multi-grouping Robust Fair Ranking* (MRFR) as follows.

Definition 1 (Multi-grouping Robust Fair Ranking). *Find a sequence of rankings Π^* which optimizes a trade-off between utility on the search sequence $\mathcal{S}$ and average (negative) unfairness over a set $\mathfrak{G}_T$ of unknown target groupings:*

$$\Pi^* = \operatorname*{argmax}_{\Pi} \mathrm{U}(\Pi;\mathcal{S}) - \frac{\lambda}{|\mathfrak{G}_T|} \sum_{\mathcal{G} \in \mathfrak{G}_T} \Delta(\Pi;\mathcal{S},\mathcal{G}) \tag{1}$$

where λ defines the desired trade-off between utility and (un)fairness.

2.2 Metrics

In this paper, we adopt the definitions of utility and unfairness used in TREC-FR [2], which we briefly describe thereafter.

Unfairness definition. A necessary component to the definition of (un-)fairness in the context of ranking is the notion of exposure – how much an item in a given position of the ranking is likely to be seen by a user browsing this ranking. Indeed, a commonly adopted definition of fairness, known as *non-disparate treatment*, is that exposure should be provided commensurately to merit (i.e., relevance) [3, 5, 6]. This fairness paradigm is also the one followed in TREC-FR. The model of exposure used in TREC-FR calculates the exposure of a producer $p \in \mathcal{P}$ in a sequence of item rankings Π returned for a sequence of searches $\mathcal{S}$ as follows:

$$\mathrm{e}(p;\Pi,\mathcal{S}) = \sum_{s \in \mathcal{S}} \sum_{k=1}^{|\mathcal{I}_{q_s}|} \left[\gamma^{k-1} \prod_{j=1}^{k-1} (1 - p(s|\pi_{s,j}, q_s)) \right] \mathbb{I}[p \in \mathcal{P}_{\pi_{s,k}}] \tag{2}$$

where $\pi_{s,k} \in \mathcal{I}_{q_s}$ is the item in the k-th position of the ranking from Π associated to search s; $\mathbb{I}[\cdot]$ is the indicator function; γ is an hyperparameter defining the continuation probability. $p(s|i,q)$ corresponds to the probability for the user to stop browsing after examining item i. It is defined proportionally to the relevance of i with respect to q: $p(s|i,q) = \epsilon \cdot \mathrm{rel}(i;q)$, where ϵ is an hyperparameter. A particularity of this exposure model is then that it depends on the relevance of the items, whereas others such as geometric exposure [3] do not have this dependency.

Similarly, the merit of a producer $p \in \mathcal{P}$ in the items returned for a sequence of searches $\mathcal{S}$ is derived from item relevance as follows:

$$\mathrm{m}(p;\mathcal{S}) = \sum_{s \in \mathcal{S}} \sum_{i \in \mathcal{I}_{q_s}} p(s|i, q_s))\ \mathbb{I}[p \in \mathcal{P}_i]. \tag{3}$$

Given a grouping $\mathcal{G}$ and a group $g \in \mathcal{G}$, the normalized group-level exposure and merit are defined as follows:

$$\mathrm{E}(g;\Pi,\mathcal{S},\mathcal{G}) = \frac{\sum_{p \in g} \mathrm{e}(p;\Pi,\mathcal{S})}{\sum_{g' \in \mathcal{G}} \sum_{p \in g'} \mathrm{e}(p;\Pi,\mathcal{S})}; \tag{4}$$

$$\mathrm{M}(g;\mathcal{S},\mathcal{G}) = \frac{\sum_{p \in g} \mathrm{m}(p;\mathcal{S})}{\sum_{g' \in \mathcal{G}} \sum_{p \in g'} \mathrm{m}(p;\mathcal{S})}. \tag{5}$$

Unfairness is then calculated as the *root mean square deviation* from the ideal situation corresponding to having an exposure that is commensurate to merit for every group:

$$\Delta(\Pi;\mathcal{S},\mathcal{G}) = \sqrt{\sum_{g \in \mathcal{G}} [\mathrm{E}(g;\Pi,\mathcal{S},\mathcal{G}) - \mathrm{M}(g;\mathcal{S},\mathcal{G})]^2}. \tag{6}$$

Utility definition. The utility of rankings is defined as the expected utility for the system users (i.e., assessed in terms of relevance) based on the same exposure model:

$$\mathrm{U}(\Pi;\mathcal{S}) = \frac{1}{|\mathcal{S}|} \sum_{s \in \mathcal{S}} \sum_{k=1}^{|\mathcal{I}_{q_s}|} \left[\gamma^{k-1} \prod_{j=1}^{k-1} (1 - p(s|\pi_{s,j}, q_s)) \right] p(s|\pi_{s,k}, q_s)). \tag{7}$$

3 METHOD

We suppose here that we have a set of 'source' groupings $\mathfrak{G}_S$ at our disposal, which differ from the true, unknown 'target' groupings $\mathfrak{G}_T$ considered in the evaluation. Possible source grouping choices will be discussed in Section 4.3. To address the MRFR problem defined in Eq. 1 using $\mathfrak{G}_S$, we propose a simple two-step method named Single-query Greedy Brute-force Re-ranking (SGBR).

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[2] Although item relevance is usually not known and often difficult to assess, we here decouple the tasks of relevance estimation and fair (re-)ranking to focus on the latter.
[3] Such assumption is reasonable as protected groups often refers to sensitive attributes such as age, gender, or ethnicity, which are not necessarily publicly disclosed.

- **Single-query**: SGBR independently enforces fairness in the rankings over the searches $\mathcal{S}_q$ associated to a unique query q, and not collectively across all the queries in $\mathcal{Q}$.
- **Greedy**: When SGBR computes the best ranking to return for a search s in the sequence $\mathcal{S}$, it only accounts for the previous searches $\mathcal{S}_{\leq s}$ and not for the whole sequence $\mathcal{S}$.
- **Brute-force**: SGBR selects a ranking by enumerating a set of possible rankings and keeping the highest scoring one.

The two first assumptions are enforced for efficiency reasons while preserving reasonable effectiveness. On the contrary, the third assumption implies a very computationally expensive approach if, given a query q, all the possible rankings of the items $\mathcal{I}_q$ were to be considered. Similarly to the candidate pre-filtering strategy from [3], our two-step method alleviates this issue by (1) pre-ordering the items to position the documents leading to potential improvement in utility and fairness at the top and (2) performing the brute-force selection to consider the rankings which permute only the top items of the pre-ordering. Note that SGBR is a general approach which can also be used for standard Fair Ranking, with known groupings.

3.1 Item pre-ordering

We assume here that we are processing search s in the sequence $\mathcal{S}$ and wish to return a ranking for s. In the pre-ordering step, we first score and rank all the items in $\mathcal{I}_{q_s}$ based on the following function:

$$\phi(i) = \mathrm{rel}(i; q_s) - \frac{\beta}{|\mathfrak{G}_S|} \sum_{\mathcal{G} \in \mathfrak{G}_S} \delta(i; \Pi_{<s}, \mathcal{S}_{<s}, \mathcal{G}) \quad (8)$$

where $\delta(i; \Pi_{<s}, \mathcal{S}_{<s}, \mathcal{G}) = \sum_{g \in \mathcal{G}_i} [\mathrm{E}(g; \Pi_{<s}, \mathcal{S}_{<s}, \mathcal{G}) - \mathrm{M}(g; \mathcal{S}_{<s}, \mathcal{G})]$ with $\mathcal{G}_i$ the set of groups in grouping $\mathcal{G}$ associated to the producers of item i. β is a trade-off hyperparameter. Intuitively, $\delta(i; \Pi_{<s}, \mathcal{S}_{<s}, \mathcal{G})$ measures whether the groups of i were *over-exposed* (> 0) or *under-exposed* (< 0) in the previous rankings $\Pi_{<s}$. Therefore, ϕ ranks at the top of this pre-ordering the items which are relevant and whose groups underwent an exposure deficit in the previous rankings.

3.2 Top-item Brute-force Re-ranking

In this second step, SGBR operates in a brute-force fashion on the top pre-ordered items (obtained as detailed in Sec. 3.1): it scores every candidate ranking formed as a permutation of the top-K items from the pre-ordered list, concatenated with the remaining items in their pre-ordered position. K is an hyperparameter which balances efficiency (small K) versus effectiveness (large K). Following Eq. 1, each candidate ranking π^c is then scored based on the combination of utility and unfairness using the following function:

$$\psi(\pi^c) = \mathrm{U}(\Pi_{<s} \cup \pi^c; \mathcal{S}_{\leq s}) - \frac{\lambda}{|\mathfrak{G}_S|} \sum_{\mathcal{G} \in \mathfrak{G}_S} \Delta(\Pi \cup \pi^c; \mathcal{S}_{\leq s}, \mathcal{G}). \quad (9)$$

Finally, $\pi_s = \mathrm{argmax}_{\pi^c}\, \psi(\pi^c)$ is the ranking returned for search s.

4 EXPERIMENTS

We performed a series of experiments on the TREC-FR collection [2] to investigate the following questions: Is our two-step SGBR approach an effective substitute for a full brute-force approach (Sec. 4.2)? What is an adequate source grouping(s) choice in a MRFR scenario, i.e., with unknown target groupings (Sec. 4.3)?

Table 1: List of compared approaches and their description.

Random: Random permutations of the documents associated to queries.	**Max-util**: Ranking of the documents by relevance to the queries.
SGBR-Bal[S,M,L]: SGBR based on a single source grouping with a small, medium or large number of balanced groups (BalS, BalM, and BalL, resp.).	**SGBR-C[4,8]S[1-3]**: SGBR based on a single source grouping from C4S or C8S. Each grouping, indexed from 1 to 3, was randomly chosen.
SGBR-Sing[A,D]: SGBR based on a single source grouping corresponding to author (A) or doc. (D) singletons.	**SGBR-AggC[4,8]S**: SGBR based on all the source groupings from either C4S or C8S, aggregated in $\mathfrak{G}_S$.

4.1 Experimental Setup

Our series of experiments is based on the collection introduced in the TREC 2019 Fair Ranking track [2]. In this collection, items are scientific papers and producers are the article authors. We used the evaluation split of the collection composed of 635 unique queries and a total of 4027 documents with groundtruth relevance. Each query is associated with an average of 6.83 documents to re-rank. The articles are written by 15,185 authors. Additionally, the collection includes 5 sequences of 25,000 searches each with repetitions of the same queries. In the experiments, we consider each sequence as a different $\mathcal{S}$, and average over the 5 sequences.

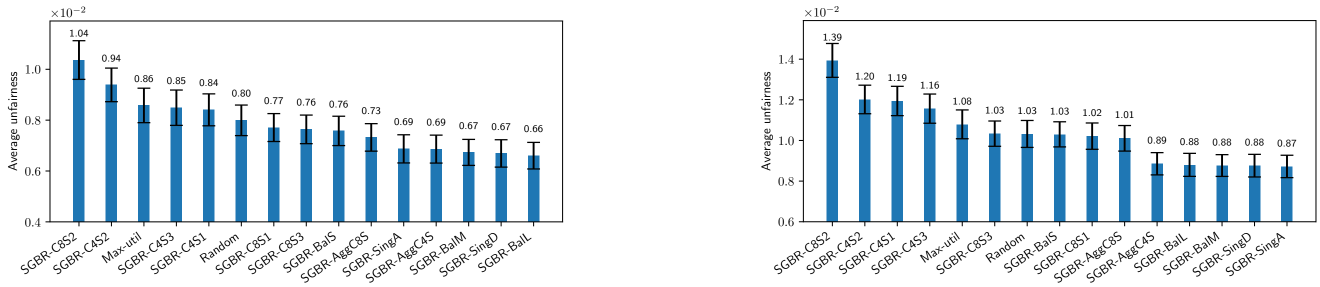
The original TREC-FR collection includes two groupings of the authors. However, as we investigate the MRFR scenario in this paper, we propose to generate a large amount of synthetic groupings to more reliably compare the average performance in terms of (un-)fairness for different approaches. Indeed, relying on merely two groupings would potentially bias the results. Additionally, the MRFR problem considers that target groupings are unknown when the rankings are formed. Therefore, we investigate different possible source groupîng strategies to address the unknown target grouping issue. All in all, we generated the following groupings:

- Two *singleton groupings*, based on authors (**SingA**) or documents (**SingD**). In these groupings, each author (or document) forms a group.
- Three *balanced groupings* made of random homogenous-size groups, with a small, medium or large number of groups (resp., 2, 5, and 8), denoted as **BalS**, **BalM**, **BalL**, respectively.
- Four times 100 *Chinese restaurant process-based groupings*. CRPs [1] are known to enforce a rich-get-richer property which is appropriate to simulate an unbalanced scenario with some minority (smaller) groups and majority (larger) groups. We set the value for the new table creation probability α to either 0.4 or 0.8, and for each we generated 100 source (S) groupings and 100 target (T) groupings. This yields four sets of 100 groupings each, denoted as **C4S**, **C4T**, **C8S**, and **C8T**.

The weight λ (in the objective function) is arbitrarily set to 1.0. The hyperparameters K (in the top-item brute-force), β (in the pre-ordering), γ (in the exposure model) and ϵ (in the stopping probability) were defined as 3, 1.0, 0.9 and 0.5, respectively. The approaches compared in the experiments are detailed in Table 1.

4.2 Validation of SGBR

To validate the efficacy of our two-step approach SGBR, we performed an ablation study by studying how each step (pre-ordering and brute-force re-ranking) performs in isolation. In particular, we focus here on the SGBR-SingA approach and analyze the value of



(a) Unfairness averaged on the target groupings from C4T

(b) Unfairness averaged on the target groupings from C8T

Figure 1: Average unfairness on the target groupings (lower is better). Error bars denote the standard error computed from 100 groupings.

Table 2: Objective function values of SGBR-SingA and variants on the source grouping (author singletons) for queries with $|\mathcal{I}_q| \leq 5$.

Approach	Utility (U)	Unfairness (Δ)	$U - \lambda \cdot \Delta$
SGBR-SingA	0.79484	0.09998	0.69486
SGBR-SingA (w/o pre-ordering)	0.79484	0.12670	0.66814
SGBR-SingA (w/o brute-force)	0.79485	0.10120	0.69365
Full brute-force (on all query docs)	0.79482	0.09985	0.69497

Table 3: Utility of the different approaches (higher is better).

Approach	Utility (U)	Approach	Utility (U)	Approach	Utility (U)
Max-util	0.828275	SGBR-SingA	0.828274	SGBR-C4S2	0.827855
SGBR-AggC4S	0.828275	SGBR-C8S2	0.828245	SGBR-C8S3	0.827682
SGBR-AggC8S	0.828275	SGBR-BalL	0.828157	SGBR-C4S1	0.826479
SGBR-SingD	0.828275	SGBR-C8S1	0.828151	SGBR-BalS	0.826142
SGBR-C4S3	0.828275	SGBR-BalM	0.828062	Random	0.736713

its objective function, based on utility and unfairness – the latter computed on the source, author singleton grouping. We consider a variant with no pre-ordering (in that case brute force is applied to the top relevant items) and another one with no brute-force re-ranking. Additionally, we compare SGBR-SingA against a full brute-force approach, which retains the best permutation of all documents attached to a query (equivalent to setting K to ∞ in SGBR). As this latter method becomes infeasible for queries with a large number of documents to re-rank, we restrain here to queries with at most 5 documents. The results are reported in Table 2. We observe that the objective function value $U - \lambda \cdot \Delta$ obtained by SGBR-SingA is higher than that of the two ablated versions, with notably lower values in terms of unfairness. In fact, SGBR-SingA reaches a performance very close to that of the full brute-force approach. These observations confirm the importance of the two steps in SGBR, and its ability to approach the performance of a full brute-force method.

4.3 Robustness to Unknown Groupings

In this section, we study the effectiveness of different source grouping strategies to address the MRFR problem. We use the groupings from C4T and C8T (100 for each) as target groupings. We compare four source grouping strategies for the SGBR approach: (S1) Use one random grouping from the source groupings C4S or C8S; (S2) Use one grouping based on the author or document singletons; (S3) Use one balanced random grouping of the authors; (S4) Use all the groupings from C4S or C8S at once. The approaches derived from these strategies are detailed in Table 1. For comparison, we also evaluated a random and a 'maximum utility' approach. The results in terms of unfairness and utility are reported in Fig. 1 and Table 3, respectively. On both C4S and C8S, we observe that 5 approaches obtain notably lower unfairness: SGBR-AggC4S, SGBR-Bal[M,L], and SGBR-Sing[A,D]. By performing a pairwise Student t-test on the 100 groupings from C4T/C8T, we noted that this difference with respect to the other approaches is significant (for $\alpha = 0.05$), whereas the results of the 5 approaches are mostly statistically equivalent. SGBR-BalS and SGBR-AggC8S (strategies S3 and S4, respectively) reported slightly higher (i.e., worse) unfairness. The worst unfairness was obtained by SGBR-C[4,8]S[1-3] (strategy S1), which confirms our intuition that using a specific, unbalanced grouping leads to a bad generalization to target groupings. In terms of utility (Table 3), we found that most approaches (except Random) performed similarly. Interestingly, SGBR-AggC[4,8]S, SGBR-SingD and SGBR-C4S3 reached the maximum utility (given by Max-util). All in all, we conclude that the singleton strategy (S2) yields the most effective and reliable way to trade-off between utility and unfairness.

5 CONCLUSION

In this study, we introduced the problem of Multi-grouping Robust Fair Ranking which addresses fair ranking with unknown target groupings. We proposed different source grouping strategies, along with an efficient SGBR method to implement them. The experiments performed on the TREC-FR benchmark revealed that the singleton grouping strategy seemed to be the most viable one. In future work, we plan to theoretically validate these results.

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