FAIR GROUP-SHARED REPRESENTATIONS WITH NORMALIZING FLOWS

Mattia Cerrato; Marius Köppel; Alexander Segner* & Stefan Kramer
Johannes Gutenberg-Universität Mainz
Saarstraße 21, Mainz, Germany

ABSTRACT

The issue of fairness in machine learning stems from the fact that historical data often displays biases against specific groups of people which have been underprivileged in the recent past, or still are. In this context, one of the possible approaches is to employ fair representation learning algorithms which are able to remove biases from data, making groups statistically indistinguishable. In this paper, we instead develop a fair representation learning algorithm which is able to map individuals belonging to different groups in a single group. This is made possible by training a pair of Normalizing Flow models and constraining them to not remove information about the ground truth by training a ranking or classification model on top of them. The overall, “chained” model is invertible and has a tractable Jacobian, which allows to relate together the probability densities for different groups and “translate” individuals from one group to another. We show experimentally that our methodology is competitive with other fair representation learning algorithms. Furthermore, our algorithm achieves stronger invariance w.r.t. the sensitive attribute.

1 INTRODUCTION

The topic of fairness in machine learning has received much attention over the last years. When machine learning technologies are trained to perform prediction tasks which impact people’s well-being, there is a growing concern that biased data can lead to biased decisions. For instance, the gender pay gap (see Weichselbaumer & Winter-Ebmer (2005)) may lead to different rates of acceptance in women’s loan requests. In this situation, a financial institution that simply maximizes its utility may further perpetrate past biases based on gender. Gender, ethnicity and similar data are usually called sensitive attributes in the group fairness literature. In group fairness, one is concerned with obtaining fair results for people which belong to different groups. This property can be represented in feature space as different values of a categorical variable \(s\). Various definitions of “fair decisions” are possible. A classifier might display disparate impact if it takes positive decisions (e.g. getting a loan) at different rates across the groups; disparate mistreatment instead refers to the situation where the classifier’s error rate is different across the groups (see Zafar et al. (2017)). Another possible way to obtain fairness is learning fair representations, i.e. representations of the original data where the groups are statistically indistinguishable from each other. Representation learning strategies that have been explored in this area include probabilistic models (see Zemel et al. (2013)), variational models (see Louizos et al. (2015b) and Moyer et al. (2018)) and reversed-gradient neural networks (see Xie et al. (2017), Cerrato et al. (2020b), Cerrato et al. (2020a) and McNamara et al. (2017)). The common thread between the plethora of work available in this area is information removal, i.e. employing a debiasing mechanism so that the new representation \(\hat{x} = f_\theta(x)\) does not contain information about \(s\). In the most general sense, perfect invariance to \(s\) can be formalized as minimal mutual information between the representation and the sensitive attribute \(I(\hat{x}; s) = 0\) (see Moyer et al. (2018) and Cerrato et al. (2020b)). In this work we start from the same objective of learning fair representations, but instead leverage normalizing flows, an invertible neural network-like model that can map an arbitrary data distribution to a known one for which density estimates are trivial to compute (e.g., a Gaussian). Our fair representation algorithm learns two models, one

*These authors contributed equally.
on all the data available ($G_A$ trained on $x$) and one on the data coming from a single “pivot” group ($G_P$ trained on $x_p$); furthermore, the latent feature space $Z$ of the two models is constrained to be the same. By leveraging the invertibility of normalizing flows, our algorithm first transforms all the data into the latent feature space $Z$; then, it uses the inverse transformation $G_P^{-1}(z)$ to obtain shared representations. In plain words, any individual belonging to a group $G_i$ may be “translated” into the feature space of pivot group $G_p$. Our approach is therefore to learn a shared feature space between groups, whereas other methods have focused on removing information about $s$ (see Cerrato et al. (2020b), Moyer et al. (2018) and Louizos et al. (2015b)).

Our contributions may be summarized as follows:

1. We present a new fair representation algorithm, FairNF, which employs normalizing flows to obtain a group-shared feature space.
2. We test the algorithm on real world datasets in the context of fair classification and fair ranking.
3. We discuss the actual invariance of the obtained representations.

2 RELATED WORKS

For transforming data to some latent space, normalizing flows can be used. The learned transformation is defined as $h : Z \rightarrow X$, where $X$ is the original data and $Z$ the latent space. One property of this mapping is that it is invertible. As formulated by Grover et al. (2019) one can use the change-of-variables formula to relate $p_X$ and $p_Z$, the marginal densities of $X$ and $Z$, respectively, by:

$$p_X(x) = p_Z(h^{-1}(x)) \left| \frac{\partial h^{-1}(x)}{\partial x^T} \right|. \tag{1}$$

Recent work has shown that such transformations can be done by deep neural networks, for example, NICE (Dinh et al. (2015b)) and Autoregressive Flows (Kingma et al. (2016)). Furthermore it was shown that evaluating likelihoods via the change-of-variables formula can be done efficiently by employing an architecture based on invertible coupling layers (Dinh et al. (2017)).

In domain adaptation, the currently developed AlignFlow by Grover et al. (2019), which is a latent variable generative framework that uses normalizing flows (Rezende & Mohamed (2016); Dinh et al. (2015b; 2017)), is used to transform samples from one domain to another. The data from each domain was modeled with an invertible generative model having a single latent space over all domains. In the context of domain adaptation, the domain class is also known during testing, which is not the case for fairness. Nevertheless, the general idea of training two Real NVP models is used for AlignFlow as well for the model proposed in this paper.

3 THE FAIR NORMALIZING FLOW FRAMEWORK

In this section we describe in detail our algorithm and how it can be employed to obtain fair representations. We define as $X$ the input feature space and the data vectors as $x$. In group fairness, one also has at least one variable $s$ for each data vector, representing a piece of sensitive information such as ethnicity, gender or age. This allows for the definition of a number of groups $G_1, \ldots, G_{|s|}$, one for each possible value of $s$. Lastly, labels $y$, representing either categorical (classification) or ordinal (ranking) information may be available in a supervised setting, which is usually the case in fair representation learning. The basic building block of our contribution is the normalizing flow model, which has been introduced in the context of generative modeling and density estimation (Dinh et al. (2015a); Papamakarios et al. (2017); Huang et al. (2018); Dinh et al. (2017)) and since then applied to the fairness-adjacent task of domain adaptation by Grover et al. (2019). A normalizing flow model can learn a bijection $f : X \rightarrow Z$, where $Z$ is a latent feature space which may be sampled easily, such as an isotropic Gaussian distribution. Then, it is possible to estimate the density $p_X$ via $f$ and the change-of-variables formula:
\[ p_X(x) = p_Z(f(x)) \left| \det \frac{\partial f}{\partial x} \right|. \]  

(2)

Our approach is to first select a pivot group \( G_p \) out of the \(|s| \) available ones. Then, a normalizing flow model \( f_p \) is trained to learn a bijection \( X_{G_p} \leftrightarrow Z \), where we denote \( X_{G_p} \) as the feature space for group \( G_p \). Then, another normalizing flow model \( f_{all} \) is trained independently to learn a bijection between the feature space \( X \) to the same known distribution \( Z \): \( f_{all} : X \leftrightarrow Z \). This makes it possible to relate the three densities \( p_X \), \( p_{X_{G_p}} \) and \( p_Z \) to one another via the change-of-variable formula:

\[ p_{X_{G_p}}(x_p) = p_Z(f_p(x_p)) \left| \det \frac{\partial f_p}{\partial x_p} \right|. \]  

(3)

\[ p_X(x) = p_Z(f_{all}(x)) \left| \det \frac{\partial f_{all}}{\partial x} \right|. \]  

(4)

Therefore, one may employ the two models to build a bijection chain \( X \xrightarrow{f_{all}} Z \xrightarrow{f^{-1}} X_p \), allowing for the transformation of vectors \( x \in X \) into vectors \( x_p \in X_{G_p} \). While a bijection cannot remove information about \( s \), as mutual information is in general invariant to invertible transformations, the procedure is helpful in practice by obfuscating the difference between \( G_p \) and \( G_{all} \), as we show in Section 4.

As commonly done in the normalization flow literature, we train our models with a log likelihood loss (see, e.g., Dinh et al. (2015a) and Papamakarios et al. (2017)). We rely on the “coupling layers” architecture, which guarantees invertibility, as introduced by Dinh et al. (2017).

To ensure that the new representations can still be used to predict the target labels \( y \), a classification or ranking model can be trained on top of them. We included a loss evaluated on the target label which is propagated through both normalizing flow models. This leads to a two-fold loss function, which can be regulated by the \( \gamma \) hyperparameter to address the relevance-fairness trade-off:

\[ L = \gamma(L_{f_p} + L_{f_{all}}) + L_y. \]  

(5)

Here, \( L_y \) can be any loss function which can be evaluated on \( y \). The gradients of \( L_{f_p} \) and \( L_{f_{all}} \) are only applied to \( f_p \) and \( f_{all} \), respectively, while the ones of \( L_y \) are applied to \( f_p \), \( f_{all} \) and the model predicting the target labels \( y \).

4 Experiments

4.1 Experimental Setup

To overcome statistical fluctuations during the experiments, we split the datasets into 3 internal and 3 external folds. On the 3 internal folds, a Bayesian grid search, optimizing the fairness measure, is used to find the best hyperparameter setting. The best setting is then evaluated on the 3 external folds.

We compare our model with a state-of-the-art algorithm called Fair Adversarial DirectRanker (AdvDR in the rest of this paper), which showed good results on commonly used fairness datasets (see Cerrato et al. (2020a)), a Debiasing Classifier (AdvCls) used in Cerrato et al. (2020b) and a fair listwise ranker (DELTR, Zehlike et al. (2020)).

Since it is from a theoretical point (to the best of our knowledge) not clear how exactly a Real NVP model is treating discrete features, we designed two different experiments whether the model is able to be trained on discrete features. For the first experiment done on the Compas dataset (see Dieterich et al. (2016)), we included discrete and continuous features. For the second experiment done on the Adult (see Kohavi (1996)) and Banks dataset (see Moro et al. (2014)) we only used continuous features.
4.2 Experimental Results

| Model    | Dataset | 1-rND     | 1-GPA    | NDCG@500 |
|----------|---------|-----------|----------|----------|
| FairNF   | Compas  | 0.838 ± 0.059 | 0.934 ± 0.030 | 0.474 ± 0.115 |
| FairNF   | Adult   | 0.922 ± 0.009 | 0.929 ± 0.025 | 0.460 ± 0.054 |
| FairNF   | Banks   | 0.859 ± 0.017 | 0.892 ± 0.016 | 0.519 ± 0.011 |
| AdvDR    | Compas  | 0.864 ± 0.061 | 0.911 ± 0.047 | 0.424 ± 0.033 |
| AdvDR    | Adult   | 0.884 ± 0.036 | 0.975 ± 0.016 | 0.647 ± 0.087 |
| AdvDR    | Banks   | 0.778 ± 0.106 | 0.735 ± 0.036 | 0.521 ± 0.086 |
| AdvCls   | Compas  | 0.823 ± 0.057 | 0.917 ± 0.032 | 0.542 ± 0.055 |
| AdvCls   | Adult   | 0.929 ± 0.007 | 0.901 ± 0.021 | 0.629 ± 0.008 |
| AdvCls   | Banks   | 0.918 ± 0.051 | 0.972 ± 0.026 | 0.198 ± 0.176 |
| DELTR    | Compas  | 0.825 ± 0.072 | 0.926 ± 0.007 | 0.438 ± 0.202 |
| DELTR    | Adult   | 0.744 ± 0.087 | 0.742 ± 0.048 | 0.142 ± 0.119 |
| DELTR    | Banks   | 0.823 ± 0.057 | 0.917 ± 0.032 | 0.542 ± 0.055 |

Table 1: Results for different fairness datasets. The used fairness metrics are 1-rND and 1-GPA used by Cerrato et al. (2020a) and the commonly used relevance metric NDCG@500. The used datasets are commonly used in fairness. For the Compas dataset (see Dieterich et al. (2016)) we used being black or white as sensitive attribute while we took the risk score as the ground truth. For the Adult dataset (see Kohavi (1996)) we used for the ground truth whether an individual’s annual salary is over 50K$ per year or not. The sensitive attribute was being a man or a woman. For the Banks dataset (see Moro et al. (2014)) the classification goal is whether a client will subscribe a term deposit. This dataset is biased against people under 25 or over 65 years.

In Table 1 the results for different fairness datasets are shown. FairNF is the proposed algorithm explained in Section 3. In terms of the two fairness measures, this algorithm is outperforming the other approaches in at least one measure over all datasets. The only algorithm that is better than FairNF in terms of fairness is AdvCls on the Banks dataset. However, on this dataset the algorithm is performing poorly on NDCG@500, while FairNF has a stable performance. In terms of relevance, FairNF and AdvDR have similar performance on the Compas and Banks dataset, while AdvDR is better on the Adult one. The other two algorithms may have weaker results on relevance (AdvCls on Banks; DELTR on Adult). Looking at the question whether the model is able to be trained on continuous features only, we cannot see any significant performance difference comparing the experiments done on Compas compared with the ones done on Adult and Banks.

5 Conclusion and Future Works

We introduced a new algorithm, called FairNF, which is able to transform unfair data into fair data by learning group-shared representations. This is made possible by training a pair of Real NVP models, with one focusing on a pivot group and the other learning from the whole dataset. The models are then used to build a bijection chain, allowing to obfuscate the difference between the sensitive groups. The two Real NVP models were constrained to still provide information about the ground truth by training a ranking or classification model on top of them and propagating the gradients throw the whole bijection chain. The proposed algorithm performed well compared to existing methods on the tested Compas, Adult and Banks dataset. We are currently investigating an extension of our framework in the context of learning a disentangled latent space $Z$. A disentangled latent space would dedicate a number of dimensions to represent all information about the sensitive attribute. The remaining dimensions may then be employed to project back into the original feature space. We expect this to provide further benefits in terms of representation invariance and fairness. Since the empirical results including both discrete and continuous features into the training data did not show any performance decrease, we would further investigate this by including a deeper theoretical analysis on this property.
REFERENCES

Julia Angwin, Jeff Larson, S.M., and Kirchner L. Machine bias. www.propublica.org, 2016.

M. Cerrato, Marius Köppel, A. Segner, R. Esposito, and S. Kramer. Fair pairwise learning to rank. 2020 IEEE 7th International Conference on Data Science and Advanced Analytics (DSAA), pp. 729–738, 2020a.

Mattia Cerrato, Roberto Esposito, and Laura Li Puma. Constraining deep representations with a noise module for fair classification. In ACM Symposium on Applied Computing (SAC), 2020b.

William Dieterich, Christina Mendoza, and Tim Brennan. Compas risk scales: Demonstrating accuracy equity and predictive parity. Northpointe Inc., 2016.

Laurent Dinh, David Krueger, and Yoshua Bengio. NICE: non-linear independent components estimation. In Yoshua Bengio and Yann LeCun (eds.), 3rd International Conference on Learning Representations, ICLR 2015, San Diego, CA, USA, May 7-9, 2015, Workshop Track Proceedings, 2015a. URL http://arxiv.org/abs/1410.8516

Laurent Dinh, David Krueger, and Yoshua Bengio. Nice: Non-linear independent components estimation, 2015b.

Laurent Dinh, Jascha Sohl-Dickstein, and Samy Bengio. Density estimation using real nvp. In International Conference on Learning Representations, 2017.

Aditya Grover, Christopher Chute, Rui Shu, Zhangjie Cao, and Stefano Ermon. Alignflow: Cycle consistent learning from multiple domains via normalizing flows, 2019.

Chin-Wei Huang, David Krueger, Alexandre Lacoste, and Aaron Courville. Neural autoregressive flows. In International Conference on Machine Learning, pp. 2078–2087. PMLR, 2018.

Durk P Kingma, Tim Salimans, Rafal Jozefowicz, Xi Chen, Ilya Sutskever, and Max Welling. Improved variational inference with inverse autoregressive flow. In D. Lee, M. Sugiyama, U. Luxburg, I. Guyon, and R. Garnett (eds.), Advances in Neural Information Processing Systems, volume 29, pp. 4743–4751. Curran Associates, Inc., 2016. URL https://proceedings.neurips.cc/paper/2016/file/ddeebdeefdb7e7e7a697e1c3e3d8ef54-Paper.pdf

Ron Kohavi. Scaling up the accuracy of naive-bayes classifiers: A decision-tree hybrid. In KDD, 1996.

Christos Louizos, Kevin Swersky, Yujia Li, Max Welling, and Richard Zemel. The variational fair autoencoder. preprint arXiv:1511.00830 2015a.

Christos Louizos, Kevin Swersky, Yujia Li, Max Welling, and Richard S. Zemel. The Variational Fair Autoencoder. ICLR 2016, abs/1511.00830, 2015b.

Daniel McNamara, Cheng Soon Ong, and Robert C Williamson. Provably fair representations. preprint arXiv:1710.04394 2017.

Sérgio Moro, Paulo Cortez, and Paulo Rita. A data-driven approach to predict the success of bank telemarketing. Decision Support Systems, 62, 06 2014. doi: 10.1016/j.dss.2014.03.001.

Daniel Moyer, Shuyang Gao, Rob Brekelmans, Greg Ver Steeg, and Aram Galstyan. Invariant representations without adversarial training. arXiv preprint arXiv:1805.09458 2018.

Harikrishna Narasimhan, Andrew Cotter, Maya Gupta, and Serena Wang. Pairwise fairness for ranking and regression. In AAAI, 2020.

George Papamakarios, Theo Pavlakou, and Iain Murray. Masked autoregressive flow for density estimation. In I. Guyon, U. V. Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan, and R. Garnett (eds.), Advances in Neural Information Processing Systems, volume 30, pp. 2338–2347. Curran Associates, Inc., 2017. URL https://proceedings.neurips.cc/paper/2017/file/6c1da886822c67822bcf3679d04369fa-Paper.pdf
Danilo Jimenez Rezende and Shakir Mohamed. Variational inference with normalizing flows, 2016.

Doris Weichselbaumer and Rudolf Winter-Ebmer. A meta-analysis of the international gender wage gap. *Journal of Economic Surveys*, 19(3):479–511, 2005.

Qizhe Xie, Zihang Dai, Yulun Du, Eduard Hovy, and Graham Neubig. Controllable invariance through adversarial feature learning. In *NIPS*, 2017.

Ke Yang and Julia Stoyanovich. Measuring fairness in ranked outputs. In *SSDBM ’17*, New York, NY, USA, 2017. Association for Computing Machinery. ISBN 9781450352826.

Muhammad Bilal Zafar, Isabel Valera, Manuel Gomez Rodriguez, and Krishna P Gummadi. Fairness beyond disparate treatment & disparate impact: Learning classification without disparate mistreatment. In *WWW*, 2017.

Meike Zehlike, Tom Sühr, Carlos Castillo, and Ivan Kitanovski. Fairsearch: A tool for fairness in ranked search results. *Companion Proceedings of the Web Conference 2020*, Apr 2020. doi: 10.1145/3366424.3383534. URL [http://dx.doi.org/10.1145/3366424.3383534](http://dx.doi.org/10.1145/3366424.3383534)

Richard Zemel, Yu Wu, Kevin Swersky, Toni Pitassi, and Cynthia Dwork. Learning fair representations. In *ICML*, 2013.
SUPPLEMENTARY MATERIAL

THE NDCG METRIC

The normalized discounted cumulative gain of top-k documents retrieved (NDCG@k) is a common used measure for performance in the field of learning to rank. Based on the cumulative gain of top-k documents (DCG@k) the NDCG@k can be computed by dividing the DCG@k by the ideal (maximum) discounted cumulative gain of top-k documents retrieved (IDCG@k):

\[
\text{NDCG}@k = \frac{\text{DCG}@k}{\text{IDCG}@k} = \sum_{i=1}^{k} \frac{x^{(d_i)} - 1}{\log_2(i+1)},
\]

where \(d_1, d_2, ..., d_n\) is the list of documents sorted by the model with respect to a single query and \(r(d_i)\) is the relevance label of document \(d_i\).

rND

To the end of measuring fairness in our models we employ the rND metric which was introduced by [Yang & Stoyanovich (2017)]. This metric is used to measure group fairness and is defined as follows:

\[
\text{rND} = \frac{1}{Z} \sum_{i \in \{10, 20, ..., \}} \frac{1}{\log_2 i} \left| \frac{|S^+_i|}{i} - \frac{|S^+|}{N} \right|.
\]

The goal of this metric is to measure the difference between the ratio of the protected group in the top-i documents and in the overall population. The maximum value of this metric is given by \(Z\) which is also used as normalization factor. This value is computed by evaluating the metric with a dummy list where the protected group is placed at the end of the list. This biased ordering represents the situation of “maximal discrimination”.

This metric also penalizes if protected individuals at the top of the list are over-represented compared to their overall representation in the population.

GROUP-DEPENDENT PAIRWISE ACCURACY

Let \(G_1, ..., G_K\) be a set of \(K\) protected groups such that every document inside the dataset \(D\) belongs to one of these groups. The group-dependent pairwise accuracy introduced in [Narasimhan et al. (2020)] \(A_{G_i > G_j}\) is then defined as the accuracy of a ranker on documents which are labeled more relevant belonging to group \(G_i\) and documents labeled less relevant belonging to group \(G_j\). Since a fair ranker should not discriminate against protected groups, the difference \(|A_{G_i > G_j} - A_{G_j > G_i}|\) should be close to zero. In the following, we call the Group-dependent Pairwise Accuracy GPA.

FAIR REPRESENTATIONS

For further investigating the fairness of the new representations we trained external classifiers on the transformed data to predict the sensitive attribute. In Table 2 the results on the original COMPAS data (\(x\)) and the transformed data \(\hat{x}\) are shown. The used classifiers are a Linear Regression (LR), Random Forest (RF) and a simple Multilayer Perceptron (MLP). They are also trained five times over the five different train/test folds. For the evaluation the F-score was taken which also takes unbalanced class representations into account. A lower score means a less precise prediction. Overall all algorithms are worse in predicting \(s\) while trained with \(\hat{x}\) compared to the results for the original dataset. Therefore, we observe gains in representation invariance by employing our methodology.

DATASETS

For evaluating on real world data the COMPAS dataset (see [Angwin et al. (2016)]), was used. This dataset was released as part of an investigative journalism effort in tackling automated discrimination. Furthermore the Adult dataset is used where the ground truth represents whether an individual’s
Table 2: ADRG, F1 and AUC scores of the representation results for the original data $x$ and the transformed data $\hat{x}$ using our framework on the COMPAS dataset. ADRG stands for “Absolute Difference from Random Guess”, i.e. the difference in accuracy from a classifier which always predicts the majority class (see Cerrato et al. (2020a)).

annual salary is over 50K$ per year or not (Kohavi (1996)). It is commonly used in fair classification, since it is biased against gender (see Louizos et al. (2015a), Zemel et al. (2013) and Cerrato et al. (2020b)). The third dataset used in our experiments is the Bank Marketing Data Set (see Moro et al. (2014)) where the classification goal is whether a client will subscribe a term deposit. The dataset is biased against people under 25 or over 65 years.

**TOY DATA**

For evaluating the FairNF algorithm we generate two sets of toy data by randomly sampling two features from different normal distributions. The mean and the standard deviation of each distribution is set to be different. The toy data is then processed using our framework. The goal for this experiment is show how the two distributions can be transformed to one.

Figure 1: In 1(a) the generated toy data is shown where the different groups are displayed with blue and red. In 1(b) the transformed toy data is shown using the FairNF algorithm.

In 1(a) the original toy data is shown while 1(b) shows the data after the transformation with the FairNF algorithm. In 1(a) the two distributions are not overlaying so they should be easily distinguished by a classification algorithm. After transforming them they heavily overlap making it harder to distinguish between the two.