Adversarial Removal of Gender from Deep Image Representations

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Abstract

In this work we analyze visual recognition tasks such as object and action recognition, and demonstrate the extent to which these tasks are correlated with features corresponding to a protected variable such as gender. We introduce the concept of “natural leakage” to measure the intrinsic reliance of a task on a protected variable. We further show that machine learning models of visual recognition trained for these tasks tend to exacerbate the reliance on gender features. To address this, we use adversarial training to remove unwanted features corresponding to protected variables from intermediate representations in a deep neural network. Experiments on two datasets: the COCO dataset (objects), and the imSitu dataset (actions), show reductions in the extent to which models rely on gender features while maintaining most of the accuracy of the original models. These results even surpass a strong baseline that blurs or removes people from images using ground-truth annotations. Moreover, we provide convincing interpretable visual evidence through an autoencoder-augmented model showing that this approach is performing semantically meaningful removal of gender features, and thus can also be used to remove gender attributes directly from images.

1. Introduction

Visual recognition systems have made great progress toward practical applications that directly affect people. However, these systems often make unwarranted implicit associations, and present a risk of amplifying societal stereotypes about people. Negative outcomes can range from issues concerning representation harm (e.g., male software engineers are being over-represented in image search results \cite{15}), issues concerning inclusiveness and awareness (e.g., facial recognition software does not work for a subset of the population \cite{4}), to life-threatening situations (e.g., the recognition rates of pedestrian detection in autonomous vehicles are not as accurate for all groups of people). As computer vision techniques have been widespread in human-centric applications, it is crucial to understand different biases encoded in the formulation of visual recognition models and design appropriate approaches to make them agnostic to protected variables such as gender, race, or age.

In this paper, we find that some visual tasks such as object recognition, and action recognition from static images, exhibit intrinsic biases with respect to gender. We introduce the notion of natural leakage by the degree to which a classifier with varying degrees of access to the true annotations for a task is a good predictor of a protected variable such as gender. Using this measure, we demonstrate that some tasks inherently correlate with protected variables due to the difference of label distribution conditioning on protected variables in the training data. Moreover, we measure the model leakage for a particular visual recognition model by similarly measuring the extent to which its outputs are correlated with a protected variable. We find that models trained on a biased task tend to amplify those biases under leakage measures and not merely replicate them. While our work focuses on gender due to the availability of annotations, it can be applied to any arbitrary variable.
As a solution, we propose to use convolutional neural networks (CNNs) to build feature representations that capture as much task specific information from its inputs (such as the appearance of objects or actions), but at the same time keep out information about a protected variable (such as information about gender). Our approach is based on the adversarial training approach, which has been used to hide protected variables in other machine learning tasks [24, 2, 28], or more generally to train generative adversarial networks (GANs) [11]. Our model is successful in removing model leakage while maintaining the accuracy of a similar model trained without any adversarial constraints. Specific to images, we further proposed an approach based on autoencoder to visualize the removal of visual features associated with gender (see example in Figure 1), and find that the model can successfully remove things such as faces, body parts, and even some contextual cues such as pink objects that are strongly correlated with gender in the dataset.

In the image domain, adversarial removal of high-level information such as the gender of people depicted in images is challenging, as people are often interacting with other objects and their surroundings in complex ways. A successful approach would remove features associated with a person but not enough to not be able to classify the action depicted, or the objects interacting with the person on the scene. This is in contrast to other domains where categorical features are explicitly provided to the model. In those cases, although not ideal, it is possible to apply the naive approach of directly removing gender from the input feature set. We demonstrate that adversarial removal works in removing features with respect to a protected variable but works best when applied to specific intermediate representations output by the last convolutional layers.

Our contributions stand as follows:

- We introduce the notion of natural leakage to analyze the extent to which complex prediction tasks in visual recognition are intrinsically correlated with a protected variable such as gender.
- We perform extensive experiments showing that adversarial training for removing leakage is effective and provide concrete recommendations for its use with visual recognition models such as ResNet [14].
- We propose an autoencoder-augmented model that allows removal of gender features directly from the input representation in order to obtain interpretable visual results.

2. Related Work

In recent years, researchers have demonstrated that machine learning models tend to replicate the societal biases present in the training data that they learn from. Concerns have been raised for applications such as recommender systems [25], credit score prediction [12], online news [20], and many others [15] and in response various approaches have been proposed to mitigate bias [1, 13]. However, most previous work deals with issues of resource allocation [7, 9] and the focus is on improving the calibration of predictions. Furthermore, works often assume that the protected variable is explicitly defined as a feature and that the goal of the calibration is more clearly defined (e.g., equal odds or equal opportunity). However in object recognition, we must infer multiple variables jointly in order to make coherent decisions and the representations for protected attributes are automatically inferred from raw data.

More recently, there has been work addressing different types of biases in image data [22, 29, 23, 18, 9]. Xie et al. [24] propose a setup for removing image brightness as the protected variable in an image classification task. Our work is, to our knowledge, the first attempt to
remove attributes in images for high-level feature such as gender and in the more general scenario of multi-label prediction. Zhao et al. [29] addresses bias in the COCO and imSitu dataset but the focus is on structured prediction models where predicting gender is a target task of these models. Moreover, the proposed method in [29] still focuses on calibrating the predictions of the structured model and not representation learning. Similar in spirit to our work, Burns et al. [5] attempt to calibrate gender predictions of a captioning system by modifying the input image. In contrast, in our work we do not aim at predicting gender, which is the more common scenario, therefore calibration methods would not be effective to debias the predictions in our proposed setup, as gender is not one of the outputs.

There has also been considerable work in learning fair representations in other domains. For example, word embedding models have been shown to carry gender stereotypes [6, 3] that affect downstream applications such as coreference resolution [30, 21]. Bolukbasi et al. [3] debiased word embeddings by finding a gender direction in the embedding space in order to reproject and build gender-neutral representations. Zemel et al. [27] similarly propose reprojecting the input representations into a set of prototype embeddings to mitigate bias. Our method is more related to the type of debiasing approaches that use adversarial training [28, 24, 8, 31, 10] during the learning of the representations. We provide further details about this family of methods in the body of the paper.

In terms of evaluation, researchers have proposed different measurements for quantifying fairness in machine learning [12, 16, 7]. In contrast to these works, we try to address removal of bias in the feature space, therefore we adopt and further develop the idea of leakage as an evaluation criteria, as proposed for the debiasing of text representations used by Elazar and Goldberg [8]. We explore the leakage formulation and further test its capacity for measuring the extent of removal of protected attributes from feature representations and further propose dataset leakage, predictive leakage, natural leakage, and model leakage as measures of bias in learned representations.

3. Methodology

Many problems in computer vision inadvertently reveal demographic information (e.g., gender) about people in images. For example, in COCO, images of plates are significantly more common with women than men and so if a model predicts that a plate is in the image, we can infer there is likely a woman in the image. We refer to this notion as leakage. In this section, we present (1) formal definitions of leakage for datasets and models, and (2) an adversarial method for reducing it. We will show in Section 5 that both imSitu and COCO leak significant information and in Section 6 show how to construct smaller versions of these datasets that do not exhibit dataset leakage.

3.1. Leakage

In this section, we discuss four types of leakage: (1) dataset leakage, (2) prediction leakage, (3) natural leakage, and (4) model leakage.

Dataset Leakage We assume we are given an annotated dataset $D$ containing instances $(i, y, g)$, where $i$ is an image annotated with a set of task-specific labels $y$ (e.g., objects), and a protected attribute $g$ (e.g., the image contains a person with perceived gender male or female). We say that a particular annotation $g$ leaks information about $y$ if there exists a function $f$ such that $g \approx f(y)$. We refer to this $f$ as an attacker because it tries to reverse engineer information about protected attributes in the input image $i$ only from its task-specific labels $y$. To measure the leakage across a dataset, we train such an attacker and evaluate it on held out data. The performance of the attacker, the fraction of instances in $D$ that leak information about $y$ through $g$, yields an estimate of leakage:

$$l_D = \frac{1}{|D|} \sum_{(i, y, g) \in D} 1[f(y) == g],$$

(1)

where $1(\cdot)$ is the indicator function.

Prediction Leakage Similar to dataset leakage, we would like to measure the degree to which the predictions of some model, $\hat{y}$, leak information about the protected variable $g$. We define model leakage as the percentage of examples in $D$, that given a predictor, $p(i)$ which produces task label $\hat{y}$, leaks information about $g$. To measure such prediction leakage, we train a different attacker to extract patterns in $\hat{y}$ that reveal information about $g$:

$$l_P = \frac{1}{|D|} \sum_{(i, y, g) \in D} 1[f(\hat{y}) == g],$$

(2)

where $\hat{y} = p(i)$, and $f$ is an attacker function trained to predict gender from the outputs of model $p$.

Natural Leakage A model $p$ may not be perfectly accurate in predicting $y$, as the attacker learns to extract $g$ from the model prediction $\hat{y} = p(i)$. If the accuracy of $\hat{y}$ is lower, the performance of the attacker will be naturally lower as well (i.e., leakage is smaller). In fact, if $p(i)$ were totally random, we expect that an attacker will not be able to extract any information about $g$ (and later in our experiments, we use a baseline based on random perturbations). Therefore,

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1 In this paper, we assume gender as binary due to the available annotations, but the work could be extended to non-binary, as well as a broader set of protected attributes, such as race or age.
直接比较两款模型的泄露程度并不公平。为了准确地校准我们的测量结果，我们定义自然泄露为已知性能水平下期望的泄露。这种被篡改的度量反映了信息模型会泄露保护的属性，即使其错误是随机生成的。形式上，我们定义自然泄露如下：

\[ l_N = \frac{1}{|D|} \sum_{(i,y,g) \in D} 1(f(y_a) = g), \]  (3)

其中\( f \)是一个误攻击者模型。我们将泄露率定义为性能水平\( a \)的自然泄露和预测泄露之间的差：

\[ l_M = l_P - l_N. \]  (4)

一个模型的\( l_M \)是零的，表示它没有泄露更多的信息于性别，而我们希望它能从来源中学习到保护属性的信息，以期达到任务定义的目标。这代表着一种对信息的依赖性，这对于我们来说是不公平的。为了在不改变模型的情况下在新数据集上学习更多，我们将信息泄露定义为一个随机预测器的性能级别。我们在下一节中展示了我们所评估的所有模型都泄露了更多的信息，表明更大的信息泄露当数据集没有泄露时。

创建攻击者

理想情况下，攻击者应该是一个贝叶斯最优分类器，它能用最少的数据获取最大信息。然而，在实践中，我们不需要训练一个能够做这种预测的模型，并使用深度神经网络。然而，我们并不保证我们已经得到了最佳的映射。这种映射用于预测保护的属性，以期达到预测任务的目标。我们将在下一节中展示所有模型都泄露了更多的信息，表明更大的信息泄露当数据集没有泄露时。

3.2. Adversarial Reduction of Leakage

我们提出一种简单的方法来减少泄露，具体见图2。我们假设模型泄露额外的信息，因为这种泄露对保护的属性过于敏感。因此，我们鼓励模型构建与这些保护的属性不相关的表示。

我们的方法依赖于构建一个批评家，\( c \)，它试图预测保护的信息，从中间表示，\( h_i \)，对于给定的图像\( i \)，一个预测器，\( p \)。批评家的目的是最小化损失，从而减少模型在图像上提取的信息量。

\[ L_c = \sum_{(i,g) \in D} L(c(h_i), g). \]

当批评家尝试最小化其损失时，而预测器却试图增加批评家的损失。

\[ L_p = \sum_{(i,y) \in D} L(p(i), y) - \lambda_1 L_c. \]

在两种情况下，\( L \)是交叉熵损失，当优化\( L_p \)时，我们不会更新\( c \)，而是权衡任务性能与对保护属性的敏感度，其中\( \lambda_1 \)。

我们还实验了直接生成图像，从能泄露保护信息的输出autoencoder作为输入到我们的模型。这与Palacio et al [19]提出的实验相似，其中autoencoder的输出被馈送到一个卷积神经网络，该网络用于识别目标来解释学习到的模式。

4. Experimental Setup

我们考虑两个数据集。首先，COCO数据集[17]，包含具有对象和文本描述的图像。在这个数据集上，我们执行多标签对象分类。另外，我们使用imSitu数据集[26]，其中每个图像都由一个结构化的元组表示，该元组包括一个活动的名称（动词）和参与者。在该数据集上，我们执行分类任务，形式为多类分类任务。

在COCO数据集中，我们使用“man”和“female”作为性别注释。在imSitu数据集中，我们考虑了场景（活动是注释的一部分，与对象和语义角色相关，这些角色是参与者的分类），即角色（动作）。在该数据集上，我们执行分类任务，形式为多类分类任务。

我们说一个图像是“male”如果我们能找到包含单词“man”的图像或者“female”如果我们能找到包含单词“woman”的图像。
“man” in the gloss of the “agent” of an activity and female if we can find the word “woman” in the gloss. Finally, for the purpose of our analysis, we exclude “person” category from COCO 80 categories. For imSitu, we filter non-human oriented activity categories that do not contain more than 50 images associated with men or women.

Models  For both COCO object classification and imSitu activity recognition, we use a standard ResNet-50 convolutional neural network pretrained on Imagenet (ILSVRC) as the underlying model by replacing the last linear layer as appropriate. When constructing attackers, we use a 4-layer multi-layer perceptron (MLP) with BatchNorm and LeakyReLU in between for both dataset and model leakage estimates. Prediction leakage was predicted from pre-activation logits while dataset leakage was predicted from binary labels. Attackers were evaluated on an equal quantity of male and female images, sampled from the original development sets.

Metrics  We evaluate using mAP, or the mean across categories of the area under the precision-recall curve, and F1 for both object and activity classification by using the discrete output predictions of the model.

Training Details  For comparability, all models are developed and evaluated on dev and test sets from the original data (even when we modify the composition of a training set). In adversarial training, we always first train linear layers for classification with 5e−5 learning rate and batch size 64 until the performance plateaus. We incorporate adversarial training when we fine-tune the model end to end using a learning rate 1e−5. Before we start adversarial training, we first train the gender classification branch so that its gradients provide useful guidance for feature removal during adversarial training. To compute leakage in COCO, we randomly sample 5,000 male images and 5,000 female images for training, and 1,500 male and 1,500 female images as dev and test set respectively. For imSitu, we randomly sample 7,000 male images and 7,000 female images for training, and 2,000 male and 2,000 female images as dev and test set respectively. If the dataset size is smaller than 5,000, we use all of them as training data. We use learning rate 5e−5 throughout the training of the attacker. As training data is not always gender balanced, we sample the same amount of male and female images in every batch to encourage the gender classifier focus on gender features.

5. Data and Model Leakage

In this section we summarize our findings showing that both imSitu and COCO leak information about gender. We also show that models trained on these datasets not only leak information but actually leak more information than would be expected. Finally, we show a method for constructing a leakage free dataset by removing examples. Unfortunately, we find that models trained on such datasets still leak significant amounts of information about gender, while performing significantly worse on the underlying classifications problems. Table 1 summarizes our results.

Dataset Leakage  Dataset leakage measures the degree to which ground truth labels can be used to estimate gender. The rows corresponding to “original” in Table 1 summarize dataset leakage in imSitu and COCO. Both datasets leak significant information about gender: the gender of a main entity in the image is extractable from ground truth annotations 70% and 75% of the time for COCO and imSitu respectively. The skew in numbers of men and woman in the dataset does not alone account for the dataset leakage implying that not only are men more represented in these datasets but that the labels also exhibit unequal associations with gender.

Model Leakage  Model leakage measures the degree to which model outputs can be used to estimate gender. Model leakage needs to calibrated with respect to the underlying accuracy of the predictor. To do so, we compute natural leakage by randomly changing ground truth labels to simulate models at different accuracy. Figure 3 shows natural leakage at different performance levels in COCO and imSitu. The relationship between F1 and leakage is roughly linear. For all models, we compare the leakage with respect to natural leakage at the appropriate F1 score, taking the difference between prediction leakage and natural leakage. In all models trained on original datasets, prediction leakage is high. Surprisingly, imSitu is more gender balanced and has lower natural leakage than COCO but models trained on imSitu actually leak significantly more information than
those trained on COCO, suggesting that the models are over relying on gender cues to make predictions.

Alternative Data Splits While the original imSitu and COCO datasets leak information about gender through their labels, it is possible to construct datasets which leak less through subsampling. We obtain splits more balanced in male and female co-occurrences with labels by imposing the constraint that neither gender occurs more frequently with any output label by a ratio greater than $\alpha$:

$$\forall y : 1/\alpha < \#(m, y)/\#(w, y)$$

where $\#(m, y)$ and $\#(w, y)$ are the number of occurrences of men with label $y$ and of women with label $y$ respectively. Enforcing this constraint in imSitu is trivial because each image is only annotated with one verb: we simply sample the over-represented gender until it fails the above constraints. For COCO dataset, since each image contains multiple object annotations, we must heuristically enforce this constraint. We try to make every object satisfy this constraint one at a time, removing images from the dataset that have the smallest number of objects. But doing so may make some other labels violate the constraint, so we iterate through all objects until this process converges and all objects satisfy the constraint. We create splits for $\alpha \in \{3, 2, 1\}$ for both datasets.

As we expect, in Table 1, decreasing values of $\alpha$ yields smaller datasets with less dataset leakage. Unsurprisingly, models trained on these datasets yield worse predictors because there is less data. Yet model leakage does not reduce as quickly as dataset leakage. In fact, in cases where data leakage is nearly zero, models still leak information. Likely this is because it is impossible to balance unlabeled co-occurring features with gender (e.g. COCO only has annotations for 80 objects) and the models still rely on these features to make predictions.

Learning Attackers is Robust Measuring leakage relies on being able to consistently estimate an attacker. To verify that leakage estimates are robust to different architectures and data settings on the attacker side, we conduct an ablation study in Table 2. We train to measure prediction leakage on the original COCO dataset, varying attacker architecture, and the amount of training data used. Beyond prediction with an attacker that is just 1 layer, none of the others vary in their estimation of leakage by more than 2 points.

6. Adversarial Reduction of Leakage

In this section we evaluate reducing leakage through adversarial training (as described in Section 3.2). We also present some qualitative examples of what our methods choose to remove from images.

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Table 1. In this table we show for different splits in COCO and imSitu, (1) dataset leakage, or the accuracy obtained by predicting gender from ground truth annotations, showing that our data balancing approach successfully achieves significantly reducing this type of leakage (2) prediction leakage, or the accuracy obtained by a model trained to predict gender on the outputs of a model trained on the target task, the last two columns show the mAP and F1 score of the model, and (3) natural leakage, or the leakage of a model with access to ground truth annotations but with added noise so that its accuracy matches that of a model trained on this data, i.e. same mAP and F1 as shown in the last two columns. (4) model leakage the difference between prediction leakage and natural leakage, indicating how much more leakage the model is exhibiting over chance.

| dataset | split | Statistics | Leakage | Performance |
|---------|-------|------------|---------|-------------|
| COCO [17] | original | #men | #women | dataset | prediction | natural | model | mAP | F1 |
| | (\(\alpha = 3\)) | 10, 859 | 6, 590 | 69.69 | 71.23 | 61.20 | 10.03 | 58.27 | 52.08 |
| | (\(\alpha = 2\)) | 8, 763 | 6, 580 | 65.86 | 69.57 | 60.04 | 9.53 | 56.97 | 51.78 |
| | (\(\alpha = 1\)) | 3, 108 | 3, 108 | 59.02 | 66.47 | 55.80 | 10.67 | 55.69 | 50.33 |
| imSitu [26] | original | 14, 199 | 10, 102 | 68.23 | 75.88 | 57.68 | 18.20 | 41.39 | 40.06 |
| | (\(\alpha = 3\)) | 11, 613 | 9, 530 | 63.60 | 75.32 | 53.94 | 21.38 | 39.69 | 37.90 |
| | (\(\alpha = 2\)) | 10, 265 | 8, 884 | 59.43 | 74.18 | 51.89 | 22.29 | 38.23 | 36.77 |
| | (\(\alpha = 1\)) | 7, 324 | 7, 324 | 50.33 | 70.13 | 50.30 | 19.83 | 34.03 | 32.97 |

Table 2. Varying attacker architecture and training data when estimating prediction leakage on the original COCO. The leakage estimate is robust to significant changes, showing that estimation of leakage with our adversaries is largely easy and stable.
Figure 4. Model leakage as a function of F1 score on COCO object classification. Models in the top left have low leakage and high F1 score. The red dashed line indicates bias and performance of adding progressively more noise to the original model representation. Our adversarial methods are the only ones which make a better trade-off between performance leakage than randomization.

Figure 5. Model leakage as a function of F1 score on imSitu activity recognition. Models in the top left have low leakage and high F1 score. Our adversarially trained models offer significantly better trade-offs than baseline methods.

Table 3. Model leakage and performance trade-offs for different baselines (rows 1-4) and our adversarial training methods (rows 5-7) on COCO object classification. Our methods make significantly better trade-offs than baselines, even improving on methods which use ground truth detection and segmentation.

| Model | Leakage pred. | Leakage natural | Leakage model | Performance mAP | Performance F1 |
|-------|----------------|-----------------|--------------|----------------|----------------|
| original | 71.23 | 61.20 | 10.03 | 58.27 | 52.08 |
| blur | 69.30 | 61.78 | 7.52 | 55.70 | 48.92 |
| blackout-segm | 68.60 | 61.32 | 7.28 | 52.71 | 47.19 |
| blackout-box | 66.03 | 59.34 | 6.29 | 46.67 | 39.65 |
| adv @ image | 67.94 | 62.44 | 5.50 | 55.56 | 51.27 |
| adv @ conv4 | 66.03 | 62.75 | 3.28 | 56.12 | 51.73 |
| adv @ conv5 | 64.43 | 62.19 | 2.24 | 57.04 | 51.25 |

Table 4. Model leakage and performance trade-offs for different baselines (rows 1-2) and our adversarial training methods (rows 3-5) on imSitu activity recognition. Our methods make significantly better trade-offs than baselines.

| Model | Leakage pred. | Leakage natural | Leakage model | Performance mAP | Performance F1 |
|-------|----------------|-----------------|--------------|----------------|----------------|
| original | 75.88 | 57.68 | 18.20 | 41.39 | 40.06 |
| blackout-box | 64.33 | 54.55 | 9.78 | 22.34 | 22.77 |
| adv @ image | 72.23 | 56.53 | 15.70 | 38.41 | 37.14 |
| adv @ conv4 | 71.48 | 57.13 | 14.35 | 41.09 | 40.05 |
| adv @ conv5 | 67.25 | 56.83 | 6.32 | 38.35 | 37.48 |

6.1. Models

**Adversarial Methods** We consider three different types of adversaries which try to remove leakage at different stages in a ResNet-50 classification network.

- **adv @ image** Removing gender information directly at the image. To do this, we train an additional U-Net which predicts a mask over the image. The original image is point-wise multiplied with this mask and then given to two branches. The first branch is a ResNet-18 which attempts to detect gender (the adversary) and the second branch is a ResNet-50 that attempts to classify. See Figure 2 for more details.

- **adv @ conv4** Removing gender information from an intermediate hidden representation of ResNet-50 (on the 4th convolutional block). We use a an adversary with 3 convolutional layers and 5 linear layers.

- **adv @ conv5** Removing gender information from the final layer before object classification of ResNet-50.

Baselines We consider several alternatives to adversarial training to reduce leakage, including some that have access to ground truth detections or segmentations.

- **Original**: the original model trained on the original data, without any attempt to reduce leakage.

- **Randomization**: adding random noise to the pre-classification embedding layer of the original model. We consider adding Gaussian noise at increasing magnitudes. We expect larger perturbations to remove more leakage while preventing the model from effectively classifying images.

- **Alternative Datasets**: we also consider constructing new datasets for imSitu and COCO through downsampling approaches that reduce dataset leakage (as defined in Section 5). We refer to this as \( \alpha = 1, 2, 3 \), as defined in that section.

- **Blurr**: blurring people masks in the image when ground truth segments are available (COCO only). Many features of the people will still be visible but harder to extract.

We use a linear adversary which takes as input a vectorized form of the output feature map and uses a 5 layer MLP for classification.
People close-ups

People doing things

People holding objects

Multiple people

Figure 6. Images before and after adversarial removal of gender in image space by using a U-Net based autoencoder as inputs to the recognition model. While people are clearly being obscured from the image, the model selectively chooses to obscure only parts that would reveal gender such as faces but tries to keep information that is useful to recognize objects.

- **Blackout - Segm**: blacking out people masks in the image when ground truth segments are available (COCO only). This obscures features such as skin, clothing while leaving pose. It may also obscure objects people are closely interacting with.
- **Blackout - Box**: blacking out people bounding boxes in the images (COCO and imSitu). This removes large regions of the image around people, likely removing many objects and body pose cues.

6.2. Results

Our results on COCO object classification and imSitu activity recognition are in Table 3 and Table 4. Adversarially trained methods offer significantly better trade-offs between leakage and performance than any other method. We are able to reduce model leakage by over 75% and 60% percent on COCO and imSitu, respectively while suffering only 1.2 and 3.04 mAP performance degradation. Figure 4 and Figure 5 further highlight that our methods are making extremely favorable trade-offs between leakage and performance. Adversarial training is the only method that consistently improves upon simply adding noise to the model representation before prediction (the red curves).  

6.3. Qualitative Results

In order to obtain interpretable results, we also proposed using a U-Net autoencoder as input to our model so that gender features can be removed in image space. Fig. 6 shows original images paired with their version after gender removal. In some instances our method removes the entire person, in some instances only the face, in other cases clothing, and garments that might be strongly associated with gender. Our approach learns to selectively obscure pixels enough to make gender prediction hard but leaving sufficient information to predict other things, especially objects that need to be recognized such as hot dog, tie, umbrella, surfboard, etc. This is in contrast to our strong baselines that remove the entire person instances using ground-truth segmentation masks. A more sensible compromise is learned through the adversarial removal of gender.

7. Conclusion

In this paper we introduced dataset leakage, prediction leakage, natural leakage, and model leakage as measures of the encoded bias with respect to a protected variable in either datasets or trained models. We also demonstrated a method for the adversarial removal of features associated with a protected variable from the intermediate representations learned by a convolutional neural network. Our approach is superior to applying various forms of random perturbations in the representations, and to applying image manipulations that have access to significant privileged information about the protected variable. We expect that the setup, methods, and results in this paper will be useful for further studies of representation bias in computer vision.
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