CAT: Controllable Attribute Translation for Fair Facial Attribute Classification

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Abstract. As the social impact of visual recognition has been under scrutiny, several protected-attribute balanced datasets emerged to address dataset bias in imbalanced datasets. However, in facial attribute classification, dataset bias stems from both protected attribute level and facial attribute level, which makes it challenging to construct a multi-attribute-level balanced real dataset. To bridge the gap, we propose an effective pipeline to generate high-quality and sufficient facial images with desired facial attributes and supplement the original dataset to be a balanced dataset at both levels, which theoretically satisfies several fairness criteria. The effectiveness of our method is verified on sex classification and facial attribute classification by yielding comparable task performance as the original dataset and further improving fairness in a comprehensive fairness evaluation with a wide range of metrics. Furthermore, our method outperforms both resampling and balanced dataset construction to address dataset bias, and debiasing models to address task bias.

Keywords: Fairness, Synthetic Face Image Generation

1 Introduction

Bias issues in machine learning methods involving protected attributes \([8, 51]\) (e.g., sex and race) have lately garnered tremendous attention \([20, 63, 6]\), such as in facial attribute classification \([69, 53]\) and sex classification \([8]\) on face dataset. Many studies \([69, 8]\) show that one of the most obvious phenomena of bias issues in these downstream tasks is that the underlying learning algorithms yield uneven performance for different demographic groups and relatively worse performance for minorities. Such unfair performance across different demographic cohorts has hampered credibility of computer vision algorithms on face dataset from both individuals and the whole society, which is urgently to be resolved.

Ensuring fairness of visual recognition on face dataset, has aroused great interest in the machine learning \([7, 41, 16, 73, 37, 28, 72, 15, 76]\). Without loss of generality, there are two main challenges with respect to two distinct types of bias — (1) lack of generalized learned representations due to the spurious correlation between prediction target and confounding factors, which could include sensitive
attribute (e.g., sex) in training dataset, referred to as sensitive attribute bias and task bias [4, 78, 62], and (2) uneven performance across cohorts caused by insufficient samples for particular demographic groups in the existing dataset, referred to as minority group bias or dataset bias [1, 54, 59].

Mainstream debiasing methods [78, 62, 34] focus on mitigating task bias, with less emphasis on tackling dataset bias. Furthermore, although these methods effectively address task bias [69], they are limited in addressing the issue of insufficient samples of minority demographics in the training dataset, as demonstrated in Table 3 with high bias scores. Instead, in the specific scenarios involving dataset bias, constructing a balanced dataset is a more appropriate way. For example, some work mitigate sex distribution differences or race distribution differences by either collecting fair dataset [31, 75] or strategically resampling from existing datasets [7, 41]. However, merely maintaining the balance across the protected attributes may not resolve the risk of dataset bias which may be implicitly derived from imbalance on other facial attributes (e.g., blond hair or chubby) [53]. Furthermore, due to the recourse limitations in academia to collect sufficient real images for minority groups, invasion of privacy while collecting more real data and the impossibility of covering all known and unknown confounding factors, it may be impractical to construct a balanced real dataset which is balanced across both protected attributes and all facial attributes so as to raise the research scenario to address dataset bias.

We therefore propose a method to iteratively generate high-quality synthetic images with desired facial attributes and combine the synthetic dataset with the original dataset to create a semi-synthetic balanced dataset by supplementing insufficient samples in both protected attribute level and facial attribute level for downstream tasks, as illustrated in Fig. 1. We use facial attribute classification and sex classification on face dataset as the proxy problem to discuss the effectiveness of our method instead of face recognition since the generation of synthetic face recognition ground truth relies on pre-trained models [74, 25], which may be already biased involving protected attributes in debiasing face recognition literature. On the other hand, the generation of facial attribute ground truth of
our synthetic dataset is bundled with synthetic images directly rather than rely on classifiers, as elaborated in Section 3. To construct semi-synthetic datasets which are balanced at both protected attribute level and facial attribute level, our method explicitly controls the facial attributes during image generation. Compared with debiasing models that focus on the process to learn fairly, our method to investigate training dataset to achieve fairness is super straightforward and effective, which is easier for generalization. Furthermore, compared with fair dataset collection restricted by long-tail distribution [79] and limited resources, the advantages of semi-synthetic dataset allow our method to generate sufficient face images with more diversity of facial attributes. Finally, different from data augmentation methods by adding slightly modified copies in existing datasets, we create a generative pipeline to first learn the facial attribute appearance of real data and then generate synthetic images with desired facial attributes. The key contributions of this paper can be summarized as follows:

- A pipeline to construct semi-synthetic face datasets to introduce fairness in facial attribute classification and sex classification.
- An investigation of the nature of dataset bias stemming from the facial attribute-level imbalance instead of the protected attribute-level imbalance.
- A comprehensive fairness evaluation for a wide range of debiasing techniques.

2 Related Work

Debiasing face datasets. Long tail distribution [79] leads to inequity towards minorities in face datasets [44, 46], and several methods have been designed to address dataset bias by collecting fair datasets, such as PPB [9], RFW [67], UTKFace [75] and FairFace [31]. Meanwhile, strategic resampling methods [66, 7, 41] attempt to balance the appearance of training data with respect to different demographic groups, referred to as domain. Since fair dataset and strategic resampling address bias issues before model training, in [30, 10], they are also referred as pre-processing methods. On the other hand, to mitigate task bias from the perspective of model training, some debiasing models have been proposed. First, adversarial forgetting methods [17, 4] manage to extract a new representation which only contains information for the recognition task and exclude the information of protected attributes. Second, domain adaptation methods [67, 77] adapt learned recognition knowledge from the majority domain to the minority domain. Third, domain independent training methods [18, 69] delicately design several separate classifiers in different demographic groups and garner an ensemble of classifiers by representation sharing.

Fairness using GANs. Over the past couple years, Generative Adversarial Network (GAN) [19] is developed further in a tremendous number of work [29, 48, 11, 26, 50, 68]. As pointed by [3], three main purposes of GAN are fidelity, diversity and privacy. Beside the mainstream developments, GAN has also been used to augment real datasets [23, 80, 55]. Some work [13, 27] manipulate latent vectors to augment real datasets to learn disentangled representations. Moreover, Balakrishnan et al. [5] proposes an experimental method with face images
generated by StyleGAN2 [33] to reveal correlation between protected attributes and fairness performance, which in nature is to study and measure bias instead of debiasing. While [35, 70, 71] use GANs to construct synthetic dataset to improve fairness, they conduct experiments on Census dataset, e.g., Adult dataset (predict whether income exceeds $50K/yr based on census data), which is inapplicable for face dataset since label and data of census dataset are both census data and can be generated together, which is different from generating accurate labels together with generated images in face dataset.

Recently, a minority route of augmentation by GANs to introduce fairness [53, 56, 57] emerged. However, as pointed out by [53], some work [14, 56, 57] need to train a new GAN per bias since different facial attributes may yield different levels of bias. By contrast, V. Ramaswamy et al. [53] use a single GAN to construct a fair synthetic dataset by generating the complementary image with the same target label but the opposite protected attribute label corresponding to the randomly generated image. However, to assign the attribute labels, [53] relies on an attribute classifier trained on the original dataset, which may be harmful for fairness since the pre-trained classifier may be already biased by skew of the original dataset. By contrast, our method does not need the pre-trained classifier or significant resources of human annotations using Amazon Mechanical Turk as in [5] to assign labels for each generated image. As elaborated in Section 3, our method only needs a small set of images with labels as seeds and then construct the whole synthetic datasets automatically with labels, which can be directly used in the following performance and fairness evaluation pipeline. Furthermore, compared with [53] using additional images for the good recognition performance, our method achieves comparable performance and better fairness even with the same-size training dataset, as elaborated in Section 4.5.

3 Approach

As discussed in Section 2, some methods [14, 56, 57] focus on applying different data augmentation techniques to mitigate different types of bias. By contrast, we train a unified GAN on the original dataset to introduce fairness for both protected attributes and all facial attributes.

In the facial attribute classification task, given an attribute dataset \( D \) involving instances \( (x_i, y_i, z_i) \), the classification model \( H \) consumes an image \( x_i \in \mathcal{X} \) annotated with a set of binary facial attributes \( y_i \in \mathcal{Y} \) (e.g., hair color) and protected attributes \( z_i \in \mathcal{Z} \) (e.g., sex), and produces the predicted facial attribute label \( y'_i \in \mathcal{Y} \). As illustrated by conditions of three fairness criteria [22] defined with conditional probability, dataset bias may be induced from skew of training dataset. Specifically, \( D \) may naturally be imbalanced across the positive samples \( Z \) and the negative samples \( \bar{Z} \) with respect to the protected attribute \( \mathcal{Z} \) (if binary), i.e., \( |D_Z| \neq |D_{\bar{Z}}| \), on which the classification model \( H \) is trained may invalidate demographic parity [22] which requires that the prediction label \( Y' \) (if binary) and the protected attribute \( \mathcal{Z} \) are independent, i.e.,

\[
P(Y' = 1) = P(Y' = 1|Z) = P(Y' = 1|\bar{Z}).
\]  (1)
Algorithm 1 Controllable Attribute Translation (CAT).

1: initialize $A_y^{\text{intra}}$ and $B_y^{\text{inter}}$ to be an empty set.
2: for $e_i \in \mathbb{R}^k$, $e_j \in S_y$ do
3:     for $e_j \in \mathbb{R}^k$, $e_j \in S_y$ do
4:         $A_{ij} = \{ l \mid |e_i^l - e_j^l| < \text{intra\_threshold}, l \in [1,k]\}$
5:         $A_y^{\text{intra}} \leftarrow A_y^{\text{intra}} \cap A_{ij}$ \Comment{Intra-class similarity.}
6:     end for
7: for $e_j \in \mathbb{R}^k$, $e_j \in S_y$ do
8:     $B_{ij} = \{ l \mid |e_i^l - e_j^l| > \text{inter\_threshold}, l \in [1,k]\}$
9:     $B_y^{\text{inter}} \leftarrow B_y^{\text{inter}} \cap B_{ij}$ \Comment{Inter-class difference.}
10: end for
11: end for
12: output $C_y \leftarrow A_y^{\text{intra}} \cup B_y^{\text{inter}}$

Furthermore, the original dataset $\mathcal{D}$ may be imbalanced at the facial attribute level across protected attributes for the facial attribute $Y$, i.e., $|D_Z^Y| \neq |D_Z^\bar{Y}|$, where $|D_Z^Y|$ is the number of positive samples $Y$ among $Z$ and $|D_Z^\bar{Y}|$ is the number of $\bar{Y}$ among $Z$ with respect to the facial attribute $Y$, which invalidates equal opportunity [22], an another criterion that requires independence between the prediction label $Y$ and the protected attribute $Z$ conditional on $Y$, i.e.,

$$P(Y' = 1|Z,Y) = P(Y' = 1|\bar{Z},Y).$$  \hspace{1cm} (2)

Finally, equalized odds [22], which is a stronger criterion, requires that $Y'$ and $Z$ are independent conditional on both $Y$ and $\bar{Y}$, i.e., with the additional constraint than equal opportunity as followed,

$$P(Y' = 1|Z,\bar{Y}) = P(Y' = 1|\bar{Z},\bar{Y}),$$  \hspace{1cm} (3)

where $\bar{Y}$ represents the negative samples with respect to the facial attribute $Y$.

To mitigate the influence from skew of training dataset under the requirements of equalized odds, $\mathcal{D}$ should be balanced across $Z$ for both $Y$ and $\bar{Y}$, i.e., $|D_Z^Y| = |D_Z^\bar{Y}|$ and $|D_Z^\bar{Y}| = |D_Z^\bar{Y}|$, where $|D_Z^Y|$ is the number of $Y$ among $Z$ and $|D_Z^\bar{Y}|$ is the number of $\bar{Y}$ among $Z$ with respect to the facial attribute $Y$.

However, even though prior methods that depend on fair dataset collection [31] or resampling [7, 41] may satisfy demographic parity by balancing dataset across protected attributes, it is hard for these methods to satisfy equal opportunity and/or equalized odds constraints which require balance at the facial attribute level due to the lack of sufficient images which are balanced across one facial attribute, much less across multiple facial attributes in the multi-attribute classification task. Thus, to mitigate the effect of dataset bias on the trained model, we generate a semi-synthetic dataset $\mathcal{D}_{syn}$ which meets requirements of all three fairness criteria by controllably translating the representation of facial attributes in latent space to image space and generate sufficient images with desired facial attributes, referred to as Controllable Attribute Translation (CAT).

Given a $k$-dimensional latent space $\mathcal{E} \in \mathbb{R}^k$, a generative model $G : \mathcal{E} \rightarrow \mathcal{I}$ trained on real dataset $\mathcal{D}$ produces the synthetic image $I_i$ from the latent vector
By human annotations denoted as $F$, we construct a succinct set of latent vectors with the facial attribute $Y$, referred to as attribute seeds $S_Y \subset \mathcal{E}$, such that $\forall e_i \in S_Y, F(G(e_i)) = Y$. We refer to $Y$ as Attribute of Interest (AOI)\(^4\).

To stably generate images with AOI, we first study the common similarity of latent vectors among $S_Y$ since $I_i$ may yield same AOI and randomly yield other facial attributes, where $I_i = G(e_i), e_i \in S_Y$. Given two randomly picked latent vectors $e_i, e_j \in S_Y$, we traverse and aggregate the dimension indices where the absolute difference is smaller than a hyperparameter $\text{intra\_threshold}$, i.e., $A_{ij} = \{l \mid |e_i^l - e_j^l| < \text{intra\_threshold}, l \in [1,k]\}$, which are the dimensions representing the attribute similarity between $e_i$ and $e_j$. Furthermore, since pairs of images generated by latent vectors from $S_Y$ may be similar in other unwanted facial attributes, to purify the similarity of AOI and find predominate dimensions controlling AOI, we traverse all combination of pairs in $S_Y$ to find $A_{ij}$ of each pair and take the intersection across all $A_{ij}$, i.e., $A_Y^{\text{intra}} = \bigcap_{e_i, e_j \in S_Y} A_{ij}$, which is the least common similarity, referred to as $\text{intra-class similarity}$ of AOI, which effectively eliminates the similarity of other unwanted facial attributes.

To select more representative dimension indices for AOI, we compensate $\text{intra-class similarity}$ with $\text{inter-class difference}$. We randomly pick $e_i \in S_Y$ and $\bar{e}_i \in S_{\bar{Y}}$, where $S_{\bar{Y}}$ is the set of latent vectors without AOI, such that $\forall \bar{e}_i \in S_{\bar{Y}}, F(G(\bar{e}_i)) = \bar{Y}$. Further, we aggregate the dimension indices where the absolute difference is greater than the other hyperparameter $\text{inter\_threshold}$, i.e., $B_{ij} = \{l \mid |e_i^l - \bar{e}_j^l| > \text{inter\_threshold}, l \in [1,k]\}$, which are the dimensions representing the attribute difference between $e_i$ and $\bar{e}_j$. We then take the intersection across all attribute difference, $B_Y^{\text{inter}} = \bigcap_{e_i \in S_Y, \bar{e}_j \in S_{\bar{Y}}} B_{ij}$, which is the least common difference, referred to as $\text{inter-class difference}$ of AOI.

Finally, we take $C_Y = A_Y^{\text{intra}} \cup B_Y^{\text{inter}}$ since the usage of $B_Y^{\text{inter}}$ is to find the representative dimensions unseen by $A_Y^{\text{intra}}$, as elaborated in Section 4.5. A pseudo code of the method is shown in Algorithm 1, which can be extended for all other AOIs and all protected attributes. With $\text{intra-class similarity}$ and $\text{inter-class difference}$, we can find the representative dimensions for both protected and facial attributes so that the generated images can properly capture the characteristics of AOI. In general, we translate the attribute appearance in images to the attribute representation in latent space.

To construct the synthetic dataset $D_{\text{syn}}$, we controllably translate the found attribute representations in the latent space back to image space. We first ran-

\(^4\) AOI is set based on interests for different experiments.
domly simulate another set of latent vectors, referred to as identity seeds $S_{ID} \subset \mathcal{E}$ following standard normal distribution $N(0, 1)$. Then, to assign a facial attribute $Y$, we perturb $e_{ID} \in S_{ID}$ to be $e_Y \in S_Y$ for the dimension indices in $C_Y$. In parallel, the label can be automatically assigned as $Y$. In practice, the latent space consists of $R$ resolutions, and each resolution is a $k$-dimensional latent space. To further ensure the appearance of assigned facial attributes and mitigate the intervention from other facial attributes across resolution spectrum, although we do not assume chosen dimensions are independent between different attributes and the latent space is not disentangled by design, we subdivide the resolution spectrum to assign different kinds of facial attributes in different resolutions (e.g., high-level facial attributes in lower resolutions and smaller scale facial attributes in higher resolutions), which is elaborated in Section 4.4.

By generating balanced synthetic dataset $D_{syn}$ with desired attributes and supplementing the minority group of the original dataset with sufficient images at both protected attribute level and facial attribute level, we can ensure the requirements of all three fairness criteria in Eqs. (1) to (3). From the perspective of information theory, assuming the whole information contained in original dataset is fixed, i.e., the best recognition performance trained on this dataset is upper-bounded, synthetic datasets generated by our method tries the best to transfer and express the recognition task-related information in a fairer way.

Advantages. By intra-class similarity and inter-class difference, we can accurately and effectively find a specific set of dimension indices representing AOI in the dimension spectrum so that we only need a small size of attribute seeds with annotations as starting seeds. Beside with the resolution separation, we have a two-dimensional separation in both latent space and resolution. Thus, we can assign multiple AOIs to one single identity seed and stably preserve randomness of other unassigned facial attributes, which endows synthetic dataset to be constructed under different facial attribute distribution with more freedom. Furthermore, we assign the attribute label to the generated image $I_i = G(e_i)$ naturally with the facial attribute $Y$ represented by $S_Y$ to which its latent vectors $e_i \in S_Y$ belongs, rather than rely on a shallow classifier.
4 Experimental Evaluation

We first investigate the nature of dataset bias by exploring each facial attribute and focus on the facial attributes which induce much bias. Furthermore, we empirically investigate the effectiveness of our method on two fashion tasks involving bias — (1) sex classification and (2) facial attribute classification. In sex classification, we concurrently manipulate multiple femininity/masculinity attributes to generate paired images with female and male appearance and construct sex-level balanced dataset. Meanwhile, in facial attribute classification, in the basis of sex-level balanced dataset, we further consider the other non-sex-related facial attributes to construct the semi-synthetic dataset which is balanced in terms of both sex and facial attribute. In both experiments, we first show that the classification performance of the model trained with synthetic datasets achieves comparable performance as the model trained on the original dataset. Then, we conduct a comprehensive fairness evaluation with a wide range of bias assessment metrics [65, 47, 12, 61, 38] to show that fairness has been improved after training with synthetic datasets compared to the model solely trained on the original dataset. Further, we demonstrate that our method outperforms both strategic resampling [7] and balanced dataset construction method with synthetic images [53] to address dataset bias, and several debiasing models [4, 77, 69] to address task bias. Finally, we present an ablation study to evaluate different factors influencing the performance of our method. Although we discuss sex as the protected attribute in this section, our method is general purpose and can be used for all protected attributes if the labels are available.

4.1 Attributes Study

Before presenting the improvement on fairness, we first conduct in-depth evaluation of dataset bias at the facial attribute level for CelebA dataset [44], which is a face dataset containing 202,599 images of celebrity faces and 40 binary attributes per image. Since our method produces a facial attribute-level balanced synthetic dataset, it is valuable to study dataset bias at facial attribute level instead of the general overall accuracy for all facial attributes. Following [53], we train a multitask facial attribute classifier with ResNet-50 [24] to recognize facial attributes on the sex-level balanced CelebA dataset. The main results are shown in Table 2 as baseline and full results are presented in the appendix.

As shown in Table 2 by results of baseline, solely balancing across sex does not guarantee fairness in facial attribute classification since even with balanced training across females and males, the imbalance of facial attribute across sex still exists. Although we know classification models tend to learn distinguishable representations from positive samples instead of negative samples [39], there are insufficient positive samples of some specific facial attributes in the minority group. Inspired by the categorization in [53] where they only categorize a subset of facial attributes, we summarize all 40 facial attributes in CelebA dataset into three groups — (1) unbiased attributes which do not yield much bias (i.e., the difference of AP between female and male is less than 5%), (2) masculinity/femininity
Table 1: Performance and fairness comparison on sex classification.

| Number of Training Images | Classification Accuracy | Information Leakage | Statistical Dependence |
|---------------------------|-------------------------|---------------------|------------------------|
|                           | Female | Male | Total | Overall | BA   | dcor^2 | RLB   |
| Origin training dataset   | 94509  | 68261| 162770| 95.2    | 97.7 | 96.6   | -0.015| 0.656 | 3.834 |
| Balanced                  | 68261  | 68261| 136522| 99.2    | 97.6 | 98.5   | -0.016| 0.611 | 3.782 |
| GAN-Debiasing [53]        | Same size| 68261| 136522| 98.8    | 97.2 | 98.0   | -0.017| 0.581 | 3.579 |
| Same size                 | 94509  | 189018| 99.2  | 97.2   | 98.3  | -0.016| 0.574 | 3.574 |
| Ours                      | Same size| 68261| 136522| 99.1    | 97.3 | 98.3   | -0.018| 0.592 | 3.742 |
| Supplement                | 94509  | 94509| 189018| 99.2    | 97.8 | 98.5   | -0.016| 0.544 | 3.481 |

attributes, which are considered as AOI in Section 4.3 to construct sex-level balanced dataset, and (3) non-sex-related facial attributes but inducing much bias even with sex-level balanced training, which are considered as AOI appending masculinity/femininity attributes in Section 4.4 to construct both sex-level and facial attribute-level balanced dataset.

4.2 Synthetic Attribute-level Balanced Datasets

To construct the synthetic dataset $D_{syn}$, we train the generative model solely on the training set of CelebA dataset containing 162,770 images to ensure the isolation from the testing set since the images generated by trained GAN are used for the following tasks. For the generative model choice to generate high-quality images (which is elaborated in appendix), we use StyleGAN2 [33] since style mixing regularization in StyleGAN2 facilitates our goal to assign different specific facial attributes and mitigate the interference from other unassigned facial attributes. We persist in training the generative model to generate more real images. As a standard metric, FID is used to evaluate sample qualities of generated images. FID of the presented results in the paper is 3.56, which is comparable to existing GANs [45, 49] trained on CelebA dataset and posted recently. Although the benchmark for FID of image generation on CelebA dataset is 2.71 [42], our objective is to utilize generated images to improve fairness of existing datasets rather than improve image quality of generated images.

To assign attributes, we use intra_threshold = $2\sqrt{2}$ and inter_threshold = $\sqrt{2}$. In general, we empirically found that any settings for these two hyperparameters among the recommended range $[\sqrt{2}, 2\sqrt{2}]$ will not significantly affect the performance of downstream classification tasks, which confirms with our theoretical discussion in Section 4.5. Furthermore, for resolution spectrum separation, StyleGAN2 [33] have already provided reference to assign different attributes in different resolutions, e.g., high-level attributes (hair style, face shape) in coarse spatial resolution ($4^2 - 8^2$), and racial appearance (colors of eyes, hair, skin) in fine spatial resolution ($16^2 - 1024^2$). The dimensionality of the latent space is 512 and the resolution of generated images is set to be 256 so that by [33] we generally have a 14-layer 512-dimensional latent space to assign attributes. Specifically, we leave $4^2$ original for the basic identity construction. For resolution choices to assign attributes, we assign face shape attributes (Chubby, Big Nose, Pointy Nose, High Cheekbones and Double Chin) in $8^2$, fine face shape attributes (Bags Under Eyes, Wavy Hair and Straight Hair) in $16^2$, hair color at-
### Table 2: Performance and fairness comparison on facial attribute classification.

| Attributes                | AP ↑ | DEO ↓ | BA ↓ | KL ↓ | dcor ↓ | RLB ↓ |
|---------------------------|------|-------|------|------|--------|-------|
| Chubby                  | 94.7 | 69.8  | 69.1 | 67.8 | 61.2   | 53.3  |
| BigNose                 | 62.1 | 32.8  | 28.7 | 26.7 | 21.1   | 15.9  |
| WavyHair                | 71.2 | 32.8  | 28.7 | 26.7 | 21.1   | 15.9  |
| PaleSkin                | 69.1 | 32.8  | 28.7 | 26.7 | 21.1   | 15.9  |
| BlondHair               | 61.2 | 32.8  | 28.7 | 26.7 | 21.1   | 15.9  |
| DoubleChin              | 58.5 | 32.8  | 28.7 | 26.7 | 21.1   | 15.9  |
| PointyNose              | 58.5 | 32.8  | 28.7 | 26.7 | 21.1   | 15.9  |
| BagsUnderEyes           | 63.5 | 32.8  | 28.7 | 26.7 | 21.1   | 15.9  |
| HighCheekbones          | 61.7 | 32.8  | 28.7 | 26.7 | 21.1   | 15.9  |
| Average                 | 63.5 | 32.8  | 28.7 | 26.7 | 21.1   | 15.9  |

**Baseline**
- Resampling [7]: 62.1, 71.2, 88.2, 69.1, 61.2, 64.9, 67.8, 95.4
- GAN-Debiasing [53]: 68.8, 71.2, 85.6, 70.6, 67.8, 69.1, 92.0, 92.1

**Resampling [7]**
- Baseline: 54.5, 62.2, 87.2, 67.2, 68.5, 90.6, 46.4, 61.7
- GAN-Debiasing [53]: 58.8, 69.5, 85.6, 90.6, 58.5, 63.5, 58.3, 61.4

**Ours**
- Baseline: 60.5, 66.5, 86.6, 90.9, 58.6, 61.4, 62.9
- GAN-Debiasing [53]: 58.6, 61.4, 62.9, 95.5, 74.7

**DEO ↓**
- Baseline: 28.7, 35.6, 33.0, 11.9, 10.8, 26.7, 32.8, 20.1
- Resampling [7]: 15.0, 12.7, 12.1, 6.2, 4.3, 4.2, 5.2, 19.2
- GAN-Debiasing [53]: 26.6, 32.7, 23.3, 10.8, 3.6, 22.1, 28.8, 16.8
- Ours: 21.2, 3.9, 11.8, 9.3, 3.5, 3.3, 3.1, 15.0

**BA ↓**
- Baseline: 1.72, 5.83, -3.27, 1.19, 0.12, 0.46, 4.78, 2.27
- Resampling [7]: 1.38, -8.69, -5.49, -0.30, -3.37, -1.73, -3.12, -9.44
- GAN-Debiasing [53]: 1.30, 5.51, -3.60, 0.20, 0.50, 0.46, 3.71, 1.14
- Ours: 1.16, -6.71, -5.10, -0.44, -4.61, -1.16, -5.35, -9.47

**KL ↓**
- Baseline: 0.39, 0.60, 0.42, 0.08, 0.46, 0.30, 0.32, 0.27
- Resampling [7]: 0.18, 0.13, 0.15, 0.07, 0.05, 0.17, 0.21, 0.26
- GAN-Debiasing [53]: 0.37, 0.54, 0.33, 0.07, 0.37, 0.29, 0.20, 0.26
- Ours: 0.33, 0.13, 0.06, 0.04, 0.34, 0.09, 0.04, 0.08

**dcor ↓**
- Baseline: 0.58, 0.61, 0.62, 0.53, 0.34, 0.58, 0.86, 0.96
- Resampling [7]: 0.58, 0.59, 0.77, 0.47, 0.69, 0.53, 0.83, 0.65
- GAN-Debiasing [53]: 0.37, 0.54, 0.50, 0.08, 0.17, 0.31, 0.39, 0.43
- Ours: 0.18, 0.31, 0.33, 0.06, 0.23, 0.17, 0.24, 0.25

**RLB ↓**
- Baseline: 0.63, 1.24, 1.56, 0.63, 1.12, 0.45, 0.55, 0.82
- Resampling [7]: 0.58, 1.13, 1.45, 0.03, 1.03, 0.44, 0.50, 0.63
- GAN-Debiasing [53]: 0.34, 1.14, 1.42, 0.03, 0.94, 0.31, 0.49, 0.61
- Ours: 0.28, 1.11, 1.30, 0.01, 0.73, 0.30, 0.09, 0.43

### 4.3 Sex Classification

As in [31, 9], the imbalance of training dataset may hamper the accuracy of sex classification, we therefore validate the fairness improvement of our synthetic datasets on sex classification in this section. To help downstream classification models to well learn the difference between female and male (the useful information for sex classification), given an identity seed, we only modify femininity/masculinity attributes and leave other facial attributes unchanged, as shown in Fig. 2, which also ensures that there are sufficient samples with large diversity of facial attributes from identity seeds in both female group and male group.

**Experiment setup.** ResNet-50 [24] is used as the backbone for sex classifier. The baseline model is trained with original CelebA dataset [44] under two settings — (1) **Original** to keep the training set of CelebA dataset fully original with the whole set of 162,770 images, and (2) **Balanced** to balance the training set across sex. For training with synthetic dataset, we also conduct two types of experiments — (1) **Same size** to combine one half of balanced original training...
Table 3: Comparison of debiasing models on facial attribute classification.

|                  | mAP ↑   | Information Leakage ↓ | Statistical Dependence ↓ |
|------------------|---------|------------------------|---------------------------|
|                  | Female  | Male       | Overall  | DEO  | BA      | KL  | dcor² [61] | RLB [38] |
| Baseline         | 75.3    | 72.2       | 74.1     | 20.9 | 0.99    | 0.27 | 0.85       | 1.33     |
| Adversarial forgetting [4] | 73.2    | 70.4       | 72.1     | 18.8 | 0.61    | 0.25 | 0.51       | 1.25     |
| Domain adaptation [77] | 74.5    | 72.3       | 73.7     | 19.7 | 0.82    | 0.21 | 0.48       | 1.28     |
| Domain independent [69] | 74.6    | 74.2       | 74.4     | 20.8 | 0.55    | 0.27 | 0.37       | 1.12     |
| Ours             | 73.0    | 73.2       | 73.1     | 8.4  | -3.26   | 0.16 | 0.24       | 0.65     |

set with a same size balanced synthetic dataset to be mixed dataset so that the number of mixed dataset is the same as the number of training images in the balanced original dataset, and (2) Supplement to supplement the lack of male images compared with female images in the original dataset so that the mixed dataset is balanced in the whole dataset scale. For comparison with the other attribute-level balance method [53], we conduct experiments under the original setting in their paper (the original CelebA dataset combined with the balanced synthetic dataset with 160,000 sex pairs of images) and two same settings of ours. The testing set is the original testing CelebA dataset for all experiments.

**Evaluation protocol.** To demonstrate the effectiveness of our method on sex classification and facial attribute classification, we use accuracy and fairness as the main evaluation metrics. First, we compare the classification performance between the model trained on synthetic datasets and the original dataset to verify that the testing accuracy on the real testing dataset is preserved at the same level, which demonstrates that the generated images yield proper facial attributes in the metrics of the real dataset. Meanwhile, we use several fairness metrics for a comprehensive fairness comparison since different types of metrics assess bias in different directions. According to the taxonomy of bias assessment metrics in [38], we select several representative metrics in these categories. We select Bias Amplification (BA) [65, 69] among information leakage-based metrics and two types of metrics based on statistical dependence, Distance Correlation (dcor²) [61, 2] and Representation-Level Bias (RLB) [38] to increase the diversity of metrics and comprehensively evaluate fairness in different ways.

**Results.** As shown in Table 1, we can see the testing accuracy of synthetic dataset is kept at the same level under both two settings, which demonstrates that the generated images yield proper femininity/masculinity attributes in the original dataset. Furthermore, although the classification accuracy is already saturated, with additional images under the Supplement setting, we improve the accuracy in minority groups. On the other hand, for fairness evaluation compared with other datasets, our method further improves fairness. Although [53] uses more images than the original dataset, our method yields even better results in both accuracy and fairness metrics with fewer training images. We elaborate the discussion on the relation between the size of the synthetic dataset and performance of our method in the appendix.
4.4 Facial Attribute Classification

Having found that the remaining dataset bias of facial attribute classification on CelebA dataset stems from imbalance at both protected attribute level and facial attribute level as discussed in Section 4.1, we construct the synthetic dataset which is balanced in both these two levels to study the effectiveness of our method for all non-sex-related facial attributes, and compare our method with methods based on sex-level balance [7] and facial attribute-level balance [53]. Furthermore, we highlight the comparisons with debiasing models [4, 77, 69].

**Experiment Setup.** We train a multitask facial attribute classifier with ResNet-50 [24]. The baseline is trained with sex-level balanced CelebA dataset constructed from original CelebA dataset. Our method combines a portion of original dataset without surplus samples of some facial attributes and the synthetic dataset which supplements insufficient samples of AOI so that the mixed dataset is balanced at both sex level and facial attribute level, as illustrated in Fig. 1.

**Evaluation protocol.** We use Average Precision (AP) as the performance metric. For bias assessment, beside BA, $dcor^2$ and RLB, Difference in Equal Opportunity (DEO) [47, 52] as a metric version of equal opportunity and KL-divergence between score distribution (KL) [12, 53] as a stronger notion stemming from equalized odds are used to verify the achievements of Eqs. (2) and (3).

**Results.** In Table 2, we present one representative facial attribute for the mutually exclusive facial attributes, e.g., Wavy Hair and Straight Hair, and full results are presented in appendix. As AP is preserved at the same level for all AOIs, our method outperforms other methods for Blond Hair and High Cheekbones. In fairness comparison with baseline, all three methods introduce fairness under all metrics in a same trend. As pointed by [38], $dcor^2$ and RLB, the metrics based on statistical dependence are more consistent and stable. In this sense, although strategically resampling [40] outperforms our method under BA, it yields second worse performance on the metrics based on statistical dependence. Furthermore, with better DEO and KL, we verify the achievement of Eqs. (2) and (3) in Section 3, which is unreachable for sex-level balanced dataset and strategically resampling. According to results of imbalanced training, due to the existence of the facial attribute-level skew in the dataset, the classifier trained with these skew datasets may be biased already. In this sense, compared with [53], our method is more stable in all facial attributes since we assign label directly rather than rely on such unreliable facial attribute classifier trained on original dataset as in [53], which may be harmful for fairness. Compared with Table 1, the range of two
metrics based on statistical dependence in sex classification are clearly higher than the range in the facial attribute classification since they directly reveal the statistical dependence between learned representations to predict sex and sex labels themselves, which better assess the bias for sex classification.

We also conduct an overall comparison of average results over all non-sex-related AOIs (7 facial attributes in the paper and 7 mutually exclusive facial attributes in appendix) with several debiasing models based on adversarial forgetting [4], domain adaptation [77] and domain independent [69]. We train a ResNet-50 [24] to classify all non-sex-related AOIs on the original CelebA dataset as baseline model. For the multi-label classification, mean Average Precision (mAP) is used to evaluate the overall performance. In Table 3 of classification performance comparison, domain independent method outperforms other methods. In parallel, without the in-process debiasing techniques usage, our method yields comparable classification performance and outperforms other methods in all bias assessment metrics, which demonstrates a comprehensive fairness improvement. In general, there is a tradeoff between classification performance and fairness performance, i.e., although domain independent method outperforms other methods in mAP, our method improves fairness mostly at an acceptable expense of classification performance. Furthermore, the proposed synthetic dataset is model-agnostic as compared under different backbones in appendix.

4.5 Ablation Study

**Intra-class similarity and inter-class difference.** In this section, we will discuss intra-class similarity and inter-class difference involving two hyperparameter intra_threshold and inter_threshold. Considered the task to generate female and male images for which, given masculinity attributes seeds $S_{\text{male}}$ and femininity attributes seeds $S_{\text{female}}$, intra-class similarity is deprecated when intra_threshold is small since there may be no dimension indice where $\forall e_i, e_j \in S_{\text{male}}, |e_i - e_j| < \text{intra_threshold}$, i.e., $A_{\text{intra}}^\text{male}$ is empty. By contrast, inter-class difference will be deprecated when inter_threshold is large. For example, given an identity latent vector $e_{\text{ID}}$ whose generated image is female, when intra-class similarity and inter-class difference are both deprecated, the generated image is same as the prime image generated from $e_{\text{ID}}$. As shown in Fig. 5a, without intra-class similarity, the generated image is apparently female. Further, when we apply intra-class similarity and deprecate inter-class difference, the generated image is transferred to be male with few femininity attributes (e.g., hair) since the generated model has learned masculinity attributes but has not fully suppressed femininity attributes. On the other hand, if intra_threshold is large or inter_threshold is small, i.e., $A_{\text{intra}}^\text{male}$ or $B_{\text{inter}}^\text{male}$ contains all dimension indices so that intra-class similarity or inter-class difference is overemphasized. As shown in Fig. 5b, compared with generated images under proper threshold settings, the generated images under strong threshold settings in the top row are cookie-cutter without the randomness from identity seeds. In the whole process, intra-class similarity contributes mostly and inter-class difference plays an auxiliary role. Since the random latent vector is simulated under standard normal
distribution $N(0, 1)$ and the difference between two latent vectors follows normal distribution $N(0, \sqrt{2})$ where standard deviation is $\sqrt{2}$, the proper range for two thresholds is $[\sqrt{2}, 2\sqrt{2}]$ so that $A_{\text{inter}}$ may contain the dimension indices in the main lobe representing attribute similarity among $S_Y$, and $B_{\text{intra}}$ may exclude the dimension indices in the main lobe representing attribute similarity of $S_Y$ and $S_{\bar{Y}}$, where $S_{\bar{Y}}$ is the set of latent vectors without Attribute of Interest $Y$.

5 Conclusion

By the investigation on the imbalance at the facial attribute level, we can clearly find the root cause for the uneven performance across protected attributes. To address the imbalance, from the perspective of information theory, we try our best to mitigate the loss of information from original data (i.e., comparable performance) and orderly express such information in a fairer way (i.e., improved fairness) while the amount of whole information is fixed. In comparison with debiasing models, we have found fairness-performance tradeoff in model training, as fairness-efficiency tradeoff in the real world. Still, the valuable remark is that although the network trained with the proposed synthetic data does not outperform the debiasing models in recognition performance, it is impressive that synthetic images can achieve consistent performance with real data and further yields better fairness. Furthermore, in the image generation process, our method overcomes the difficulty to obtain labels by intra-class similarity and inter-class difference instead of relying on a shallow attribute classifier or significant extra human annotations. Therefore, our method can be scalably used in the model fully trained with synthetic datasets in the future. Besides, it is a good direction for future researchers to extend our method to other face datasets and introduce fairness for more facial attributes. Finally, our work presents a good example for the probability of the same-level performance for computer vision models partially or fully trained with synthetic dataset.

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Appendix

We include additional studies of our method in the following sections.

A Difference from face-attribute manipulation.

Our work first applies face synthesis methods (*e.g.*, StyleGAN2) to systematically and methodically synthesize images to construct high-quality fair dataset to theoretically satisfy the fairness criteria rather than solely propose a pipeline to synthesize the facial attributes dataset. FaderNet [36] and STGAN [43] manipulate face attributes to generate different realistic face images based on GANs. Different from [36, 43] which take image generation as the main objective, we focus on fairer dataset construction.

B Comparison with different backbones.

We follow the same experiment setup in Section 4.4 to train a ResNet-50 as backbone to classify all non-sex-related AOIs and evaluate the classification and fairness performance trained with other backbones including ResNet-101 [24], Inception-v3 [60] and VGG-16 [58]. The mAP over all backbones is $73.1 \pm 0.2$. For the representative of two kinds of bias scores, KL is $0.16 \pm 0.02$ and RLB is $0.65 \pm 0.05$. The small variations demonstrate our proposed synthetic dataset is model-agnostic.

C Discussion on the size of synthetic dataset.

In this section, we further discuss the relation between the number of synthetic images usage and performance on sex classification. As shown in Fig. 6, fairness has been improved as the number of synthetic training images increases. Although BA converges in the beginning, the other two metrics based on statistical dependence decrease quickly before green point, which demonstrates skew of original dataset harms fairness, and finally converge at the lower bound as more training images are used. The lower bound of these metrics infers the upper bound of fairness, which is the best performance of our method. Since there are two main challenges with respect to dataset bias and task bias, and our method is based on the facial attributes-level balance to address dataset bias, the remaining bias may stem from the lack of generalized representation, *i.e.*, task bias, which should be resolved by debiasing models. Specifically, after training with facial attribute-level balanced dataset, the recognition difficulty in the minority demographic group may be due to the intrinsic difficulty from specialty of facial attributes instead of imbalanced training.

D Choice of GAN Backbone

We use StyleGAN2 [33] as our facial image generator. Even compared with StyleGAN3 [32] where style mixing is not naturally supported, style mixing is
one of the main strengths of StyleGAN2, which requires less time to train and yields better style mixing images. On the other hand, StyleGAN3 is an Alias-Free GAN with translation/rotation equivalence without the need to align the training dataset, which is less important to our proposed methods compared to style mixing since Aligned & Cropped subset of CelebA dataset [44] is available and has been demonstrated to be of good quality [21, 64].

E Attributes Study

In Section 4.1, we study the nature of dataset bias in CelebA dataset at the facial attribute level. In this section, we supplement more details of the experiment and results.

Experiment Setup. We train separate attribute classifiers with ResNet-50 [24] to recognize 39 facial attributes on the sex-level balanced CelebA dataset sampled from original CelebA dataset. Together with Average Precision (AP), we present the positive sample rate among female images and male images for each attribute. Difference in Equal Opportunity (DEO) is calculated by the absolute value of the difference between AP among females and AP among males. We make statistics based on 50 trials of random choice to balance the origin dataset at the sex level.

Results. As shown in Table 4, we can find that the remaining bias even after sex-level balanced training is due to the distribution difference of facial attributes instead of apparently sex difference. Based on listed positive sample rate and AP, we can find a roughly proportional relationship between the number of positive samples and AP. More specifically, neural networks tend to learn discriminative representations from positive samples instead of negative samples [39]. However, although positive samples are more easily learned for neural networks than negative samples, there are insufficient positive samples of some specific attributes in the minority domain. Thus, we propose a pipeline to generate synthesized datasets with both protected attribute-level balance and facial attribute-level balance to effectively fix this gap by mitigating the facial attributes or appearance difference across sex.
Table 4: Dataset bias exists in sex-level balanced CelebA dataset by long tail distribution in the real world.

| Attribute Type       | Positive Rate (%) | AP | Fairness |
|----------------------|-------------------|----|----------|
| **Masculinity Attributes** |                   |    |          |
| Female | Male | Overall | Female | Male | Overall | DEO ↓ |
| 5'o clock shadow | 0.0 | 27.0 | 13.5 | - | 82.1 | 82.1 | - |
| Bald | 0.0 | 5.0 | 2.5 | - | 84.5 | 84.5 | - |
| Bushy Eyebrows | 7.0 | 24.0 | 15.5 | 55.6 | 85.1 | 76.7 | 29.5 |
| Goatee | 0.0 | 15.0 | 7.5 | - | 80.5 | 80.5 | - |
| Mustache | 0.0 | 10.0 | 5.0 | - | 65.0 | 65.0 | - |
| Receding Hairline | 5.0 | 12.0 | 8.5 | 58.8 | 64.3 | 61.7 | 5.5 |
| Sideburns | 0.0 | 13.0 | 6.5 | - | 86.2 | 86.2 | - |
| Wearing necktie | 0.0 | 17.0 | 8.5 | - | 73.3 | 73.3 | - |
| **Femininity Attributes** |                   |    |          |
| Female | Male | Overall | Female | Male | Overall | DEO ↓ |
| Arched Eyebrows | 42.0 | 5.0 | 23.5 | 77.6 | 47.6 | 75.8 | 30.0 |
| Attractive | 68.1 | 28.0 | 48.0 | 94.0 | 72.4 | 91.2 | 21.6 |
| Heavy makeup | 66.0 | 0.0 | 33.0 | 96.7 | - | 96.7 | - |
| No beard | 100.0 | 61.0 | 80.5 | 100.0 | 97.9 | 99.8 | 2.0 |
| Oral Face | 33.0 | 22.0 | 27.5 | 65.4 | 43.4 | 59.5 | 22.0 |
| Rosy cheeks | 11.0 | 0.0 | 5.5 | 68.7 | - | 68.7 | - |
| Wearing Earrings | 31.0 | 2.0 | 16.5 | 86.0 | 46.8 | 84.8 | 39.2 |
| Wearing lipstick | 80.1 | 1.0 | 40.6 | 99.0 | 22.1 | 98.9 | 76.9 |
| Wearing Necklace | 19.9 | 2.0 | 11.0 | 41.3 | 13.6 | 40.4 | 27.8 |
| **Unbiased Attributes** |                   |    |          |
| Female | Male | Overall | Female | Male | Overall | DEO ↓ |
| Bangs | 20.0 | 8.0 | 14.0 | 94.4 | 89.6 | 93.4 | 4.8 |
| Big lips | 30.0 | 16.0 | 23.0 | 55.6 | 60.6 | 58.2 | 4.9 |
| Blurry | 5.0 | 6.0 | 5.5 | 66.8 | 61.8 | 64.6 | 5.0 |
| Eyeglasses | 2.0 | 12.0 | 7.0 | 98.9 | 98.3 | 98.4 | 0.6 |
| Mouth slightly open | 52.3 | 42.0 | 47.2 | 98.8 | 98.1 | 98.6 | 0.7 |
| Narrow Eyes | 11.0 | 12.0 | 11.5 | 54.7 | 53.6 | 54.2 | 1.0 |
| Smiling | 54.0 | 40.0 | 47.0 | 98.8 | 96.8 | 98.3 | 2.0 |
| Wearing Hat | 2.9 | 8.0 | 5.4 | 91.0 | 95.8 | 94.4 | 4.8 |
| Young | 88.0 | 64.0 | 76.0 | 97.8 | 93.3 | 96.8 | 4.5 |
| **Attribute of Interest** |                   |    |          |
| Female | Male | Overall | Female | Male | Overall | DEO ↓ |
| Black Hair | 20.0 | 29.0 | 24.5 | 86.3 | 92.8 | 98.9 | 6.5 |
| Blond Hair | 24.0 | 2.0 | 13.0 | 92.6 | 58.7 | 91.2 | 33.9 |
| Brown Hair | 24.0 | 15.0 | 19.5 | 77.3 | 70.2 | 75.4 | 7.1 |
| Chubby | 1.0 | 12.0 | 6.5 | 36.3 | 62.0 | 58.5 | 25.7 |
| Gray Hair | 1.0 | 9.0 | 5.0 | 62.7 | 79.4 | 76.8 | 16.7 |
| Pale skin | 6.0 | 2.0 | 4.0 | 68.2 | 46.6 | 64.1 | 21.6 |
| Straight Hair | 19.0 | 24.0 | 21.5 | 61.7 | 67.7 | 64.0 | 6.0 |
| Wavy Hair | 45.0 | 14.0 | 29.5 | 90.0 | 66.8 | 87.1 | 23.2 |
| High cheekbones | 56.0 | 31.0 | 43.5 | 97.2 | 84.4 | 94.8 | 12.8 |
| Bags under Eyes | 10.0 | 35.0 | 22.5 | 52.7 | 67.0 | 62.8 | 14.3 |
| Big nose | 10.0 | 42.0 | 26.0 | 46.4 | 75.9 | 68.4 | 29.5 |
| Double chin | 1.0 | 10.0 | 5.5 | 27.3 | 61.7 | 57.2 | 34.4 |
| Pointy nose | 36.0 | 16.0 | 26.0 | 66.2 | 43.8 | 61.8 | 22.3 |
F Taxonomy of Facial Attributes in CelebA Dataset

In Section 4.1, we summarize all 39 facial attributes in CelebA dataset into three groups. In this section, we present more details for each group.

First, unbiased attributes are the facial attributes which do not yield much bias (i.e., DEO is less than 5 as shown in Table 4), e.g., Bangs, Big Lips, Blurry, Eyeglasses, Mouth Slightly Open, Narrow Eyes, Smiling, Wearing Hat, Young. To reserve resources for the biased facial attributes, unbiased attributes may be secondary to be balanced at the facial attribute level.

Besides, masculinity/femininity attributes are considered as Attribute of Interest (AOI) in Section 4.3 (sex classification). Specifically, masculinity attributes include 5'o Clock Shadow, Bald, Bushy Eyebrows, Goatee, Mustache, Receding Hairline, Sideburns, Wearing Necktie, and femininity attributes include Arched Eyebrows, Heavy Makeup, No Beard, Oral Face, Rosy Cheeks, Wearing Earrings, Wearing Lipstick, Wearing Necklace, Attractive.

Finally, we categorize the attributes which are not sex-related but induce dataset bias even with sex-level balanced training as AOI appending masculinity/femininity attributes in Section 4.4 (facial attribute classification), e.g., Black Hair, Blond Hair, Brown Hair, Chubby, Gray Hair, Pale Skin, Straight Hair, Wavy Hair, High Cheekbones, Bags Under Eyes, Big Nose, Double Chin, Pointy Nose.

G Mutually Exclusive Attributes

In Section 4.4, we present one representative facial attribute for the mutually exclusive facial attributes. In this section, we provide the additional results of other facial attributes.

As shown in Table 5, although strategically resampling [7] outperforms our method under BA, the performances under $d_{cor^2}$ and RLB (which are more consistent and stable as pointed by [38]) are not good. Furthermore, with better DEO and KL, we verify the achievement of equal opportunity and equalized odds in Section 3, which is not achievable for sex-level balanced dataset and strategically resampling.
Table 5: Performance and fairness comparison on facial attribute recognition.

|                | GrayHair | BlackHair | BrownHair | StraightHair | Average |
|----------------|----------|-----------|-----------|--------------|---------|
| **Baseline**   | 78.8     | 90.6      | 77.1      | 66.7         | 78.3    |
| Resampling [7] | 71.8     | 72.3      | 72.0      | 66.2         | 70.6    |
| GAN-Debiasing [53] | 77.9 | 88.1      | 74.1      | 57.7         | 74.4    |
| **Ours**       | 78.5     | 89.9      | 75.0      | 64.5         | 77.0    |

|                | GrayHair | BlackHair | BrownHair | StraightHair | Average |
|----------------|----------|-----------|-----------|--------------|---------|
| **Baseline**   | 25.5     | 6.2       | 8.0       | 6.0          | 11.4    |
| Resampling [7] | 9.6      | 5.0       | 7.5       | 5.3          | 6.9     |
| GAN-Debiasing [53] | 25.3 | 0.8       | 3.8       | 5.2          | 8.8     |
| **Ours**       | 13.1     | 0.9       | **2.6**   | 5.5          | **5.5** |

|                | GrayHair | BlackHair | BrownHair | StraightHair | Average |
|----------------|----------|-----------|-----------|--------------|---------|
| **Baseline**   | 0.47     | -0.16     | 0.75      | 1.13         | 0.55    |
| Resampling [7] | -3.59    | -3.51     | -3.65     | -0.01        | **-2.69** |
| GAN-Debiasing [53] | -0.61 | -0.94     | -0.40     | 0.39         | -0.39   |
| **Ours**       | -0.55    | -0.76     | -1.62     | 0.90         | -0.51   |

|                | GrayHair | BlackHair | BrownHair | StraightHair | Average |
|----------------|----------|-----------|-----------|--------------|---------|
| **Baseline**   | 0.24     | 0.13      | 0.07      | 0.03         | 0.12    |
| Resampling [7] | 0.11     | 0.10      | 0.07      | **0.02**     | 0.08    |
| GAN-Debiasing [53] | 0.23 | 0.03      | 0.04      | 0.03         | 0.08    |
| **Ours**       | 0.21     | **0.02**  | **0.03**  | 0.03         | **0.07** |

|                | GrayHair | BlackHair | BrownHair | StraightHair | Average |
|----------------|----------|-----------|-----------|--------------|---------|
| **Baseline**   | 0.67     | 0.30      | 0.31      | 0.39         | 0.42    |
| Resampling [7] | 0.38     | 0.28      | 0.30      | 0.30         | 0.31    |
| GAN-Debiasing [53] | 0.36 | 0.27      | **0.27**  | **0.22**     | **0.28** |
| **Ours**       | **0.34** | **0.25**  | **0.27**  | 0.28         | **0.28** |

|                | GrayHair | BlackHair | BrownHair | StraightHair | Average |
|----------------|----------|-----------|-----------|--------------|---------|
| **Baseline**   | 0.75     | 0.54      | 0.94      | 1.65         | 0.97    |
| Resampling [7] | 0.53     | 0.43      | 0.90      | 0.85         | 0.68    |
| GAN-Debiasing [53] | **0.39** | 0.48      | 0.92      | 1.61         | 0.85    |
| **Ours**       | 0.56     | **0.38**  | **0.67**  | **0.84**     | **0.61** |