BriarPatches: Pixel-Space Interventions for Inducing Demographic Parity

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Abstract

We introduce the BriarPatch, a pixel-space intervention that obscures sensitive attributes from representations encoded in pre-trained classifiers. The patches encourage internal model representations not to encode sensitive information, which has the effect of pushing downstream predictors towards exhibiting demographic parity with respect to the sensitive information. The net result is that these BriarPatches provide an intervention mechanism available at user level, and complements prior research on fair representations that were previously only applicable by model developers and ML experts.

Figure 1: Effect of a BriarPatch trained to remove perceived gender information. Probabilities for the man and woman labels (see footnote 1 in Section 4) given by a pre-trained Inception V3 classifier are reduced after patch application. Images used with permission.

1 Introduction: Fair Representation Learning from the Client Side

Recent papers in the machine learning fairness literature have proposed the idea of increasing fairness by reducing or removing a deep network’s ability to model a sensitive characteristic [1, 2, 3]. These methods have been shown to be effective, but can only be employed by model developers at the time that the model is trained. From the perspective of an end user, some additional mechanism may be useful on the client side to similarly reduce or remove the influence of a sensitive characteristic in any downstream models that may make predictions based on that image. This may be especially important for downstream models trained on data with strong correlations between a sensitive characteristic, such as gender, and classification targets such as athlete the model is attempting to predict.

This paper presents a method that empowers end users to limit the influence of sensitive characteristics, such as gender, in downstream image models. Building on recent work on adversarial instance generation [4], the method takes the form of a patch of pixels that, when applied to an image, reduces the amount of information about a chosen sensitive characteristic contained in the representation computed using off-the-shelf models without unduly affecting the human perception of the image.

This approach can be viewed as inducing a fair representation of the image that ensures all downstream prediction tasks using the model output exhibit demographic parity. We call this method for bias
We assume that the end user who provided each image has some sensitive attribute that they intend to obscure their sensitive information from the prediction vendor. Specifically, we design a transformation $\text{patch}(\cdot)$ to induce certain statistical parities in the representation $r(\text{patch}(X))$ when the patch is applied across the population.

### 3 Patch Models

Our goal is to design a patch transformation so that the sensitive attribute $A$ cannot be recovered from the representation $r(\text{patch}(x))$. In a similar approach to [2], we frame the problem in terms of thwarting an adversarial vendor who attempts to recover $A$ from $r(\text{patch}(X))$ using some classifier $h$ while maintaining the utility of the original multi-class classifier $f$.

**General case** In full generality, we seek a patch transformation, $\text{patch}(\cdot)$ corresponding to the following objective:

$$
\arg\min_{\text{patch}\in \mathcal{P}} \max_{h \in \mathcal{H}} \mathbb{E}[\mathcal{L}_A \{A, h \circ r(\text{patch}(X))\} + \lambda \mathcal{L}_R \{Y_{\ell(A)}, f \circ r(\text{patch}(X))\}].
$$

Here, $\mathcal{L}_A$ and $\mathcal{L}_R$ are classification losses for predicting $A$ and $Y$ respectively. The $\mathcal{L}_A$ term corresponds to the adversarial vendor’s objective, whereas the $\mathcal{L}_R$ term is a regularizer that constrains the patch to trade off thwarting the adversary with maintaining the utility of the original classifier, $f \circ r(X)$.

Here, we define the family of patch transformations $\mathcal{P}$ as a set of image transformations parameterized by a patch – a small circular array of pixels. Following [4], the patch transformation, $\text{patch}(\cdot)$, randomly rotates the patch and overpaints it on a random location on the image. Thus, a patch corresponding to the $\text{patch}(\cdot)$ transformation that successfully solves the optimization problem should have properties that are, in expectation, translation and rotation invariant.
Figure 2: Effects of patches on representations. (a) Image representation change in the (man, woman, athlete) logit space. (b) logit $P(A = \text{man} \mid r(x))$ from an adversarial linear classifier before (x-axis) and after (y-axis) applying the patch.

**Linear adversary and relaxations** In this work, we consider a special case of Eq. 1 where the sensitive attribute $A$ is binary, and the family of adversarial classifiers $\mathcal{H}$ is constrained to be linear.

In addition, we relax the objective in Eq. 1 in two ways. First, we replace the adversarial optimization of $L_A$ with a maximum mean discrepancy (MMD) [8]:

$$\max_{\mathcal{H}} \left[E[h \circ r(\text{patch}(X)) \mid A = 1] - E[h \circ r(\text{patch}(X)) \mid A = 0]\right].$$

When $\mathcal{H}$ is the set of linear functions, this MMD has a closed form, and reduces to the $L_2$ distance between the group means. Secondly, we replace the original classifier loss $L_R$ with the $L_2$ distance between the un-patched and patched image representations. This regularizer encourages the patched logits of non-sensitive attributes to remain close to their un-patched values, with the goal of preserving some of the utility of the original classifier $f$. This yields the following objective:

$$\arg \min_{\text{patch} \in \mathcal{P}} \|E[r(\text{patch}(x)) \mid A = 1] - E[r(\text{patch}(x)) \mid A = 0]\|^2 + \lambda E[\|r(x) - r(\text{patch}(x))\|^2]. \tag{2}$$

Figure 1 shows an example patch trained according to this objective.

4 **Experimental Results and Discussion**

In our experiments we sought to remove perceived gender information from the predictions made by an Inception V3 model trained on the OpenImages V1 dataset. This model predicts 6012 binary labels for a given image, including labels for man and woman, a number of labels that strongly correlate with it in the dataset (e.g. athlete).

To explore the simplest case, we limited ourselves to de-biasing representations formed by concatenating the logit of a single binary target label (e.g. athlete) and the gender logits man and woman. We measured success in removing gender information by AUC-ROC of a binary gender logistic regression classifier trained on representations formed by patched images. We measured classifier utility on the single binary target label with the Average Precision (AP) metric. Patches were trained and evaluated on disjoint gender-balanced subsets of images from the OpenImages V3 validation set, which contained either the woman or the man label, but not both simultaneously. Patches were trained for 200 epochs using SGD with a learning rate of $10^{-3}$ and a batch size of 128.

We measured the effect of the patch with several metrics related to classifier performance and fairness, and also explored the qualitative effect of patch application on downstream representations.

**Representation effects** In Figure 2 we show the representation-space transformation $r(x) \mapsto r(\text{patch}(x))$ induced by a patch. To remove distinctions between images with man and woman labels, the patch maps representations toward the boundary between the regions primarily occupied by man

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1 Although these provided labels are used as placeholders for perceived gender for these experiments, we acknowledge the limitations of this approach and recognize that gender is inherently a non-binary concept.
Figure 3: The effect of BriarPatch on classifier output. Results shown for the athlete label, but are representative of other labels. **Left:** Utility-separability trade-off for patches trained with different levels of regularization. Metric standard deviations (shown as shaded areas) were obtained by training 10 different patches per regularization and evaluating each of them 25 times on each image. Results for random noise patch are provided as a baseline for a patch that randomly masks out a part of the image. **Center:** When applying the patch only to images with the woman label, we find a regime around $\log_{10}\lambda = 4.69$ where separability is decreased but utility is unaffected. **Right:** Gender prediction accuracy using the original Inception classifier ($\text{logit}(\text{man}) - \text{logit}(\text{woman})$; original), classifiers trained on the unpatched and patched representations (unpatched and patched respectively), and a classifier trained on the unpatched representation used to make prediction on the patched images (cross). and woman images in the original representation. We also show the effects of the patch on the logits of an adversarial linear classifier attempting to recover the gender attribute from the representation. The patch makes these logits less separable between the man and woman classes, although it does not make their distributions indistinguishable. Importantly, the logits are squeezed toward zero for most images, reducing the certainty with which an adversary can classify individual images on the basis of the image representation.

**Separability and Utility** Varying the regularization amount $\lambda$ allowed us to assess the separability-utility trade-off attainable by the patch. Figure 3 (left) shows that the patch undergoes a regime switch, where it transitions from having little effect on the classifier’s ability to predict the athlete label on the test set (right side of the plot) and little success in de-biasing the logit representation to reducing the amount of the sensitive gender information at the cost of reducing the classifier utility (left side of the plot; $\Delta\text{AUC} \approx 0.16$ and $\Delta\text{AP} \approx -0.27$).

Interestingly, as shown in Figure 3 (center), there is a regime where separability is decreased but utility remains unaffected for images with the woman label. This suggests that voluntary application of the patch can improve fairness with minimal utility loss.²

**Effects on Demographic Parity** BriarPatch controls the worst-case downstream demographic disparity by minimizing an adversarial vendor’s ability to recover the sensitive attribute from patched representations [2]. This guarantees that any other vendor (e.g. a vendor predicting the athlete label) will have a smaller demographic disparity than the adversarial one. When the patch is unable to remove all sensitive information from $r(x)$, this guarantee permits the patch to reduce the vendor’s demographic parity as shown in Figure 3.

**Confusing the original gender classifier** We found that even when trained with little or no regularization, the patch intervention was unable to completely remove gender information from the considered representations (see Figure 3). This means that a determined vendor may use these representations to recover the gender from the obfuscated logits. However, we also found that the trained patches succeeded in confusing a naïve vendor that directly used the original man and woman logits in the patched representation for recovering the gender (AUC $\approx 0.5$; Figure 3 (right)).

² The patch as it is currently trained is not optimized for this use case. When patch application is voluntary, increasing the patch strength too much (low regularization) leads to conspicuous representation changes that allow the vendor to detect patch application; meanwhile, decreasing the patch strength too much (high regularization) does not allow the patch to obscure sensitive characteristics effectively (see Figure 3). We speculate that this accounts for the peak in Figure 3 (center). Patches tailored to voluntary application could potentially eliminate this tension.
Acknowledgements  We would like to thank Eric Breck, Erica Greene, and Shreya Shankar for contributing to earlier versions of this project and Pallavi Baljeka for insightful discussions.

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A Appendix

Figure 4: Evolution of logit representations for patches with regularisation levels corresponding to points left of- (left; $\log_{10} \lambda = 3.55$), on the- (center; $\log_{10} \lambda = 4.69$) and right of (right; $\log_{10} \lambda = 5.59$) the separability peak in Figure 3 (center).

(a) (Adversarial) vendor classifier score distributions. (b) Demographic discrepancy bound.

Figure 5: Effects on downstream demographic parity. (a) Distribution of scores for a classifier trained to predict the sensitive gender attribute (i.e. an adversarial vendor; right column) and a classifier trained to predict the athlete label (athlete vendor; left column) on the original (top row) and patched (bottom row) representations shown for a single patch. Differences between the score distributions reflect the demographic parity gap between the sensitive groups. Applying the patch makes the gender classifier scores less separable between the groups, but does not necessarily have the same effect on the athlete classifier scores. (b) AUC for predicting the sensitive gender attribute using the adversarial vendor scores (green), and using the athlete scores (purple); unpatched baselines are shown as dashed lines. The adversarial vendor’s AUC is consistently above that of the athlete vendor, and serves as an upper bound that BriarPatch minimizes. However, subject to this upper bound, the demographic discrepancy of the vendor may increase (e.g. around $\log \lambda = 4$). At low regularization the vendor’s demographic discrepancy is decreased beyond the baseline and approaches the optimal value of $\text{AUC} = 0.5$. 