Edward Raff¹² Jared Sylvester¹

Abstract

No methods currently exist for making arbitrary neural networks fair. In this work we introduce GRAD, a new and simplified method to producing fair neural networks that can be used for autoencoding fair representations or directly with predictive networks. It is easy to implement and add to existing architectures, has only one (insensitive) hyper-parameter, and provides improved individual and group fairness. We use the flexibility of GRAD to demonstrate multi-attribute protection.

1. Introduction

Artificial Neural Network methods are quickly becoming ubiquitous in society, spurred by advances in image, signal, and natural language processing. This pervasiveness leads to a new need for considering the fairness of such networks from many perspectives, including: how they are used, who can access them and their training data, and potential biases in the model itself. There are many reasons for desiring fair classification algorithms. These include legal mandates to be non-discriminative, ensuring a moral or ethical goal, or for use as evidence in legal proceedings (Romei & Ruggieri, 2014). Despite the long-standing need and interest in this problem, there are few methods available today for training fair networks.

When we say that a network is fair, we mean fair with respect to a protected attribute a_p , such as age or gender. Our desire is that a model's predicted label \hat{y} given a feature vector xis invariant to changes in a_p . An initial reaction may be to simply remove a_p from the feature vector x. While intuitive, this "fairness through unawareness" does not remove the correlations with a_p that exist in the data, and so the result will still produce a biased model (Pedreshi et al., 2008).

For this reason we need to devise approaches that explicitly remove the presence of a_p from the model's predictions. We do so in this work by introducing a new method to train fair neural networks. Our approach, termed Gradient Reversal Against Discrimination (GRAD), makes use of a network which simultaneously attempts to predict the target class y and protected attribute a_p . The key is that the gradients resulting from predictions of a_p are reversed before being used for weight updates. The result is a network which is capable of learning to predict the target class but effectively inhibited from being able to predict the protected attribute. GRAD displays competitive accuracy and improved fairness when compared to prior approaches. GRAD's advantage comes from increased simplicity compared to prior approaches, making it easier to apply and applicable to a wider class of networks. Prior works in this space are limited to one attribute (but see Zafar et al., 2017) and require the introduction of multiple hyper-parameters. These parameters must be cross-validated, making the approaches challenging to use. Further, our approach can be used to augment any current model architecture, where others have been limited to auto-encoding style architectures.

2. Gradient Reversal Against Discrimination

We now present our new approach to developing neural networks that are fair with respect to some protected attribute. We call it *Gradient Reversal Against Discrimination* (GRAD), and is inspired by recent work in transfer learning. Notably, Ganin et al. (2016) introduced the idea of domain adaptation by attempting to jointly predict a target label and a domain label (i.e., which domain did this data instance come from?). By treating the protected attribute as the new domain, we can use this same approach to instead prevent the network from being biased by the protected attribute a_p .

After several feature extraction layers the network forks. One branch learns to predict the target y, while the other attempts to predict the protected attribute a_p . We term the portion of the network before the splitting point the "trunk," and those portions after the "target branch" and the "attribute branch." The final loss of the network is sum of the losses of both branches, giving $\ell(y, a_p) = \ell_t(y) + \lambda \cdot \ell_p(a_p)$. Here, λ determines the relative importance of fairness compared to accuracy. In practice, we find that performance is insensitive to particular choices of λ , and any value of $\lambda \in [50, 2000]$ would perform equivalently. In our experiments we will use

¹Booz Allen Hamilton ²University of Maryland, Baltimore County. Correspondence to: Edward Raff <raff_edward@bah.com>.

Proceedings of the 5th Workshop on Fairness, Accountability and Transparency in Machine Learning, Stockholm, Sweden, 2018. Copyright 2018 by the author(s).



Figure 1. Diagram of GRAD architecture. Red connection indicates normal forward propagation, but back-propagation will reverse the signs.

 $\lambda = 100$ without any kind of hyper-parameter optimization.

The values of both $\ell_t(y)$ and $\ell_p(a_p)$ are calculated and used to determine gradients for weight updates as usual, with one important exception. When the gradients have been back-propagated from the attribute branch they are reversed (i.e., multiplied by -1) before being applied to the trunk. This moves the trunk's parameters *away* from optima in predictions of a_p , crippling the ability to correctly output the protected attribute. Since the target branch also depends on the trunk parameters, it inherits this inability to accurately output the value of the protected attribute. No such reversal is applied to the gradients derived from y, so the network's internal state representations are suitable for predicting ybut nescient of a_p .

It is instructive to consider why it may be insufficient to set up a loss function which directly punishes the network for correctly predicting a_p . If this were the case, the network could achieve low loss by forming internal representation which are very good at predicting the protected attribute, and then "throw the game" by simply reversing the correct prediction in the penultimate layer. (That is, a potential, reliable strategy to getting the wrong answer is to become very good at getting the right answer, and then lying about what one thinks the answer should be.) If this strategy is adopted then the representations necessary for correctly recovering a_p from x would be available to the target branch when making its prediction of y, which is the situation we aim to prevent.

Architecture Variants

As mentioned above, many of the other neural approaches to fair classification take an autoencoder or representation learning approach. This approach has its advantages. For instance, it allows the person constructing the fair model to be agnostic about the ultimate task that it will be applied to. Others like ALFR consider a target value directly, and so can not be re-used for other tasks, but may perform better in practice on the specific problem they were constructed for.

Our GRAD approach, thanks to its comparative simplicity,

can be used in both formulations. This makes it the only neural network-based approach to fairness that offers both task flexibility and specificity.

GRAD-Auto will designate our approach when using an auto-encoder as the target branch's loss. That is, if x is the input feature, \tilde{x} will be the feature vector derived from x such that the protected attribute $a_p \notin \tilde{x}$. We then use $\ell_t^{\text{Auto}}(\cdot) = ||h_{\text{target}} - \tilde{x}||_2^2$ as the loss function for the target branch, where h_{target} is the activation vector from the last layer of the target branch. This approach is in the same style as LFR and VFA, where a hidden representation invariant to a_p is learned, and then Logistic Regression is used on the outputs from the trunk sub-network to perform classification.

GRAD-Pred will designate our task-specific approach, where we use the labels y_i directly. Here we simply use the standard logistic loss $\ell_t^{\text{Pred}}(\cdot) = \log(1 + \exp(-y \cdot h_{\text{target}}))$. In this case the target branch of the network will produce a single activation, and the target branch output itself is used as the classifier directly.

Since we are dealing with binary protected attributes, both GRAD-Auto and GRAD-Pred will have the attribute branch of the network use $\ell_p(a_p) = \log(1 + \exp(-a_p \cdot h_{\text{attribute}}))$.

In the spirit of minimizing the effort needed by the practitioner, we do not perform any hyper-parameter search for the network architecture either. Implemented in Chainer (Tokui et al., 2015) we use two fully-connected layers for every branch of the network (trunk, target, & attribute) where all hidden layers have 40 neurons. Each layer will use batchnormalization followed by the the ReLU activation function. Training is done using the Adam optimizer for gradient decent. We emphasize that the heart of GRAD is the inclusion of the attribute branch with reversed gradient; this technique is flexible enough to be used regardless of the particular choices of layer types, sizes, etc. We train each model for 50 epochs, and use a validation set to select the model from the best epoch. We define best by the model having the lowest Discrimination (see §3.1) on the validation set, breaking ties by selecting the model with the highest accuracy. When multiple attributes are protected, we use the lowest average Discrimination.

3. Methodology

There is currently ongoing debate about what it means for a machine learning model to be fair. We choose to use the same evaluation procedure laid out by Zemel et al. (2013). This makes our results comparable with a larger body of work, as their approach and metrics have been widely used through the literature (e.g., Landeiro & Culotta, 2016; Bechavod & Ligett, 2017; Dwork et al., 2017). We use the same evaluation procedure and metrics: Discrimination, Consistency, Delta, and Accuracy.

3.1. Metrics

Given a dataset $\{x_1, \ldots, x_n\} \in \mathcal{D}$, we define the ground true label for the *i*th datum as y_i and the model's prediction as \hat{y}_i . Each are with respect to the binary target label $y \in \{0, 1\}$. While we define both y_i and \hat{y}_i , we emphasize that only the predicted label \hat{y}_i is used in the fairness metrics. This is because fairness is not directly related to accuracy by equality of treatment.

Discrimination is a macro-level measure of "group" fairness, and computed by the taking the difference between the average predicted scores for each attribute value, assuming a_p is a binary attribute.

Discrimination =
$$\left| \frac{\sum_{x_i \in T_{a_p}} \hat{y}_i}{|T_{a_p}|} - \frac{\sum_{x_i \in T_{\neg a_p}} \hat{y}_i}{|T_{\neg a_p}|} \right| \quad (1)$$

The second metric is Consistency, which is a micro-level measure of "individual" fairness. For each $x_i \in \mathcal{D}$, we compare its prediction y_i with the average of its k nearest neighbors and take the average of this score across \mathcal{D} .

Consistency =
$$1 - \frac{1}{N} \sum_{i=1}^{N} \left| \hat{y}_i - \frac{1}{k} \sum_{j \in k - \text{NN}(x_i)} \hat{y}_j \right|$$
 (2)

Because Consistency and Discrimination are independent of the actual accuracy of the method used, we also consider the Delta = Accuracy – Discrimination. This gives a combined measure of an algorithm's accuracy that penalizes it for biased predictions.

We use these metrics in the same manner and on the same datasets as laid out in Zemel et al. (2013) so that we can compare our results with prior work. This includes using the same training, validation, and testing splits. When training our GRAD approaches, we perform 50 epochs of training, and select the model to use from the validation performance. Specifically, we choose the epoch that had the lowest discrimination and broke ties by selecting the highest accuracy.

3.2. Models Evaluated

As a baseline for comparison against GRAD-Pred and GRAD-Auto, we will consider the same architecture but with the attribute branch removed. This produces a standard neural network, and will be denoted as *NN*. For comparison with other fairness-seeking neural network algorithms, we present prior results for Learning Fair Representations (LFR) (Zemel et al., 2013), Variation Fair Autoencoders (VFA) (Louizos et al., 2016), and Adversarial Learned Fair Representations (ALFR) (Edwards & Storkey, 2016) approaches. For all models on all datasets, we report the metrics as presented in their original publications, as we were unable to replicate VFA and ALFR's results.

4. Results

The results are given in Table 1. For values unreported in their original work, we show a dash ("—") in the table. Our GRAD approach is shown in the top rows. The bottom three rows include the other approaches as explained in subsection 3.2.

When we compare the standard neural network (NN) with its GRAD counterpart, we can see that the GRAD approach *always* increases the Delta and Consistency scores, and reduces the Discrimination. This shows its applicability across network types (classifying and auto-encoding). We can even see the GRAD approach improve accuracy on the Adult dataset by 5 percentage points. While we would not expect this behavior (i.e. a negative cost of fairness) in the general case, it is nonetheless interesting and it may indicate the protected attribute allows overfitting.

Comparing the GRAD algorithms to the other neural networks LFR, VFA and ALFR, we see that GRAD is usually best or 2nd best in each metric. On both the German and Adult datasets, it achieves the best Discrimination and Consistency scores compared to any of the algorithms tested. On the German dataset VFA obtains a higher Delta score by having a high accuracy, though VFA has 4% discrimination compared to GRAD-Pred's 0.06%. On the Health dataset, GRAD-Auto and GRAD-Pred have near identical results. This is overall significantly better than the LFR approach which has an 11 percentage point difference in Accuracy and Delta scores compared to the GRAD approaches. The VFA algorithm is similarly within a fractional distance, though Consistency is not reported for VFA.

GRAD consistently produces the highest Consistency. On the Adult dataset where VFAE and ALFR get better accuracy, it may have come at a cost of lower Consistency. This couldn't be confirmed since we could not replicate their results.

4.1. Multiple Protected Attributes

In almost all prior works that we are aware, it is always assumed that there is only *one* attribute that needs to be protected. However, this is a myopic view of the world. All of the protected attributes that have been tested individually in this work, like age, race and gender, may all co-occur and interact with each other. We show this in Table 2 using the Diabetes dataset used in Edwards & Storkey (2016), which has both Race and Gender as features in the corpus. In this case GRAD-Pred and GRAD-Auto are protecting Race and Gender attributes. GRAD-Pred-R shows the results for protecting only Race, and GRAD-Pred-G shows for only protecting Gender. GRAD-Auto follows the same convention.

Since Discrimination is computed with respect to specific

Algorithm	German				Adult				Health			
	Acc	Delta	Discr	Cons	Acc	Delta	Discr	Cons	Acc	Delta	Discr	Cons
NN-Auto	0.7350	0.5334	0.2016	0.8730	0.7635	0.7191	0.0444	0.9850	0.8506	0.7939	0.0567	0.9730
GRAD-Auto	0.6750	0.6296	0.0454	0.8705	0.7554	0.7452	0.0102	0.9924	0.8491	0.8491	0.0000	1.0000
NN-Pred	0.7500	0.3637	0.3863	0.6945	0.7022	0.6268	0.0754	0.8168	0.8440	0.7511	0.0929	0.9453
GRAD-Pred	0.6750	0.6744	0.0006	0.9705	0.7543	0.7543	0.0000	1.0000	0.8493	0.8486	0.0007	0.9999
LFR	0.5909	0.5867	0.0042	0.9408	0.7023	0.7018	0.0006	0.8108	0.7365	0.7365	0.0000	1.0000
VFAE	0.7270	0.6840	0.0430	—	0.8129	0.7421	0.0708	—	0.8490	0.8490	0.0000	—
ALFR					0.8251	0.8241	0.0010					

Table 1. For each dataset we show Accuracy, Delta, Discrimination, and Consistency. Best results shown in **bold**, second best in *italics*.

Table 2. Accuracy, Delta, Discrimination (with respect to Race and Gender), and Consistency for our new method on the Diabetes dataset. Last four rows show GRAD models when only Race (R) or Gender (G) are protected.

			Discrin			
Algorithms	Acc	Delta	Race	Gender	Cons	
NN-Auto	0.5735	0.5392	0.0412	0.0275	0.6411	
GRAD-Auto	0.5765	0.5723	0.0055	0.0030	0.6288	
NN-Pred	0.6286	0.5848	0.0418	0.0458	0.6464	
GRAD-Pred	0.5980	0.5949	0.0028	0.0034	0.7180	
GRAD-Auto-R	0.5851	0.5749	0.0003	0.0201	0.6404	
GRAD-Auto-G	0.5640	0.5143	0.0981	0.0013	0.6093	
GRAD-Pred-R	0.5844	0.5478	0.0020	0.0713	0.7538	
GRAD-Pred-G	0.5941	0.5526	0.0785	0.0045	0.6849	

attributes, in the table we show the discrimination scores with respect to both of the protected attributes. Since we have two protected attributes a_{p^1} and a_{p^2} , we compute Delta = Accuracy -(Discrimination $(a_{p^1}) +$ Discrimination (a_{p^2}))/2. In doing so, we can see that when two protected variables are present, the GRAD approach is able to reduce Discrimination and increase Delta for both the Autoencoder and the standard softmax predictive network. GRAD-Pred also continues to increase the Consistency with respect to the naive neural network.

Comparing GRAD-Pred with GRAD-Pred-R and GRAD-Pred-G is also critical to show that protecting both attributes simultaneously provides a significant benefit. On the Diabetes data, we see the model increase its discrimination with respect to Gender when only Race is protected. Similarly, when we protect Gender, discrimination with respect to Race increases. Explicitly protecting both is the only safe way to reduce discrimination on both.

The model shifting to leverage other protected features is not surprising. When we penalize a feature which provides information, the model must attempt to recover discriminative information in other (potentially non-linear) forms from the other features. Thus the importance and utility of



Figure 2. Plots show the performance of GRAD-Pred as a function of λ on the x-axis (log scale). A dashed vertical black line shows the value $\lambda = 100$ used in all experiments.

GRAD to protect both simultaneously is established.

4.2. Robustness to λ

We have discussed so far that a benefit of the GRAD approach is a simplicity in application due to the having only one hyper-parameter λ . We now show that this value λ is largely robust to the value used. In Figure 2 we plot the Accuracy, Discrimination, and Consistency as a function of λ for values in the range [1, 2000], which shows GRAD's consistent behavior. On the Adult dataset, we see results stabilize after $\lambda \geq 10$. The Health dataset looks flat through the entire plot since the variation is on the order of 10^{-3} , making it indiscernible. Only the Adult and Health plots are shown due to space limitations. The Diabetes plot is similar, and the German dataset has more variability due to its small size (n = 1000).

5. Conclusions

We have introduced GRAD, a flexible approach for building fair neural networks that can be used to augment any general neural network, and does not mandate the auto-encoding approach of prior work or the use of cumbersome additional hyper-parameters. GRAD is competitive with prior work, can protect multiple attributes, and often delivers superior fairness through low discrimination.

Acknowledgments

We would like to thanks Steven Mills and Paul Terwilliger for their support of this work.

References

- Bechavod, Yahav and Ligett, Katrina. Learning Fair Classifiers: A Regularization-Inspired Approach. In FAT ML Workshop, 2017. URL http://arxiv.org/abs/ 1707.00044.
- Dwork, Cynthia, Immorlica, Nicole, Kalai, Adam Tauman, and Leiserson, Max. Decoupled classifiers for fair and efficient machine learning. In *FAT ML Workshop*, 2017. doi: 1707.06613. URL https://arxiv.org/pdf/ 1707.06613.pdf.
- Edwards, Harrison and Storkey, Amos. Censoring Representations with an Adversary. In *International Conference on Learning Representations (ICLR)*, 2016. URL http://arxiv.org/abs/1511.05897.
- Ganin, Yaroslav, Ustinova, Evgeniya, Ajakan, Hana, Germain, Pascal, Larochelle, Hugo, Laviolette, François, Marchand, Mario, and Lempitsky, Victor. Domainadversarial Training of Neural Networks. J. Mach. Learn. Res., 17(1):2030–2096, 1 2016. ISSN 1532-4435. URL http://dl.acm.org/citation.cfm?id=2946645.2946704.
- Landeiro, Virgile and Culotta, Aron. Robust Text Classification in the Presence of Confounding Bias. In *Proceedings of the Thirtieth AAAI Conference on Artificial Intelligence*, AAAI'16, pp. 186–193. AAAI Press, 2016. URL http://dl.acm.org/citation.cfm?id=3015812.3015840.
- Louizos, Christos, Swersky, Kevin, Li, Yujia, Welling, Max, and Zemel, Richard. The Variational Fair Autoencoder. In International Conference on Learning Representations (ICLR), 2016. URL http://arxiv.org/abs/ 1511.00830.
- Pedreshi, Dino, Ruggieri, Salvatore, and Turini, Franco. Discrimination-aware Data Mining. In Proceedings of the 14th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, KDD '08, pp. 560–568, New York, NY, USA, 2008. ACM. ISBN 978-1-60558-193-4. doi: 10.1145/1401890.1401959. URL http: //doi.acm.org/10.1145/1401890.1401959.
- Romei, Andrea and Ruggieri, Salvatore. A multidisciplinary survey on discrimination analysis. *The Knowledge Engineering Review*, 29(05):582–638, 11 2014. ISSN 0269-8889. doi: 10.1017/S0269888913000039. URL http://www.journals.cambridge.org/ abstract_S0269888913000039.

- Tokui, Seiya, Oono, Kenta, Hido, Shohei, and Clayton, Justin. Chainer: a Next-Generation Open Source Framework for Deep Learning. In Proceedings of Workshop on Machine Learning Systems (LearningSys) in The Twenty-ninth Annual Conference on Neural Information Processing Systems (NIPS), 2015. URL http://learningsys.org/papers/ LearningSys_2015_paper_33.pdf.
- Zafar, Muhammad Bilal, Valera, Isabel, Rogriguez, Manuel Gomez, and Gummadi, Krishna P. Fairness constraints: Mechanisms for fair classification. In *Artificial Intelligence and Statistics*, pp. 962–970, 2017.
- Zemel, Rich, Wu, Yu, Swersky, Kevin, Pitassi, Toni, and Dwork, Cynthia. Learning Fair Representations. In Dasgupta, Sanjoy and McAllester, David (eds.), *Proceedings of the 30th International Conference on Machine Learning*, volume 28 of *Proceedings of Machine Learning Research*, pp. 325–333, Atlanta, Georgia, USA, 2013. PMLR. URL http://proceedings.mlr. press/v28/zemel13.html.