Neural Styling for Interpretable Fair Representations

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Abstract

We observe a rapid increase in machine learning models for learning data representations that remove the semantics of protected characteristics, and are therefore able to mitigate unfair prediction outcomes. This is indeed a positive proliferation. All available models however learn latent embeddings, therefore the produced representations do not have the semantic meaning of the input. Our aim here is to learn fair representations that are directly interpretable in the original input domain. We cast this problem as a data-to-data translation; to learn a mapping from data in a source domain to a target domain such that data in the target domain enforces fairness definitions, such as statistical parity or equality of opportunity. Unavailability of fair data in the target domain is the crux of the problem. This paper provides the first approach to learn a highly unconstrained mapping from source to target by maximizing (conditional) dependence of residuals – the difference between data and its translated version – and protected characteristics. The usage of residual statistics ensures that our generated fair data should only be an adjustment of the input data, and this adjustment should reveal the main difference between protected characteristic groups. When applied to CelebA face image dataset with gender as protected characteristic, our model enforces equality of opportunity by adjusting eyes and lips regions. In Adult income dataset, also with gender as protected characteristic, our model achieves equality of opportunity by, among others, obfuscating wife and husband relationship. Visualizing those systematic changes will allow us to scrutinize the interplay of fairness criterion, chosen protected characteristics, and the prediction performance.

1 Introduction

Machine learning algorithms are having more and more of an impact in our day to day lives [1]. In the US criminal justice system, machine learning algorithms are used to inform decisions about, e.g., which defendants are low risk enough to be released on a bail pending trial. The time has therefore come that the most important area in machine learning is the implementation of algorithms that adhere to ethical and legal requirements. For example, as per EU’s General Data Protection Regulation and US’s Fair Credit Reporting Act, data must be processed in a way that is fair/unbiased and lawful. Having biased algorithms can cause allocative and/or representational harms [2]. Allocative harm happens when a machine learning system allocates an opportunity, e.g., being released on bail, more favourably to certain groups than to others. Representational harm, on the other hand, happens when a system reinforces the subordination of people sharing certain protected characteristics such as race and gender, regardless whether this system is being used to allocate an opportunity. This representational harm is of course harder to formalize and track, and confounds with allocative harm whenever the system that represents society is subsequently being used to allocate an opportunity [2].

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Fortunately, the machine learning community has responded to these representational and allocative harms. The number of papers addressing unfairness in machine learning models has grown exponentially in the last three years [3, 4, 5, 6, 7, 8, 9, 10]. Several criteria for mitigating allocative harm have been proposed, such as, statistical or demographic parity [3, 4] in which opportunities (positive predictions) across groups are allocated equally, and equalized odds [5, 11] in which the allocator/predictor and protected characteristics must be independently conditional on the actual outcome (and called equality of opportunity [6, 11] if it is conditional only on the positive – or negative – outcome). These criteria have also been used to learn fair representations of the given data [4, 7, 8, 9, 10]. Learning fair representation is a step in the direction towards mitigating representational harm. Without a doubt, it is a step in a very specific context, that is when the system is intended to be used in a pre-defined classification task to allocate a specific opportunity. This limitation has recently been generalized such that the learned fair representations will also be useful for novel classification tasks [10]. All fair representation models, however, learn latent embeddings, therefore the produced representations do not have the semantic meaning of the input, such as occupation, education, and relationship status when we have census data, for example. Our paper addresses this important gap in the literature, that is to learn fair representations which have semantic meaning in the input domain. When we have image data, our method will make a semantic change to the appearance of an image to deliver a certain fairness criterion. To achieve this, we perform a data-to-data translation by learning a mapping from data in a source domain to a target domain.

Mapping from source to target domain is a standard procedure, and many methods are available. For example, in the image domain, if we have aligned source/target as training data, we can use the pix2pix method of [12], which is based on conditional generative adversarial networks (cGANs) [13]. Zhu et al.’s CycleGAN [14], and Choi et al.’s StarGAN [15] solve a more challenging setting in which only unaligned training examples are available. However, in our case this standard source-to-target mapping has even greater challenge - we do not have data in the target domain (e.g. fair images), and we can not simply reuse existing methods. To illustrate the difficulty, consider that we are given images of people faces and a male/female protected characteristic. We want to have an automated job interview invitation system that uses people faces as an input. For achieving fairness, it is tempting to simply use GAN-driven methods, e.g. CycleGAN, to translate female faces to male. We will require training data of female faces (source domain) and male faces (target domain), and only unaligned training data are needed. This solution is however fundamentally flawed; who gets to decide that we should translate in this direction? Is it fairer if we translate male faces to female instead? A more sensible approach would be to translate both male and female faces (source domain) to appropriate middle ground faces (target domain). This challenge is actually multi-dimensional, it contains at least two sub-problems: a) how to have a general approach that can handle image data as well as tabular data/databases, and b) how to find a middle-ground with a multi-value (e.g. race) or continuous value (e.g. age) protected characteristic or even multiple protected characteristics (e.g. race and age).

We propose a solution to the multi-dimensional challenge described above by reinterpreting neural style transfer. Neural style transfer is a process of synthesizing a novel image by combining the content of one image with the style of another image based on matching second order statistics of pre-trained features [16]. This method can be viewed as an image-to-image translation, translating a content image to a stylized image (a pastiche if the style image is an art image). We reinterpret neural style transfer in the sense that we use higher order statistics of pre-trained features as a way to restyle our data to its fair version. For image data, the pre-trained features are deeper layers of a normalized 19-layer VGG network [17], and for tabular data, we use random Fourier features of Rahimi and Recht [18]. We maximize (conditional) dependence of residuals - between content image and its translated version – and protected characteristics. The intuition is that instead of generating a new translated image given the content image, we should simply adjust our content image to produce the desired translated image. Importantly, this will also allow us to enforce the required (conditional) independence of statistical parity and equalized odds criteria. We use the Hilbert-Schmidt norm of the cross-covariance operator between reproducing kernel Hilbert spaces (Hilbert–Schmidt independence criterion (HSIC); [19]) as an empirical estimate to measure (conditional) independence; this will allow us to take into account higher order dependence, and handle a multi-value/continuous value protected characteristic and multiple protected characteristics.
Related work  We focus on expanding the related topic of learning fair, albeit uninterpretable, representations. The aim of fair representation learning is to learn an intermediate representation of the data that preserves as much information about the data as possible, while simultaneously removing protected characteristic information such as age and gender. Zemel et al. [4] learn a probabilistic mapping of the data point to a set of latent prototypes that is independent of protected characteristic (statistical parity criterion), while retaining as much class label information as possible. Louizos et al. [7] extend this by employing a deep variational auto-encoders (VAE) framework for finding the fair latent representation. In recent years, we see increased adversarial learning methods for fair representations. Ganin et al. [20] propose adversarial representation learning for domain adaptation by requiring the learned representation to be indiscriminate with respect to differences in the domains. Multiple data domains can be translated into multiple demographic groups. Edwards and Storkey [21] make this connection and propose adversarial representation learning for the statistical parity criterion. To achieve other notions of fairness such as equality of opportunity, Beutel et al. [3] show that the adversarial learning algorithm of Edwards and Storkey [21] can be reused but we only supply training data with positive outcome to the adversarial component. Madras et al. [10] use a label-aware adversary to learn fair and transferable latent representations for the statistical parity as well as equalized odds criteria. None of the above learn fair representations while simultaneously retaining the semantic meaning of the data. There is an orthogonal work on feature selection using human perception of fairness (e.g. [22]), while this approach undoubtedly retains the semantic meaning of tabular data, it will be hard to generalize to image data.

2 The Styling Model for Interpretability in Fairness

We will use the same illustrative example mentioned in the introduction to describe our proposed method in detail. Given input images of people faces $x^n \in \mathcal{X}$, output labels of performed well or not well $y^n \in \mathcal{Y} = \{+1, -1\}$, and protected characteristic values, such as race or gender, $s^n \in \{A, B, C, D, \ldots\}$, or age, $s^n \in \mathbb{R}$, we would like to train a classifier $f$ that decides whether or not to invite a person for an interview. We want the classifier to predict outcomes that are accurate with respect to $y^n$ but fair with respect to $s^n$. We have options for the fairness criterion, for example statistical or demographic parity, in which the classifier $f$ and protected characteristic $s$ must be statistically independent, i.e. $f \perp s$. When we have binary protected characteristics, this independence criterion requires that positive decisions of group B individuals must be at the same rate as positive decisions of group A individuals, $\mathbb{P}(f(x) = +1 | s = A) = \mathbb{P}(f(x) = +1 | s = B)$. Another fairness criterion, equalized odds, requires the classifier $f$ and the protected characteristic $s$ to be independent conditional on the actual label $y$, i.e. $f \perp s | y$. With binary protected characteristic, this reads as equal discrepancies between decisions and actual labels across the two groups, $\mathbb{P}(f(x) = +1 | s = A, y) = \mathbb{P}(f(x) = +1 | s = B, y)$ for $y \in \{+1, -1\}$. Equality of opportunity criterion is a variant of equalized odds in which the independence is enforced for only the positive (or negative) actual label. Kleinberg et al. [23] and Chouldechova [24] show that independence (i.e. statistical parity) and conditional independence (i.e. equalized odds) criteria are mutually exclusive, and each fairness criterion is in conflict with learning well-calibrated classifiers, therefore trade-offs are necessary.

We want to learn a data representation $\tilde{x}^n$ for each input $x^n$ such that: a) it is able to predict the output label $y^n$, b) it protects $s^n$ according to a certain fairness criterion, c) it lies in the same space as $x^n$, that is $\tilde{x}^n \in \mathcal{X}$. The third requirement ensures the learned representation to have the same semantic meaning as the input. For example, for images of people faces, the goal is to modify facial appearance in order to remove the protected characteristic information. For census (tabular) data, we desire systematic changes in values of categorical features such as workclass (private, self-employed, etc.) and relationship (husband, wife, not-in-family, etc.). Visualizing those systematic changes will give evidence on how our algorithm enforces a certain fairness criterion. This will be a powerful tool, albeit all the powers hinge on observational data, to scrutinize the interplay between fairness criterion, protected characteristics, and classification accuracy.
2.1 Residual dependence maximization

We are given training triplets \((x^1, s^1, y^1), \ldots, (x^N, s^N, y^N) \subset X \times \{A, B, C, \ldots\} \times \{1, \ldots, \text{Class}\}\). Here we consider a general case with a multi-class classification task, and a multi-value protected characteristic. We first assume the following decomposition on \(x\):

\[
\phi(x) = \phi(\hat{x}) + \phi(\tilde{x}),
\]

with \(\hat{x}\) denoting the component of \(x\) that is dependent on \(s\), \(\tilde{x}\) to be the component that is independent of \(s\), and \(\phi(\cdot)\) is some pre-trained feature map. We will discuss about the specific choice of this pre-trained feature map for both image and tabular data later in the section. What we want is to learn a mapping from a source domain (input features) to a target domain (fair features with the semantics of the input domain), i.e. \(T : x \rightarrow \tilde{x}\), and we will parameterize this mapping \(T = T_\omega\) where \(\omega\) is a class of autoencoding transformer network. For our architectural choice of transformer network on image and tabular data, please refer to Section 3.

Taking into consideration that we do not have training data about the target fair features \(\tilde{x}\), we should not desire the transformer network to take the input feature \(x\) and generate a new output \(\tilde{x}\). Instead, it should just learn how to adjust our input \(x\) to produce the desired output \(\tilde{x}\). This can be achieved by exploiting our data decomposition assumption in (1), and by defining a concept of residual fairness:

\[
\phi(x) - \phi(\tilde{x}) = \phi(x) - \phi(T_\omega(x)) = \phi(\hat{x}),
\]

where the last term is the data component that is dependent on a protected characteristic \(s\). We can use the above observation as a mechanism to learn the transformer network \(T_\omega\): we want to find \(\omega\) such that the statistical dependence between \(R = \{\phi(\hat{x}^1), \ldots, \phi(\hat{x}^N)\}\) and \(S = \{s^1, \ldots, s^N\}\) is maximized. In the fair and interpretable representation learning task, we believe using residual fairness is well-motivated because we know that our generated fair features should be somewhat similar to our input features. Residuals will make learning the transformer network easier. The concept of residuals is universal, for example, a residual block has been used to speed up and to prevent over-fitting of a very deep neural network. While in image data we use the total variation (TV) penalty on the fair representation to ensure spatial smoothness, we do not enforce any regularization term for tabular data. We adopt the following definition of total variation penalty:

\[
TV(T_\omega(x)) = \sum_{i,j}(T_\omega(x)_{ij} - T_\omega(x)_{ij+1})^2 + \sum_{i,j}(T_\omega(x)_{ij} - T_\omega(x)_{i+1,j})^2.
\]

In summary, we learn a new representation \(\tilde{x}\) that removes the dependency on the protected characteristic \(s\). For statistical parity, we ensure \((\tilde{x} \perp \perp s)\) and for equalized odds/equality of opportunity we ensure the conditional independence criterion \((\tilde{x} \perp \perp s)|y\). We can then train any classifier \(f\) using this new representation and it will inherently satisfy the fairness criterion.
pre-trained feature map \( \phi(\cdot) \) is high dimensional) requires sophisticated bias correction methods \cite{28}. Instead of mutual information, we use the Hilbert Schmidt Independence Criterion (HSIC) \cite{19} as our measure of statistical dependence. HSIC is the Hilbert-Schmidt norm of the cross covariance operator between reproducing kernel Hilbert spaces. It has several advantages: first, it does not require density estimation, and second, it has very little bias, even in high dimensions. Given a sample \( Z = \{(r^1, s^1), \ldots, (r^N, s^N)\} \) of size \( N \) drawn from \( \mathbb{P}_r, \) an empirical estimate of HSIC is given by

\[
\text{HSIC}_{\text{emp.}} = (N - 1)^{-2} \text{tr} \, HKHL = (N - 1)^{-2} \text{tr} \, \tilde{K} \tilde{L}.
\] (4)

where \( K, L \in \mathbb{R}^{N \times N} \) are the kernel matrices for the residual set \( R \) and the protected characteristic set \( S \) respectively, i.e. \( K_{ij} = k(r^i, r^j) \) and \( L_{ij} = l(s^i, s^j) \). We use a Gaussian RBF kernel function for both \( k(\cdot, \cdot) \) and \( l(\cdot, \cdot) \). Moreover, \( H_{ij} = \delta_{ij} - N^{-1} \) centres the observations of set \( R \) and set \( S \) in RKHS feature space. Finally, \( \tilde{K} := HKH \) and \( \tilde{L} := HLH \) denote the centred versions of \( K \) and \( L \) respectively. For complete statistical properties of the empirical estimator in (4) refer to \cite{19}.

**Pre-trained feature space** Excellent results \cite{16, 29, 30, 31} on neural style transfer rely on pre-trained features. Following this spirit, we also use a “pre-trained” feature mapping \( \phi(\cdot) \) in defining our “style” loss. For image data, we take advantage of the powerful representation of deep convolutional neural networks (CNN) to define the mapping function \cite{16}. The feature maps of \( x \) in the layer \( l \) of a CNN are denoted by \( F^l_x \in \mathbb{R}^{N_l \times M_l} \) where \( N_l \) is the number of the feature maps in the layer \( l \) and \( M_l \) is the height times the width of the feature map. We use the vectorization of \( F^l_x \) as the required mapping \( \phi(x) = \text{vec}(F^l_x) \). Several layers of a CNN will be used to define the full mapping (see Section 3). For tabular data, we use the following random Fourier feature \cite{13} mapping \( \phi(x) = \sqrt{2/D} \cos(\langle \theta, x \rangle + b) \) with a bias vector \( b \in \mathbb{R}^D \) that is uniformly sampled in \([0, 2\pi]\), and a matrix \( \theta \in \mathbb{R}^{d\times D} \) where \( \theta_{ij} \) is sampled from a Gaussian distribution. We have assumed the input data lies in a \( d \)-dimensional space, and we transform them to a \( D \)-dimensional space.

### 2.2 Connections to adversarial model for fair *yet uninterpretable* representations

For the case of a binary protected characteristic and a binary decision, we need to minimize the distance between two conditional distributions in order to achieve statistical parity, equality of opportunity, or equalized odds. The conditioning variable is the protected characteristic. We have three options for measuring the distance between two conditional distributions in order to achieve statistical parity, equality of opportunity, or equalized odds. These options are:

1. **f-divergence**
   - Measures the distance between two distributions using a divergence function.
   - Common choices include KL divergence and Jensen-Shannon divergence.
2. **Integral Probability Metrics (IPM)**
   - Uses a metric to measure the distance between two distributions.
   - Examples include 1-Wasserstein distance and Hellinger distance.
3. **Optimal Transport (OT)**
   - A more flexible approach that can handle general cost functions.
   - In the context of fairness, OT can be used to enforce fairness constraints.

Adversarial latent fair representation methods (e.g. \cite{21, 10}) use the bottleneck layer of an autoencoder network as the discriminator input. By design, the bottleneck layer will not be in the same dimensional space as the input, therefore the learned representation will not have the semantic meaning of the input domain. We can also play the adversarial game with Maximum Mean Discrepancy (MMD) \cite{34}; this is minimizing an instance of IPM with the metric defined by a characteristic kernel function \cite{35}. Several methods learn a **latent** fair representation (e.g. \cite{7}) via MMD. The advantage of an MMD approach is that we do not need to train a discriminator but this comes at the expense of a restricted function class of the underlying discriminator. Finally, we can also use 1-Wasserstein distance (an instance of OT), and minimize the Kantorovich-Rubinstein dual formulation of it; this leads to Wasserstein GAN \cite{36}. This OT measure, however, has not been explored in the context of fairness.

To enforce fairness, instead of minimizing the distance between two conditional distributions, equivalently, we can minimize the distance between a joint distribution – over protected characteristics and representation – and the product of its marginal distributions (a joint distribution is equal to the product of its marginals if and only if they are independent). This viewpoint, also adopted in this paper, will allow us to handle a multi-value, continuous value, and even multiple protected characteristics. All previously mentioned latent fair representation methods can then be generalized to a multi-value/continuous/multiple protected characteristics by replacing the distance between two conditional distributions with some distance between a joint and the
product of its marginal distributions. Pérez-Suay et al. \cite{37} measure the distance using MMD (equivalent to HSIC) for statistical parity in regression and dimensionality reduction problems. The similarity between \cite{37} and our approach stops at the usage of HSIC, since we use very different statistics (residuals) and applications (interpretable fair representations). One note is that we can use conditional HSIC (e.g. \cite{38, 39}) for equalized odds when we have a multi-class classification or a regression problem.

2.3 Connections to styling model for artistic applications

Image-to-image translation is a class of vision and graphics problems where the goal is to learn a mapping between images in a source domain and images in a target domain using a training set of aligned image pairs \cite{14}. Adversarial learning techniques for unaligned image pairs are recently available (e.g. \cite{14, 15}). Those advancements are, unfortunately, not suitable for our problem as we do not have data in the target domain (vide Section 1). Neural style transfer NST (e.g. \cite{16, 29}) is another way to perform image-to-image translation by minimizing the distance between second-order statistics of a style image and the translated image (style loss). There is another loss (content loss) on the distance between a content (source) image and the translated (target) image.

The content and style losses are reminiscent of our optimization problem in (3), but NST and our problem setups are different. In NST, we are given two disjoint set of images, a set of content images and a set of style images. Typically, the set of style images is a singleton, but it has been recently extended to a non-singleton set \cite{40}. In our setting, we are only given a single set of images (the style images are also the content images). The style loss in NST can be cast in the form of an MMD metric with a second order polynomial kernel over spatial locations of the feature map, not over images \cite{41}. Minimizing this style loss corresponds to generating a stylized image(s) that is difficult to differentiate from a style image(s). To make connections with our setup, we need to consider a non-singleton set of style images, furthermore those style images will have a “protected characteristic” feature such as produced by a famous/not famous painter. The aim is to adjust style images to become stylized images, and to remove the semantics of the painter.

Lastly, there are two groups of NST techniques: an optimization technique (e.g. \cite{16}) and a transformer technique (e.g. \cite{29}). In the optimization technique, we minimize the content loss and the style loss by backpropagating them w.r.t. the stylized image itself. In the transformer technique, we instead backpropagate w.r.t. the weights of an autoencoder transformer network. At test time, the latter will produce the stylized images instantly, and our paper adopts this approach.

3 Experiments

We conduct the experiments using two publicly available datasets: the Adult income dataset\cite{42} from the UCI repository and the CelebA image dataset\cite{43}. The Adult dataset has a total of 45,222 data instances, each with 14 features such as gender, marital status, educational level, number of work hours per week, for example. The binary target outcome is whether or not income is greater than 50K dollars. For this dataset, we follow \cite{44} and consider gender as a binary protected characteristic. We use 28,222 instances for training, 15,000 instances for testing and 2,000 instance for validation. The CelebA dataset has a total of 202,599 celebrity images. The images are annotated with 40 attributes that reflect appearance (hair color and style, face shape, for example), emotional state (smiling), gender, attractiveness, age. For this dataset, we use gender as a binary protected characteristic, and attractiveness as the binary target outcome. We randomly select 4,000 images (balanced across gender and prediction task) for testing and use the rest for training the model. We enforce equality of opportunity as the fairness criteria throughout both experiments.

\[^{1}\text{https://archive.ics.uci.edu/ml/datasets/adult}\]
\[^{2}\text{http://mmlab.ie.cuhk.edu.hk/projects/CelebA.html}\]
Figure 1: Benchmarking results across 10 repeats. **Left:** original $x \in \mathcal{X}$. **Right:** fair $\tilde{x} \in \mathcal{X}$. Both original and fair representations lie in the same dimensional space. The axes show the accuracy and the difference in the true positive rate $1 - (\text{TPR}_{s_0} - \text{TPR}_{s_1})$, where $\text{TPR}_{s_n}$ indicates the true positive rate where the protected characteristic label $s = n$ (the closer to 1 the better).

### 3.1 The Adult income dataset

We compare our method against an unmodified $x$ using the following baseline classifiers: 1) **Logistic Regression** and 2) **SVM** with cross validation using a grid search over 10 regularization values. 3) **Feldman** [5] A ‘fair’ preprocessing method by amending the distribution of each attribute (except the label) so that subsets of that attribute are equal for each protected characteristic. We then used this preprocessed data to train an SVM. 4) **Kamishima** [45] Adds a fairness regularization term to the logistic regression. 5) **Zafar Disparate Mistreatment** [11] A Disciplined Convex-Concave Programming problem for equalized odds and equal opportunity. 6) **Zafar Disparate Impact** [46] This is for statistical parity. Whilst 2 approaches can be taken, optimizing for accuracy under fairness constraints, or optimising for fairness under accuracy constraints, we have included the first approach due to the latter not converging to an optimal result on the unaltered dataset across any of 10 repeats. **N.B.** The Kamishima, Feldman-SVM and Zafar Disparate Impact methods all enforce statistical parity as the fairness criteria, which is at-odds with our selected fairness criteria. We use these methods to demonstrate that our learned representation ($\tilde{x}$) is classifier-agnostic.

**Benchmarking** We follow the evaluation protocol of Friedler et al. [47]. We train our model for 50,000 iterations using a network with 1 hidden layer of 40 nodes for both the encoder and decoder, with the predictor acting on the bottleneck of this network. We then use this model to translate training and test sets into $\tilde{x}$, and evaluate all the methods using $x$ and $\tilde{x}$ representations.

In Figure 1 we show sensitivity plots based on 10 repeats. The centre of each box is the mean, height encodes standard deviation with regard to accuracy and width encodes standard deviation with regard to the fairness criterion. Consistently our translated representation $\tilde{x}$ promotes the fairness criterion (TPR Diff around 1) for all methods, with only a small penalty in accuracy. Whilst the Feldman model doesn’t perform as well as the others, this model also pre-processes the data, but for statistical parity, which is at odds with equality of opportunity [23].

**Interpretability** In Figure 2 $\tilde{x}$ promotes equality of opportunity for the positive group (actual salary > 50K USD), and results were gathered by training an SVM. We look at features that have been translated in the test set to make negative predictions become positive predictions.

This is a powerful technique for understanding how methods adjust the data for fairness. For example in Figure 2 (left) we can see that our method deals with the notorious problem of a husband or wife relationship status being a direct proxy for gender. Our method recognises this across all repeats and reduces the wife category which is associated with a negative prediction. Other categories that have less correlation with the
Figure 2: Boxplots show how the “Relationship Status” and “Race” categorical features have been translated to make incorrect negative (below 50K USD) predictions becoming positive (above 50K USD) predictions. **Left of each**: original \( x \in X \). **Right of each**: fair \( \tilde{x} \in X \).

Figure 3: Translated (top) and residual (bottom) images on CelebA to make incorrect negative (non-attractive) predictions becoming positive (attractive) predictions. Refer to text for discussion.

protected characteristic, such as race, largely remain unmodified (Figure 2 (right)).

3.2 The CelebA dataset

**Transformer network and parameters** Our autoencoder transformer network is based on the architecture of the transformer network in [29] with three convolutional layers, five residual layers and three deconvolutional/upsampling layers in combination with instance weight normalization [31]. The output image is produced using a non-linear tanh activation. Similarly to [16, 48, 29] we use the activations in the deeper layers of the 19-layered network VGG19 [17] as feature representations of the input and the translated images for computing the loss terms. Specifically, we use activations in the conv3_1, conv4_1 and conv5_1 layers for style loss, the conv3_1 layer activations for content loss, and pool5 activations for prediction loss. The activations are computed given an 178x178 color input image (after ReLU), the final features are flattened and \( l_2 \) normalized. For each style layer, we use a Gaussian RBF kernel \( k(x_1, x_2) = \exp(-\gamma \|x_1 - x_2\|^2) \) width \( \gamma = 1.0 \) for image features, and \( \gamma = 0.25 \) for protected characteristics (as one over squared distance in the protected attribute space). We then add the contributions across all style layers to compute the style loss. We set the trade-off parameters of the content loss and the style loss to 1.0, and the tv regularization strength to \( 10^{-3} \). Training was carried out for 50 epochs with a batch size of 80 images and took approximately 4 hours on an NVIDIA Tesla V100 GPU. We use minibatch SGD and apply the Adam solver [49] with learning rate \( 10^{-3} \), the implementation was carried out in Tensorflow.
**Benchmarking and interpretability** As the fairness criterion we enforce equality of opportunity of males versus females \(|TPR_{x=-1} - TPR_{x=1}|\), i.e. equal true positive rates, given the prediction of their attractiveness \(y = +1\). In this scenario attractiveness is what could give someone a job opportunity or an advantaged outcome as defined in [6]. To test the hypothesis that we have learned a fairer image representation, we compare the performance and fairness of a standard SVM classifier trained using original images and the translated fair images. We use the pool5 image features of the VGG19 network. We observe that using original images SVM has 74.00% accuracy and 36.90 equality of opportunity rate (difference in true positive rates, 55.30 and 92.20 across males and females groups). Using the translated fair images, SVM has 75.52% accuracy and improved 23.90 equality of opportunity rate (84.50 and 60.60 across groups accordingly). We visualize fair counterparts of the real images and interpret what are the features that capture dependence on the protected characteristics value. We visualize a subset of the test set in Figure 3. Those images have been rightly corrected from non-attractive in the original space to attractive in the transformed space. We observe a consistent localized area in face, namely *lips* and *eyes*, that were affected in most of the attractive male images. Interestingly, the female faces without prominent lipstick often get this transformation as well.

There are several arguments that support these findings. The CelebA dataset has a large diversity in visual appearance of females and males (hair style, color) and their ethnic groups, so a more localized facial areas were found to equalize attractiveness across groups. These results also support earlier works on the importance of eyes and eye brows in gender classification [50] and references therein. Lastly, in the CelebA dataset, the proportion of attractive to unattractive males is around 30% to 70%, and it is opposite for females. Lips are very often coloured in the females celebrity faces, hence the prediction task picks up and masks those prominent features in the minority group (males) increasing its recall and therefore improving the equality of opportunity criterion.

4 Discussion and Conclusion

Interpretability in machine learning models can help to ascertain qualitatively whether fairness is met [1, 51]. This paper makes a step further and advocates interpretability to ascertain qualitatively how fairness is met, once we have agreed to enforce fairness (e.g. equality of opportunity) into machine learning models. We specifically focus on enforcing fairness in representation learning. Unlike other fair representation learning methods that learn latent embeddings, our method learns representation that is in the same space as the original input data, therefore retains the semantic of input domain. To achieve this, we maximize (conditional) dependence of residuals – the difference between data and its learned representation – and protected characteristics. The usage of residual statistics ensures that the generated fair representation adjusts the input data whenever original input has features associated with protected characteristics. Our method picks up consistently in 9 out of 10 repeated experiments whether a person is a husband or wife as a direct proxy for gender, and subsequently reduces the wife category which is associated with a negative bias. In our experiments with people faces, eyes and lips are considered to be the direct proxy for gender attractiveness. As a potential future direction, we plan to supplement observational data with counterfactual models for interpretability in fairness.
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