Prediction Sensitivity: Continual Audit of Counterfactual Fairness in Deployed Classifiers

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As AI-based systems increasingly impact many areas of our lives, auditing these systems for fairness is an increasingly high-stakes problem. Traditional group fairness metrics can miss discrimination against individuals and are difficult to apply after deployment. Counterfactual fairness describes an individualized notion of fairness, but is even more challenging to evaluate after deployment. We present prediction sensitivity, an approach for continual audit of counterfactual fairness in deployed classifiers. Prediction sensitivity helps answer the question: would this prediction have been different, if this individual had belonged to a different demographic group—for every prediction made by the deployed model. Prediction sensitivity can leverage correlations between protected status and other features, and does not require protected status information at prediction time. Our empirical results demonstrate that prediction sensitivity is effective for detecting violations of counterfactual fairness.

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1 INTRODUCTION
∗ As AI-based systems take increasingly larger roles in high-stakes decisions, ensuring fairness in these systems represents a growing concern. Previous work has examined the questions of how to audit data and classifiers for bias before they are deployed [10, 32], and how to mitigate bias either during training or as a post-processing step (e.g. [12, 13, 22, 45]).

Many existing approaches use metrics that offer formal processes for “measuring” fairness. Group fairness metrics [19, 22] measure disparate treatment of groups in aggregate. These metrics are useful to demonstrate unfairness, but previous work has shown that group-fair classifiers can still make clearly unfair predictions for individuals [28]. Individual fairness metrics [17] require that similar individuals be treated the same, but the difficulty of formalizing similarity metrics makes the framework challenging to apply.

Counterfactual fairness [27] requires that a fair classifier would have made the same prediction if the individual had belonged to a different demographic group. Demonstrating that a classifier satisfies counterfactual fairness typically requires causal information about the underlying data distribution [25–27], which presents a major challenge in deploying practical audit systems based on counterfactual fairness. An important exception is the recent FlipTest [8]
system, which uses an optimal transport mapping (rather than causal information) to demonstrate counterfactual fairness. Like other existing techniques, FlipTest is designed for auditing models before they are deployed. Far less work has examined methods for ensuring that classifiers continue to perform well after deployment—even though novel examples encountered after deployment are likely to reveal bias in trained classifiers [3, 10].

This paper proposes a new approach called prediction sensitivity for continual audit of counterfactual fairness in deployed classifiers. In contrast to FlipTest, which requires the generation and evaluation of explicit counterfactual testing data during a distinct audit phase of model development (i.e. before the model is deployed), prediction sensitivity helps answer the question: would this prediction have been different, if this individual had belonged to a different demographic group—for every prediction made by the deployed model.

This kind of continual audit allows deployed systems to raise an alarm before making a potentially unfair prediction, even for novel examples. This capability represents an important difference from previous work, which may miss sources of unfairness due to missing training data. Prediction sensitivity, by contrast, will be able to catch the resulting discrimination when it occurs and is visible—after the model is deployed.

Prediction sensitivity uses the gradient of the model’s prediction with respect to the input to approximate how the prediction would have changed if specific parts of the input had been different. Specifically, our approach involves training a protected status model capable of weighting input features according to their importance for determining the protected status, and then weighting elements of the gradient using this information. Moreover, the protected status model captures correlations between the protected attribute and other input features, which is significant, since previous work has shown removing the protected attribute [16] or just flipping [8] its value can still cause discrimination in the model’s predictions. We require knowledge of the protected status of individuals at training time (to train the protected status model), but not at prediction time.

Prediction sensitivity can help avoid making biased predictions and can notify system maintainers of problems with their models. As a metric for counterfactual fairness, it can be automatically and efficiently calculated for each prediction and compared against a threshold set by the system maintainer. The protected status of individuals (i.e. the protected attribute) does not need to be present at prediction time in order to calculate prediction sensitivity.

We evaluate prediction sensitivity on both synthetic and real data, using experiments inspired by FlipTest [8]. We construct match sets (similar to FlipTest’s flipsets)—examples for which a trained classifier would have made the same prediction if the protected status had been different. Non-members of the match set represent failures of counterfactual fairness. Our results suggest that prediction sensitivity is effective at detecting these failures.

Contributions. In summary, we make the following contributions:

- We propose prediction sensitivity, a gradient-based method for measuring counterfactual fairness
- We show how to use prediction sensitivity to detect biased predictions at the individual level in deployed models
- We present experimental results suggesting that prediction sensitivity is effective for detecting biased predictions

2 BACKGROUND & RELATED WORK

Deep learning. In this paper, we focus on machine learning models represented by artificial neural networks [21]. A model $F$ is parameterized by a set of weights which are optimized during training; we write $F(x)$ to represent a
prediction made by the trained model on an example \( x \). Deep learning models are typically trained by optimizing a loss function \( L \) by calculating the gradient of the loss with respect to the weights and updating the model accordingly.

**Fairness in machine learning.** The bulk of previous work on fairness in machine learning attempts to improve group fairness metrics at training time, often by the introduction of new kinds of regularization [4, 5, 7, 11–14, 18, 22, 29, 30, 34, 35, 39, 41, 43–46]. Many of these approaches are suitable for deep learning, and have been empirically validated using the metrics described above. These approaches typically apply when each example’s features include a protected attribute \( z \in x \) to indicate the example’s protected status (as a member or non-member of a protected class). Existing approaches focus on notions of group fairness, and are validated using metrics for group fairness. As a result, they can sometimes produce models that give blatantly unfair predictions for specific individuals, even though they score well on group fairness metrics [17, 28].

**Counterfactual fairness.** Counterfactual fairness [27] requires that each prediction a classifier makes would have been the same if the protected attribute had been different. Counterfactual augmentation [25, 26] focuses on counterfactual statements about individuals in the original training data. Most approaches involve a manual process of asking a human expert to construct a new training example that is identical to an existing one, except for the protected attribute. For example, in the NLP setting, classifiers often associate the profession of nursing with women [9], due to the large volume of (biased) statements in the training data that involve female nurses. For each statement about a female nurse in the training data, we might ask the expert to write an identical statement about a male nurse—and a classifier trained on the augmented data will be less likely to associate nursing with women as a result.

Counterfactual augmentation has proven extremely effective in models for language [20, 24, 47] and images [15], where an explicit protected attribute is often not present. In these domains, counterfactual augmentation is generally a manual process; recent work provides support [31, 42] but not complete automation. Prediction sensitivity (defined in Section 3) can be viewed as a way of measuring counterfactual fairness. Because our evaluation is done in the simpler setting of a binary protected attribute, we are able to use a relatively simple algorithm for automatic counterfactual augmentation.

**FlipTest.** Our work is most closely related to FlipTest [8], an approach for generating augmented datasets for auditing the counterfactual fairness of classifiers. FlipTest determines whether a model is sensitive to the protected status of an individual or subgroup using optimal transport mapping. It reveals salient patterns in a model’s behavior by constructing approximate mappings using a Generative Adversarial Network (GAN). Using these mappings, flipsets and a transparency report are created, which are utilized to determine which individuals or subgroups are discriminated against, as well as identify those features which may be associated with it.

The major advantage of our approach is the ability to audit classifiers during deployment. Unlike FlipTest, our approach does not require the explicit generation of datasets to measure counterfactual fairness; instead, it provides a measurement for each prediction the classifier makes, with no other inputs required. Our approach also has the novel ability to detect failures of counterfactual fairness resulting from previously-unseen data.

**Interpretability in deep learning.** The related field of interpretable AI seeks to enable auditability by understanding why a model made a specific prediction. The problem of interpretability has been studied extensively in the setting of image classification, where the goal is to understand which pixels of the image were most important in deciding its class. Numerous gradient-based approaches have been proposed [6, 23, 33, 36–38]; our approach to prediction sensitivity draws on these ideas.
3 PREDICTION SENSITIVITY

This section describes prediction sensitivity, an easily calculated metric for auditing the counterfactual fairness of deployed models. For a single prediction, our goal is to answer the same question as FlipTest [8]: had the individual been of a different protected status, would the model have treated them differently?

We consider a classifier $F$ and an individual input $x$. Let the counterfactual individual $x'$ represent the same individual as $x$, but with a different protected status. We would like to know if $F(x) = F(x')$. Prediction sensitivity answers this question by computing two gradients with respect to the input $x$, as depicted in Figure 1: the protected status feature weights (§ 3.1) and the per-feature influence (§ 3.2). The final prediction sensitivity is the dot product of the two components—a measure of how changes in the input $x$ would lead to changes in $F$’s prediction, weighted by each feature’s influence on the individual’s protected status. Both components are inspired by gradient-based approaches for interpretability (especially SmoothGrad [37]).

3.1 Protected Status Feature Weights

The protected status feature weights measure how the features of $x$ contribute to the $x$’s protected status. We calculate the protected status feature weights by training a protected status model $A$ to predict $x$’s protected status, and computing the weights using the gradient of $A(x)$. If $A$ captures the correlation between input features and protected status, then these weights encode the strength of each feature’s value on protected status.

The protected status of an individual may be encoded in an explicit protected attribute $a \in x$, and $A$ will learn that the correlation between $a$ and the protected status. When the protected attribute is not present at prediction time, or other features are correlated with protected status, $A$ will discover the appropriate correlations. The specifics of the protected status model $A$ depend on the problem setting. In our experiments, we use a simple neural network with a similar architecture to the classifier we are auditing. The primary requirement is that $A$ should capture correlations between features in $x$ and the protected status $s$.

Definition 3.1 (Protected Status Feature Weights). The protected status feature weights for an example $x \in \mathbb{R}^k$ are a length-$k$ vector defined as follows:

$$PSW(x) = \text{abs}(\nabla A(x))$$

where $\text{abs}$ denotes element-wise absolute value.

3.2 Per-Feature Influence & Prediction Sensitivity

The second component of prediction sensitivity is the per-feature influence, a vector that captures the influence of each input feature on the classifier’s prediction. The per-feature influence describes how much a hypothetical change in each
Prediction sensitivity is defined as the dot product of this gradient with the protected status feature weights for $x$.

**Definition 3.2 (Prediction sensitivity).** The prediction sensitivity $PS(x) \in \mathbb{R}$ for an example $x$ is defined as:

$$PS(x) = PSW(x) \cdot \text{abs}(\nabla F(x))$$

$$= \text{abs}(\nabla A(x)) \cdot \text{abs}(\nabla F(x))$$

where $\nabla A(x)$ is the gradient of $A(x)$ (with respect to $x$) and $\text{abs}$ denotes element-wise absolute value.

### 3.3 Prediction Sensitivity as a Measure of Counterfactual Fairness

Prediction sensitivity is designed to answer the question: *had the individual been of a different protected status, would the model have treated them differently?* Prediction sensitivity is thus likely to be a close approximation of a measurement of counterfactual fairness in most settings. Formally, counterfactual fairness is defined as follows:

**Definition 3.3 (Counterfactual fairness [27]).** A predictor $\hat{Y}$ of $Y$ is counterfactually fair given the sensitive attribute $A = a$ and any observed variables $X$ if:

$$\Pr[\hat{Y}_{A=a} = y \mid X = x, A = a] = \Pr[\hat{Y}_{A=a'} = y \mid X = x, A = a]$$

for all $y$ and $a' \neq a$ (i.e. $a'$ denotes a different protected status than $a$).

This definition requires that the distribution of $\hat{Y}$ does not change when $A$ changes, as long as things which are not causally dependent on $A$ are held constant. Demonstrating counterfactual fairness thus requires knowledge about the causal relationships between variables (in particular, about the causal relationships between $A$ and other attributes).

In our approach, the protected status model $A$ encodes correlations between the features of $x$ and the protected status ($A$ in the above definition). Our $A$ model can be seen as an overapproximation of the required causality knowledge, in the sense that it may learn correlations that are not causal. Prediction sensitivity therefore may produce false positives (i.e. it may be high, even for a prediction that satisfies counterfactual fairness), but as long as the $A$ model correctly captures correlations with the protected status, it will not produce false negatives.

A second important condition for the correspondence between prediction sensitivity and counterfactual fairness is that the gradient should provide good information about the influence of individual features on the prediction (for both the $A$ and $F$ models). When the gradient is smooth, then prediction sensitivity should be an effective way to measure counterfactual fairness for individual predictions.
4 USING PREDICTION SENSITIVITY TO AUDIT DEPLOYED MODELS

Prediction sensitivity can be calculated at training time, using a test set, to measure fairness properties of the trained classifier. However, the real strength of prediction sensitivity is that it can also be used at prediction time—calculating prediction sensitivity requires neither the true label nor the protected attribute. Prediction sensitivity can thus be deployed alongside production classifiers, to continually measure fairness properties of the predictions those classifiers make over time, as shown in Figure 2.

**Training time.** At training time, we train both the classifier $F$ and the protected status model $A$, as shown in Figure 2(a). Training $A$ requires information about protected status to be present in the training data. The classifier $F$ can be trained to satisfy fairness conditions using training-time techniques (e.g. [5, 11, 22, 41, 43, 44]), and can be audited before it is deployed using group fairness metrics and approaches like FlipTest [8]).

We can also use prediction sensitivity to audit the trained classifier for counterfactual fairness at training time. We compute prediction sensitivity for examples in the test set and ensure that (1) both the mean and variance of the prediction sensitivity are low, and (2) there are no outliers representing disadvantaged individuals. The mean prediction sensitivity for the classifier on the test set can be saved as a baseline for use during deployment.

**Deployment time.** After the classifier is deployed, prediction sensitivity can be calculated for each prediction and compared against the baseline by a monitor deployed with the system, as shown in Figure 2(b). If a particular prediction results in prediction sensitivity much higher than the baseline, then it is likely that counterfactual fairness has been violated. In this case, the monitor can raise an alarm.

**Reacting to high prediction sensitivity.** When the classifier fails to satisfy counterfactual fairness, prediction sensitivity can help guide action to correct the situation.

1. Most importantly, the prediction should not be used to make decisions, since it may cause harm. The system should fall back on manual intervention by an expert, or a backup system (e.g. a default decision).
2. Properties of the individual whose prediction caused the failure of counterfactual fairness may immediately suggest an approach for improving the classifier $F$. Such failures may be due to a lack of similar individuals in the training data; here, the classifier can be improved by re-training on additional data.
3. The feature-wise prediction sensitivity may indicate that the classifier has focused on specific features in making discriminatory predictions. Particular attention should be paid to these features when improving the training data.

**Auditing by third parties.** Prediction sensitivity can only be calculated with whitebox access to the classifier $F$ and protected status model $A$, because of the gradient calculations involved. This limits the use of prediction sensitivity to the party who trained and deployed the model; it is not feasible for third parties to audit a deployed system using prediction sensitivity without access to the classifiers involved.

This limitation means that prediction sensitivity is not a useful tool for helping journalists or other third parties to discover discriminatory behavior in existing systems. However, corporations face increasing public pressure to ensure that their systems do not discriminate; this pressure provides a significant incentive for companies to adopt approaches like prediction sensitivity to improve their models and provide evidence of fairness to their users.

5 EVALUATION ON SYNTHETIC DATA VIA CAUSAL MODELING

This section describes an empirical evaluation of prediction sensitivity as a measure for counterfactual fairness using synthetic data. Using synthetic data allows us to precisely model our desired fairness definition (including causal information), and measure the effectiveness of our approach.
5.1 Evaluation Approach

Prediction sensitivity is intended to answer the question, had the individual been of a different protected status, would the model have treated them differently? Given a dataset of otherwise identical individuals with different protected statuses, we could ask our model to make a prediction for each one and compare them; differing predictions for corresponding individuals represent failures of counterfactual fairness. However, actually constructing this dataset is typically very challenging [8, 17]. By employing synthetic data, we can use an alternative approach that avoids this challenge but accomplishes the same goal.

Our approach is to train two classifiers and then compare their predictions to detect failures of counterfactual fairness. One is the “original” classifier $\mathcal{F}$, which may not satisfy counterfactual fairness. The second model is the unbiased classifier $\hat{\mathcal{F}}$, trained on modified data to ensure counterfactual fairness. We evaluate the counterfactual fairness of $\mathcal{F}$ by comparing its predictions on the test set against those of $\hat{\mathcal{F}}$. When the two models make different predictions, this indicates a possible failure of counterfactual fairness. We call the set of individuals in the test set for whom the two models make matching predictions the match set. We evaluate prediction sensitivity as a measure of counterfactual fairness by checking whether prediction sensitivity can effectively distinguish members of the match set from non-members.

Modeling counterfactual fairness in synthetic data. We generate two synthetic datasets according to the causal models shown in Figure 3. The causal model in Figure 3(a) includes a causal relationship between protected status and outcome, and is thus likely to result in biased classifiers. In our evaluation, we train the classifier $\mathcal{F}$ using data generated according to this model—so we expect that $\mathcal{F}$ will not always satisfy counterfactual fairness. The causal model in Figure 3(b) lacks this causal relationship. We train the unbiased classifier $\hat{\mathcal{F}}$ using data generated according to this model, so that $\hat{\mathcal{F}}$ satisfies counterfactual fairness.

In our evaluation, following Lipton et al. [28], we generate a synthetic dataset with two features and binary labels. Augmenting this dataset with a protected attribute (gender) chosen at random will produce a dataset consistent with the causal model in Figure 3(b). Models trained on this dataset score well on group fairness metrics like statistical parity and disparate impact, since gender is completely independent of the label and other features. We use this dataset to train the model $\hat{\mathcal{F}}$. We introduce bias in our synthetic dataset by generating the protected attribute based on the label:

$$\Pr(z = \text{woman}) = \begin{cases} .25 & \text{if } y = \text{positive} \\ .75 & \text{if } y = \text{negative} \end{cases}$$
This model clearly introduces bias against women—men are much more likely to be members of the positive class, while women are much more likely to be members of the negative class. We use this dataset to train the model \( \mathcal{F} \).

**Enumerating match sets.** The next step is to find individuals for whom \( \mathcal{F} \) and \( \hat{\mathcal{F}} \) make different predictions. Since \( \hat{\mathcal{F}} \) is defined to satisfy counterfactual fairness, such a mismatch likely indicates a failure of counterfactual fairness for \( \mathcal{F} \). We call the set of individuals for whom both models make the same predictions a *match set*. The classifier \( \hat{\mathcal{F}} \) likely satisfies counterfactual fairness for members of the match set, and likely violates it for non-members. For counterfactually fair classifiers, the match set should include the entire test set.

**Evaluating prediction sensitivity.** The final step of our evaluation is to demonstrate that prediction sensitivity is effective for distinguishing members of the match set from non-members. We calculate the prediction sensitivity for \( \mathcal{F} \)'s predictions on the test set, and use it to build a classifier \( \mathcal{D} \) to distinguish match set members from non-members. \( \mathcal{D} \) is defined as follows (where \( p \) is the prediction sensitivity associated with an example, and \( \theta \) is a threshold):

\[
\mathcal{D}(p, \theta) = \begin{cases} 
\text{member} & \text{if } p \leq \theta \\
\text{non-member} & \text{if } p > \theta 
\end{cases}
\]

Here, the threshold \( \theta \) allows trading off between false negatives and false positives.

**Comparison to FlipTest evaluation.** FlipTest [8] calculates a similar set of individuals—called a flipset—by directly generating datasets of counterfactuals. For each individual \( x \) in the test set, FlipTest uses a generative adversarial network (GAN) to generate an in-distribution individual \( x' \) with the opposite protected status. Then, FlipTest asks the classifier under evaluation (\( \mathcal{F} \)) to make predictions on each individual and their corresponding counterfactual. Matching predictions are considered counterfactually fair, since the model treats both individuals the same; non-matching predictions are considered failures of counterfactual fairness. FlipTest calls the set of non-matching predictions a flipset—the set of individuals for whom the prediction flips when protected status changes. Our approach has a similar goal—the flipset serves the same purpose as our match set, and inspires its name—but our approach does not require the construction of a GAN or the enumeration of counterfactual individuals.

### 5.2 Experiment Setup

We used Scikit-learn to generate synthetic datasets consistent with the causal models shown in Figure 3. We trained the classifier \( \mathcal{F} \) using data consistent with the model in Figure 3(a), and the counterfactually fair classifier \( \hat{\mathcal{F}} \) using data consistent with the model in Figure 3(b). We trained \( \mathcal{A} \), \( \mathcal{F} \), and \( \hat{\mathcal{F}} \), then computed prediction sensitivities and constructed the distinguisher \( \mathcal{D} \) consistent with the process described in the last section. We constructed receiver operating characteristic (ROC) curves and calculated area under the curve (AUC) values for the distinguisher by varying \( \theta \). Due to nondeterminism in the training process, we performed 30 trials of the experiment.

### 5.3 Results

The results of our experiment on synthetic data appear in Figure 4. Figure 4(a) shows that average prediction sensitivity is much higher for non-members of the match set than it is for members, suggesting that prediction sensitivity is able to distinguish individuals for whom the classifier \( \mathcal{F} \) fails to satisfy counterfactual fairness.

Figure 4(b) shows a receiver operating characteristic (ROC) curve and its area under the curve (AUC) value for the distinguisher \( \mathcal{D} \) built using prediction sensitivity. We plot one curve per trial we performed (30 curves in total) and give the average AUC over all trials. The results show that prediction sensitivity is capable of distinguishing members of the match set from non-members, even for low false positive rates.
Fig. 4. Using prediction sensitivity to audit models trained on synthetic data. (a) shows that prediction sensitivity is low for members of the match set, but high for non-members (note the logarithmic scale in the vertical axis). (b) shows that a distinguisher based on prediction sensitivity is effective at detecting failures of counterfactual fairness.

6 EVALUATION ON REAL DATA VIA COUNTERFACTUAL AUGMENTATION

In Section 5, we were able to generate synthetic data consistent with causal models we designed ourselves, enabling the comparison of the two models ($F$ and $\hat{F}$) to build match sets. A similar process is impossible for real data, since the underlying causal model is unknown.

For our evaluation on real datasets, we instead approximate the same procedure using counterfactual augmentation. Counterfactual augmentation [25, 26] attempts to ensure counterfactual fairness in trained classifiers by adding new training examples. For each individual $x$ in the training data, we add a corresponding individual $x'$ with a different protected status but the same outcome. Classifiers trained on the augmented data will be more likely to satisfy counterfactual fairness, because each training example has a corresponding counterfactual also present during training. Previous work has shown this approach to be effective in training classifiers that also score well on group fairness metrics [25, 26].

6.1 Evaluation Approach

Our evaluation on real data follows the same process as our synthetic data evaluation described in Section 5, but using counterfactual augmentation to construct training data for the counterfactually fair model $\hat{F}$.

**Constructing augmented datasets.** In complex domains like NLP, counterfactual augmentation is a manual process. In our simpler setting of binary classification with an explicit, binary protected attribute, it is possible to automate this process. In particular, for each example in the original dataset, we can construct a new example with the opposite value for the protected attribute. For each training example $x$, we construct a new one $x'$ in which the protected attribute is replaced by its negation. The label remains the same. The resulting dataset has exactly twice the original number of
examples. This approach is simple and effective, but it requires the protected attribute to be discrete (ideally, binary) and be explicitly included in the data (in e.g. NLP data, it often is not).

**Evaluating prediction sensitivity.** Having constructed an augmented dataset, we can evaluate prediction sensitivity in the same way as in Section 5, by constructing a match set and a distinguisher.

**Limitations of our implementation of counterfactual augmentation.** The goal of counterfactual augmentation is to approximate data drawn from a similar distribution to the original data, but without the causal relationship between protected status and outcome. However, our approach modifies only the protected attribute, and leaves other (possibly correlated) features alone. If other features are correlated with the protected attribute, then the correlations between those features and the individual’s original protected status may still exist.

Consider the Adult dataset [1] (used in our empirical evaluation), which includes job category and gender (a protected attribute) as features, and income as the label. It is likely that job category is correlated with gender, but our approach for counterfactual augmentation ignores this correlation. As a result, the classifier $\hat{F}$ may fail to satisfy counterfactual fairness in some cases, even though it is trained on counterfactually augmented data, because it may learn to discriminate based on features correlated with the protected attribute (rather than the protected attribute itself).

This is a limitation of our evaluation approach—not of prediction sensitivity itself. As described in Section 3, prediction sensitivity does capture correlations between all features and protected status, via the protected status model.

**Comparison to FlipTest evaluation.** As described in Section 5, the match sets we generate in our evaluation are similar to FlipTest’s flipsets. However, FlipTest uses a generative adversarial network (GAN) to generate the augmented data to construct flipsets, while we use a simpler form of counterfactual augmentation. The GAN-based approach can better capture correlations between the protected attribute and other features, but it is more complex and may also fail to generate out-of-distribution counterfactuals that would have exposed failures in the classifier being tested.

### 6.2 Experiment Setup

We follow the same experimental setup as in Section 5, training $F$ on the original data and $\hat{F}$ on the augmented data. We calculated prediction sensitivity for each of $F$’s predictions on the test set as described in Section 3, training the protected status model $A$ using the original training data used for $F$. We defined the distinguisher $D$ based on these prediction sensitivity values. As in Section 5, we performed 30 trials.

**Datasets.** Our evaluation considers two commonly-used datasets in the AI fairness literature: the Adult [1] and COMPAS [2] datasets. Statistics of the two datasets are shown in Table 1. Both involve classification tasks: the Adult dataset’s task is predicting whether an individual’s income is greater than or less than $50,000, and the COMPAS dataset’s task is predicting recidivism risk. Both datasets are known to contain embedded bias: models trained on the Adult dataset tend to predict that white males have the highest chance of having high income, and models trained on the COMPAS dataset tend to predict that Black suspects are most likely to re-offend. We augment both datasets with counterfactual training examples as described earlier. This process produces datasets that are exactly twice as large as the originals. For each male instance in the Adult dataset, for example, we add a female instance that is identical (including the label) except for the protected attribute.

**Model architectures.** As shown in Table 1, we use a linear network architecture with a single hidden layer and the ReLU activation function. The sigmoid activation function is applied on the output layer. The loss function is the binary cross entropy loss and Adam is chosen as the optimizer with a learning rate of 0.001. We find that a wider model (256
Table 1. Information about the datasets and models used in our experiments.

| Dataset | Dataset Size | Model Properties |
|---------|--------------|-------------------|
|          | Features | Train | Test | Layers | Layer Width | Activation | Accuracy |
| Adult [1] | 95 | 24752 | 6188 | 3 | 32 | ReLU | 84.6% |
| COMPAS [2] | 399 | 4937 | 1235 | 3 | 256 | ReLU | 67.9% |

Table 2. Comparison of average area under the curve (AUC) for original and augmented test sets. Results averaged over 30 trials.

| Dataset & Prot. Attr. | Training Epochs | Classifier Accuracy | Prediction Sens. AUC |
|-----------------------|-----------------|---------------------|---------------------|
|                       |                 | Original | Augmented | Original | Augmented |
| Adult [1] (sex)       | 10              | 84.0% ± 1.65  | 84.3% ± 1.53 | 57.4% ± 0.17  | 59.3% ± 0.15 |
|                       | 40              | 84.4% ± 1.52  | 85.1% ± 0.84 | 69.8% ± 0.15  | 69.9% ± 0.17 |
| Adult [1] (race)      | 10              | 84.3% ± 1.74  | 84.1% ± 1.82 | 57.5% ± 0.18  | 60.4% ± 0.17 |
|                       | 40              | 84.6% ± 1.55  | 84.0% ± 2.13 | 66.7% ± 0.19  | 66.3% ± 0.19 |
| COMPAS [2] (sex)      | 10              | 67.7% ± 0.60  | 66.8% ± 0.74 | 77.7% ± 0.07  | 79.4% ± 0.06 |
|                       | 40              | 66.7% ± 0.54  | 66.0% ± 0.79 | 76.4% ± 0.05  | 77.5% ± 0.04 |
| COMPAS [2] (race)     | 10              | 67.9% ± 0.40  | 66.9% ± 0.42 | 79.2% ± 0.07  | 78.0% ± 0.07 |
|                       | 40              | 66.6% ± 0.47  | 65.9% ± 0.47 | 74.8% ± 0.05  | 75.1% ± 0.05 |

neurons) works better for the COMPAS dataset, while a narrower one (32 neurons) suffices for the Adult dataset. We train each classifier for 40 epochs, and achieve roughly state-of-the-art accuracy for both datasets.

Test sets. When evaluating the fairness of a classifier, should we also augment the test set via counterfactual augmentation? Wick et al. [40] argue in favor of an unbiased test set (i.e. “fair” data) to evaluate fairness. In particular, a fair classifier may produce lower test accuracy on biased data, leading to the (false) conclusion that improvements to fairness have “hurt” accuracy. We ran our experiments twice: once using test sets containing original data only (20% of the original dataset), and once using counterfactually augmented test sets. We report results for the augmented test sets, since we found essentially no differences between the two settings (more in Section 6.3).
6.3 Results

The results of our experiments on real data appear in Figures 5, 6, and 7, and Table 2; we summarize them below.

**Counterfactual augmentation improves group fairness metrics (Figure 5).** Figure 5 shows that as expected, classifiers trained on counterfactually-augmented data score much better according to common group fairness metrics than classifiers trained on the original data. This result is expected, and consistent with previous work [8, 25, 26].

**Prediction sensitivity detects violations of counterfactual fairness (Figures 6 and 7).** Figure 6 plots the distribution of prediction sensitivities for members and non-members of the match sets (“matching” and “non-matching,” respectively). In both datasets, and for both protected attributes, members of the match set have consistently smaller prediction sensitivity; on average, non-members have significantly higher values for prediction sensitivity.

Figure 7 plots receiver operating characteristic (ROC) curves and corresponding average area under the curve (AUC) values for the distinguisher $D$ built using prediction sensitivity for each dataset. Each plot contains 30 ROC curves, one per trial of the experiment. The results show that prediction sensitivity is an effective approach for distinguishing between members and non-members of the match set, and thus it is likely effective at detecting failures of counterfactual fairness. The results also demonstrate considerable variability, especially for the Adult dataset. Both figures contain results based on a counterfactually-augmented test set. Further discussion of these results appears in Section 6.4.

**Results are consistent for original and augmented test sets (Table 2).** As described in Section 6.2, we performed each experiment twice—once with the original test set, and once with a counterfactually-augmented test set. Table 2 compares the results of these two experiments. The results are nearly identical, suggesting that prediction sensitivity is effective in both settings. Table 2 also compares fully-trained classifiers (40 epochs) against partially-trained classifiers (10 epochs). The impact of the fine-tuning that occurs in later stages of training depends on the dataset; prediction sensitivity is more effective for detecting violations in the fully-trained classifier for the Adult dataset, but it is less effective in this setting for the COMPAS dataset.
6.4 Discussion

The results described in Section 6.3 suggest that prediction sensitivity is an effective measure of counterfactual fairness. However, the average area under the curve (AUC) for our experiments on real datasets is significantly lower than the AUC for our synthetic data experiments. We suspect two possible contributing factors. First, it could be that bias is less severe in the real datasets, so failures of counterfactual fairness are harder to detect. This would also explain the difference in AUC between the two real datasets. Second, our approach to counterfactual augmentation could be missing significant correlations between other features and protected status. This could cause low AUC by invalidating
the match set (prediction sensitivity could be correct, while the match set is wrong). In particular, this factor may be responsible for the plateaus in ROC curves for some trials on the Adult dataset (Figure 7).

Our results suggest that prediction sensitivity is effective at detecting unfair predictions, but they also reflect the inherent challenge of this task. Individual predictions with extremely high prediction sensitivity are likely to be blatantly unfair, and should be easily detected using prediction sensitivity; however, borderline cases may be more difficult to detect, as demonstrated by the variability in the ROC curves in Figure 7.

7 CONCLUSION

We have presented a new, end-to-end approach for continual auditing of counterfactual fairness in deployed deep learning systems. We propose prediction sensitivity, an efficiently computed metric for counterfactual fairness. Prediction sensitivity can be used at prediction time, on deployed classifiers, to raise an alarm when the classifier makes an unfair prediction. Prediction sensitivity handles correlations between features and protected status, and does not require access to individuals’ protected status at prediction time. Our empirical evaluation on synthetic and real datasets suggests that prediction sensitivity is effective for detecting failures of counterfactual fairness.

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