Policy Learning for Fairness in Ranking

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Abstract

Conventional Learning-to-Rank (LTR) methods optimize the utility of the rankings to the users, but they are oblivious to their impact on the ranked items. However, there has been a growing understanding that the latter is important to consider for a wide range of ranking applications (e.g. online marketplaces, job placement, admissions). To address this need, we propose a general LTR framework that can optimize a wide range of utility metrics (e.g. NDCG) while satisfying fairness of exposure constraints with respect to the items. This framework expands the class of learnable ranking functions to stochastic ranking policies, which provides a language for rigorously expressing fairness specifications. Furthermore, we provide a new LTR algorithm called FAIR-PG-RANK for directly searching the space of fair ranking policies via a policy-gradient approach. Beyond the theoretical evidence in deriving the framework and the algorithm, we provide empirical results on simulated and real-world datasets verifying the effectiveness of the approach in individual and group-fairness settings.

1. Introduction

Interfaces based on rankings are ubiquitous in today's multisided online economies (e.g., online marketplaces, job search, property renting, media streaming). In these systems, the items to be ranked are products, job candidates, or other entities that transfer economic benefit, and it is widely recognized that the position of an item in the ranking has a crucial influence on its exposure and economic success. Surprisingly, though, the algorithms used to learn these rankings are typically oblivious to the effect they have on the items. Instead, the learning algorithms blindly maximize the utility of the rankings to the users issuing queries to the systems (Robertson, 1977), and there is evidence (e.g. (Kay et al., 2015; Singh & Joachims, 2018)) that this does not

necessarily lead to rankings that would be considered fair or desirable in many situations.

In this paper, we ask the question of how to design Learningto-Rank (LTR) algorithms that not only maximize utility to the users, but that also obey given fairness constraints towards the items. Depending on the application, such fairness constraints may be required to conform with anti-trust legislation (Scott, 2017), to alleviate winner-takes-all dynamics in a music streaming service (Mehrotra et al., 2018), to implement anti-discrimination measures (Edelman et al., 2017), or to implement some variant of search neutrality (Introna & Nissenbaum, 2000; Grimmelmann, 2011). Focusing on notions of fairness around the key scarce resource that search engines arbitrate, namely the relative allocation of exposure based on the items' merit, we present the first learning algorithm - named FAIR-PG-RANK - that rigorously incorporates fairness constraints in the LTR framework. In this way, FAIR-PG-RANK is different from existing fairranking methods that are applied as a post-processing step after learning and that assume that relevances are known (Singh & Joachims, 2018; Biega et al., 2018), or methods that use heuristics to incorporate constraints into the learning process (Zehlike & Castillo, 2018).

From a technical perspective, the main contributions of the paper are three-fold. First, we develop a conceptual framework in which it is possible to formulate fair LTR as a policy learning problem subject to a fairness constraint. We show that viewing fair LTR as a problem of learning a stochastic ranking policy leads to a rigorous formulation that can be addressed via Empirical Risk Minimization (ERM) on both the utility and the fairness constraint. Second, we propose a class of fairness constraints for ranking that incorporates notions of both individual and group fairness. And, third, we propose a policy-gradient method for implementing the ERM procedure that can directly optimize any information retrieval utility metric and a wide range of fairness criteria. Across a number of empirical evaluations, we find that the policy gradient method is a competitive LTR procedure in its own merit, that FAIR-PG-RANK can identify and avoid biased features when trading-off utility for fairness, and that it can optimize notions of individual and group fairness on real-world datasets.

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2. Related Work

Before introducing our learning framework for fairness in rankings, we first survey four related branches of prior work. First, we draw on the concepts of algorithmic fairness for supervised learning in the presence of sensitive attributes. Second, we relate our contributions to recent work on fairness for rankings. Third, we contrast the idea of fairness with the well-studied area of diversified rankings in information retrieval. Finally, we survey a few Learning-to-rank algorithms to present their limitations for our purpose of learning fair rankings.

As algorithmic techniques, especially machine learning methods, start to make an entry into decision-making applications, it has become important to study its societal impact (Barocas & Selbst, 2016). In supervised learning, there have been numerous attempts to define notions of fairness for tasks that involve subjects with sensitive attributes such as race or gender. The individual fairness perspective states that two individuals that are similar w.r.t. to the task should also have similar outcomes (Dwork et al., 2012). A group fairness perspective defines fairness in terms of outcomes for the entire groups. For example, demographic parity asserts equal proportion of positive outcomes for different groups (Calders et al., 2009; Zliobaite, 2015), while equalized odds defines fairness as equality of false positive and true positive rates across groups (Hardt et al., 2016). Several recent works have focused on learning algorithms compatible with these definitions of fair classification (Zemel et al., 2013; Woodworth et al., 2017; Zafar et al., 2017), while some works propose a causal approach to fairness (Kilbertus et al., 2017; Kusner et al., 2017). In this paper, we draw on many of these ideas to define notions of fairness for individual and group perspectives for rankings, and we develop LTR algorithms for these notions.

Fairness for rankings has been a relatively unexplored domain despite the growing influence of online information systems on the society and the economy, and their strong dependence on ranking interfaces. Several recent works have raised the question of group fairness in rankings along the lines of statistical parity, and proposed definitions and methods that either minimize the difference in the representation of different groups in a prefix of the ranking (Yang & Stoyanovich, 2017), or bound the number of items belonging to a particular demographic in the top-k (Zehlike et al., 2017; Celis et al., 2017; Asudehy et al., 2017). More recent works have argued that fairness of these ranking systems comes from the allocation of exposure to individual items or group of items (Singh & Joachims, 2018; Biega et al., 2018). These works specify fairness constraints on the allocation of exposure based on relevance in expectation over multiple presentations of a ranking or in an amortized fashion over a set of queries. In our work, we build upon

the framework proposed by Singh & Joachims (2018) to make these constraints more general as well fix their limitations. Furthermore, unlike Singh & Joachims (2018) our approach generalizes to unseen queries where the relevances are unknown. Zehlike & Castillo (2018) present a learning method to implement the exposure-based statistical parity constraint by using a heuristic to define a ranking loss and a group fairness regularizer based on the top-1 probability of each item. This heuristic does not ensure fairness and utility throughout the whole ranking, which is a limitation that our approach overcomes by directly optimizing both utility and fairness.

The problem of fairness and incorporating diversity in information retrieval might seem related at first glance. However, their motivations and mechanisms are fundamentally different. Diversified rankings aim to deal with the ambiguity in user's information need (extrinsic diversity) (Radlinski et al., 2008; Carbonell & Goldstein, 1998) or with the need of diversity as a part of the information need by introducing novelty and avoiding redundancy (intrinsic diversity) (Clarke et al., 2008; Radlinski et al., 2009). While these forms of diversity in information retrieval still aim to maximize user utility alone, our approach to fairness in rankings trades-off user utility against merit-based guarantees to the items being ranked.

Conventional LTR methods that maximize user utility are either designed to optimize over a smoothed version of a specific utility metric, such as SVMRank (Joachims et al., 2009), RankNet (Burges et al., 2005) etc., or use heuristics to optimize over probabilistic formulations of rankings (e.g. SoftRank (Taylor et al., 2008)). Our LTR setup, however, defines ranking functions as stochastic ranking policies which allows us to use policy-gradient techniques to learn these functions. We use a probabilistic setup that is similar to ListNet (Cao et al., 2007), however in comparison, instead of choosing a heuristic loss function, we directly optimize the utility metric using a policy gradient update. A recent LTR method, that also uses policy gradients, models the process of ranking as a Markov Decision Process (MDP) with a reward for each position (Wei et al., 2017). Our approach is more general, since we assign a reward to the entire ranking, thus allowing to incorporate list-wise metrics for both utility and fairness.

3. Learning Fair Ranking Policies

The key goal of our work is to learn ranking policies where the allocation of exposure to items is not an accidental byproduct of maximizing utility to the users, but where one can specify a merit-based exposure-allocation constraint that is enforced by the learning algorithm. An illustrative example adapted from Singh & Joachims (2018) is that of ranking 10 job candidates, where the true relevances of 5 male job

candidates are {0.89, 0.89, 0.89, 0.89, 0.89} and those of 5 female candidates are {0.88, 0.88, 0.88, 0.88, 0.88}. If these 10 candidates were ranked by probability of relevance – thus maximizing utility to the users under virtually all information retrieval metrics (Robertson, 1977) – the female candidates would get far less exposure (ranked 6,7,8,9,10) than the male candidates (ranked 1,2,3,4,5) even though they have almost the same relevance. We, therefore, argue that it should be possible to explicitly specify how exposure should be allocated (e.g. make exposure proportional to relevance), that this specified exposure allocation is truthfully learned by the ranking policy (e.g. no systematic bias towards one of the groups), and that the ranking policy maintains a high utility to the users.

Generalizing from this illustrative example, we develop our fair LTR framework as guided by the following three goals:

Goal 1: Exposure allocated to an item is based on its merit. More merit means more exposure.

Goal 2: Enable the explicit statement of how exposure is allocated relative to the merit of the items.

Goal 3: Optimize the utility of the rankings to the users while satisfying *Goal 1* and *Goal 2*.

We will illustrate and further refine these goals as we develop our framework in the rest of this section. In particular, we first formulate the LTR problem in the context of empirical risk minimization (ERM) where exposure-allocation constraints are included in the empirical risk. We then define concrete families of allocation constraints for both individual and group fairness.

3.1. Learning to Rank as Policy Learning via ERM

Let $\mathcal Q$ be the distribution from which queries are drawn. Each query q has a candidate set of documents $d^q = \{d_1^q, d_2^q, \dots d_{n(q)}^q\}$ that needs to be ranked, and a corresponding set of real-valued relevance judgments, $\operatorname{rel}^q = (\operatorname{rel}_1^q, \operatorname{rel}_2^q \dots \operatorname{rel}_{n(q)}^q)$. Our framework is agnostic to how relevance is defined, and it could be the probability that a user with query q finds the document relevant, or it could be some subjective judgment of relevance as assigned by a relevance judge. Finally, each document d_i^q is represented by a feature vector $x_i^q = \Psi(q, d_i^q)$ that describes the match between document d_i^q and query q.

We consider stochastic ranking functions $\pi \in \Pi$, where $\pi(r|q)$ is a distribution over the rankings r (i.e. permutations) of the candidate set. We refer to π as a ranking policy and note that deterministic ranking functions are merely a special case. However, a key advantage of considering the full space of stochastic ranking policies is their ability to distribute expected exposure in a continuous fashion, which provides more fine-grained control and enables gradient-based optimization.

The conventional goal in LTR is to find a ranking policy π^* that maximizes the expected utility of π

$$\pi^* = \operatorname{argmax}_{\pi \in \Pi} \mathbb{E}_{q \sim \mathcal{Q}} [U(\pi|q)],$$

where the utility of a stochastic policy π for a query q is defined as the expectation of a ranking metric Δ over π

$$U(\pi|q) = \mathbb{E}_{r \sim \pi(r|q)} \left[\Delta(r, \text{rel}^q) \right].$$

Common choices for Δ are DCG, NDCG, Average Rank, or ERR. For concreteness, we focus on NDCG, which is the normalized version of

$$\Delta_{\mathrm{DCG}}(r, \mathrm{rel}^q) = \sum_{j=1}^{n_q} \frac{u(r(j)|q)}{\log(1+j)}.$$

u(r(j)|q) is the utility of the document placed by ranking r on position j for q as a function of relevance, for example, Chapelle & Chang (2011) uses $u(i|q) = 2^{\mathrm{rel}_i^q} - 1$. NDCG normalizes DCG via $\Delta_{\mathrm{NDCG}}(r,\mathrm{rel}^q) = \frac{\Delta_{\mathrm{DCG}}(r,\mathrm{rel}^q)}{\max_r \Delta_{\mathrm{DCG}}(r,\mathrm{rel}^q)}$.

Fair Ranking policies. Instead of single-mindedly maximizing this utility measure like in conventional LTR algorithms, we include a constraint into the learning problem that enforces an application-dependent notion of fair allocation of exposure. To this effect, let's denote with $\mathcal{D}(\pi|q) \geq 0$ a measure of unfairness or the disparity, which we will define in detail in Section § 3.2. We can now formulate the objective of fair LTR by constraining the space of admissible ranking policies to those that have expected disparity less than some parameter δ .

$$\pi_{\delta}^* = \operatorname{argmax}_{\pi} \mathbb{E}_{q \sim \mathcal{Q}} [U(\pi|q)] \text{ s.t. } \mathbb{E}_{q \sim \mathcal{Q}} [\mathcal{D}(\pi|q)] \leq \delta$$

Since we only observe samples from the query distribution \mathcal{Q} , we resort to the ERM principle and estimate the expectations with their empirical counterparts. Denoting the training set as $\mathcal{T} = \{(\mathbf{x}^q, \mathrm{rel}^q)\}_{q=1}^N$, the empirical analog of the optimization problem becomes

$$\hat{\pi}^*_{\delta} = \operatorname{argmax}_{\pi} \frac{1}{N} \sum_{q=1}^{N} U(\pi|q) \text{ s.t. } \frac{1}{N} \sum_{q=1}^{N} \mathcal{D}(\pi|q) \leq \delta.$$

Using a Lagrange multiplier, this is equivalent to

$$\hat{\pi}^*_{\delta} = \operatorname{argmax}_{\pi} \min_{\lambda \geq 0} \frac{1}{N} \!\! \sum_{q=1}^{N} \!\! U(\pi|q) - \lambda \! \left(\!\! \frac{1}{N} \!\! \sum_{q=1}^{N} \!\! \mathcal{D}(\pi|q) \! - \! \delta \! \right).$$

In the following, we avoid minimization w.r.t. λ for a chosen δ . Instead, we steer the utility/fairness trade-off by chosing a particular λ and then computing the corresponding δ afterwards. This means we merely have to solve

$$\hat{\pi}_{\lambda}^* = \operatorname{argmax}_{\pi} \frac{1}{N} \sum_{q=1}^{N} U(\pi|q) - \lambda \frac{1}{N} \sum_{q=1}^{N} \mathcal{D}(\pi|q) \quad (1)$$

and then recover $\delta_{\lambda} = \frac{1}{N} \sum_{q=1}^{N} \mathcal{D}(\hat{\pi}_{\lambda}^{*}|q)$ afterwards. Note that this formulation implements our third goal from the opening paragraph, although we still lack a concrete definition of \mathcal{D} .

3.2. Defining a Class of Fairness Measures

To make the training objective in Equation (1) fully specified, we still need a concrete definition of the unfairness measure \mathcal{D} . To this effect, we adapt the "Fairness of Exposure for Rankings" framework from Singh & Joachims (2018), since it allows a wide range of application dependent notions of group-based fairness, including Statistical Parity, Disparate Exposure, and Disparate Impact. In order to formulate any specific disparity measure \mathcal{D} , we first need to define position bias and exposure.

Position Bias. The position bias of position j, \mathbf{v}_j , is defined as the fraction of users accessing a ranking who examine the item at position j. This captures how much attention a result will receive, where higher positions are expected to receive more attention than lower positions. In operational systems, position bias can be directly measured using eye-tracking (Joachims et al., 2007), or indirectly estimated through swap experiments (Joachims et al., 2017) or intervention harvesting (Fang et al., 2018). For simplicity of notation and without loss of generality, we ignore that position bias may depend on the query (Fang et al., 2018).

Exposure. For a given query q and ranking distribution $\pi(r|q)$, the exposure of a document is defined as the expected attention that a document receives. This is equivalent to the expected position bias from all the positions that the document can be placed in. Exposure is denoted as $v_{\pi}(d_i)$ and can be expressed as

Exposure
$$(d_i|\pi) = v_{\pi}(d_i) = \mathbb{E}_{r \sim \pi(r|q)} \left[\mathbf{v}_{r(d_i)} \right],$$
 (2)

where $r(d_i)$ is the position of document d_i under ranking r.

Allocating exposure based on merit. Our first two goals from the opening paragraph postulate that exposure should be based on an application dependent notion of merit. We define the *merit* of a document as a function of its relevance to the query (e.g., rel_i , rel_i^2 or $\sqrt{\operatorname{rel}_i}$ depending on the application). Let's denote the merit of document d_i as $M(\operatorname{rel}_i) \geq 0$, or simply M_i , and we state that each document in the candidate set should get exposure proportional to its merit M_i .

$$\forall d_i \in d^q : \text{Exposure}(d_i|\pi) \propto M(\text{rel}_i)$$

For many queries, however, this set of exposure constraints is infeasible. As an example, consider a query where one document in the candidate set has relevance 1, while all other documents have small relevance ϵ . For sufficiently small ϵ , any ranking will provide too much exposure to the

 ϵ -relevant documents, since we have to put these documents somewhere in the ranking. This violates the exposure constraint, and this shortcoming is also present in the Disparate Exposure measure of Singh & Joachims (2018) and the Equity of Attention constraint of Biega et al. (2018).

To overcome this problem of overabundance of exposure, we instead consider the following set of inequality constraints where $\forall d_i, d_j \in d^q$ with $M(\text{rel}_i) \geq M(\text{rel}_j) > 0$,

$$\frac{\operatorname{Exposure}(d_i|\pi)}{M(\operatorname{rel}_i)} \leq \frac{\operatorname{Exposure}(d_j|\pi)}{M(\operatorname{rel}_j)}.$$

This set of constraints still enforces proportionality of exposure to merit, but allows the allocation of overabundant exposure. This is achieved by only enforcing that higher merit items don't get exposure beyond their merit, since the opposite direction is already achieved through utility maximization. This counteracts unmerited rich-get-richer dynamics, as present in the motivating example from above.

Measuring disparate exposure. We can now define the following disparity measure \mathcal{D} that captures in how far the fairness-of-exposure constraints are violated

$$\mathcal{D}_{\text{ind}}(\pi|q) = \frac{1}{|H_q|} \sum_{(i,j) \in H_q} \max \left[0, \frac{v_{\pi}(d_i)}{M_i} - \frac{v_{\pi}(d_j)}{M_j} \right], \quad (3)$$

where $H_q = \{(i, j) \text{ s.t. } M_i \geq M_j > 0\}$. The measure $\mathcal{D}_{\text{ind}}(\pi|q)$ is always non-negative and it equals zero only when the individual constraints above are exactly satisfied.

Group fairness disparity. The disparity measure from above implements an individual notion of fairness, while other applications ask for a group-based notion. Here, fairness is aggregated over the members of each group. A group of documents can refer to sets of items sold by one seller in an online marketplace, to content published by one publisher, or to job candidates belonging to a protected group. Similar to the case of individual fairness, we want to allocate exposure to groups proportional to their merit. Hence, in the case of only two groups G_0 and G_1 , we can define the following group fairness disparity for query q as

$$\mathcal{D}_{\text{group}}(\pi|q) = \max\left(0, \frac{v_{\pi}(G_i)}{M_{G_i}} - \frac{v_{\pi}(G_j)}{M_{G_j}}\right), \quad (4)$$

where G_i and G_j are such that $M_{G_i} \geq M_{G_j}$ and $\operatorname{Exposure}(G|\pi) = v_\pi(G) = \frac{1}{|G|} \sum_{d_i \in G} v_\pi(d_i)$ is the average exposure of group G, and the merit of the group G is denoted by $M_G = \frac{1}{|G|} \sum_{d_i \in G} M_i$.

4. FAIR-PG-RANK: A Policy Learning Algorithm for Fair LTR

In the previous section, we defined a general framework for learning ranking policies under fairness-of-exposure constraints. What remains to be shown is that there exists a stochastic policy class Π and an associated training algorithm that can solve the objective in Equation (1) under the disparities \mathcal{D} defined above. To this effect, we now present the FAIR-PG-RANK algorithm. In particular, we first define a class of Plackett-Luce ranking policies that incorporate a machine learning model, and then present a policy-gradient approach to efficiently optimizing the training objective.

4.1. Plackett-Luce Ranking Policies

The ranking policies π we define in the following comprise of two components: a scoring model that defines a distribution over rankings and its associated sampling method. Starting with the scoring model h_{θ} , we allow any differentiable machine learning model with parameters θ , for example a linear model or a neural network. Given an input \mathbf{x}^q representing the feature vectors of all query-document pairs of the candidate set, the scoring model outputs a vector of scores $h_{\theta}(\mathbf{x}^q) = (h_{\theta}(x_1^q), h_{\theta}(x_2^q), \dots h_{\theta}(x_{n_q}^q))$. Based on this score vector, the probability $\pi_{\theta}(r|q)$ of a ranking $r = \langle r(1), r(2), \dots r(n_q) \rangle$ under the Plackett-Luce model is the following product of softmax distributions

$$\pi_{\theta}(r|q) = \prod_{i=1}^{n_q} \frac{\exp(h_{\theta}(x_{r(i)}^q))}{\exp(h_{\theta}(x_{r(i)}^q)) + \dots + \exp(h_{\theta}(x_{r(n_q)}^q))}.$$
(5)

Note that this probability of a ranking can be computed efficiently, and that the derivative of $\pi_{\theta}(r|q)$ and $\log \pi_{\theta}(r|q)$ exists whenever the scoring model h_{θ} is differentiable.

Sampling a ranking under the Plackett-Luce model is efficient as well. To sample a ranking, starting from the top, documents are drawn recursively from the probability distribution resulting from Softmax over the scores of the remaining documents in the candidate set, until the set is empty.

4.2. Policy-Gradient Training Algorithm

The next step is to search this policy space Π for a model that maximizes the objective in Equation (1). This section proposes a policy-gradient approach (Williams, 1992; Sutton, 1998), where we use stochastic gradient descent (SGD) updates to iteratively improve our ranking policy. However, since both U and \mathcal{D} are expectations over rankings sampled from π , computing the gradient brute-force is intractable. In this section, we derive the required gradients over expectations as an expectation over gradients. We then estimate this expectation as an average over a finite sample of rankings from the policy to get an approximate gradient.

Directly optimizing the ranking policy via policy-gradient learning has two advantages over most conventional LTR algorithms, which optimize upper bounds or heuristic proxy measures. First, our learning algorithm directly optimizes a specified user utility metric and has no restrictions in the choice of the IR metric. Second, we can use the same policy-

gradient approach on our disparity measure \mathcal{D} as well, since it is also an expectation over rankings. Overall, the use of policy-gradient optimization in the space of stochastic ranking policies elegantly handles the non-smoothness inherent in rankings.

4.2.1. PG-RANK: MAXIMIZING USER UTILITY

The user utility of a policy π_{θ} for a query q is defined as $U(\pi|q) = \mathbb{E}_{r \sim \pi_{\theta}(r|q)} \Delta \big(r, \operatorname{rel}^q \big)$. Note that taking the gradient w.r.t. θ over this expectation is not straightforward, since the space of rankings is exponential in cardinality. To overcome this, we use sampling via the log-derivative trick pioneered in the REINFORCE algorithm (Williams, 1992) as follows:

$$\nabla_{\theta} U(\pi_{\theta}|q) = \nabla_{\theta} \mathbb{E}_{r \sim \pi_{\theta}(r|q)} \Delta(r, \text{rel}^{q})$$

$$= \nabla_{\theta} \frac{1}{n_{q}!} \sum_{r \in \sigma(n_{q})} \pi_{\theta}(r|q) \Delta(r, \text{rel}^{q})$$

$$= \frac{1}{n_{q}!} \sum_{r \in \sigma(n_{q})} \nabla_{\theta} [\pi_{\theta}(r|q)] \Delta(r, \text{rel}^{q})$$

$$= \frac{1}{n_{q}!} \sum_{r \in \sigma(n_{q})} \pi_{\theta}(r|q) \nabla_{\theta} [\log \pi_{\theta}(r|q)] \Delta(r, \text{rel}^{q})$$

$$= \mathbb{E}_{r \sim \pi_{\theta}(r|q)} [\nabla_{\theta} \log \underbrace{\pi_{\theta}(r|q)}_{\text{Eq. (5)}} \Delta(r, \text{rel}^{q})]$$
(6)

This transformation exploits that the gradient of the expected value of the metric Δ over rankings sampled from π can be expressed as the expectation of the gradient of the log probability of each sampled ranking multiplied by the metric value of that ranking. The final expectation is approximated via Monte-Carlo sampling from the Plackett-Luce model in Eq. (5).

Note that this policy-gradient approach to LTR, which we call PG-RANK, is novel in itself and beyond fairness. It can be used as a standalone LTR algorithm for virtually any choice of utility metric Δ , including NDCG, DCG, ERR, and Average-Rank. Furthermore, PG-RANK also supports non-linear metrics, IPS-weighted metrics for biased and partial information feedback (Joachims et al., 2017), and listwise metrics that do not decompose as a sum over individual documents (Zhai et al., 2003; Clarke et al., 2008).

Using baseline for variance reduction. Since making stochastic gradient descent updates with this gradient estimate is prone to high variance, we subtract a baseline term from the reward (Williams, 1992) to act as a control variate for variance reduction. Specifically, in the gradient estimate in Eq. (6), we replace $\Delta(r, \mathrm{rel}^q)$ with $\Delta(r, \mathrm{rel}^q) - b(q)$ where b(q) is the average Δ for the current query.

Entropy Regularization While optimizing over stochastic policies, entropy regularization is used as a method for en-

couraging exploration as to avoid convergence to suboptimal deterministic policies (Mnih et al., 2016; Williams & Peng, 1991). For our algorithm, we add the entropy of the probability distribution $\operatorname{Softmax}(h_{\theta}(\mathbf{x}^q))$ times a regularization coefficient γ to the objective.

4.2.2. MINIMIZING DISPARITY

When a fairness-of-exposure term \mathcal{D} is included in the training objective, we also need to compute the gradient of this term. Fortunately, it is has a structure similar to the utility term, so that the same Monte-Carlo approach applies. Specifically, for the individual-fairness disparity measure in Eq. (3), the gradient can be computed as

$$\begin{split} \nabla_{\theta} \mathcal{D}_{\text{ind}} &= \nabla_{\theta} \left[\frac{1}{|H|} \sum_{(i,j) \in H} \max \left(0, \frac{v_{\pi}(d_i)}{M_i} - \frac{v_{\pi}(d_j)}{M_j} \right) \right] \\ &\quad (H = \{(i,j) \text{ s.t. } M_i \geq M_j\}) \\ &= \nabla_{\theta} \left[\frac{1}{|H|} \sum_{(i,j) \in H} \max \left(0, \text{pdiff}_q(\pi,i,j) \right) \right] \\ &= \frac{1}{|H|} \sum_{(i,j) \in H} \mathbb{I}[\text{pdiff}_q(\pi,i,j) > 0] \nabla_{\theta} \text{pdiff}_q(\pi,i,j) \\ \nabla_{\theta} \text{pdiff}_q(\pi,i,j) &= \nabla_{\theta} \left[\frac{v_{\pi}(d_i)}{M_i} - \frac{v_{\pi}(d_j)}{M_j} \right] \\ &= \nabla_{\theta} \mathbb{E}_{r \sim \pi_{\theta}(r|q)} \left[\frac{v_r(d_i)}{M_i} - \frac{v_r(d_i)}{M_j} \right) \nabla_{\theta} \log \pi_{\theta}(r|q) \right] \\ &= \mathbb{E}_{r \sim \pi_{\theta}(r|q)} \left[\left(\frac{v_r(d_i)}{M_i} - \frac{v_r(d_i)}{M_j} \right) \nabla_{\theta} \log \pi_{\theta}(r|q) \right] \\ &\quad \text{(using the log-derivative trick)} \end{split}$$

For the group-fairness disparity measure defined in Eq. (4), the gradient can be derived as follows:

 $\nabla_{\theta} \mathcal{D}_{\text{group}}(\pi | G_0, G_1, q) = \nabla_{\theta} \max(0, \xi_q \text{diff}(\pi | q))$

where
$$\operatorname{diff}(\pi|q) = \left(\frac{v_{\pi}(G_0)}{M_{G_0}} - \frac{v_{\pi}(G_1)}{M_{G_1}}\right)$$
, and $\xi_q = +1$ if $M_{G_0} \geq M_{G_1}$, -1 otherwise. Further,
$$\nabla_{\theta} \mathcal{D}_{\operatorname{group}}(\pi|G_0, G_1, q) = \mathbb{I}\left[\xi_q \operatorname{diff}(\pi|q) > 0\right] \xi_q \nabla_{\theta} \operatorname{diff}(\pi|q)$$
 where,
$$\nabla_{\theta} \operatorname{diff}(\pi_{\theta}|q) = \nabla_{\theta} \left[\frac{v_{\pi}(G_0)}{M_{G_0}} - \frac{v_{\pi}(G_1)}{M_{G_1}}\right]$$

$$= \nabla_{\theta} \left[\frac{\frac{1}{|G_0|} \sum_{d \in G_0} \mathbb{E}_{r \sim \pi_{\theta}} v_r(d)}{\frac{1}{|G_0|} \sum_{d \in G_0} M(\operatorname{rel}_d)} - \frac{\frac{1}{|G_1|} \sum_{d \in G_1} \mathbb{E}_{r \sim \pi_{\theta}} v_r(d)}{\frac{1}{|G_1|} \sum_{d \in G_1} M(\operatorname{rel}_d)}\right]$$

$$= \nabla_{\theta} \mathbb{E}_{r \sim \pi_{\theta}} \left[\frac{\sum_{d \in G_0} v_r(d)}{\sum_{d \in G_0} M(\operatorname{rel}_d)} - \frac{\sum_{d \in G_1} v_r(d)}{\sum_{d \in G_1} M(\operatorname{rel}_d)}\right]$$

$$= \mathbb{E}_{r \sim \pi_{\theta}} \left[\left(\frac{\sum_{d \in G_0} v_r(d)}{\sum_{d \in G_0} M(\operatorname{rel}_d)} - \frac{\sum_{d \in G_1} v_r(d)}{\sum_{d \in G_0} M(\operatorname{rel}_d)}\right) \nabla_{\theta} \log \pi_{\theta}(r|q)\right]$$

The expectation of the gradient in both the cases can be estimated as an average over a Monte Carlo sample of rankings from the distribution. The size of the sample is denoted by S in the rest of the paper.

4.2.3. SUMMARY OF THE FAIR-PG-RANK ALGORITHM

Algorithm 1 FAIR-PG-RANK

Input: $\mathcal{T} = \{(\mathbf{x}^q, \mathrm{rel}^q)\}_{i=1}^N$, disparity measure \mathcal{D} , utility/fairness trade-off λ

Parameters: model h_{θ} , learning rate η , entropy reg γ Initialize h_{θ} with parameters θ_0

repeat

 $q = (\mathbf{x}^q, \mathrm{rel}^q) \sim \mathcal{T}$ {Draw a query from training set} $h_{\theta}(\mathbf{x}^q) = (h_{\theta}(x_1^q), h_{\theta}(x_2^q), \dots h_{\theta}(x_{n_q}^q))$ {Obtain scores for each document}

for i = 1 to S do

 $r_i \sim \pi_{\theta}(r|q)$ {Plackett-Luce sampling § 4.1}

end for

 $\nabla \leftarrow \hat{\nabla_{\theta}}U - \lambda \hat{\nabla_{\theta}}\mathcal{D}$ {Compute gradient as an average over all r_i using $\S 4.2.1$ and $\S 4.2.2$ } $\theta \leftarrow \theta + \eta \nabla$ {Update}

until convergence on the validation set

5. Empirical Evaluation

We conduct experiments on simulated and real-world datasets to empirically validate our setup. First, we validate that our policy-gradient approach to LTR is indeed able to learn accurate ranking policies without fairness constraints, and that it is competitive with conventional LTR approaches. Second, we use a simulated dataset to verify visually that FAIR-PG-RANK is able to learn models effectively tradeoff between utility to the users and group fairness for the items. Third, to evaluate the effectiveness of our algorithm in achieving fairness goals in the real world, we conduct experiments on the Yahoo! Learning to Rank dataset and German Credit Dataset (Dheeru & Karra Taniskidou, 2017) for individual fairness and group fairness respectively. For all the experiments, we use NDCG as the utility metric, define merit using the identity function M(rel) = rel, and set the position bias \mathbf{v} to follow the same distribution as the gain factor in DCG i.e. $\mathbf{v}_j \propto \frac{1}{\log_2(1+j)}$ where $j=1,2,3,\ldots$ is a position in the ranking.

5.1. Can PG-RANK learn accurate ranking policies?

To validate that our policy-gradient approach is indeed a highly effective LTR method, we conduct experiments with the Yahoo! Learning to rank challenge dataset (Chapelle & Chang, 2011). We use the standard experiment setup on the SET 1 dataset, which consists of 19,944 training queries and 6,983 queries in the test set. We optimize NDCG using FAIR-PG-RANK, which is equivalent to finding the optimal policy in Eq. (1) with $\lambda=0$.

Table 1. Comparison of PG-RANK's performance on Yahoo Learning to Rank SET 1 test dataset. Comparison is made against a linear and a non-linear baseline from Chapelle & Chang (2011).

	NDCG@10	ERR
RankSVM (Joachims, 2006)	0.75924	0.43680
GBDT (Ye et al., 2009)	0.79013	0.46201
PG-RANK (Linear model)	0.76145	0.44988
PG-RANK (Neural Network)	0.77082	0.45440

We train FAIR-PG-RANK for two kinds of scoring models: a linear model, and a neural network with one hidden layer of size 32 and ReLU activation function. All the weights were randomly initialized between (-0.001, 0.001) for the linear model and $(-1/\sqrt{32}, 1/\sqrt{32})$ for the neural network. We use an Adam optimizer with a learning rate of 0.001 for the linear model and 5×10^{-5} for the neural network. For both the cases, we set the entropy regularization constant to $\gamma = 1.0$, use a baseline, and use a sample size of S = 10to estimate the gradient. Both models are trained for 20 epochs over the training dataset, updating the model one query at a time. The policy learned by our method is a stochastic policy that assigns a probability distribution over rankings, however, for the purpose of evaluation in this task, we use the highest probability ranking of the candidate set for each query and compute the average NDCG@10 and ERR (Expected Reciprocal Rank) over all the test set queries. We compare our evaluation scores with two baselines from Chapelle & Chang (2011) – a linear RankSVM (Joachims, 2006) and a non-linear regression based ranker that uses Gradient-boosted Decision Trees (GBDT) (Ye et al., 2009).

Table 1 shows that PG-RANK achieves competitive performance compared to the conventional LTR methods. When comparing PG-RANK to RankSVM for training linear models, our method outperforms RankSVM in terms of both NDCG@10 and ERR. This verifies that the policy-gradient approach is very effective at optimizing utility without having to rely on a possibly lose convex upper bound like RankSVM. PG-RANK with the non-linear neural network model further improves on the linear model. While it does not reach the same performance as the boosted decision trees, it is unclear in how far this is attributable to the difference in model class. Furthermore, additional parameter tuning and a large range of variance-control techniques from policy optimization are likely to further boost the performance of PG-RANK, but are outside the scope of this paper.

5.2. Can FAIR-PG-RANK effectively trade-off between utility and fairness?

We designed a synthetic dataset that allows us to inspect how FAIR-PG-RANK trades-off between user utility and fairness of exposure. The dataset consists of a set of 100 queries,

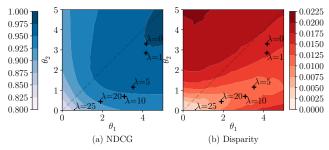


Figure 1. Experiments on Simulated dataset. The shaded regions show different ranges of the values of (a) NDCG, (b) Group Disparity ($\mathcal{D}_{\text{group}}$), with varying model parameters $\theta = (\theta_1, \theta_2)$. The (+) points show the models learned by FAIR-PG-RANK under different values of λ .

each consisting of a candidate set with 10 documents. In expectation, 8 of those documents belong to the majority group G_0 and 2 belong to the minority group G_1 . For each document we independently and uniformly draw two values x_1 and x_2 from the interval (0,3), and set the relevance of the document to $x_1 + x_2$ clipped between 0 and 5. For the documents from the majority group G_0 , the features vector representing the documents is (x_1, x_2) , providing perfect information about relevance. For documents in the minority group G_1 , however, the feature x_2 is corrupted by replacing it with zero so that the information about relevance for documents in G_1 only comes from x_1 . This leads to a biased representation between groups, and any use of x_2 is prone to producing unfair exposure between groups.

In order to validate that FAIR-PG-RANK can detect and neutralize this biased feature, we consider a linear scoring model $h_{\theta}(\mathbf{x}) = \theta_1 x_1 + \theta_2 x_2$ with parameters $\theta = (\theta_1, \theta_2)$. Figure 1 shows the contour plots of NDCG and \mathcal{D}_{group} evaluated for different values of the model parameters θ . Note that not only the direction of θ affects both NDCG and \mathcal{D}_{group} , but also its length as it determines the amount of stochasticity in π_{θ} . We use PG-RANK to train this linear model to maximize NDCG and minimize \mathcal{D}_{group} . The dots in Figure 1 denote the models learned by FAIR-PG-RANK for different values of λ . For small values of λ , FAIR-PG-RANK puts more emphasis on NDCG and thus learns parameter vectors along the $\theta_1 = \theta_2$ direction. As we increase emphasis on group fairness disparity \mathcal{D}_{group} by increasing λ , the policies learned by FAIR-PG-RANK become more stochastic and it correctly starts to discount the biased attribute by learning models where increasingly $\theta_1 >> \theta_2$.

5.3. Can FAIR-PG-RANK learn fair ranking policies on real-world data?

To study the trade-off between fairness and utility on real-world datasets, we use FAIR-PG-RANK with varying fairness coefficient λ in two sets of experiments – one with Individual Fairness on the Yahoo! Learning to Rank dataset,

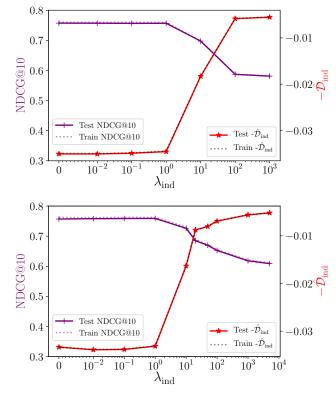


Figure 2. Effect of varying λ on NDCG@10 (user utility) and \mathcal{D}_{ind} (individual fairness disparity). Top shows linear model, bottom shows neural network. The overlapping dotted curves represent the training set NDCG@10 and Disparity, while solid curves show test set performance.

and a second one with Group fairness on the German Credit dataset.

For Individual Fairness, we train FAIR-PG-RANK with both a linear scoring model and a neural network scorer using learning rates 0.001 and 5×10^{-5} respectively, and with no regularization. For each scenario, the evaluation is done for the stochastic policy over a sample of 100 rankings for each query to calculate an expected value of both NDCG@10 and \mathcal{D}_{ind} . Figure 2 shows the variation of NDCG@10 (the user utility metric) and \mathcal{D}_{ind} (individual disparity) for different values of λ . As desired, FAIR-PG-RANK emphasizes lower disparity over higher NDCG as the value of λ increases. Furthermore, comparing the dotted curves (training set performance) and the solid curves (test set performance) verifies that FAIR-PG-RANK is able to generalize both with respect to NDCG and disparity. Both curves match closely, which shows that optimizing for a specific trade-off between NDCG and \mathcal{D}_{ind} on the training set leads to the same trade-off also for new queries. This is not surprising since both training quantities concentrate around their expectation as the training set size increases.

To validate whether FAIR-PG-RANK can also optimize for

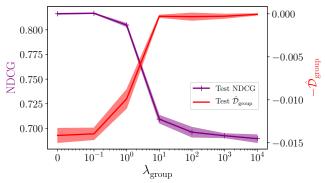


Figure 3. Effect of varying λ on the test set NDCG and \mathcal{D}_{group} for the German Credit Dataset. The shaded area shows the standard deviation over five runs of the algorithm on the data

Group fairness, we adapt the German Credit Dataset from the UCI dataset repository (Dheeru & Karra Taniskidou, 2017) for a learning-to-rank task. The original dataset consists of 1000 individuals, each described by a feature vector x_i consisting of 20 attributes with both numerical and categorical features, as well as a label rel_i classifying it as creditworthy ($rel_i = 1$) or not ($rel_i = 0$). We adapt this binary classification task to a learning-to-rank task in the following way: for each query q, we sample a candidate set of 10 individuals each, randomly sampling irrelevant documents (non-creditworthy individuals) and relevant documents (creditworthy individuals) in the ratio 4:1. Each individual is identified as a member of group G_0 or G_1 based on their gender attribute. We train FAIR-PG-RANK using a linear scoring model with Adam learning rate 0.001, no regularization, and sample size S=25, for different values of λ . Figure 3 shows the tradeoff between NDCG and $\mathcal{D}_{\text{group}}$, showing that FAIR-PG-RANK is again able to effectively trade-off NDCG and fairness. Here we also plot the standard deviation to illustrate that FAIR-PG-RANK reliably converges to solutions of similar performance over multiple runs.

6. Conclusion

We presented a framework for learning ranking functions that not only maximize utility to their users, but that also obey application specific fairness constraints on how exposure is allocated to the ranked items based on their merit. Based on this framework, we derived the FAIR-PG-RANK policy-gradient algorithm that directly optimizes both utility and fairness without having to resort to upper bounds or heuristic surrogate measures. We demonstrated that our policy-gradient approach is effective for training high-quality ranking functions, that FAIR-PG-RANK can identify and neutralize biased features, and that it can effectively learn ranking functions under both individual fairness and group fairness constraints.

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References

- Asudehy, A., Jagadishy, H., Stoyanovichz, J., and Das, G. Designing fair ranking schemes. *arXiv preprint arXiv:1712.09752*, 2017.
- Barocas, S. and Selbst, A. D. Big data's disparate impact. *Cal. L. Rev.*, 104:671, 2016.
- Biega, A. J., Gummadi, K. P., and Weikum, G. Equity of attention: Amortizing individual fairness in rankings. In *SIGIR*, pp. 405–414. ACM, 2018.
- Burges, C., Shaked, T., Renshaw, E., Lazier, A., Deeds, M., Hamilton, N., and Hullender, G. Learning to rank using gradient descent. In *ICML*, pp. 89–96. ACM, 2005.
- Calders, T., Kamiran, F., and Pechenizkiy, M. Building classifiers with independency constraints. In *Data mining* workshops, ICDMW, pp. 13–18, 2009.
- Cao, Z., Qin, T., Liu, T.-Y., Tsai, M.-F., and Li, H. Learning to rank: from pairwise approach to listwise approach. In *ICML*, pp. 129–136. ACM, 2007.
- Carbonell, J. and Goldstein, J. The use of mmr, diversity-based reranking for reordering documents and producing summaries. In *SIGIR*, pp. 335–336. ACM, 1998.
- Celis, L. E., Straszak, D., and Vishnoi, N. K. Ranking with fairness constraints. *arXiv preprint arXiv:1704.06840*, 2017.
- Chapelle, O. and Chang, Y. Yahoo! learning to rank challenge overview. In *Proceedings of the Learning to Rank Challenge*, pp. 1–24, 2011.
- Clarke, C. L., Kolla, M., Cormack, G. V., Vechtomova, O., Ashkan, A., Büttcher, S., and MacKinnon, I. Novelty and diversity in information retrieval evaluation. In *SIGIR*, pp. 659–666. ACM, 2008.
- Dheeru, D. and Karra Taniskidou, E. UCI machine learning repository, 2017. URL http://archive.ics.uci.edu/ml.
- Dwork, C., Hardt, M., Pitassi, T., Reingold, O., and Zemel, R. Fairness through awareness. In *ITCS*, pp. 214–226, 2012.

- Edelman, B., Luca, M., and Svirsky, D. Racial discrimination in the sharing economy: Evidence from a field experiment. *American Economic Journal: Applied Economics*, 9(2):1–22, 2017.
- Fang, Z., Agarwal, A., and Joachims, T. Intervention harvesting for context-dependent examination-bias estimation. arXiv preprint arXiv:1811.01802, 2018.
- Grimmelmann, J. Some skepticism about search neutrality. *The Next Digital Decade: Essays on the future of the Internet*, pp. 435, 2011. URL https://ssrn.com/abstract=1742444.
- Hardt, M., Price, E., and Srebro, N. Equality of opportunity in supervised learning. In *NIPS*, pp. 3315–3323, 2016.
- Introna, L. D. and Nissenbaum, H. Shaping the web: Why the politics of search engines matters. *The information society*, 16(3):169–185, 2000.
- Joachims, T. Training linear syms in linear time. In *KDD*, pp. 217–226. ACM, 2006.
- Joachims, T., Granka, L., Pan, B., Hembrooke, H., Radlinski, F., and Gay, G. Evaluating the accuracy of implicit feedback from clicks and query reformulations in web search. ACM Transactions on Information Systems (TOIS), 25(2):7, 2007.
- Joachims, T., Finley, T., and Yu, C.-N. J. Cutting-plane training of structural syms. *Machine Learning*, 77(1): 27–59, 2009.
- Joachims, T., Swaminathan, A., and Schnabel, T. Unbiased learning-to-rank with biased feedback. In *WSDM*, pp. 781–789. ACM, 2017.
- Kay, M., Matuszek, C., and Munson, S. Unequal representation and gender stereotypes in image search results for occupations. In *CHI*. ACM, April 2015.
- Kilbertus, N., Carulla, M. R., Parascandolo, G., Hardt, M., Janzing, D., and Schölkopf, B. Avoiding discrimination through causal reasoning. In *NIPS*, pp. 656–666, 2017.
- Kusner, M. J., Loftus, J., Russell, C., and Silva, R. Counterfactual fairness. In *NIPS*, pp. 4069–4079, 2017.
- Mehrotra, R., McInerney, J., Bouchard, H., Lalmas, M., and Diaz, F. Towards a fair marketplace: Counterfactual evaluation of the trade-off between relevance, fairness & satisfaction in recommendation systems. In *CIKM*, pp. 2243–2251. ACM, 2018.
- Mnih, V., Badia, A. P., Mirza, M., Graves, A., Lillicrap, T., Harley, T., Silver, D., and Kavukcuoglu, K. Asynchronous methods for deep reinforcement learning. In *ICML*, pp. 1928–1937, 2016.

- Radlinski, F., Kleinberg, R., and Joachims, T. Learning diverse rankings with multi-armed bandits. In *ICML*, pp. 784–791, 2008.
- Radlinski, F., Bennett, P. N., Carterette, B., and Joachims, T. Redundancy, diversity and interdependent document relevance. In *ACM SIGIR Forum*, volume 43, pp. 46–52, 2009.
- Robertson, S. E. The probability ranking principle in ir. *Journal of documentation*, 33(4):294–304, 1977.
- Scott, M. Google Fined Record \$2.7 Billion in E.U. Antitrust Ruling. New York Times, 2017. URL https://www.nytimes.com/2017/06/27/technology/eu-google-fine.html.
- Singh, A. and Joachims, T. Fairness of exposure in rankings. In *KDD*, pp. 2219–2228. ACM, 2018.
- Sutton, R. S. *Introduction to reinforcement learning*, volume 135. 1998.
- Taylor, M., Guiver, J., Robertson, S., and Minka, T. Softrank: Optimizing non-smooth rank metrics. In *WSDM*, pp. 77–86. ACM, 2008.
- Wei, Z., Xu, J., Lan, Y., Guo, J., and Cheng, X. Reinforcement learning to rank with markov decision process. In *SIGIR*, pp. 945–948. ACM, 2017.
- Williams, R. J. Simple statistical gradient-following algorithms for connectionist reinforcement learning. *Machine learning*, 8(3-4):229–256, 1992.
- Williams, R. J. and Peng, J. Function optimization using connectionist reinforcement learning algorithms. *Connection Science*, 3(3):241–268, 1991.
- Woodworth, B., Gunasekar, S., Ohannessian, M. I., and Srebro, N. Learning non-discriminatory predictors. arXiv preprint arXiv:1702.06081, 2017.
- Yang, K. and Stoyanovich, J. Measuring fairness in ranked outputs. SSDBM, 2017.
- Ye, J., Chow, J.-H., Chen, J., and Zheng, Z. Stochastic gradient boosted distributed decision trees. In *CIKM*, pp. 2061–2064. ACM, 2009.
- Zafar, M. B., Valera, I., Gomez Rodriguez, M., and Gummadi, K. P. Fairness beyond disparate treatment & disparate impact: Learning classification without disparate mistreatment. In WWW, pp. 1171–1180, 2017.
- Zehlike, M. and Castillo, C. Reducing disparate exposure in ranking: A learning to rank approach. *arXiv* preprint *arXiv*:1805.08716, 2018.

- Zehlike, M., Bonchi, F., Castillo, C., Hajian, S., Megahed, M., and Baeza-Yates, R. FA* IR: A Fair Top-k Ranking Algorithm. *CIKM*, 2017.
- Zemel, R., Wu, Y., Swersky, K., Pitassi, T., and Dwork, C. Learning fair representations. In *ICML*, pp. 325–333, 2013.
- Zhai, C. X., Cohen, W. W., and Lafferty, J. Beyond independent relevance: Methods and evaluation metrics for subtopic retrieval. In *SIGIR*, pp. 10–17. ACM, 2003.
- Zliobaite, I. On the relation between accuracy and fairness in binary classification. *FATML Workshop at ICML*, 2015.