

iFair: Learning Individually Fair Data Representations for Algorithmic Decision Making

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Abstract—People are rated and ranked, towards algorithmic decision making in an increasing number of applications, typically based on machine learning. Research on how to incorporate fairness into such tasks has prevalently pursued the paradigm of *group fairness*: ensuring that each ethnic or social group receives its fair share in the outcome of classifiers and rankings. In contrast, the alternative paradigm of *individual fairness* has received relatively little attention. This paper introduces a method for probabilistically clustering user records into a low-rank representation that captures individual fairness yet also achieves high accuracy in classification and regression models. Our notion of individual fairness requires that users who are similar in all task-relevant attributes such as job qualification, and disregarding all potentially discriminating attributes such as gender, should have similar outcomes. Since the case for fairness is ubiquitous across many tasks, we aim to learn general representations that can be applied to arbitrary downstream use-cases. We demonstrate the versatility of our method by applying it to classification and learning-to-rank tasks on two real-world datasets. Our experiments show substantial improvements over the best prior work for this setting.

I. INTRODUCTION

Motivation: People are rated, ranked and selected or not selected in an increasing number of online applications, towards algorithmic decisions based on machine learning models. Examples are approvals or denials of loans or visas, predicting recidivism for law enforcement, or rankings in job portals. As algorithmic decision making becomes pervasive in all aspects of our daily life, societal and ethical concerns [1, 2, 3, 4] are rapidly growing. A basic approach is to establish policies that disallow the inclusion of potentially discriminating attributes such as gender or race (i.e., ethnic background) and ensure that classifiers and rankings operate solely on task-relevant attributes such as job qualifications.

The problem has garnered significant attention in the data-mining and machine-learning communities. Most of this work considers so-called *group fairness* models, most notably, the statistical parity of outcomes in binary classification tasks, as a notion of fairness. Typically, classifiers are extended to incorporate demographic groups in their loss functions, or include constraints on the fractions of groups in the accepted class [5, 6, 7, 8, 9, 10]. For example, computing a shortlist of people invited for job interviews should have a gender mix that is proportional to the base population of job applicants.

Obviously, this means that the classifier objective is faced with a fundamental trade-off between utility (i.e., typically accuracy) and fairness, and needs to aim for a good compromise. Recently, other definitions of group fairness have been proposed [11, 12, 13]. Also, variants of group fairness have been applied to learning-to-rank tasks [14, 15, 16]. In all these cases, fair classifiers or regression models need an explicit specification of sensitive attributes such as gender, and often the identification of a specific *protected attribute-value group* such as gender equals female (*protected groups* for short).

The Case for Individual Fairness: Dwork et al. [17] argued that group fairness, while being appropriate for policies regarding demographic groups, does not really capture the real-world goal of treating individual people in a fair manner. This led to the definition of *individual fairness*: similar individuals should be treated similarly. In settings with binary classifiers, this means that individuals who are similar on the task-relevant attributes (e.g., job qualifications) should have nearly the same probability of being accepted by the classifier. This kind of fairness is very intuitive and captures aspects that group fairness alone does not handle. It does not rely on an explicit choice of “protected groups”, and is thus more flexible and versatile. Unfortunately, this rationale for capturing fairness has not received much follow-up work (the most notable exception being [18] as discussed below).

Example: Table I presents a real-world example showcasing the issue of unfairness for individual people. We randomly select 3 (of 57) popular job search queries on a well-known job search engine in Germany named *Xing* (www.xing.com); that data was originally used in Zehlike et al. [14]. For each query we randomly select a user who belongs to a “protected” minority group, for example, “female” for query “Field Engineer” and “male” for query “Daycare”. We then compute the k nearest neighbors set ($k = 10$) of this individual, in terms of job qualifications and disregarding the gender attribute. Table I presents the attributes of randomly selected individuals from this candidate set. We do not have knowledge about the workings of the proprietary algorithm that has produced the ranking. However, we observe that (nearly) equally qualified candidates have largely dissimilar outcomes. This situation cannot be resolved by any notion of group fairness, but calls for individual fairness.

Candidate	Job	Work Experience (months)	Education Experience (months)	Profile Views	Xing Rank	Minority Group
male	Field Engineer	301	49	374	4	female
female	Field Engineer	319	51	857	15	female
male	Front End Developer	30	0	154	4	female
female	Front End Developer	30	25	128	18	female
female	Daycare	333	83	780	13	male
male	Daycare	541	89	1027	33	male

TABLE I: Ranking results from www.xing.com (Jan 2017) for a variety of job search queries.

Search query	Work experience	Education experience	Profile views	Candidate	Xing ranking
Brand Strategist	146	57	12992	male	1
Brand Strategist	327	0	4715	female	2
Brand Strategist	502	74	6978	male	3
Brand Strategist	444	56	1504	female	4
Brand Strategist	139	25	63	male	5
Brand Strategist	110	65	3479	female	6
Brand Strategist	12	73	846	male	7
Brand Strategist	99	41	3019	male	8
Brand Strategist	42	51	1359	female	9
Brand Strategist	220	102	17186	female	10

TABLE II: Top k results on www.xing.com (Jan 2017) for the job search query “Brand Strategist”.

Consider the top-10 ranked results for the query “Brand Strategist” on *Xing* presented in Table II. It is easy to observe that the Xing ranking satisfies group fairness, as defined by Zehlike et al. [14]. According to that work, a top-k ranking τ is fair if for every prefix $\tau|i = \langle \tau(1), \tau(2), \dots, \tau(i) \rangle$ where $1 \leq i \leq k$, the set $\tau|i$ satisfies statistical parity with statistical significance α . However the outcomes in Table II are far from being fair for the individual users. This demonstrates that applications can cursorily satisfy group-fairness policies, while still being unfair to individuals.

State of the Art and its Limitations: Prior work on fairness for ranking tasks has exclusively focused on group fairness [14, 15, 16], disregarding the dimension of individual fairness. For the restricted setting of binary classifiers, the most notable work on individual fairness is [18]. That work addresses the fundamental trade-off between utility and fairness by defining a combined loss function to learn a low-rank data representation. The loss function reflects a (hyper-parameter-)weighted sum of classifier accuracy, statistical parity for a single pre-specified protected group, and individual fairness in terms of reconstruction loss of data. This model, called *LFR*, is powerful and elegant, but has major limitations:

- It is geared for binary classifiers and does not generalize to a wider class of machine-learning tasks. Most importantly, there is no support for regression models, i.e., learning-to-rank tasks.
- Its data representation is tied to a specific use case with a single protected group that needs to be specified upfront. So, once learned, the representation cannot be

dynamically adjusted to different settings later, for example, when the attribute-value for the protected group varies (e.g., female for some jobs, but male for others) or a new, initially unforeseen, application mandates the inclusion of further attributes into the sensitive set.

- Its objective function strives for a compromise over three components: application utility (i.e., classifier accuracy), group fairness and individual fairness. While this appears most comprehensive on first glance, it tends to burden the learning with too many aspects that cannot be reconciled.

Our approach, presented in this paper, overcomes these limitations by developing a more flexible and versatile model for representation learning.

Approach and Contribution: The approach that we put forward in this paper, called *iFair*, is to learn a generalized data representation that preserves the fairness-aware similarity between individual records while also aiming to minimize or bound the data loss. This way, we aim to reconcile individual fairness and application utility, and we intentionally disregard group fairness as an explicit criterion.

iFair resembles the model of [18] in that we also learn a representation via probabilistic clustering, using a form of gradient descent for optimization. However, our approach differs from [18] on a number of major aspects:

- *iFair* learns flexible and versatile representations, instead of committing to a specific downstream application like binary classifiers. This way, we open up applicability to arbitrary classifiers and support regression tasks (e.g., rating and ranking people) as well.
- *iFair* does not depend on a pre-specified protected group. Instead, it supports multiple sensitive attributes where the “protected values” are known only at run-time after the application is deployed. For example, we can easily handle situations where the critical value for gender is female for some ranking queries and male for others.
- *iFair* does not consider any notion of group fairness in its objective function. However, as we empirically demonstrate in this paper, optimizing for individual fairness also helps group-fairness criteria like equal-odds or equal-opportunity [11]. This design choice relaxes the optimization problem, and we achieve much better utility with very good fairness in both classification and ranking tasks.

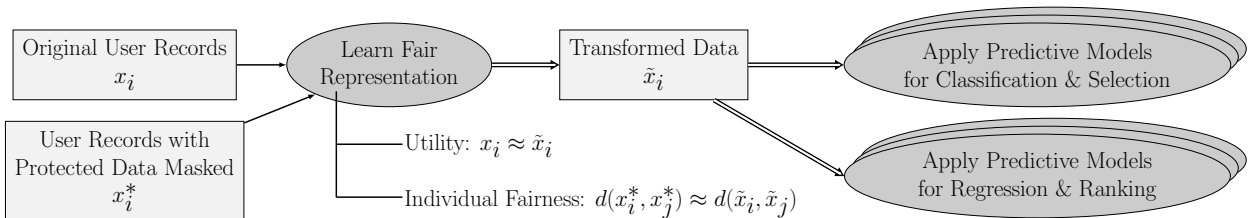


Fig. 1: Overview of decision-making pipeline. *iFair* learns data representations in an application-agnostic way, which can be used to train and apply any machine learning model.

The novel contributions of the *iFair* model are: 1) the first method, to the best of our knowledge, that provides individual fairness for learning-to-rank tasks; 2) an application-agnostic framework for learning low-rank data representations that reconcile individual fairness and utility such that application-specific choices on sensitive attributes and values do not require learning another representation; 3) experimental studies with classification and regression tasks for downstream applications, empirically showing that *iFair* can indeed reconcile strong individual fairness with high utility. The overall decision-making pipeline, including our representation learning component, is illustrated in Figure 1.

II. RELATED WORK

Fairness Definitions and Measures: Much of the work in algorithmic fairness has focused on supervised machine learning, specifically on the case of binary classification tasks. To this end, several notions of *group fairness* have been proposed in the literature. The most widely used notion of fairness is *statistical parity* and its variants [5, 6, 7, 8, 9, 10]. Intuitively, statistical parity states that the predictions \hat{Y} of a classifier are fair if members of sensitive subgroups, such as people of certain nationalities or ethnic backgrounds, have an acceptance likelihood proportional to their share in the entire data population. This is equivalent to requiring that a priori knowledge of the classification outcome of an individual should provide no information about her membership to such subgroups. However, for many applications, such as risk assessment for credit worthiness, statistical parity is neither feasible nor desirable as it would mandate that the fractions of positive outcomes across groups be the same irrespective of their data properties.

Various alternative notions of group fairness have been defined. Hardt et al. [11] proposed *equal odds* as a fairness goal which requires that the rates of true positives and false positives be the same across groups. Intuitively, this punishes classifiers which perform well only on specific groups. Hardt et al. [11] also proposed a relaxed version of equal odds called *equal opportunity* which demands only the equality of true positive rates. Other definitions of group fairness proposed in the literature include *calibration* [19, 20] and *disparate mistreatment* [12]. A recent line of work highlights the inherent incompatibility between several notions of group fairness and the impossibility of achieving them simultaneously [20, 21, 22, 23].

Dwork et al. [17] gave the first broader definition of fairness independent of a specific machine-learning task. Their definition of fairness, appropriately named *individual fairness*, argues for the fairness of outcomes for individuals and not merely as a group statistic. Individual fairness mandates that *similar individuals should be treated similarly*. [17] further develops a theoretical framework for mapping individuals to a probability distribution over outcomes, which satisfies the Lipschitz property (i.e., distance preservation) in the mapping. In this paper, we follow up on this definition of individual fairness and present a generalized framework for learning individually fair representations of the data.

Fairness in Machine Learning: A parallel line of work in the area of algorithmic fairness uses a specific definition of fairness in order to design fairness models that achieve fair outcomes. To this end, there are two general strategies. The first strategy consists of *de-biasing* the input data by appropriate preprocessing [6, 8, 9]. This typically involves data perturbation such as modifying the value of sensitive attributes or class labels in the training data to satisfy certain fairness conditions, such as equal proportion of positive (negative) class labels in both protected and non-protected groups. The second strategy consists of designing fair algorithmic models - based on *constrained optimization* [5, 7, 11, 12]. Here, fairness constraints are usually introduced as regularization terms in the objective function.

Fairness in IR: Recently, definitions of group fairness have been extended to learning-to-rank tasks. Yang and Stoyanovich [15] introduced statistical parity in rankings. Zehlike et al. [14] built on [15] and proposed to ensure statistical parity at all top-k prefixes of the ranked results. Singh and Joachims [16] proposed a generalized fairness framework for a larger class of group fairness definitions (e.g., disparate treatment and disparate impact). However, all this prior work has focused on group fairness alone. It implicitly assumes that individual fairness is taken care of by the ranking quality, disregarding situations where trade-offs arise between these two dimensions. The recent work of Biega et al. [24] addresses individual fairness in rankings from the perspective of giving fair exposure to items over a series of rankings, thus mitigating the position bias in click probabilities. In their approach they explicitly assume to have access to scores that are already individually fair. As such, their work is complementary to ours as they do not address how such a score, which is individually fair can be computed.

Representation Learning: The line of work most related to this paper is the learning of fair data representations. In this space, the work of Zemel et al. [18] is the closest to ours in that it also learns low-rank representations by probabilistic mapping of data records. However, the methods deviates from our in important ways. First, its fair representations are tied to a particular classifier by assuming a binary classification problem with pre-specified labeling target attribute and a single protected group. In contrast, the representations learned by *iFair* are agnostic to the downstream learning tasks and thus easily deployable for new applications. Second, the optimization in [18] aims to combine three competing objectives: classifier accuracy, statistical parity, and data loss (as a proxy for individual fairness). The *iFair* approach, on the other hand, addresses a more streamlined objective function by focusing on classifier accuracy and individual fairness.

Approaches similar to [18] have been applied to learn censored representations for fair classifiers via adversarial training [25, 26]. In particular, group fairness definitions (statistical parity and its variants) are optimized in the presence of an adversary. These approaches do not consider individual fairness at all.

III. MODEL

We consider user records that are fed into a learning algorithm towards algorithm decision making. A fair algorithm should make its decisions solely based on non-sensitive attributes (e.g., technical qualification or education) and should disregard sensitive attributes that bear the risk of discriminating users (e.g., ethnicity/race). This dichotomy of attributes is specified upfront, by domain experts and follows legal regulations and policies. Ideally, one should consider also strong correlations (e.g., geo-area correlated with ethnicity/race), but this is usually beyond the scope of the specification. We start with introducing preliminary notations and definitions.

Input Data: The input data for M users with N attributes is an $M \times N$ matrix X with binary or numerical values (i.e., after unfolding or encoding categorical attributes). Without loss of generality, we assume that the attributes $1 \dots l$ are non-protected and the attributes $l + 1 \dots N$ are protected. We denote the i -th user record consisting of all attributes as x_i and only non-protected attributes as x_i^* . Note that, unlike in prior works, the set of protected attributes is allowed to be empty (i.e., $l = N$). Also, we do not assume any upfront specification of which attribute values form a protected group. So a downstream application can flexibly decide on the critical values (e.g., male vs. female or certain choices of citizenships) on a case-by-case basis.

Output Data: The goal is to transform the input records x_i into representations \tilde{x}_i that are directly usable by downstream applications and have better properties regarding fairness. Analogously to the input data, we can write the entire output of \tilde{x}_i records as an $M \times N$ matrix \tilde{X} .

Individually Fair Representation: Inspired by the Dwork et al. [17] notion of individual fairness, “individuals who are

similar should be treated similarly”, we propose the following definition for individual fairness:

Definition 1. (Individual Fairness) *Given a distance function d in the N -dimensional data space, a mapping ϕ of input records x_i into output records \tilde{x}_i is individually fair if for every pair x_i, x_j we have*

$$|d(\phi(x_i), \phi(x_j)) - d(x_i^*, x_j^*)| \leq \epsilon \quad (1)$$

The definition requires that individuals who are (nearly) indistinguishable on their non-sensitive attributes in X should also be (nearly) indistinguishable in their transformed representations \tilde{X} . For example, two people with (almost) the same technical qualifications for a certain job should have (almost) the same low-rank representation, regardless of whether they differ on protected attributes such as gender, religion or ethnic group. In more technical terms, a distance measure between user records should be preserved in the transformed space.

Note that this definition intentionally deviates from the original definition of *individual fairness* of [17] in that with x_i^*, x_j^* we consider only the non-protected attributes of the original user records, as protected attributes should not play a role in the decision outcomes of an individual.

A. Problem Formulation: Probabilistic Clustering

As individual fairness needs to preserve similarities between records x_i, x_j , we cast the goal of computing good representations \tilde{x}_i, \tilde{x}_j into a formal problem of *probabilistic clustering*. We aim for K clusters, each given in the form of a *prototype vector* v_k ($k = 1..K$), such that records x_i are assigned to clusters by a record-specific probability distribution that reflects the distances of records from prototypes. This can be viewed as a low-rank representation of the input matrix X with $K < M$, so that we reduce attribute values into a more compact form. As always with soft clustering, K is a hyper-parameter.

Definition 2. (Transformed Representation) *The fair representation \tilde{X} , an $M \times N$ matrix of row-wise output vectors \tilde{x}_i , consists of*

- (i) $K < M$ prototype vectors v_k , each of dimensionality N ,
- (ii) a probability distribution u_i , of dimensionality K , for each input record x_i where u_{ik} is the probability of x_i belonging to the cluster of prototype v_k .

The representation \tilde{x}_i is given by

$$\tilde{x}_i = \sum_{k=1..K} u_{ik} \cdot v_k \quad (2)$$

or equivalently in matrix form: $\tilde{X} = U \times V^T$ where the rows of U are the per-record probability distributions and the columns of V^T are the prototype vectors.

Definition 3. (Transformation Mapping) *We denote the mapping $x_i \rightarrow \tilde{x}_i$ as ϕ ; that is,*

$$\phi(x_i) = \tilde{x}_i = \sum_{k=1..K} u_{ik} \cdot v_k \quad (3)$$

using Equation 2.

Utility Objective: Without making any assumptions on the downstream application, the best way of ensuring high utility is to minimize the data loss induced by ϕ .

Definition 4. (Data Loss) *The reconstruction loss between X and \tilde{X} is the sum of squared errors*

$$L_{util}(X, \tilde{X}) = \sum_{i=1}^M \|x_i - \tilde{x}_i\|_2 = \sum_{i=1}^M \sum_{j=1}^N (x_{ij} - \tilde{x}_{ij})^2 \quad (4)$$

Individual Fairness Objective: Following the rationale for Definition 1, the desired transformation ϕ should preserve pair-wise distances between data records on non-protected attributes.

Definition 5. (Fairness Loss) *For input data X , with row-wise data records x_i , and its transformed representation \tilde{X} with row-wise \tilde{x}_i , the fairness loss L_{fair} is*

$$L_{fair}(X, \tilde{X}) = \sum_{i,j=1..M} (d(\tilde{x}_i, \tilde{x}_j) - d(x_i^*, x_j^*))^2 \quad (5)$$

Overall Objective Function: Combing the data loss and the fairness loss yields our final objective function that the learned representain should aim to minimize.

Definition 6. (Objective Function) *The combined objective function is given by*

$$L = \lambda \cdot L_{util}(X, \tilde{X}) + \mu \cdot L_{fair}(X, \tilde{X}) \quad (6)$$

where λ and μ are hyper-parameters.

B. Probabilistic Prototype Learning

So far we have left the choice of the distance function d open. Our methodology is general and can incorporate a wide suite of distance measures. However, for the actual optimization, we need to make a specific choice for d . In this paper, we focus on the family of *Minkowski p -metrics*, which is indeed a metric for $p \geq 1$. A common choice is $p = 2$, which corresponds to a Gaussian kernel.

Definition 7. (Distance Function) *The distance between two data records x_i, x_j is*

$$d(x_i, x_j) = \left[\sum_{n=1}^N \alpha_n (x_{i,n} - x_{j,n})^p \right]^{1/p} \quad (7)$$

where α is an N -dimensional vector of tunable or learnable weights for the different data attributes.

This distance function d is applicable to original data records x_i , transformed vectors \tilde{x}_i and prototype vectors v_k alike. In our model, we avoid the quadratic number of comparisons for all record pairs, and instead consider distances only between records and prototype vectors (cf. also [18]). Then, these distances can be used to define the probability vectors u_i that hold the probabilities for record x_i belonging

to the cluster with prototype v_k (for $k = 1..K$). To this end, we apply a softmax function to the distances between record and prototype vectors.

Definition 8. (Probability Vector) *The probability vector u_i for record x_i is*

$$u_{i,k} = \frac{\exp(-d(x_i, v_k))}{\sum_{j=1}^K \exp(-d(x_i, v_j))} \quad (8)$$

The mapping ϕ that transforms x_i into \tilde{x}_i can now be written as

$$\phi(x_i) = \sum_{k=1}^K \frac{\exp(-d(x_i, v_k))}{\sum_{j=1}^K \exp(-d(x_i, v_j))} \cdot v_k \quad (9)$$

With these definitions in place, the task of learning fair representations \tilde{x}_i now amounts to computing K prototype vectors v_k and the N -dimensional weight vector α in d such that the overall loss function L is minimized.

Definition 9. (Optimization Objective) *The optimization objective is to compute v_k ($k = 1..K$) and α_n ($n = 1..N$) as argmin for the loss function*

$$\begin{aligned} L &= \lambda \cdot L_{util}(X, \tilde{X}) + \mu \cdot L_{fair}(X, \tilde{X}) \\ &= \lambda \cdot \sum_{i=1}^M \sum_{j=1}^N (x_{ij} - \tilde{x}_{ij})^2 + \mu \cdot \sum_{i,j=1..M} (d(\tilde{x}_i, \tilde{x}_j) - d(x_i^*, x_j^*))^2 \end{aligned}$$

where \tilde{x}_{ij} is substituted using Equations 9 and d uses Equation 7.

The N -dimensional weight vector α controls the influence of each attribute. Given our definition of individual fairness (which intentionally deviates from the original definition in Dwork et al. [17]), a natural setting is to give no weight to the protected attributes as these should not play any role in the similarity of (qualifications of) users. In our experiments, we observe that giving (near-)zero weights to the protected attributes increases the fairness of the learned data representations (see Section V).

C. Gradient Descent Optimization:

Given this setup, the learning system minimizes the combined objective function given by

$$L = \lambda \cdot L_{util}(X, \tilde{X}) + \mu \cdot L_{fair}(X, \tilde{X}) \quad (10)$$

where L_{util} is the data loss, L_{fair} is the loss in individual fairness, and λ and μ are hyper-parameters. We have two sets of *model parameters* to learn

- (i) v_k ($k = 1..K$), the N -dimensional prototype vectors,
- (ii) α , the N -dimensional weight vector of the distance function in Equation 7.

We apply the *L-BFGS* algorithm [27], a quasi-Newton method, to minimize Equation 10 and learn the model parameters.

IV. PROPERTIES OF THE *iFair* MODEL

We discuss properties of *iFair* representations and empirically compare *iFair* to the *LFR* model by Zemel et al. [18]. To this end, we generate synthetic data with systematic parameter variation as follows. For simpler illustration, we restrict ourselves to the case of a binary classifier.

We generate 100 data points with 3 attributes: 2 real-valued and non-sensitive attributes $X1$ and $X2$ and 1 binary attribute A which serves as the protected attribute. We first draw two-dimensional datapoints from a mixture of Gaussians with two components: (i) isotropic Gaussian with unit variance and (ii) correlated Gaussian with covariance 0.95 between the two attributes and variance 1 for each attribute. To study the influence of membership to the protected group (i.e., A set to 1), we generate three variants of this data:

- Random: A is set to 1 with probability 0.3 at random.
- Correlation with $X1$: A is set to 1 if $X1 \leq 3$.
- Correlation with $X2$: A is set to 1 if $X2 \leq 3$.

So the three synthetic datasets have the same values for the non-sensitive attributes $X1$ and $X2$ as well for the outcome variable Y . The datapoints differ only on membership to the protected group and its distribution across output classes Y .

Figure 2 shows these three cases row-wise: subfigures a-c, d-f, g-i, respectively. The left column of the figure displays the original data, with the two labels for output Y depicted by marker: “o” for $Y = 0$ and “+” for $Y = 1$ and the membership to the protected group by color: orange for $A = 1$ and blue for $A = 0$. The middle column of Figure 2 shows the learned *iFair* representations, and the right column shows the representations based on *LFR* [18]. Note that the values of importance in Figure 2 (middle and right column) are position of the data points in the two-dimensional plane and the classifier decision boundary (solid line). The color of the datapoints as well as the markers (o and +) depict the true class and true group membership, and not the learned values. They are visualized merely to aid the reader in relating original data with transformed representations. Further, small differences in the learned representation are expected due to random initializations of model parameters. The solid line in the charts denotes the predicted classifiers’ decision boundary applied on the learned representations. Hyper-parameters for both *iFair* as well as *LFR* are chosen by performing a grid search on the set $\{0, 0.05, 0.1, 1, 10, 100\}$ for optimal individual fairness of the classifier. For each of the nine cases, we indicate the resulting classifier accuracy Acc , individual fairness in terms of consistency yNN with regard to the $k = 10$ nearest neighbors [18] (formal definition given in Section V-C), the statistical parity $Parity$ with regard to the protected group $A = 1$, and equality-of-opportunity $EqOpp$ [11] notion of group fairness.

Overview: Main findings of this section are: (i) representations learned via *iFair* remain nearly the same irrespective of the distribution of protected attributes (ii) *iFair* significantly outperforms *LFR* on utility, individual fairness and group fairness (using equality-of-opportunity), whereas *LFR* wins on

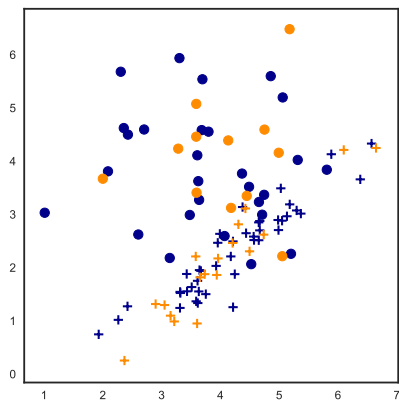
statistical parity. In the remainder of this section we discuss our findings and their implications.

Influence of Protected Group: The middle column in Figure 2 shows that the *iFair* representation remains largely unaffected by the changes in the distribution of sensitive data points and their group memberships. In other words, changing the value of the protected attribute of individual datapoints, all other values remaining the same, has no influence on the learned representation; consequently it has no influence on the outcome made by the decision-making algorithms trained on these representations. This is an important and interesting characteristic to have in a fair representation, as it directly relates to the definition of *individual fairness*. In contrast, the membership to the protected group has a pronounced influence on the learned representation of the *LFR* model (refer Figure 2 right column). Recall that the color of the datapoints as well as the markers (o and +) are taken from the original data. They depict the true class and membership to group of the datapoints, and are visualized to aid the reader.

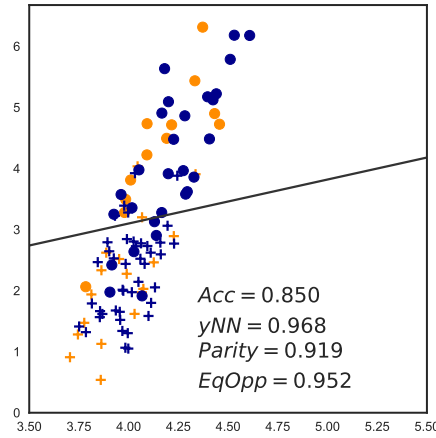
Tension in Objective Function: The optimization via *LFR* Zemel et al. [18] has three components: classifier accuracy as utility metric, individual fairness in terms of data loss, and group fairness in terms of statistical parity. We observe that by pursuing group fairness and individual fairness together, the tension with utility is very pronounced. The learned representations are stretched on the compromise over all three goals, ultimately leading to sacrificing utility. In contrast, *iFair* pursues only utility and individual fairness, and disregards group fairness. This clearly helps to make the multi-objective optimization more tractable. *iFair* clearly outperforms *LFR* not only on accuracy, with better decision boundaries, but also wins in terms of individual fairness. There is no direct conflict between utility and individual fairness, hence the model has a larger feasible search space.

Individual Fairness vs. Group Fairness: Although group fairness is not part of our objective function, we observe that *iFair*’s goal of individual fairness indirectly helps *EqOpp* group fairness as well (see Section V-C for formal definition). In Figure 2, Charts (a) through (c), the *base rates* across the two values of the protected attribute A are similar; that is, the fraction of the positive class (marked +) is similar for $A = 0$ (blue) and $A = 1$ (orange). In such settings, optimizing for individual fairness gives high scores for group fairness as well. On the other hand, when base rates across groups are highly skewed, as in Charts (d) through (f), group fairness criteria cannot be satisfied without harming fairness for individuals.

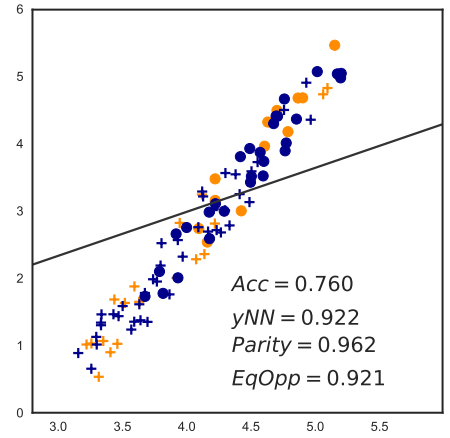
Utility-Fairness Trade-off: The improvement that *iFair* achieves in individual fairness comes at the expense of a small drop in utility, although the two criteria are not directly conflicting. The trade-off is caused by the loss of information in learning representative prototypes. The choice of the mapping function in Equation 9 and the pairwise distance function $d(\cdot)$ in Definition 7 affects the ability to learn prototypes. Our framework is flexible and easily supports other kernels and distance functions. Exploring these influence factors is a direction for future work.



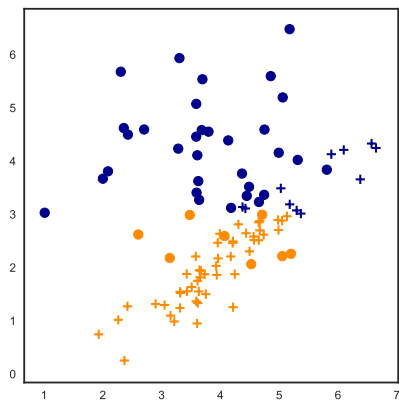
(a) original data (random)



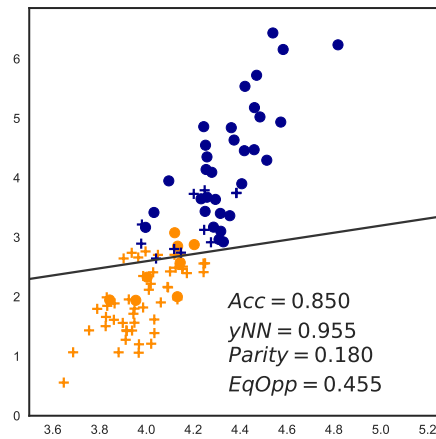
(b) Learned representation via *iFair*



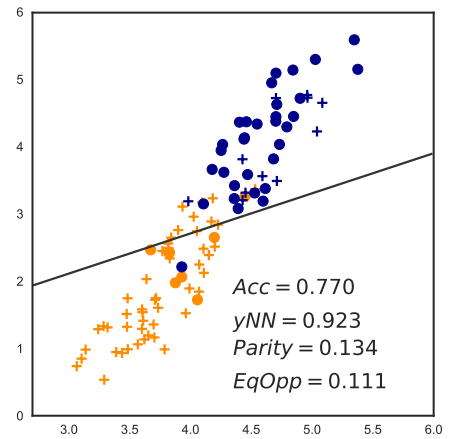
(c) Learned representation via *LFR*



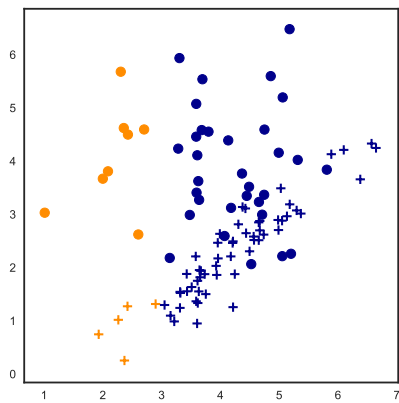
(d) original data ($X_1 \leq 3$)



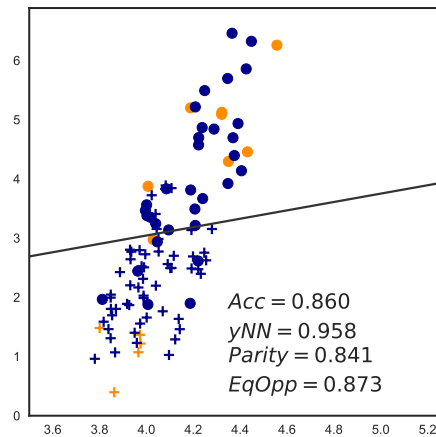
(e) Learned representation via *iFair*



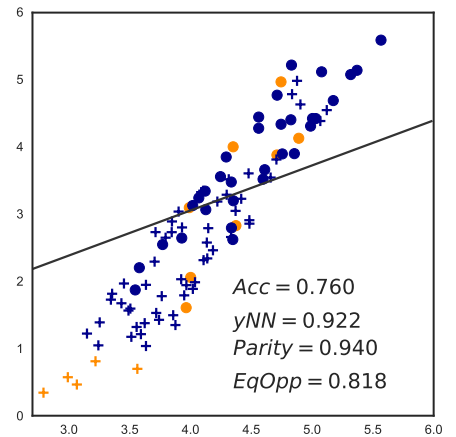
(f) Learned representation via *LFR*



(g) original data ($X_2 \leq 3$)



(h) Learned representation via *iFair*



(i) Learned representation via *LFR*

Fig. 2: Illustration of properties of data representations on synthetic data. (left: original data, center: *iFair*, right: *LFR*). Output class labels: o for $Y=0$ and + for $Y=1$. Membership in protected group: blue for $A=0$ and orange for $A=1$. Solid lines are the decision boundaries of the respective classifiers. *iFair* outperforms *LFR* on all metrics except for statistical parity.

V. EXPERIMENTS

A. Datasets

We apply the *iFair* framework to two real-world, publicly available datasets:

- **ProPublica’s COMPAS** recidivism dataset [1], a widely used test case for fairness in machine learning and algorithmic decision making. We set *race* as a protected attribute, and use the binary indicator of recidivism as the outcome variable Y .
- **Xing**, a popular job search portal in Germany (similar to LinkedIn). We use the anonymized JSON files given by [14]. They consist of top 40 profiles returned for 54 job queries on a people search and recruitment website (<https://www.xing.com>) to construct this dataset. For each candidate we collect information about job category, work experience, education experience, number of hits on the profile, and gender. We set *gender* as the protected attribute. We use the sum of work experience, education experience and number of hits as an ad-hoc score to define the ground-truth *deserved score*.

The COMPAS dataset is used for experiments on classification, and the Xing data is used for experiments on learning-to-rank regression. We choose the protected attributes to be in line with the literature. In practice, however, such decisions would be made by domain experts and according to official policies and regulations. The flexibility of our framework allows for multiple protected attributes (or none) and multivariate outcome variables.

B. Setup and Baselines

In each dataset, categorical attributes are transformed using one-hot encoding, and all features vectors are normalized to have unit variance. We randomly split the datasets into three parts. We use one part to train the model to learn model parameters, the second part as a validation set to choose hyper-parameters by performing a grid search (details follow), and the third part as a test set. We use the same data split to compare all methods.

We evaluate all data representations – *iFair* against various baselines – by comparing the results of a standard classifier (*logistic regression*) and a learning-to-rank regression model (*linear regression*) applied to

- **Full Data:** the original dataset.
- **Masked Data:** the original dataset without protected attributes.
- **SVD:** transformed data by performing dimensionality reduction via singular value decomposition (SVD), with two variants of data: (a) full data and (b) masked data. We name these variants *SVD* and *SVD-masked*, respectively.
- **LFR:** the learned representation by the method of Zemel et al. [18].
- **iFair:** the representation learned by our model. We perform experiments with two kinds of initializations for the model parameter α (attribute weight vector): (a) initializing all attribute weights with random values from

uniform distribution in $(0, 1)$ and (b) initializing non-protected attributes weights with random values from uniform distribution in $(0, 1)$, but protected attributes weights with (near-)zero values, to reflect the intuition that protected attributes should be discounted in the distance-preservation of individual fairness (and avoiding zero values to allow slack for the numerical computations in learning the model). We call these two methods *iFair-a* and *iFair-b*, respectively.

Model Parameters: All the methods were trained in the same way. We initialize model parameters (v_k vectors and the α vector) to random values from uniform distribution in $(0, 1)$ (unless specified otherwise, for the *iFair-b* method). To compensate for variations caused due to initialization of model parameters, for each method and at each setting, we report the results from the best of 3 runs.

Hyper-Parameters: As for hyper-parameters (e.g., λ and μ for *iFair*), including the dimensionality K of the low-rank representations, we perform a grid search over the set $\{0, 0.05, 0.1, 1, 10, 100\}$ for mixture coefficients and the set $\{10, 20, 30\}$ for the dimensionality K . Recall that the input data is pre-processed with categorical attributes unfolded into binary attributes; hence the choices for K .

The mixture coefficients (λ, μ, \dots) control the trade-off between different objectives: utility, individual fairness, group fairness (when applicable). Since it is all but straightforward to decide which of the multiple objectives is more important, we tune hyper-parameters based on different choices for the optimization goal (e.g., maximize utility alone or maximize a combination of utility and individual fairness). Thus, our evaluation results report multiple observations for each model, depending on the goal for tuning the hyper-parameters. When possible, we identify Pareto-optimal choices with respect to multiple objectives; that is, choices that are not consistently outperformed by other choices for all objectives.

C. Evaluation Measures

- **Utility:** measured as the area under the ROC curve (AUC) for the classification task, and as Kendall’s Tau (KT) and average precision at 10 (AP) for the learning-to-rank task.
- **Individual Fairness:** measured as the *consistency* of the outcome \hat{y}_i of an individual with the outcomes of his/her $k=10$ nearest neighbors. This metric has been introduced by [18]¹ and captures the intuition that similar individuals should be treated similarly. Note that nearest neighbors of an individual, $kNN(x_i)$, are computed on the original data records excluding protected attributes, x_i^* , whereas the predicted response variable \hat{y}_i is computed on the output of the learned representations \tilde{x}_i .

$$yNN = 1 - \frac{1}{M} \cdot \frac{1}{k} \cdot \sum_{i=1}^M \sum_{j \in kNN(x_i^*)} |\hat{y}_i - \hat{y}_j|$$

¹Our version slightly differs from that in [18] by fixing a minor bug in the formula.

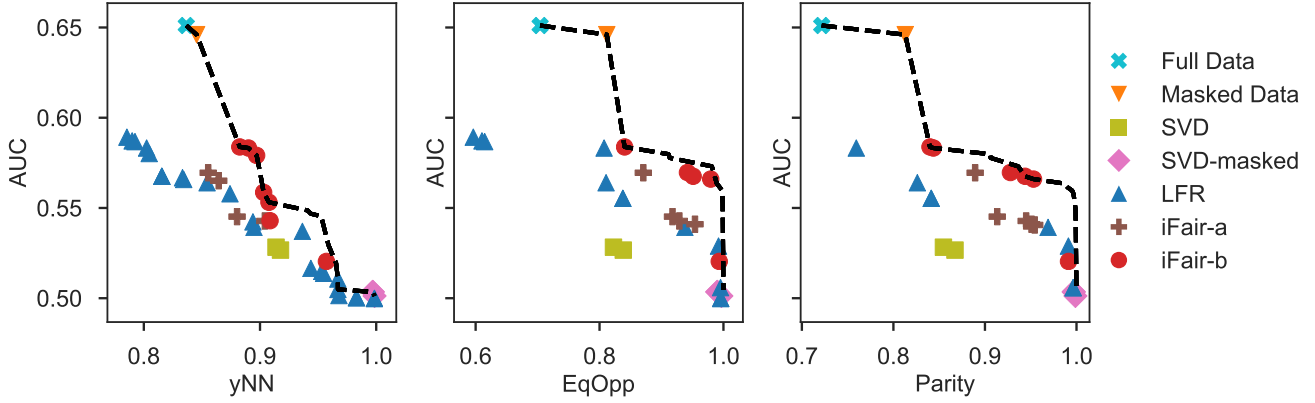


Fig. 3: Experimental results on classification task using ProPublica COMPAS data.

• **Group Fairness:** measured as

- *Equality of Opportunity (EqOpp)* [11]: the difference in the *True Positives* rates between the protected group X^+ and the non-protected group X^- ;
- *Statistical Parity* defined as:

$$Parity = 1 - \left| \frac{1}{|X^+|} \sum_{i \in X^+} \hat{y}_i - \frac{1}{|X^-|} \sum_{j \in X^-} \hat{y}_j \right|$$

We use the modern notion of *EqOpp* as our primary metric of group fairness, but report the traditional measure of *Parity* as well. Note that, these group fairness notions are specifically geared for binary classification task. Hence, we do not compute these measures in our evaluation on learning-to-rank task.

D. Evaluation on Classification Task

This section evaluates the effectiveness of *iFair* and its competitors on a classification task. We focus on the utility-fairness tradeoff that learned representations alleviate when used to train classifiers. Figure 3 shows the results for the COMPAS data, plotting utility (AUC) against three different measures of fairness (yNN, EqOpp, Parity), for all the methods. The dotted lines show methods that are Pareto-optimal with regard to a combination of two of the four measures. Hyper-parameters were tuned (via grid search) for each of the shown combinations.

We observe that there is a considerable amount of unfairness in the original dataset, which is reflected in the results of *Full Data* in Figure 3. *Masked Data* shows an improvement in fairness; however, there is still substantial unfairness hidden in the data in the form of correlated attributes. Among the two SVD variants, the *SVD-masked* representation achieves very high fairness but completely fails on utility (AUC). The transformed data learned by *LFR* and *iFair* clearly dominate all other methods in coping with the trade-off. *iFair-b* is the overall winner: it is consistently Pareto-optimal for all three pairs of measures and all but the degenerate extreme points. Note that this superiority of *iFair-b* holds not just for its design point of reconciling utility and individual fairness, but also for

the two notions of group fairness. For the extreme points in the trade-off spectrums, no method can achieve near-perfect utility without substantially losing fairness and no method can be near-perfectly fair without substantially losing utility.

Figure 4 shows detailed results for five choices of tuning hyper-parameters (via grid search): (a) considering utility (AUC) only, (b) considering group fairness (EqOpp) only, (c) considering individual fairness (yNN) only, (d) using the harmonic mean of utility and group fairness, and (e) using the harmonic mean of utility and individual fairness as tuning target.

Here we focus on the *LFR* and *iFair* methods, as the other baselines do not have hyper-parameters to control trade-offs and are good only at extreme points of the objective space anyway. The charts in Figure 4 confirm and further illustrate the findings of Figure 3. The two *iFair* methods, tuned for the combination of utility and individual fairness (case (e)), achieve the best overall results: decent utility and high fairness. *LFR*, on the other hand, has a severe penalty on utility. As a consequence of its ambitious objective function that strives for utility, individual fairness and group fairness altogether, its compromises tend to become inferior no matter how its hyper-parameters are tuned.

E. Evaluation on Learning-to-Rank Task

This section evaluates the effectiveness of *iFair* on a regression task for ranking people on the Xing data. Here, notions of group fairness do not apply – so we report only utility, in terms of Kendall’s Tau (KT) and Average Precision (AP), and individual fairness in terms of consistency (yNN). We evaluate our results against the *deserved scores* of individuals as ground truth.

As stated in Section V-A, the deserved score is the sum of the true qualifications of an individual, that is, work experience, education experience and number of profile views. We observe that the scores predicted by *iFair* are highly correlated to the deserved scores. Table III shows results for four randomly selected job search queries, and Figure 5 plots the *iFair*-predicted scores against the deserved scores. Note that the baselines used for the classification experiment, most

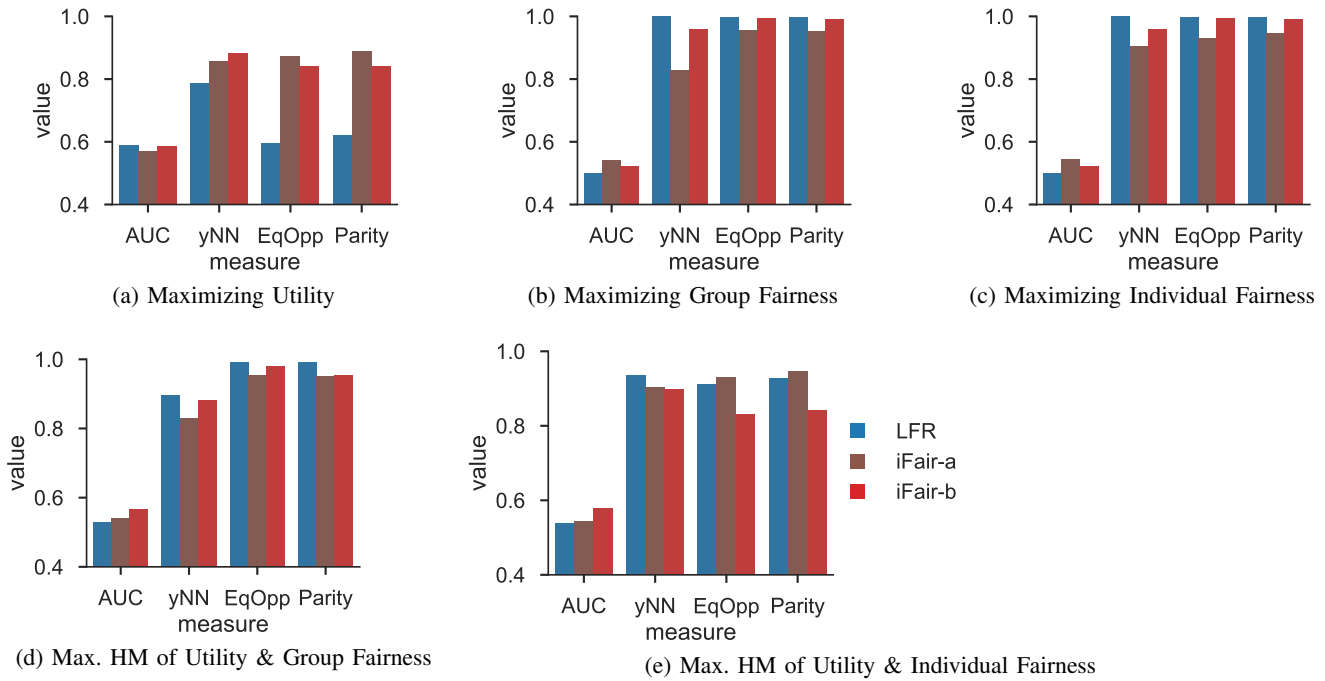


Fig. 4: Comparison of utility (AUC), individual fairness (yNN) and group fairness (EqOpp and Parity) on the ProPublica COMPAS data, with hyper-parameter tuning for criterion (a) maximizing utility (b) maximizing group fairness, (c) maximizing individual fairness, (d) maximizing the harmonic mean of utility and group fairness, and (e) maximizing the harmonic mean of utility and individual fairness.

notably *LFR*, are not geared for regression tasks and thus omitted here.

Xing Query	Top 10 Positions										KT	AP	yNN
Art Director	m	m	f	m	m	m	m	m	f	m	0.82	0.60	0.998
Auditor	m	m	m	f	m	f	m	f	m	m	0.78	0.51	0.996
Receptionist	f	m	f	f	f	f	f	m	f	m	1.00	1.00	0.992
legal advisor	m	m	m	f	m	m	f	f	m	f	0.91	0.67	0.995

TABLE III: Predicted rankings by *iFair* for a subset of four randomly selected job search queries on Xing data. Mean KT across all 54 queries is 0.701; mean AP across all 54 queries is 0.733; mean yNN across all 54 queries is 0.993.

Since, we do not have any information on the proprietary Xing ranking model, we do not comment on their scores. However, it is interesting to note that in comparison to the original ranking on the Xing website, we observe in Table III that our ranking increases the number of individuals belonging to a protected gender in the top 10 positions. That is, the ranking produced by *iFair* increases the ranking exposure that equally deserving individuals receive in the top positions. This improvement in ranking is indeed correlated to the deserved scores of the individuals, and not an improvement made at the expense of lowering the rank of other deserving candidates from the non-protected group. For illustration, Table IV presents the top 10 candidates retrieved via *iFair* scores for the query “Brand Strategist”. Observe that, *iFair* ranks candidates with higher qualifications (work experience, education and profile views) at the top of the list. As expected, candidates

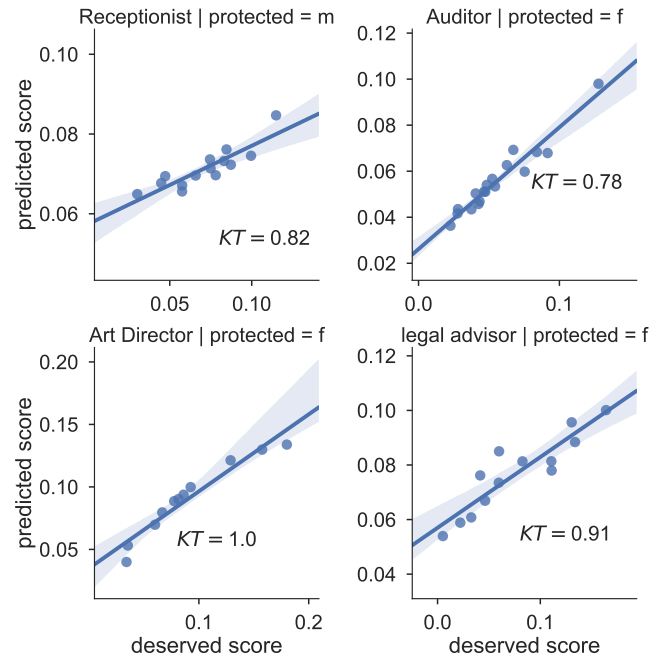


Fig. 5: Predicted scores by *iFair* vs. deserved scores for individuals on Xing dataset for four randomly selected job search queries. All scores are normalized.

with similar qualifications (highlighted in grey) are close in their ranking positions.

<i>iFair</i> ranking	candidate	work experience	education experience	profile views	improvement in ranking $\uparrow\downarrow$
1	female	226	207	5342	27
2	male	502	74	6978	1
3	female	220	102	17186	7
4	male	313	79	1285	33
5	male	156	103	4823	8
6	male	190	88	11514	16
7	male	359	63	6437	9
8	female	444	56	1504	-4
9	male	188	87	5132	18
10	male	367	45	1164	8

TABLE IV: Top-k results by *iFair* scores for the the job search query “Brand Strategist”.

VI. CONCLUSIONS

We proposed a generic and versatile framework to perform a probabilistic transformation of data into individually fair representations. We applied our model to two real-world datasets in order to learn their fair representations. Applying standard classifier and regression to the transformed representation leads to algorithmic decisions that are substantially fairer – both individually as well as group-wise – than the decisions made on the original data. Inevitably, the gain in fairness comes at the expense of a small loss in utility.

Our approach is the first method to compute individually fair results in learning-to-rank tasks. For classification tasks, it outperforms the state-of-the-art prior work on individual fairness. Moreover, it can be applied to input of all data-types, including multiple, multivariate, non-binary protected attributes, and even in the settings where access to protected attributes is restricted due to privacy concerns.

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