Differential Parity: Relative Fairness Between Two Sets of Decisions

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Abstract

With AI systems widely applied to assist human in decision-making processes such as talent hiring, school admission, and loan approval; there is an increasing need to ensure that the decisions made are fair. One major challenge for analyzing fairness in decisions is that the standards are highly subjective and context-dependent — there is no consensus for what absolute fairness means for every scenario. Not to say that different fairness standards often conflict with each other. To bypass this issue, this work aims to test relative fairness in decisions. That is, instead of defining what are “absolutely” fair decisions, we propose to test the relative fairness of one decision set against another with differential parity — the difference between two sets of decisions should be independent from a certain sensitive attribute. This proposed differential parity fairness notion has the following benefits: (1) it avoids the ambiguous and contradictory definition of “absolutely” fair decisions; (2) it reveals the relative preference and bias between two decision sets; (3) differential parity can serve as a new group fairness notion when a reference set of decisions (ground truths) is provided. One limitation for differential parity is that, it requires the two sets of decisions under comparison to be made on the same data subjects. To overcome this limitation, we propose to utilize a machine learning model to bridge the gap between the two decisions sets made on difference data and estimate the differential parity.

1 Introduction

Recently, much research has focused on mitigating bias and discrimination in AI systems. This is because AI systems are increasingly being used to make decisions that affect people’s lives and sometimes the learned models behave in a biased manner that gives undue advantages to a specific group of people (where those groups are determined by sex, race, etc.). Such biased decisions can have severe consequences with AI systems being used in deciding whether a patient gets released from hospital [Kharpal, 2018], which loan applications are approved [Olson, 2011], whether citizens are released or sentenced to jail [Angwin et al., 2016], and whether universities/companies accept/hire them [Dastin, 2018].

One major challenge for analyzing fairness in decisions is that, the standard for “absolute” fairness are highly subjective and context-dependent [Abu-Elyounes, 2020]. For example, College 1 demands equality and admits students without considering gender/race (individual fairness [Dwork et al., 2012]) while College 2 demands equity and admits same percentage of students from each gender/race group (demographic parity in group fairness [Dwork et al., 2012]). Neither College 1 or 2 is wrong but these are often contradictory standards and lead to very different outcomes — they are impossible to be satisfied simultaneously [Friedler et al., 2021].

One way to bypass this issue is to test relative fairness between different decision sets. That is, instead of defining what are “absolutely” fair decisions, we measure the relative fairness of one decision set against another. In the field of machine learning algorithmic fairness [Hardt et al., 2016], two group fairness criteria were proposed to measure whether a machine learning model’s prediction $R$ is relatively fair when compared to a set of reference set $Y$ (ground truth) over a certain sensitive attribute $A$. These are (1) separation $R \perp A \mid Y$ requiring the model’s prediction $R$ to be conditionally independent from the sensitive attribute $A$ given the reference set $Y$; and (2) sufficiency $Y \perp A \mid R$ requiring the reference set $Y$ to be conditionally independent from the sensitive attribute $A$ given the model’s prediction $R$. In the case of binary classification, group fairness notion equalized odds (or true positive rate parity and false positive rate parity) ensures separation while predictive parity ensures sufficiency [Hardt et al., 2016]. However, separation and sufficiency cannot be satisfied simultaneously when $A$ and $Y$ are not statistically independent (unless $R = Y$ is a perfect predictor) [Friedler et al., 2021]. In addition, it is not always possible to have a ground truth reference set $Y$ of “absolutely” fair decisions. In the comparison of two decision sets, the choice of the reference set $Y$ largely affects the result of separation and sufficiency. For example, the results can be Decision Set A satisfies separation but not sufficiency when compared to Decision Set B while Decision Set B satisfies sufficiency but not separation when compared to Decision Set A. It is hard to tell whether these two decision sets are relatively fair to each other.

In this work, we propose a novel and general relative fairness notion called differential parity. Differential parity re-
quires the difference between two sets of decisions to be independent from a certain sensitive attribute \((R_0 - R_1) \perp A\). Different from separation and sufficiency, which decision set is chosen as \(R_0\) does not affect whether differential parity is satisfied. In the case that differential parity is violated, its result can also tell the relative preference between \(R_0\) and \(R_1\) over the sensitive attribute \(A\)—one decision set is constantly overrating one sensitive group over the other when compared to the other decision set. For example, Human Resource (HR) \(0\) always rates female candidates one point higher than HR 1’s ratings and HR 0 also rates male candidates two points lower than HR 1’s ratings. In this case, there is a differential parity between HR 0 and 1’s ratings over gender and we can see that HR 0 is overrating female candidates over male candidates compared to HR 1 (or HR 1 is overrating male candidates over female candidates compared to HR 0). Although we do not know whether HR 0 or HR 1 is fairer, we do know the relative bias between HR 0 and 1—HR 0 prefers female candidates more than HR 1. This definition of differential parity has the following benefits: (1) it avoids the ambiguous and contradictory definition of what absolutely fair decisions are—no need to choose a ground truth set; (2) it reveals the relative preference or bias between different decision sets; (3) differential parity can serve as a new group fairness notion (other than separation and sufficiency) when a reference set (of ground truth) is provided. For the previous example, College 1 can provide a reference set where admission decisions were made regardless of gender/race while College 2 provides a different reference set where the same ratio of students were admitted in each gender/race group. With differential parity between College 1 and 2, we will know that College 2 is unfair if the admission decisions should be made regardless of gender/race while College 1 is unfair if the same ratio of students should be admitted in each gender/race group.

One limitation of differential parity is that it requires the two sets of decisions to be made on the same data. This won’t be a problem when one of the decision set comes from a machine learning model. However, when both decision sets are from human beings, such overlapping decisions are not always available even for the same task—e.g. there might be multiple HRs screening for the same job application, but one application is only screened by one HR to avoid wasting of human effort. To overcome this limitation, we propose an estimation framework of differential parity between Human 0’s decisions \(R_0(x \in X_0)\) on data \(X_0\) and Human 1’s decisions \(R_1(x \in X_1)\) on data \(X_1\) by (1) fitting a machine learning model \(f\) with \((X_0, R_0(x \in X_0))\); (2) testing the differential parity of the model’s predictions on data \(X_1\)—\(f(x \in X_1)\) against \(R_1(x \in X_1)\). In this way, the machine learning model \(f\) serves as a bridge connecting the decisions made on two different sets of data. Both theoretically and empirically, we show that, the differential parity between \(R_0\) and \(R_1\) can be estimated using the differential parity between \(R_0(x \in X_0)\) and \(f(x \in X_0)\), and the differential parity between \(R_1(x \in X_1)\) and \(f(x \in X_1)\). Note that, this work does not evaluate differential parity between decisions made for different tasks or in different contexts. When we say decisions made on different data, we mean different data from the same dataset (for the same decision task).

### 1.1 Motivating Example

In this section, we demonstrate the potential application of the proposed relative fairness notion differential parity with the following example scenarios.

**Scenario 1:** Test a machine learning model \(f\)’s relative fairness against the ground truth labels \(Y(X)\) of a test set \(X\). Differential parity can be calculated between the model’s predictions on the test set \(f(X)\) and the ground truth labels \(Y(X)\) over a certain sensitive attribute \(A\) (e.g. Sex). Possible outcomes are (1) differential parity is satisfied \((f(X) - Y(X)) \perp A\); the model is relatively fair with respect to the ground truth and thus should be considered as fair; (2) differential parity is violated \((f(X) - Y(X)) \not\perp A\); the proposed differential parity metrics in Section 2.2 will show whether the model overly prefers \(A = \text{Male}\) or \(A = \text{Female}\) compared to the ground truth.

**Scenario 2:** Test the relative fairness between two sets of decisions made on different data (for the same task) \(R_0(x \in X_0)\) and \(R_1(x \in X_1)\). For example, admission decisions were made from two consecutive years. The differential parity between the decisions of the current year and those of the previous year can be estimated with our proposed algorithms in Section 2.3. E.g., decisions made by a new committee member this year can be tested against the consensus decisions from the previous year to detect unwanted biases from that member. Furthermore, the relative fairness between the consensus decisions of the two consecutive years can be utilized to guide the admission process towards a specific fairness goal, e.g. increasing the female student ratio.

### 1.2 Contributions

The contributions of this work include:

- The proposed relative fairness notion differential parity covers not only algorithmic fairness but also relative fairness in human decisions.
- Two machine learning-based algorithms are proposed to estimate the violation of differential parity between decisions made on different data.
- The empirical results demonstrating the consistency and robustness of the proposed differential parity metrics and the effectiveness of estimating the relative bias between decision sets with the proposed algorithms.

### 2 Methodology

#### 2.1 Relative Fairness—Differential Parity

**Definition 1. Differential Parity.** Given a set of data \(X \in \mathbb{R}^d\) with a sensitive attribute \(A(x \in X) \in \mathbb{R}\), two sets of decisions \(R_0(x \in X), R_1(x \in X) \in \mathbb{R}\) made on this data set satisfy differential parity over the sensitive attribute \(A(x)\) if and only if

\[
(R_0(x) - R_1(x)) \perp A(x).
\]

**Definition 1** provides a general definition of differential parity that can be applied to almost any scenario. However, it is difficult to evaluate directly. Therefore, we also consider
the following definition of differential parity for binary sensitive attributes.

**Definition 2. Differential Parity for Binary Sensitive Attributes.** Given a set of data \( X \in \mathbb{R}^d \) with a binary sensitive attribute \( A(x \in X) \in \{0, 1\} \). Two sets of decisions \( R_0(x \in X), R_1(x \in X) \in \mathbb{R} \) on this data set satisfy differential parity over the sensitive attribute \( A(x) \) if and only if the difference of the decisions on each sensitive group follow the same distribution:

\[
R_\Delta(A = 0) \overset{d}{=} R_\Delta(A = 1)
\]

where

\[
R_\Delta(A = a) = \{R_0(x) - R_1(x) \mid A(x) = a, x \in X\}.
\]

Definition 2 is equivalent to Definition 1 in the case of binary sensitive attributes. Since the two sets of decisions are independent given the data \( x \in X \), the decision differences \( R_\Delta(A = a) \) are independent and identically distributed (i.i.d.). Based on the central limit theorem and the law of large numbers, the sampled mean of \( R_\Delta(A = a) \) follows a normal distribution in large samples:

\[
\overline{R_\Delta}(A = a) = \mu(R_\Delta(A = a)) \pm \frac{\sigma(R_\Delta(A = a))}{\sqrt{|A = a|}} N(0, 1),
\]

(1)

where \( \mu(R_\Delta(A = a)) \) and \( \sigma(R_\Delta(A = a)) \) are the mean and standard deviation of the distribution of \( R_\Delta(A = a) \).

### 2.2 Metrics For Differential Parity

Given (1), we define two metrics to measure the violation of differential parity—whether the decision differences on each sensitive group follow the same distribution. We first measure the probability of the difference between \( \overline{R_\Delta}(A = 0) \) and \( \overline{R_\Delta}(A = 1) \) arises from random chance with null hypothesis testing [Anderson et al., 2000]; and then measure the strength of the difference with effect size testing [Chow, 1988]. Welch’s t-test [Welch, 1947] and Cohen’s \( d \) [Cohen, 2013] are applied to test the null hypothesis and effect size respectively.

**Definition 3. Null hypothesis testing for relative bias.** Given a set of data \( X \in \mathbb{R}^d \) with sensitive attribute \( A(x \in X) \in \{0, 1\} \), and two sets of decisions on the data \( R_0(x \in X), R_1(x \in X) \in \mathbb{R} \), the differential parity \( t \) (DPT) score of \( R_0 \) over \( R_1 \) on \( A(X) \) is calculated as (2).

\[
DPT(R_0, R_1, A) = \frac{\overline{R_\Delta}(A = 1) - \overline{R_\Delta}(A = 0)}{\sqrt{s^2(\overline{R_\Delta}(A = 1)) + s^2(\overline{R_\Delta}(A = 0))}}
\]

\[
DoF(R_0, R_1, A) = \frac{(s^2(\overline{R_\Delta}(A = 1)))^2 + (s^2(\overline{R_\Delta}(A = 0)))^2}{(|A = 1| - 1)(|A = 0| - 1)}.
\]

Here \( DoF(R_0, R_1, A) \) is the degrees of freedom measured with Welch’s t-test and \( s^2(\overline{R_\Delta}(A = a)) = \frac{s^2(\overline{R_\Delta}(A = a))}{|A = a|} \) is the sampled variance of \( \overline{R_\Delta}(A = a) \).

**Definition 4. Effect size for relative bias.** Given a set of data \( X \in \mathbb{R}^d \) with sensitive attribute \( A(x \in X) \in \{0, 1\} \), and two sets of decisions on the data \( R_0(x \in X), R_1(x \in X) \in \mathbb{R} \), the differential parity \( d \) (DPD) score of \( R_0 \) over \( R_1 \) on \( A(X) \) is calculated as (3).

\[
DPD(R_0, R_1, A) = \frac{\overline{R_\Delta}(A = 1) - \overline{R_\Delta}(A = 0)}{s}
\]

where \( s = \sqrt{\frac{|A = 1|s^2(\overline{R_\Delta}(A = 1)) + |A = 0|s^2(\overline{R_\Delta}(A = 0))}{|A = 0| + |A = 0| - 2}} \) is the pooled standard deviation.

**Relative bias:** Utilizing the two metrics, \( R_0 \) is relatively biased towards \( A = 1 \) compared to \( R_1 \) if the null hypothesis is rejected at more than 95% confidence— one tailed \( p \leq 0.05 \) given the t value \( DPT(R_0, R_1, A) \) and degrees of freedom \( DoF(R_0, R_1, A) \), vice versa. The magnitude of the relative bias will be determined by the \( DPD \) value following the same magnitude descriptor as Cohen’s \( d \) in Table 1.

| Effect Size | \( d \) |
|-------------|-------|
| Very Small  | 0.01  |
| Small       | 0.2   |
| Medium      | 0.5   |
| Large       | 0.8   |
| Very Large  | 1.2   |
| Huge        | 2.0   |

Note that, in the binary classification setting where \( R_0(x), R_1(x) \in \{0, 1\} \), this definition of differential parity is related to demographic parity of \( R_0 \) and \( R_1 \):

\[
\overline{R_\Delta}(A = 1) - \overline{R_\Delta}(A = 0) = (\overline{R_0}(A = 1) - \overline{R_0}(A = 0)) - (\overline{R_1}(A = 1) - \overline{R_1}(A = 0)) = P(R_0(x) = 1 \mid A(x) = 0) - P(R_1(x) = 1 \mid A(x) = 1).
\]

However, differential parity is different from the difference of demographic parity since it also takes into consideration the variance of the differences which is unavailable from the statistics of \( R_0(x) \) or \( R_1(x) \) alone.

### 2.3 Differential Parity Between Decisions On Different Data

**Problem statement:** Given two non-overlapping data \( X_0, X_1 \in \mathbb{R}^d \) drawn from the same distribution, and two decision sets \( R_0(x \in X_0), R_1(x \in X_1) \in \mathbb{R} \) made by different entities, test the differential parity between the two decision sets over a binary sensitive attribute \( A(x \in X) \in \{0, 1\} \).

**Unbiased Bridge**

The first approach, unbiased bridge, trains a machine learning model \( f(x) \) on \( (X_0, R_0(x \in X_0)) \). Under a naive assumption that \( f(x) \) always inherits the bias from its training data, the predictions of \( f(x \in X_1) \) will have the same bias as \( R_0(x \in X_1) \) and thus can be used to compare against \( R_1(x \in X_1) \) for differential parity. As shown in Algorithm 1, \( DPT(R_0, R_1, A) \) and \( DPD(R_0, R_1, A) \) are estimated as \( DPT(f(x \in X_1), R_1(x \in X_1), A) \) and \( DPD(f(x \in X_1), R_1(x \in X_1), A) \).
Algorithm 1 Unbiased Bridge.

**Input**: Decisions on one data set \((X_0, A(x \in X_0), R_0(x \in X_0))\).
Decisions on another data set \((X_1, A(x \in X_1), R_1(x \in X_1))\).
A predictor \(f(x)\).

**Output**: Differential parity of \(R_0\) over \(R_1\) on \(A\).

1: Fit \(f(x)\) on \((X_0, R_0(x \in X_0))\).
2: \(dpt = \text{DPT}(f(X_1), R_1(x \in X_1), A)\).
3: \(dpd = \text{DPD}(f(X_1), R_1(x \in X_1), A)\).
4: return \(dpt, dpd\)

**Biased Bridge**

Without the naive assumption of \(f(x)\) always inheriting every bias in \(R_0\), the second approach, biased bridge, utilizes \(f(x)\) as a bridge between the two decision sets made on different data \(X_0\) and \(X_1\). Given that \(f(x)\) may not have the same bias as \(R_0\), we utilize both its predictions on \(X_0\) and \(X_1\) for the estimation of differential parity. Since the errors of the model’s predictions are i.i.d., their sampled means should follow normal distribution in large samples:

\[
\frac{\mathcal{E}_0(A = a) - \mu(E_0(A = a))}{\sigma(E_0(A = a))} \sim \mathcal{N}(0, 1) \quad (4)
\]

\[
\frac{\mathcal{E}_1(A = a) - \mu(E_1(A = a))}{\sigma(E_1(A = a))} \sim \mathcal{N}(0, 1) \quad (5)
\]

where \(E_0(A = a) = \{ f(x) - R_0(x) \mid A(x) = a, x \in X \}\) and \(E_1(A = a) = \{ f(x) - R_1(x) \mid A(x) = a, x \in X \}\) are the errors of \(f(x)\) compared to \(R_0\) and \(R_1\). Given that \(R_0(A = a) = \{ R_0(x) - R_1(x) \mid A(x) = a, x \in X \} = E_1(A = a) - E_0(A = a)\), we can estimate:

\[
R_\Delta(A = a) = \mathcal{E}_1(A = a, x \in X) - \mathcal{E}_0(A = a, x \in X)
\]

\[
= \mathcal{E}_1(A = a, x \in X_1) - \mathcal{E}_0(A = a, x \in X_0)
\]

\[
s^2(R_\Delta(A = a)) \approx s^2(\mathcal{E}_1(A = a, x \in X_1))
\]

\[
+ s^2(\mathcal{E}_0(A = a, x \in X_0)). \quad (7)
\]

As shown in Algorithm 2, the relative bias metrics can then be calculated as (2) and (3).

Algorithm 2 Biased Bridge.

**Input**: Decisions on one data set \((X_0, A(x \in X_0), R_0(x \in X_0))\).
Decisions on another data set \((X_1, A(x \in X_1), R_1(x \in X_1))\).
A predictor \(f(x)\).

**Output**: Differential parity of \(R_0\) over \(R_1\) on \(A\).

1: Fit \(f(x)\) on \((X_0, R_0(x \in X_0))\).
2: Estimate \(R_\Delta(A = a)\) as (6).
3: Estimate \(s^2(R_\Delta(A = a))\) as (7).
4: return \(\text{DPT}(R_0, R_1, A), \text{DPD}(R_0, R_1, A)\)

Summarizing Section 2, Figure 1 illustrates how relative fairness is tested with differential parity.

### 3 Experiment Design

In this section, we design experiments with a real-world case study\(^1\) to explore the following research questions:

- **RQ1**: Do the differential parity metrics consistently reflect the relative fairness between two sets of decisions made on the same data?
- **RQ2**: Do the algorithms correctly estimate the differential parity between decisions made on different data?

#### 3.1 Case study on the face beauty rating data

As shown in Table 2, we select the SCUT-FBP5500 dataset [Liang et al., 2018] as our case study because it has 5,500 face images, each of the face image has two sensitive attributes—Sex and Race, and each image has been rated with a 1 (least beautiful) to 5 (most beautiful) subjective beauty score by the same 60 human raters. This is the only dataset we found which has both sensitive attributes and decisions from different human annotators. The only disadvantage of this dataset is that, there is usually no ethical issue in having biased ratings of the beauty scores (e.g., there is nothing to blame if one rater prefers Asian Male over Caucasian Male.) But this is also the reason why this dataset can be available online for us to safely analyze the bias from different human raters. In this case study, we utilized the ratings from the first three human raters \((R_1, R_2, \text{and } R_3)\) and the average ratings of the 60 humans \((R_{Avg})\) as four different decision sets. The image set is randomly split into 60% for training \((X_0)\) and 40% for testing \((X_1)\). In addition to these four decision sets, we also trained a machine learning model to predict for each of the decision set, e.g. \(f_1(x)\) is trained on \((X_0, R_1(x \in X_0))\) and \(f_0(x)\) is trained on \(X_0, R_{Avg}(x \in X_0)\). We have tested multiple deep neural network architectures including ResNet-50, VGG-16, and AlexNet. Among them, the VGG-16 model [Simonyan and Zisserman, 2014] with pre-trained weights on the ImageNet data and last four layers being replaced by a dense layer of size 256 and a one node linear output layer achieved the best prediction performance. These four models are trained to minimize Huber loss for a maximum of 50 epochs with batch size = 10. The training time of fine-tuning the VGG-16 model on one decision set was around 30 minutes with four NVIDIA A100 Tensor Core GPUs.

#### 3.2 RQ1: Consistency and robustness

RQ1 evaluates the reliability of the proposed differential parity metrics by checking whether the differential parity metrics between the same pair of raters are consistent across different data, e.g. whether the differential parity between \(R_1(x \in X_0)\) and \(R_2(x \in X_0)\) is consistent with the differential parity between \(R_1(x \in X_1)\) and \(R_2(x \in X_1)\). In another word, RQ1 evaluates how robust differential parity is against sampling bias. The predictions of the models \(f_i(x \in X_0)\) and

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\(^1\)The source code of the experiment is available at the anonymous repo https://anonymous.4open.science/r/DP-5DF8.
### 4 Experimental Results

Table 3 shows the experimental results on the SCUT-FBP5500 dataset. In this table, two differential parity metrics, the p value of DPT for null hypothesis testing and the DPD score for effect size, are calculated or estimated by the p value of DPT for null hypothesis testing and the DPD score for effect size, respectively.

| Image Size | #Images | Sensitive Attributes A | Beauty Rating R | # Raters |
|------------|---------|------------------------|-----------------|----------|
| 350 × 350  | X = 5,500 | Sex-Female: 2,750 Sex-Male: 2,750 Race-Asian: 4,000 Race-Caucasian: 1,500 | R_i(x) ∈ {1, 2, 3, 4, 5} | i ∈ [1, 60] |

#### 3.3 RQ2: Estimation performance

RQ2 evaluates the estimation performance of the proposed Unbiased Bridge and Biased Bridge approaches. Each time we assume that only decisions made on two different data R_i(x ∈ X_0) and R_j(x ∈ X_1) are available. The relative fairness between R_i and R_j is then estimated with f_i(x) trained on {X_0, R_i(x ∈ X_0)}. The differential parity results between R_i(x ∈ X_0) and R_j(x ∈ X_0) or between R_i(x ∈ X_1) and R_j(x ∈ X_1) are used as the ground truth differential parity to test which estimation approach is more accurate.

As shown in Algorithm 1, this is also the unbiased bridge estimation of the differential parity between R_i and R_j.

### RQ1: Do the differential parity metrics consistently reflect the relative fairness between two sets of decisions made on the same data?

In RQ1, we evaluate how robust differential parity is against sampling bias by comparing the differential parity results of the same pair of decisions on different data samples (X_0 and X_1). First, we compare the differential parity results between the rows of Label Train and Label Test. These results show the differential parity between R_i and R_j on X_0 and X_1 separately. For example, the Label Train result for R_2 vs R_1 on Sex is colored as green with p = 0.00 and DPD = 0.43. This means R_2 is more biased towards Sex = 0 compared to R_1. Meanwhile, the Label Test result for R_2 vs R_1 on Sex is also colored as green with p = 0.00 and DPD = 0.47. The conclusions are consistent in this case. Out of the 32 cases, we can see 5 inconsistent cases, e.g. results of R_3 vs R_1 on Race are inconsistent. Therefore the rate of consistency is 27/32 = 84.375%. Then, we compare the differential parity results between the rows of Model Train and Model Test. These results show the differential parity between f(x) (trained on R_i(x ∈ X_0)) and R_j on X_0 and X_1 separately.
Table 3: Results are shown with numbers of (p value of DPT) and DPD value. Results with p value $\leq 0.05$ are colored as green if DPD$>0$ or red if DPD$<0$.

|       | Sex | Race | Sex | Race | Sex | Race | Sex | Race | Sex | Race |
|-------|-----|------|-----|------|-----|------|-----|------|-----|------|
| Label Train | (0.50) | 0.00 | (0.50) | 0.00 | (0.00) | 0.43 | (0.00) | 0.24 | (0.00) | 0.49 | (0.00) | 0.09 |
| Label Test   | (0.50) | 0.00 | (0.50) | 0.00 | (0.00) | 0.47 | (0.00) | 0.20 | (0.00) | 0.50 | (0.00) | 0.27 |
| Model Train  | (0.00) | -0.08 | (0.25) | -0.20 | (0.00) | 0.41 | (0.00) | 0.27 | (0.00) | 0.48 | (0.00) | 0.10 |
| Model Test   | (0.05) | -0.09 | (0.10) | -0.09 | (0.00) | 0.45 | (0.00) | 0.19 | (0.00) | 0.44 | (0.31) | -0.04 |
| Biased Bridge| (0.21) | -0.05 | (0.14) | -0.07 | (0.00) | 0.47 | (0.01) | 0.16 | (0.00) | 0.43 | (0.30) | -0.03 |
| Label Train  | (0.00) | -0.43 | (0.00) | -0.24 | (0.50) | 0.00 | (0.50) | 0.00 | (0.02) | 0.06 | (0.00) | -0.15 |
| Label Test   | (0.00) | -0.47 | (0.00) | -0.20 | (0.50) | 0.00 | (0.50) | 0.00 | (0.34) | 0.02 | (0.01) | -0.16 |
| Model Train  | (0.00) | -0.48 | (0.00) | -0.26 | (0.03) | -0.06 | (0.00) | 0.10 | (0.09) | 0.04 | (0.00) | -0.15 |
| Model Test   | (0.00) | -0.65 | (0.00) | -0.33 | (0.43) | -0.01 | (0.40) | -0.02 | (0.12) | -0.07 | (0.00) | -0.30 |
| Biased Bridge| (0.00) | -0.57 | (0.00) | -0.29 | (0.36) | 0.02 | (0.15) | -0.07 | (0.24) | -0.04 | (0.00) | -0.26 |
| Label Train  | (0.00) | -0.49 | (0.00) | -0.09 | (0.02) | -0.06 | (0.00) | 0.15 | (0.50) | 0.00 | (0.50) | 0.00 |
| Label Test   | (0.00) | -0.50 | (0.27) | -0.04 | (0.34) | -0.02 | (0.01) | 0.16 | (0.50) | 0.00 | (0.50) | 0.00 |
| Model Train  | (0.00) | -0.53 | (0.00) | -0.11 | (0.01) | -0.08 | (0.00) | 0.17 | (0.04) | -0.05 | (0.44) | 0.01 |
| Model Test   | (0.00) | -0.62 | (0.04) | -0.13 | (0.32) | -0.03 | (0.02) | 0.15 | (0.05) | -0.10 | (0.11) | -0.09 |
| Biased Bridge| (0.00) | -0.55 | (0.06) | -0.11 | (0.41) | -0.01 | (0.04) | 0.12 | (0.13) | -0.06 | (0.11) | -0.08 |
| Label Train  | (0.00) | -0.47 | (0.00) | -0.25 | (0.00) | 0.12 | (0.01) | 0.08 | (0.00) | 0.16 | (0.00) | -0.14 |
| Label Test   | (0.00) | -0.50 | (0.00) | -0.20 | (0.00) | 0.17 | (0.09) | 0.09 | (0.01) | 0.14 | (0.02) | -0.15 |
| Model Train  | (0.00) | -0.53 | (0.00) | -0.27 | (0.08) | 0.08 | (0.00) | 0.14 | (0.00) | 0.13 | (0.00) | -0.15 |
| Model Test   | (0.00) | -0.72 | (0.00) | -0.36 | (0.01) | 0.15 | (0.14) | 0.07 | (0.28) | 0.04 | (0.00) | -0.32 |
| Biased Bridge| (0.00) | -0.59 | (0.00) | -0.29 | (0.00) | 0.16 | (0.40) | 0.01 | (0.13) | 0.06 | (0.00) | -0.26 |

Out of the 32 cases, we can see 7 inconsistent cases, e.g. results of $f(x)$ (trained on $R_2(x \in X_0)$) vs $R_2$ on both Sex and Race are inconsistent. Therefore the rate of consistency is $35/32 = 83.75\%$. In addition, we can see that there is not a single case where the detected relative biases are opposite (green vs red). And every inconsistency case has small effect size of $DPD \leq 0.1$. This means when the results are inconsistent, they are not very different (at least no opposite conclusions).

**Answer to RQ1.** The proposed differential parity metrics is robust against sampling bias when evaluating relative fairness between two sets of human decisions. However, it is less robust against sampling bias when one of the decision set is generated by a machine learning model.

**RQ2: Do the algorithms correctly estimate the differential parity between decisions made on different data?**

To evaluate the accuracy of the proposed differential parity estimation algorithms, we compare their estimations of decisions made on different data (Model Test and Biased Bridge) against the direct measurements of differential parity between decisions made on the same data (Label Train and Label Test). One estimation is considered as correct when the estimation is consistent with at least one direct measurement. For example, the biased bridge estimates that $R_2$ is more biased towards Sex= 0 than $R_1$ with a p value $= 0.00 \leq 0.05$ and $DPD = 0.47$. This estimation is consistent with both Label Train and Label Test. Therefore it is considered as one accurate estimation. Meanwhile, the unbiased bridge estimates that $R_3$ and $R_1$ are relatively fair to each other on Race given p value $= 0.30 > 0.05$. Although this estimation is different from Label Train which finds that $R_3$ is more biased towards Race= 0 than $R_1$ with a p value $= 0.00 \leq 0.05$ and $DPD = 0.09$ on $X_0$, it is still considered as an accurate estimation since it is consistent with Label Test where $R_3$ and $R_1$ are relatively fair to each other on Race.

5 Related Work

5.1 Evaluation of fairness on one decision set

Research on decision fairness is difficult. This is because the standard for “absolute” fairness are highly subjective and contextual [Abu-Elyounes, 2020]. Fairness criteria for one decision sets (such as equity and equality) are often contradictory standards and lead to very different outcomes— they are impossible to be satisfied simultaneously [Friedler et al., 2021]. For example, Sap et al. [Sap et al., 2019] studied several datasets of social media posts annotated for the presence of hate speech. They showed that when the posts are written in the African American English (AAE) dialect or are authored by users who self identify as Black the posts are more
likely to be labeled (both by human annotators and the models learned from them) as hate speech than if they are not written in AAE or are authored by users who self identify as White. Two different reasons could lead to this finding—(1) the human annotators are biased towards AAE dialect or black post authors; or (2) posts authored by users who self identify as Black or written in the AAE dialect tend to be more offensive. If it is caused by the first reason, we want to fix such bias caused by annotators. If it is caused by the second reason, the annotations should be considered correct. However, without the ground truth fairness standard, there is no way to know which reason leads to this finding.

5.2 Relative fairness in algorithmic fairness

Given the difficulty of obtaining the standard for “absolute” fairness, we turn to the testing of relative fairness between different decision sets. Previous research on machine learning algorithmic fairness has utilized a reference set to define group fairness criteria of separation and sufficiency [Hardt et al., 2016]. Fairness notions such as equalized odds and predictive parity [Hardt et al., 2016] are developed to evaluate separation and sufficiency, respectively, on binary sensitive attributes. The choice of reference set is crucial to such group fairness criteria since it should be considered as “absolutely” fair. Such “absolutely” fair reference set is sometimes available when testing the algorithmic fairness of a machine learning model on a dataset of ground truth. However, it is not always available especially on datasets of human decisions. Attempts have been made to estimate the ground truth by acquiring multiple annotations on the same data. Several studies have shown that, for binary labeling, 3–10 annotators per item is sufficient to obtain reliable labels (evaluated using inter-annotator agreement scores [Artstein, 2017] such as Cohen’s kappa and Krippendorff’s alpha). [Dawid and Skene, 1979] used the EM algorithm to iteratively estimate the ground ground labels, along with the (two sided) error rate of each annotator, for binary labeling problems. This model has been later extended by other researchers for other scenarios [Kairam and Heer, 2016; Raykar et al., 2010; Weld et al., 2011; Ipeirotis et al., 2010; Pasternack and Roth, 2010; Felt et al., 2014; Hovy et al., 2013]. Liu and others have taken the more radical approach of treating the ground truth of each label not as a single value, but as a distribution over the answers that a population of (mostly hidden) annotators would provide, where the actual labels obtained are merely an observed sample of this hidden population’s responses [Liu et al., 2019; Weerasooriya et al., 2020; Weerasooriya et al., 2022]. However, (1) high inter-annotator agreement scores do not necessarily suggest the consensus decisions are fair; and (2) these approaches are expensive and do not scale up.

5.3 Relative fairness between human decisions

Previously, there is no clear definition of relative fairness on human decisions. And these previous studies analyzed data without strict controls. For example, [Price and Wolfers, 2010] concluded that, white NBA referees tend to award more extra fouls towards black players than black NBA referees by regressing the number of fouls called per 48 minutes for each player-game observation in which the referee participated, against an indicator variable for whether the offending player is black. The data for each referee come from different games played by different players. Therefore the conclusion can be misled by coincidences such as black players happened to commit more fouls in games with white referees. Another study by [Welch et al., 1988] analyzed the correlation between races of judges and the punishment decisions. It concluded that black and white judges weighted case and offender information in similar ways when making punishment decisions, although black judges were more likely to sentence both black and white offenders to prison. This conclusion is also not reliable since the punishment decisions are made on different offenders.

6 Conclusion and Future Work

In summary, this paper aims to evaluate the relative bias between two sets of decisions—whether one decision set is more biased towards a certain sensitive group than another decision set. Such relative fairness alleviates the need for strictly defining what is considered to be absolutely fair. In addition, if there exists a reference set of decisions that is well-accepted to be fair in a specific context, relative fairness of other decisions against that reference decision set can reflect their fairness in that context. Differential parity $R_0 - R_1 \perp A$ is as the novel relative fairness criterion. Next, two metrics are developed to evaluate the violation of differential parity in the case of binary sensitive attributes. Two novel machine learning-based approaches are proposed to enable the evaluation of differential parity between two decision sets made on different data. Assumptions and analyses are provided for when and how the proposed approaches work. Empirical results on two real world datasets with ratings from multiple humans showed that, the Biased Bridge approach achieved more accurate estimation than the Unbiased Bridge approach since it takes into consideration of the training error and training relative biases. This work suffers from the following limitations:

L1 The metrics for differential parity and the two estimation approaches are currently defined for binary sensitive attributes and numerical output. New definitions are required for continuous sensitive attributes or multi-label.

L2 There is a risk of companies/humans using the relative fairness of their decisions against one specific reference decision set to justify their fairness in the decision making process. Without the definition of fairness for the context and external checking of the reference decision set, relative fairness can be misleading—a decision set can be biased when it is relatively fair against another biased decision set.

To resolve these limitations, we will explore the future work:

• The metrics of differential parity for continuous sensitive attributes and multi-label settings.

• Applications of the proposed relative fairness testing framework on other realistic scenarios where humans and AI collaborate in decision-making.
Overall, we believe that this work could benefit the AI research community by presenting a new way of analyzing relative human biases with the help of machine learning.

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