Fair Visual Recognition via Intervention with Proxy Features

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Abstract

Deep learning models often learn to make predictions that rely on sensitive social attributes like gender and race, which poses significant fairness risks, especially in societal applications, e.g., hiring, banking, and criminal justice. Existing work tackles this issue by minimizing information about social attributes in models for debiasing. However, the high correlation between target task and social attributes makes bias mitigation incompatible with target task accuracy. Recalling that model bias arises because the learning of features in regard to bias attributes (i.e., bias features) helps target task optimization, we explore the following research question: Can we leverage proxy features to replace the role of bias feature in target task optimization for debiasing? To this end, we propose Proxy Debiasing, to first transfer the target task’s learning of bias information from bias features to artificial proxy features, and then employ causal intervention to eliminate proxy features in inference. The key idea of Proxy Debiasing is to design controllable proxy features to one hand replace bias features in contributing to target task during the training stage, and on the other hand easily to be removed by intervention during the inference stage. This guarantees the elimination of bias features without affecting the target information, thus addressing the fairness-accuracy paradox in previous debiasing solutions. We apply Proxy Debiasing to several benchmark datasets, and achieve significant improvements over the state-of-the-art debiasing methods in both of accuracy and fairness.

Figure 1: Illustration of the algorithmic bias problem, conventional debiasing method (Adversarial Debiasing) and the proposed proxy debiasing. Adversarial Debiasing method potentially removes partial target features in removing bias features, while our method uses proxy features to replace bias feature in learning of target task, which avoids unwittingly harming target features.

Recent studies [Locatello et al. 2019; Creager et al. 2019] realized that learning bias features (e.g., gender features) is one of the key factors causing unfairness. As shown in the first row in Figure 1 models with standard learning inherit biased patterns in training data, and the learned decision rules thus depend on both target and bias features. This realization spawned a lot of works to prevent models from learning bias features. Towards this goal, the most direct method (d’Alessandro, O’Neil, and LaGatta 2017) removes bias features from the training data (e.g., directly removing all information about gender). However, this only works for structured data and not for visual data, because the target features and bias features in the sample are tightly entangled. In visual recognition, popular bias mitigation methods (Raff and Sylvester 2018; Kim et al. 2019; Jung et al. 2021) employ regularization terms to train models not to encode bias features of samples. Typical approaches, such as Adversarial Debiasing, adversarially train models to discriminate target attribute labels but fail to discriminate bias attribute labels. These works remove bias features in data representation, therefore enhancing output invariance to bias attribute. However, since target features and bias features have
strong correlations in biased training data, these methods potentially remove partial target features and cause accuracy degradation in debiasing (cf., Figure 1). Also due to this correlation, solving the target task inevitably promotes the representation of bias features, leading to limited debiasing effects. This zero-sum game between target task learning and debiasing task leads to the fairness-accuracy paradox.

In this paper, we aim to address the incompatibility between fairness and accuracy in debiasing. To this end, we introduce Proxy Debiasing that eliminates model bias without destroying the information of the target task. As illustrated in Figure [1], the key idea of Proxy Debiasing is to use the artificial proxy features to replace the model’s dependence on bias features in target task learning. The basic premise that the proxy feature can act as a proxy for the bias feature is that the proxy feature distribution should be consistent with the bias feature. To the end, we attach corresponding proxy features to samples with different bias attributes to satisfy distribution consistency, e.g., male sample and female sample are respectively attached with different proxy features in training, as shown in Figure 4. Then, to eliminate the influence of proxy features on inference stage, we replace proxy features with intervention features based on causal intervention. Note that we do not need any prior information of sample, i.e., the intervention features imposed on all samples are the same.

We also conducted proxy effect analysis and reached a concluding observation: the model does not naturally learn bias information entirely from proxy features, and still learns bias information from bias features, which results in the inability to completely eliminate bias. To solve this issue, we propose to maximize the contribution of proxy features to the target task to enhance the proxy effect of proxy features on bias features in the training of target task, which we call Active Proxy Debiasing. For the contribution of proxy features, we borrow the idea of counterfactual explanations to measure. Avoiding the zero-sum game between debiasing and target task learning in previous methods, our proxy debiasing method improves over previous methods on both fairness and accuracy.

We summarize our main contributions as follows:
• We propose a novel debiasing method Proxy Debiasing that employ proxy features to replace bias features in the target task’s learning of bias information, which avoids the competition between target task and debias task in previous methods.
• We introduce proxy effect enhancement that actively enhances the contribution of proxy features to the target task to improve the proxy effect of proxy features on bias features.
• Extensive experiments demonstrate that our method significantly improves over baselines on both accuracy and fairness. The effectiveness on debiasing multiple bias attributes is also verified.

### Related Work

**Bias mitigation.** Existing bias mitigation methods can be roughly divided into three families depending on the training pipelines they are applied to: pre-processing methods (Louizos et al. 2015; Quadranto, Sharmanska, and Thomas 2019) refine dataset to mitigate the source of unfairness before training; in-processing methods (Elkan 2001; Jiang and Nachum 2020) introduce fairness constraints into the training process; and post-processing methods (Kamiran, Karim, and Zhang 2012; Pleiss et al. 2017) adjust the prediction of models according to fairness criterion after training. Among them, in-processing methods have been the most studied due to no data recollection burden and significant accuracy drop.

Typical in-processing researches employ additional fairness constraint as regularization term for mitigating bias. (Zhang, Lemoine, and Mitchell 2018; Wang et al. 2019b) enforce the model to produce fair outputs with adversarial training techniques by minimizing the ability of a discriminator to predict the bias attribute. (Kim et al. 2019) further minimizes the mutual information between representation and bias attributes to eliminate their correlations for debiasing. (Tartaglione, Barbano, and Grangetto 2021) devises a regularization term with a triplet loss formulation to minimize the entanglement of bias features. (Jung et al. 2021) tries to distill fair knowledge by enforcing the representation of student model to get close to that of the teacher model averaged over the bias attributes. However, the high correlation between target task and bias attributes that exist in the data itself leads to the limited accuracy in debiasing. Meanwhile, some methods try to convert the target task to not actively extract bias information. (Wang et al. 2020b) trains different target models separately for each group in terms of bias attributes so that the target task does not attempt to rely on bias features. (Du et al. 2021) trains classification head with neutralized representations, which discourages the classification head from capturing the undesirable correlation between target and bias information. However, these methods still suffer from fairness-accuracy paradox due to the bias in the data itself. In this paper, our method leverages artifacts features to proxy the bias feature in data itself for unraveling the fairness-accuracy paradox.

**Proxy features.** (Arpit et al. 2017) finds that models tend to learn features of easy patterns to proxy features of complex patterns in the data. Furthermore, the underlying mechanism of Shortcut (Geirhos et al. 2020) can be seen as shortcut features proxying the intended features that humans want the model to use. Inspired by this, we propose the concept of
proxy feature that actively replaces essence-related features with essence-independent features in model learning.

Causal intervention. Causal intervention has been widely used across many tasks to improve the robustness of deep learning models. Backdoor adjustment (Pearl 2014) is one of the most widely used implementations of causal intervention. (Yue et al. 2020) leverage backdoor adjustment for eliminating the confounding factor in few-shot classification and weakly supervised segmentation. (Wang et al. 2020a) employs backdoor adjustment to train feature extractors with commonsense knowledge. Unlike existing work that applies causal intervention in the training phase, we apply causal intervention in the inference phase to remove the influence of proxy features.

Methodology

Visual recognition models, which are expected to only rely on target feature $X_T$ of the input $X$, are susceptible to making predictions based on the bias features $X_B$ of the data $X$, as illustrated in Figure 2(a). We aim to eliminate the model’s dependence on $X_B$, i.e., the model output $T$ is independent of the bias features $X_B$, and prevent useful target features $X_T$ from being unintentionally corrupted in debiasing.

Inspired by (Arpit et al. 2017), it is observed that among multiple features containing the same information, the model may only learn partial features, such as features with simple patterns. We propose a Proxy Debiasing method that performs debiasing in two stages: (1) Guide the model to preferentially use proxy features $P$ with simple patterns to learn bias information in target task training learning, so the model no longer needs to pay attention to bias features $X_B$ (cf., Figure 2(b)); (2) Introduce causal intervention mechanism in testing to eliminate the influence of proxy features on output $T$ (cf., Figure 2(c)).

The direct way to realize Proxy Debiasing is to attach predefined proxy features with simple patterns to original features, and the model then learns from this composite feature (see Figure 3). This leads to the basic version of our solution, which we call Naive Proxy Debiasing and will be introduced in the next subsection. However, subsequent analysis shows that proxy features with simple patterns do not naturally replace bias features. To ensure the proxy effect of proxy features, we further propose to enhance the target task’s attention to proxy features, which we call Active Proxy Debiasing and as a complete version of our solution.

Naive Proxy Debiasing

Training with proxy features. In fair visual recognition problem, input $x \in X$ is given two types of labels: target task attribute $t \in T$ and bias attribute $b \in B$.

The premise of realizing proxying to bias features $X_B$ is that the proxy features $P$ should provide the same bias information as the bias features. To this end, we construct proxy features that are consistent with the distribution of bias features. As illustrated in Figure 2 due to the simple pattern is easy to learn, we preset all zeros or all ones vector as proxy features, and then utilize bias attribute label $b$ to select the corresponding proxy feature $p_b \in P$ and append it to the feature representation of the sample $x$.

Then, we train the target task in this composite data:

$$\min_{\{x, p_b\}} L_{\text{target}}(\{x, p_b\}, t)$$  \hspace{1cm} (1)

Where $\{x, p_b\}$ is the model input that composite image $x$ and proxy feature $P_p$, $t$ is the target task label of $x$.

Inference with intervention feature. Then, the dependence of trained models on bias information is based on proxy features $P$ rather than bias features $X_B$. However, as shown in Figure 2, this introduces $P$ as a new source of bias in model inference:

$$Pr(T | X) = Pr(T | X_T, P)$$  \hspace{1cm} (2)

And now, we need to remove the model bias brought about by proxy features $P$ in testing. Inspired by causal intervention use Do operation to exclude the influence of confounder, we employ Do operation to eliminate the effect of $P$ in the inference stage. Toward this, using the do to prevent the introduction of causal effects of $P$ to $T$, the causal effects of target features $X_T$ to model output $T$ can be derived:

$$Pr(T | do(X_T)) = \sum_b Pr(T | X_T, p_b)Pr(p_b)$$  \hspace{1cm} (3)

Where $p_b$ is proxy feature corresponding to bias labels $b$. The underlying mechanism of Do is to force $X_T$ to incorporate every $p_b$ fairly, subject to its prior $Pr(p_b)$. For low computation cost in testing, we replace $\sum_b Pr(Y | X_T, p_b)Pr(x_b)$ with $Pr(Y | X_T, \mathbb{E}_b[p_b])$ due to NWGM linear approximation proved in (Xu et al. 2015):

$$Pr(Y | do(X_T)) = Pr(Y | X_T, \mathbb{E}_b[p_b])$$  \hspace{1cm} (4)

Where $\mathbb{E}_b[p_b]$ is mathematical expectation of $p_b$ subject to $b$, i.e., the mean of $\bar{p}_{male}$, and is called intervention feature. Finally, we use intervention feature $\mathbb{E}_b[p_b]$ to instead specify specific proxy features $p_b$ in inference. As shown in Figure 4 we use a vector of all 0.5. Note that another benefit of using intervention features is that we do not need to know the bias label of samples in inference.

Analysis of the Proxy Features

Taking face attribute recognition in CelebA (Liu et al. 2015) as an example, we examine the gender debiasing performance of Naive Proxy Debiasing on Blonde and Attractive recognition tasks. As shown in Table 1 compared to vanilla, we improve both fairness (lower model bias) and accuracy. However, neither model bias nor accuracy changes significantly in attractive recognition.

| Task     | Method   | Acc(%) | Bias(%) | Counter@P |
|----------|----------|--------|---------|-----------|
| Blonde   | Vanilla  | 78.76  | 40.82   | -         |
|          | Naive PD | 91.53 (+12.77) | 10.09 (-30.73) | 0.26 |
| Attractive| Vanilla | 76.71  | 26.09   | -         |
|          | Naive PD | 77.25 (+0.54) | 24.06 (-2.03) | 0.01 |

Table 1: The accuracy(in %), model bias (described in Sec.4) and Counter@P of Naive Proxy Debiasing (Naive PD).
Since we use the same configuration for both tasks, we conjecture that the reason for the above inconsistency in the two tasks might lie in the differences in the two tasks learning of proxy features. To test that, we look into the effect of changing the proxy features in test samples. To this end, we guide the model actively to learn bias information from proxy features during target task training (Eq. 1) so that the target task does not need to focus on bias features $X_B$.

$$
\alpha^c = Y_c(x, p_b) - Y_c(x, \text{anchor})
$$

(6)

Where $\alpha^c$ indicates the importance of proxy features to target class $c$ (e.g., attractive or non-attractive), $Y_c(\cdot)$ denotes the logit output corresponding to class $c$, $p$ is the trainable proxy features corresponding to bias label $b$ of $x$. The anchor is the preset counterfactual contrast point by randomly initializing, which is used as the counterfactual feature of $p$.

To reinforce the importance of proxy features for the model, we update proxy features $P$ and target task head $h$ to maximize the importance of proxy features with softmax normalization:

$$
\max_{P, h} \frac{\exp(\alpha^t)}{\sum_{c=1}^{C} \exp(\alpha^c)}
$$

(7)

Where $t$ is the target label of input $x$. By iteratively optimizing Eq. 1 and Eq. 7, the trainable proxy features $P$ are guaranteed to continuously hold the proxy effect to bias feature $X_B$.

Active Proxy Debiasing

The above observations suggest that simple proxy features may be trivial to target task, we propose Active Proxy Debiasing that adds additional Proxy Effect Enhancement module (red dash line in Figure 3) to Naive Proxy Debiasing. As reported in Table 1, we note that in Naive Proxy Debiasing, for poor debiasing performance task (Attractive), the model has no significant dependence on proxy features (lower $\text{Counter}_p$). However, high debiasing performance task (Blonde) achieves significantly high $\text{Counter}_p$. This depicts that models do not always learn the simple pattern proxy features preferentially, even prioritizing learning of bias features, and therefore the proxy features $P$ cannot replace the model’s reliance on bias features $X_B$.

Active Proxy Debiasing

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Algorithm 1: Active Proxy Debiasing (Active PD)

**Input:** Training set \( \mathcal{D} = \{(x_k, t_k, b_k)\}_{k=1}^{N_M} \), the dimension of proxy features \( M \), the number of bias classes \( N \).

**Output:** Fair model

1. Initialization: Model parameter \( \theta \), \( N \times M \)-dimensional trainable proxy features \( P \), one \( M \)-dimensional counterfactual contrast point \( \text{anchor} \)
2. for epoch 1,...,K do
3. for minibatch \( \{(x_k, t_k, b_k)\}_{k=1}^{N} \) do
4. Step 1: Select \( \{(p_{b_k})\}_{k=1}^{N} \) form \( P \) according to \( \{(b_k)\}_{k=1}^{N} \)
5. Step 2: Update \( \theta \) by minimizing target task loss (using Eq. [1])
6. Step 3: Get factual output \( Y(x_k, p_k) \) of model
7. Step 3: Get counterfactual output \( Y(x_k, \text{anchor}) \) of model with replacing \( (p_{b_k})_{k=1}^{N} \) with \( \text{anchor} \)
8. Step 4: Update trainable proxy features \( P \) and target task head \( h \in \theta \) to enhance proxy effect of proxy features for model (using Eq. [7])
9. end for
10. end for
11. Compute \( \mathbb{E}_b \{ p_b \} \)
12. Set the proxy feature of model to \( \mathbb{E}_b \{ p_b \} \)
13. return model \( \theta \)

Equal opportunity and Equalodds \cite{Hardt2016}. Statistical parity requires that the probability of positive output of different groups is exactly equal, ignoring the label distribution of the test set itself. Equal opportunity measure bias by comparing true positive rate between different groups. However, the fairness of positive and negative outputs is equally important, such as blonde (Pos.) and non-blonde (Neg.) in hair color recognition. Equalodds comprehensively considers fairness on all target labels as follows:

\[
\frac{1}{|T|} \sum_t \left| P_{\theta^T}(\tilde{T} = t \mid T = t) - P_{\theta^T}(\tilde{T} = t \mid T = t) \right|
\]

where \( T \) denotes target labels such as blonde, \( \tilde{T} \) denotes target outputs, and \( b^0 \) and \( b^1 \) represents different groups in terms of bias attributes such as male and female.

**Datasets.** We evaluate the debiasing performance of Proxy Debiasing on CelebA \cite{Liu2015} and UTKFace \cite{Zhang2017}. CelebA consists of more than 200,000 face images annotated with 40 binary attributes including two social concepts: Male and Young. We set Male(m) and Young(y) as bias attributes, and select Attractive(a), Blonde(bl) and BigNose(bn) as target attributes, due to vanilla trained models show unfairness in these target attributes. For UTKFace, we set Male(m) and Ethnicity(e) as target and bias attributes. For construct biased dataset, we truncate a portion of data to force the correlation \( P_{r}(T \mid B) \) between target(T) and bias(B) attributes to be 0.9. For unbiased evaluation of the accuracy and fairness, the test set was constructed to have same number of samples for each target and each bias on both CelebA and UTKFace.

**Baselines.** We compare our Active Proxy Debiasing to state-of-the-art methods on both CelebA and UTKFace. Table 2 shows the accuracy and the model bias(EqualOdds) of models on diverse combinations of target and bias attributes of CelebA. Averaging over all combinations, Vanilla records the most severe model bias due to it is optimized to capture the statistical properties of training data without hindrance. Notably, our Active Proxy Debiasing (Active PD for short) outperforms the previous methods on model bias and accuracy with a large margin. The fairness-accuracy compatibility validates our motivation that utilizes proxy features to prevent the zero-sum game between target task learning and debiasing, which results in a win-win for our method in terms of accuracy and fairness. Furthermore, methods (AdvDebias, LNL, END and MFD) based on removing bias features from representation demonstrate insignificant debiasing performance. This suggests that the zero-sum game between target task learning and debiasing limits not only the accuracy but also the performance of debiasing. Other methods solve this issue by controlling the contribution of bias attributes to indirect debiasing. Notably, the accuracy and model bias of DI is second only to ours. We conjecture that this is because DI is an implicit form of avoiding competition between target tasks and debiasing, where separate target task classifiers are trained for each bias group.

Table 3 summarizes the performance for different methods on UTKFace. The consistent observations with the above CelebA debiasing evaluation include: (1) Vanilla records the most severe model bias. (2) Our Active PD outperforms the previous methods in both model bias and accuracy (3) DI performs second best in both model bias and accuracy due to DI trains separate target task classifiers for each group. New observations include: For the case where the target attribute and the bias attribute are interchangeable (\( T = e/\bar{B} = g \) and \( T = g/B = e \)), our method can significantly eliminate the model bias, which shows that the debiasing ability of our method is independent of the setting of target attribute and bias attribute.
Table 2: The accuracy(%) and model bias(Equalodds) of models trained on CelebA. Here T and B respectively represent target and bias attributes. Here a, bl, bm, and y respectively denote attractive, blonde, bignose, male, and young.

Table 3: The accuracy(%) and model bias(Equalodds) of models trained on UTKFace. Here e and m respectively denote ethnicity and male.

Table 4: The results of multiple biases debiasing. Bias_m and Bias_y respectively represent the male bias and young bias in mitigation of corresponding single bias. Acc.@2, Bias_m@2 and Bias_y@2 denote accuracy, male bias and young bias when both biases are eliminated simultaneously.

Mitigation of Multiple Biases

Previous debiasing researches focus only on the debiasing of single bias. To verify the debiasing performance on multiple biases, we modify these methods to debiasing for two biases. For Active Proxy Debiasing, we construct two types of proxy features in each sample, representing male/female and young/old, respectively. For AdvDebias, LNL and MFD, we incorporate fairness constraint in two bias attributes to eliminate two biases. For DI, we train 4 classifiers in terms of the male and young. And RNF cannot be adapted to multiple bias attributes debiasing by simple modification.

Taking male and young as two bias attributes, as shown in Table 4 we report the debiasing performance in the attractive recognition task. The results show that Active Proxy Debiasing outperforms other methods in both accuracy and fairness, and the negligible model bias and accuracy gap between Multiple biases and single bias demonstrate our method can be applied to real-world multiple biases debiasing scenarios rather than only single bias debiasing simulations in laboratory settings. Besides, other methods are not suitable for the mitigation of multiple biases. Particularly, Mitigation of Multiple biases by AdvDebias severely reduces accuracy compared to mitigation of single bias (from 77.62% to 64.21%). Degradation of accuracy in AdvDebias suggests that the fairness constraints on multiple biases have stronger competition with the learning of the target task, and result in the further fairness-accuracy paradox of mixing two biases. In contrast, our debiasing method avoids being an adversary for target task learning, thereby having the ability to eliminate multiple biases.

Controlled Experiments in Various Data Bias

There are many cases of data imbalance in the real world. To simulate various data imbalances, we construct different datasets with various data imbalance ratio on UTKFace to evaluate the effectiveness and robustness of each method in various imbalance ratios. For more details, we truncate a portion of data to force the correlation $Pr(T|B)$ between target(male) and bias(ethnicity) attributes to be a list from 0.3 to 0.9 to simulate varying bias levels.
In Figure 5, we show the accuracy and model bias of vanilla and our method in various $Pr(T|B)$. It can be clearly noticed that both accuracy and fairness of Active Proxy Debiasing are basically not changed by the improvement of data bias $Pr(T|B)$, maintaining a greater advantage over Vanilla at all the intensities. And as $Pr(T|B)$ increases, accuracy gap between ours and vanilla becomes larger. This indicates that our method is robust to a variety of data bias scenarios, and our method can bring more gains in scenarios with more severe data bias.

**Qualitative Analysis with t-SNE Visualization**

To qualitatively investigate how Active Proxy Debiasing successfully reduces the discrimination, we visualize t-SNE embeddings of models trained with Vanilla and Active Proxy Debiasing in Figure 6(a) and (b). The points of the figure are divided into two groups in terms of bias attribute (i.e., male and female), which are visualized in different colors.

In Vanilla, the representation has separability for two bias attributes, especially in the oval region in Figure 6(a), suggesting that the models learn bias features attribute in target task learning. In contrast, in Active Proxy Debiasing, the representation cannot be divided by bias attribute, that is, our method does not learn biased features in data. This visualization shows that our method mitigates the discrepancies between different groups.

**The Effectiveness of Proxy Effect Enhancement**

We qualitatively validate the effectiveness of proxy effect enhancement module, i.e., optimizing proxy features and models to actively make the target task depend on proxy features so that the model can obtain sufficient bias information only from the proxy features.

To validate, we use Counter@P described in Eq. 5 to measure how dependent the model is on proxy features in the Naive and Active Proxy Debiasing. In Figure 7(a), we report the Counter@P of two methods in six debiasing tasks on CelebA. The plots demonstrate that Active Proxy Debiasing significantly improves the dependence of the target task on proxy features (i.e., higher Counter@P in all debiasing tasks). Also, we use model bias to measure how dependent the model is on real bias features in two Proxy Debiasing methods as shown in Figure 7(b). Combining the two plots, we can find that the stronger the model’s dependence on proxy features, the more the model does not rely on real bias features. This indicates that when our active proxy strategy makes the target task already obtain enough bias information from the proxy features, the model will no longer use the real bias features as a decision-making basis.

**Proxy Feature Dimension Sensitivity**

We also conduct parameter sensitivity studies on proxy feature dimension on UTKFace. We ran Active Proxy Debiasing at different proxy feature dimension settings, and Figure 8 reports the Counter@P (a) and debiasing performance (b). It clearly shows that the choice of proxy feature dimension has no significant effect on proxy effort (Counter@P) and debiasing. This result shows that we can achieve debiasing using lower-dimensional proxy features, which means that debiasing can be achieved with lower computational cost in our method.

**Conclusion**

In this paper, we propose to employ proxy features to replace the target task’s dependence on bias features towards visual debiasing. The proposed solution couples the operation of proxy effect enhancement and inference with the intervention feature, avoiding the use of bias features in training and proxy features in testing, respectively. The introduction of proxy features breaks through the fairness-accuracy paradox in previous methods, and the experimental results demonstrate its effectiveness in consistently improving fairness and accuracy.
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