Cascaded Debiasing: Studying the Cumulative Effect of Multiple Fairness-Enhancing Interventions

Bhavya Ghai  
Stony Brook University  
New York, USA  
bghai@cs.stonybrook.edu

Mihir Mishra  
Los Altos High School  
California, USA  
mihir.mishra@gmail.com

Klaus Mueller  
Stony Brook University  
New York, USA  
mueller@cs.stonybrook.edu

ABSTRACT
Understanding the cumulative effect of multiple fairness-enhancing interventions at different stages of the machine learning (ML) pipeline is a critical and underexplored facet of the fairness literature. Such knowledge can be valuable to data scientists/ML practitioners in designing fair ML pipelines. This paper takes the first step in exploring this area by undertaking an extensive empirical study comprising 60 combinations of interventions, 9 fairness metrics, 2 utility metrics (Accuracy and F1 Score) across 4 benchmark datasets. We quantitatively analyze the experimental data to measure the impact of multiple interventions on fairness, utility, and population groups. We found that applying multiple interventions results in better fairness and lower utility than individual interventions on aggregate. However, adding more interventions does not always result in better fairness or worse utility. The likelihood of achieving high performance (F1 Score) along with high fairness increases with larger number of interventions. On the downside, we found that fairness-enhancing interventions can negatively impact different population groups, especially the privileged group. This study highlights the need for new fairness metrics that account for the impact on different population groups apart from just the disparity between groups. Lastly, we offer a list of combinations of interventions that perform best for different fairness and utility metrics to aid the design of fair ML pipelines.

CCS CONCEPTS
• Computing methodologies → Machine learning.

KEYWORDS
fairness, debiasing, bias mitigation, fair ML pipeline

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1 INTRODUCTION
Algorithmic bias is a complex socio-technical problem whose impact can be felt in all sub-disciplines of machine learning [14, 18–20, 22, 33]. Recent years have seen a huge surge of fairness-enhancing interventions that operate at different stages of the ML pipeline. However, the problem is far from being solved if that is even possible [17]. Hence, there is a need for better interventions to reduce bias even further. Moreover, algorithmic bias can virtually emerge from any single or multiple stage(s) of the machine learning pipeline, right from problem formulation, dataset selection/creation to model formulation, deployment, and so on [23]. The existing literature primarily focuses on curbing algorithmic bias by intervening at a particular stage of the ML pipeline (see Figure 1) [24]. However, algorithmic bias might still flourish via other stages/components of the ML pipeline. So, our focus should be on ensuring fairness across the ML pipeline instead of a single stage of the pipeline. This issue is also backed by a recent study with ML practitioners that elaborated on the disconnect between academic research and real world needs [23]. One of the findings was to consider fairness as a system level property where the focus is on evaluating the impact of ML system as a whole instead of monitoring individual components.

An intuitive solution to enhance fairness across the ML pipeline can be to apply multiple fixes (interventions) at different stages of the ML pipeline where bias can emerge from. We will refer to such a series of fairness-enhancing interventions as cascaded interventions. For example, one might choose to debias the dataset, train a fairness-aware classifier over it and then post-process the model’s predictions to achieve more fairness. This approach is inline with the real world where different laws/policies/guidelines try to alleviate social inequality by intervening at multiple stages of life like education, employment, promotion, etc. Examples include Affirmative action in the US and Caste-based reservation in India. This begs the question if it were possible to achieve more fairness in the ML world by intervening at multiple different stages of the ML pipeline and what might be its possible fallbacks.

Figure 1: Three different types of fairness-enhancing interventions and how they fit into the standard ML pipeline.
In this work, we undertake an extensive empirical study to understand the impact of individual interventions as well as the cumulative impact of cascaded interventions on utility metrics like accuracy, different fairness metrics and on the privileged/unprivileged groups. Here, we have focused on the binary classification problem over tabular datasets with a single sensitive (protected) attribute. We have considered 9 different interventions where 2 operate at the data stage, 4 operate at the modeling stage and 3 operate at the post-modeling stage. We also consider all possible combinations of these interventions as shown in Figure 3. To execute multiple interventions in conjunction, we feed the output of one intervention as input to the next stage of the ML pipeline. We simulate multiple three-stage ML pipelines that are acted upon by different combinations of interventions. We measure the impact of all these interventions on 9 fairness metrics and 2 utility metrics over 4 different datasets. Thereafter, we perform quantitative analyses on the results and try to answer the following research questions:

**R1.** Effect of cascaded interventions on fairness metrics
Does intervening at multiple stages reduce bias even further? If so, does it always hold true? What is the impact on group fairness metrics and individual fairness metrics?

**R2.** Effect of cascaded interventions on utility metrics
How do utility metrics like accuracy and F1 score vary with different number of interventions? Existing literature discusses the presence of fairness-utility tradeoff for individual interventions. Does it hold true for cascaded interventions?

**R3.** Effect of cascaded interventions on population groups
How are the privileged and unprivileged groups impacted by cascaded interventions in terms of F1 score, false negative rate, etc.? Are there any negative impacts on either groups?

**R4.** How do different cascaded interventions compare on fairness and utility metrics?

## 2 BACKGROUND AND LITERATURE REVIEW

### 2.1 Fairness-Enhancing Interventions

Bias mitigation techniques can be broadly classified into 3 stages: Pre-processing, In-processing and Post-processing (Fig. 1). In the following, we discuss a few interventions that we have considered in this work, in the context of the intervention stage they operate.

#### 2.1.1 Pre-processing
Interventions at the Pre-processing stage operate on the raw dataset to generate its debiased version. The debiased dataset can then be fed back into the standard ML pipeline for fairer predictions. Specifically:

- **Optimized Preprocessing (OP)** — uses convex optimization to transform the underlying dataset such that fairness is enhanced and utility is preserved with limited data distortion [8].

- **Disparate Impact Remover (DIR)** — edits the feature set of a given dataset such that the predictability of the protected variable is impossible while preserving rank ordering within groups [16].

#### 2.1.2 In-processing
Interventions in this stage operate at the data modeling stage to train a fair ML model. Specifically:

- **Gerry Fair Classifier (GFC)** — formulates fairness as a zero-sum game between a Learner (the primal player) and an Auditor (the dual player) to compute an equilibrium for this game [27].

- **Prejudice Remover (PR)** — adds a specialized regularization term to the learning objective such that the classifier becomes independent of the sensitive information [26].

- **Exponential Gradient Reduction (EGR)** — reduces fair classification to a sequence of cost-sensitive classification problems, returning a randomized classifier with the lowest empirical error subject to fair classification constraints [1].

- **Grid Search Reduction (GSR)** — operates in a similar fashion as EGR. However, it returns a deterministic classifier instead of a randomized classifier [1, 2].

#### 2.1.3 Post-processing
Such interventions operate on the model’s predictions to yield more fair predictions. Specifically:

- **Calibrated Equalized Odds Postprocessing (CEOP)** — changes classifier results based on calibrated score outputs and an equalized odds goal [35].

- **Reject Option Classification (ROC)** — reduces discrimination by assigning positive labels to the unprivileged groups and negative labels to the privileged groups for the data points that lie close to the decision boundary [25].

- **Equalized Odds Postprocessing (EOP)** — solves a linear program to find probabilities whose corresponding labels will optimize the equalized odds goal [21, 35].

Existing literature has studied the above mentioned interventions in isolation. In this work, we explore if a combination of these interventions can lead to enhanced fairness across the ML pipeline.
We have used IBM’s AIF 360 open source toolkit to conduct all experiments for this paper. More specifically, we leveraged 4 datasets, 9 fairness enhancing interventions and 11 evaluation metrics from this toolkit as shown in Fig. 2. To have a more even comparison, we have used the same ML model, i.e., logistic regression (linear model) across the board. Moreover, we only selected those in-processing interventions that are based on or compatible with linear models.

**Interventions.** Among the 9 interventions, 2 belong to the preprocessing stage, 4 belong to the in-processing stage and 3 belong to the post-processing stage. Apart from these individual interventions, we also execute different combinations of these interventions in groups of 2 and 3. For example, one might choose to intervene at any 2 stages (say a pre-processing intervention followed by a post-processing intervention) or choose to intervene at all 3 stages of the ML pipeline. To form all possible combinations, we cycle through all available options (interventions) for a given ML stage along with a ‘No Intervention’ option and repeat it for all the 3 stages. This results in 8 combinations of pre-processing and in-processing interventions, 12 combinations of in-processing and post-processing interventions, 6 combinations of pre-processing and post-processing interventions and 24 combinations of all 3 types of interventions (see Fig. 3). In totality, we perform 9 individual interventions, 30 different combinations of interventions and a baseline case (No intervention for all stages) for each of the 4 datasets. Here, we have used the default set of hyperparameters for all interventions. In this paper, we will refer to the different interventions by their acronyms like PR for Prejudice Remover as defined in subsection 2.1. For cascaded interventions, we will concatenate the respective acronyms with a ‘+’ sign. For example, OP+PR means that we performed the Optimized Preprocessing (OP) intervention followed by the Prejudice Remover (PR) intervention. The baseline case is referred as ‘Logistic Regression’.

**Evaluation Metrics.** The impact of the different interventions is captured using a diverse set of 11 evaluation metrics. Two of them, namely accuracy and F1 score, are utility metrics that measure the ability of a ML model to learn the underlying patterns from the training dataset. Here, we have included the F1 score as it can better deal with imbalanced output class distributions. Both of these metrics range between 0 and 1. Higher values mean better performance. The remaining 9 metrics each capture some facet of fairness. Two of the fairness metrics, namely Consistency and Theil index, subscribe to the notion of individual fairness. Here, the Consistency metric can be understood as the degree to which k-nearest neighbors for different instances having the same output labels (k=5). On the other hand, Theil index comes from the family of inequality measures called the Generalized Entropy Measures. Higher values for Consistency and lower values for the Theil index mean more fairness. All other fairness metrics subscribe to the notion of group fairness, namely false positive rate difference (FPR Diff), false negative rate difference (FNR Diff), statistical parity difference (SPD), false discovery rate difference (FDR Diff), false omission rate difference (FOR Diff), accuracy difference (Accuracy Diff) and F1 score difference (F1 Score Diff). All group fairness metrics measure disparity between groups based on some measure such as false positive rate (FPR). A lower absolute value for the group fairness metrics means more fairness. The sign of these metrics represents the group that is getting the upper/lower hand. A value of 0 means perfect fairness.

**2.2 Measuring Fairness**
Quantifying fairness for ML algorithms is an active research area. Numerous fairness metrics have been proposed in the literature which mathematically encode different facets of fairness like group fairness, individual fairness, counterfactual fairness, etc. [3, 4, 9, 11, 12, 29, 34]. For e.g., group fairness implies that members of one group should receive a similar proportion of positive/negative outcomes as other groups [3, 9], individual fairness implies that similar individuals should be treated similarly [11, 12], etc. In this work, we have opted for a diverse set of 9 fairness metrics to paint a more comprehensive picture.

**2.3 Fairness across ML Pipeline**
Research that focuses on fairness in a multi-stage ML system has received some attention and is still in its early stages [6, 24, 30, 36, 37]. Biswas et al. studied the impact of data preprocessing techniques like standardization, feature selection, etc. on the overall fairness of the ML pipeline [6]. They found certain data transformations like sampling to enhance bias. Hirzel et al. also focused on the data preprocessing stage [30]. They present a novel technique to split datasets into train/test that is geared towards fairness. Wang et al. focused on fairness in the context of multi-component recommender systems [36]. They found that overall system’s fairness can be enhanced by improving fairness for individual components. Our work focuses on how different combinations of interventions at 3 stages of the ML pipeline can be leveraged to enhance fairness across the ML pipeline.

There is a related line of work that discusses fairness in the context of compound decision making processes [7, 13, 15]. In such data systems, there is a sequence of decisions to be made where each decision can be thought of as a ML classification problem. This line of work focuses on fairness over multiple tasks and does not pay much attention towards enhancing fairness for an individual task. In this work, we study how different combinations of interventions can affect fairness for a single decision making process.

**3 EXPERIMENT SETUP**
We have used IBM’s AIF 360 open source toolkit to conduct all experiments for this paper. More specifically, we leveraged 4 datasets, 9 fairness enhancing interventions and 11 evaluation metrics from
Datasets. Each of the 4 tabular datasets used in this paper, as listed in Figure 2, have been used extensively in the fairness literature. They deal with a binary classification problem and typically contain one or more binary protected attributes such as gender, race, etc. We describe the datasets briefly as follows:

Adult Income Dataset. After pre-processing, this dataset consists of 45,222 rows and 99 columns that are derived from the 1994 Census database. Each row represents a person characterized by variables like education, gender, race, workclass, etc. These attributes are used to predict if an individual makes more than $50k a year. Here, we have used gender as the sensitive attribute with males as the privileged group and females as the unprivileged group.

German Credit Dataset. After pre-processing, this dataset consists of 1,000 rows and 9 columns which was originally prepared by Prof. Hofmann. The task is to predict if an individual has good or bad credit risk based on features like credit amount, credit history, sex, etc. Here, the sensitive attribute is age. Individuals older than 25 years belong to the privileged group and vice versa.

COMPAS Recidivism Dataset. After pre-processing, this dataset contains 6,167 rows and 402 columns which pertains to the COMPAS algorithm used for scoring defendants in Broward County, Florida. The task is to predict if an individual will recommit a crime within a two year period based on personal attributes like charge degree, prior count, etc. Here, the sensitive attribute is race with Caucasians as the privileged group and vice versa.

Bank Marketing Dataset. After pre-processing, this dataset consists of 30,488 rows and 53 columns; it pertains to a direct marketing campaign of a Portuguese banking institution. The classification task is to predict if a client will buy a term deposit based on features like type of job, marital status, education, etc. Here, the sensitive attribute is age. Individuals (clients) younger than 25 years belong to the unprivileged group and vice versa.

The positive outcome label for all these datasets refer to the favorable outcome for the recipient. For e.g., the positive outcome label for the adult income dataset refers to an income greater than $50k. Similarly, for the COMPAS dataset, it refers to not recommitting a crime in 2 years. This information will help interpret measures like false positive rate, false negative rate, etc.

Method. After pre-processing, we standardize all input features for each dataset. Thereafter, each dataset is randomly divided into train and test dataset in the ratio 70:30. For the baseline case, we train a logistic regression model on the training dataset and then compute different evaluation metrics using the test data. Next, we execute all individual and cascaded interventions using the train dataset and record their impact on different utility and fairness metrics using the test dataset. This entire process is repeated 3 times for each dataset with different random splits between train and test dataset to counter sampling bias. Lastly, we compute the mean values for all evaluation metrics across the 3 iterations for each intervention. For each dataset, these results can be represented in tabular format with 60 rows and 11 columns where each row represents an intervention and each column represents an evaluation metric. Apart from these evaluation metrics, we also record statistics like false negative rate (FNR), false positive rate (FPR), base rate, F1 score, etc. for the privileged and unprivileged groups.

4 RESULTS

In this section, we analyze the empirical data from our experiments to answer the 4 research questions laid out in section 1.

4.1 Effect on Fairness Metrics (R1)

We first gauge the effect of cascaded interventions on fairness as a whole (across fairness metrics). We start by grouping all interventions into 4 buckets, i.e., 0 intervention, 1 intervention, 2 interventions and 3 interventions, respectively. For each bucket, we compute the average score for different fairness metrics and repeat this process for all datasets. It is important to note that different fairness metrics are not directly comparable as they are based on different interpretations of fairness and may also vary in terms of their numerical distribution (range, mean, etc.). So, we compare the mean value of a fairness metric with its counterpart for a different bucket. We count the percentage of times one bucket performs better than another across fairness metrics and datasets. This data is visualized using a heatmap of size 4 x 4 in Figure 4(A). Each row and column represents a bucket (number of interventions). Here, a cell (i,j) represents the percentage of times j interventions performs better than i interventions. For example, the cell (2,1) is labeled 44%. It means that a single intervention yielded better fairness scores
than two interventions for 44% of cases. A bucket j will be considered favorable over another bucket i if the value for the cell (i,j) is greater than 50% and vice versa.

It should be noted that different fairness metrics might be incompatible with each other. So, the net trend (cell values) might appear a bit faded as some fairness metrics might cancel the effect of another. Looking at the row i=0, we find that any number of interventions greater than 0 provide better overall fairness than having no interventions. Looking at the row i=1, we find that the columns j=2 and j=3 have values more than 50%, i.e., two or three interventions yielded better fairness than a single intervention. Moving to the row i=2, we find that the value of the cell (2,3) is 50%. Perhaps surprisingly, this means that it is equally likely for either buckets to outperform each other. Overall, it appears that fairness improves from 0 to 2 interventions and becomes constant thereafter. However, it is important to note that the heatmap encodes frequency and not the magnitude of difference between fairness metrics. So, it is possible that three interventions reduce bias significantly more (in terms of magnitude and not the count of fairness metrics) than the two interventions case and might still appear to be no better than the two interventions case.

The heatmap provides an aggregate picture of how fairness metrics vary for different numbers of interventions. Now, let us dig a bit deeper and gauge the impact of cascaded interventions on group fairness and individual fairness. For individual fairness, we plot the mean values for the Theil index and Consistency for different numbers of interventions. For the group fairness metrics, we compute the percentage of times the absolute value of each constituting metric is less than 0.01. As we can see from Figure 5 (A), the percent of times the group fairness metrics are below a threshold increases steadily with higher numbers of interventions from 2% to 12%. In other words, group fairness improves with more interventions on aggregate. This observation largely concurs with our findings from Figure 4(A). On the other hand, we get mixed signals from the individual fairness metrics. The Consistency metric shows a slight improvement in fairness while the Theil index shows a downfall in fairness with higher numbers of interventions.

It is important to note that all of these patterns reflect the aggregate trend and may not apply for all cases. For example, Figure 6 shows the absolute values for the accuracy difference metric across different interventions for the Adult Income dataset. In this case, we observe multiple instances where a larger number of interventions did not lead to more fairness (lower values). This observation is contrary to the aggregate trend for group fairness that we observed in Figure 5(A). So, it is not always the case that more interventions will result in more fairness. One needs to choose the right combination of interventions to get the best results. We will discuss which combinations work for different metrics in subsection 4.4.

### 4.2 Effect on Utility Metrics (R2)

We start off by analyzing how different number of interventions compare against each other on utility metrics as a whole. Following a similar procedure as defined in subsection 4.1, we plot a heatmap for utility metrics instead of fairness metrics (see Figure 4 (B)). Here, a cell (i,j) represents the percentage of cases where j interventions yielded lower utility than i interventions. As expected, we observe that any non-zero number of interventions results in lower utility than the baseline case (see row i=0). Similarly, we observe that two interventions yields worse utility metrics than one intervention (see cell(1,2)) and three interventions yields worse utility metrics than two interventions (see cell(2,3)). Overall, this reveals a strong downward trend for utility metrics with more number of interventions. Looking at Figure 4 (A) and (B) in conjunction, we observe that three interventions perform on par with two interventions on fairness. However, 75% of the times three interventions performed worse on utility metrics than two interventions. This observation
we computed the mean accuracy and F1 score for different number of interventions across datasets. These mean scores are visualized in Figure 7. In line with our findings in Figure 4(B), we observe that both accuracy and F1 score steadily decrease as the number of interventions increase. This trend shows that there is a cost to be paid for adding more interventions. So, one should not blindly opt for more interventions. ML practitioners should consider the potential loss in utility metrics while designing fair ML pipelines.

So far, we have looked at the effect of cascaded interventions on utility metrics and fairness metrics in isolation. Now, let us investigate the effect of cascaded interventions on the bivariate relationship between utility metrics and fairness metrics. We start off by grouping all experimental data across datasets by the number of interventions. For each group, we compute the Spearman correlation coefficient between different fairness metrics and F1 score as shown in Table 1. Here, we have used absolute values for group fairness metrics. We observe that there is a significant positive correlation between fairness metrics and F1 score for the baseline case. For all fairness metrics except for the consistency metric, a higher value means more bias (less fairness). Hence, a positive correlation suggests that F1 score and fairness are negatively linked. In other words, interventions with high F1 score generally result in poor fairness and vice versa. This observation is in line with existing literature which discusses a tradeoff between accuracy and fairness for individual interventions [32].

As the number of interventions increases, we observe a steady decline in the correlation coefficient across fairness metrics. Here, the correlation coefficient for consistency moves in the opposite direction as unlike all other fairness metrics higher values means more fairness. The decrease in correlation suggests the likelihood of attaining a high F1 score along with high fairness increases with higher numbers of interventions. As an example, we plot the bivariate relation between Statistical parity difference and F1 score for different numbers of interventions (see Figure 9). The decrease in correlation coefficient $\rho$ is evident from the decrease in the slope of the regression line as we move towards higher numbers of interventions. If the reduction in F1 score caused by different interventions was in proportion to the corresponding increase in fairness, the correlation coefficient would have remained constant across different number of interventions. So, the observed decrease in correlation coefficient suggests the efficacy of cascaded interventions in reducing bias without sacrificing too much on performance (F1 Score).

### 4.3 Effect on Population Groups (R3)

In our experimental setup, we kept a log of different statistics like false positive rate, false negative rate, F1 score, base rate, etc. for the privileged and unprivileged groups across all interventions. We analyzed this data to understand the impact of different interventions on these two groups. Figure 8 shows the aggregate impact of different number of interventions on accuracy and F1 score. In line with our earlier finding (see Figure 7), we observe that these utility metrics deteriorate for both groups with more number of interventions. However, the impact on the underprivileged group is more severe than the privileged group for the F1 metric. The F1 score for the privileged group dropped 8 percent points from 69% to 61% while it dropped 14 percent points for the underprivileged group from 63% to 49%. This disproportionate impact also lead to an increase in disparity between the groups in terms of F1 Score from 6% to 12%. In the case of accuracy, the impact on both groups is roughly even and the disparity between groups remains almost constant (~3%) across different number of interventions.

The decrease in utility metrics signal an increase in error rates. So, let us look at the effect on the false positive rate (FPR) and false negative rate (FNR). As shown in Figure 10, we observe a large percentage of cases where individual interventions resulted in higher error rates for both the privileged and the unprivileged group compare to the baseline (no intervention case). As we go for higher numbers of interventions, the percentage of such cases generally increases further. This trend is in agreement with the decreasing trend in utility metrics for more number of interventions. On comparing between groups, we find that interventions are more likely to result in higher FNR for the privileged group than the unprivileged one. It means that individuals from the privileged group are more likely to be misclassified with the unfavorable outcome than the unprivileged group. This disproportionate impact also lead to an increase in disparity between the groups in terms of F1 Score from 6% to 12%. In the case of accuracy, the impact on both groups is roughly even and the disparity between groups remains almost constant (~3%) across different number of interventions.

![Figure 7: Mean Accuracy and F1 Score for different number of interventions. Error bars represent standard error.](image)

![Figure 8: Mean F1 Score and Accuracy for the privileged and the unprivileged group across different number of interventions. Error bars represent standard error.](image)
we look at base rate over the entire population, we find that the
we do not observe a reduction in error rates for individual groups
where the number of favorable outcomes is fixed such as hiring.
Table 1: Spearman correlation coefficient between F1 score and fairness metrics for different number of interventions (repre-
sented as rows). We observe that the correlation coefficient decreases as the number of interventions increase across metrics.

| Interventions | FPR Diff | FNR Diff | Accuracy Diff | FOR Diff | FDR Diff | SPD | F1 Score Diff | Theil Index | Consistency |
|---------------|----------|----------|---------------|----------|----------|-----|---------------|-------------|-------------|
| 0             | 0.748    | 0.42     | 0.385         | 0.42     | 0.329    | 0.678| 0.58          | 0.708       | -0.986      |
| 1             | 0.343    | -0.054   | 0.211         | 0.354    | 0.176    | 0.263| 0.253         | 0.148       | -0.628      |
| 2             | 0.228    | -0.11    | 0.15          | 0.24     | 0.148    | 0.109| 0.115         | -0.144      | -0.481      |
| 3             | 0.119    | -0.185   | 0.189         | 0.058    | -0.112   | -0.056| 0.073         | -0.282      | -0.167      |

Figure 9: Relation between Statistical Parity difference and F1 score for different numbers of interventions from 0 to 3 (A - D). Each green ‘x’ marker corresponds to a specific intervention executed on one of the 3 random subsets of a given dataset. The grey line represents the regression line that best fits all the points. It visually indicates the strength of the correlation.

atleast be partially explained by the tendency of the interventions
to assign more positive outcomes to the unprivileged group and negative outcomes to the privileged group.

Next, let us look at the impact on base rate for different groups (see Figure 11). Here, base rate is defined as the proportion of positive outcomes for different groups. It is computed over model’s prediction for the test data post all relevant interventions. For the no intervention case, we observe a 12% disparity in favor of the privileged group. With more interventions, the base rate for the unprivileged group steadily increases from 34% to 44% (10 % jump). On the other hand, the base rate for the privileged group decreases a bit for the one and two interventions case and increases by 4% for the three interventions case. Overall, this leads to a decrease in disparity between groups from 12% to 5% for the two intervention case. In a context where equality between base rates is a priority, two interventions seems to be the way to go. It is also important to note that some of the interventions can negatively impact the privileged group. This is evident from the drop in base rate for the privileged group for the one and two interventions case and increases by 4% for the three interventions case. Such means (interventions) of reducing disparity can be deemed as socially undesirable.

Existing group fairness metrics solely focus on disparity and are in-
different to how disparity is reduced. This finding points to a need for
new fairness metrics that account for the specific impact on individual
groups apart from just the gap between those groups. Such metrics
should give preference to interventions that reduce disparity by
improving error rates for all population groups (at least not making
it worse for any population group).

There can be different ways to interpret the empirical findings
based on one’s value system. One way to interpret these numbers
can be from a pure ML perspective where the focus is to train a
ML model that best fits the underlying dataset. Here, the objective
of an intervention is to ensure that the model performs equally
well for different groups in terms of accuracy, false positive rate,
false negatives rate, etc. From this viewpoint, many of the inter-
ventions are counterproductive as they increase error rates and
decrease accuracy/F1 score for different groups (see Figure 8 and
Figure 10). Going from individual interventions to cascaded in-
terventions makes things worse as the error rates for population
groups increases further and the accuracy/F1 score further deteri-
orates. Ideally, one would reduce disparity by reducing the error
rates for different groups but not making it worse for any of them.
Figure 10: Percentage of times false negative rate (Left) and false positive rate (Right) increases compared to the baseline (No Intervention) across different number of interventions for all datasets.

Figure 11: Mean base rate for the privileged and unprivileged groups across different number of interventions.

Figure 12: Change in false negative rate compared to the baseline across different interventions for the Adult Income dataset. Here, negative values are desirable.

For example, 3 interventions in Figure 12 reduce disparity (FNR Diff metric) by reducing FNR for both groups. Similarly, mitigating discrimination against one group at the cost of another is self-defeating and unethical. For illustration, we find 5 interventions in Figure 12 where FNR decreases for the unprivileged group and increases for the privileged group compared to the baseline. In other words, some high income individuals from the privileged group were misclassified as low income in an effort to increase fairness. This is not a one off case. Our experiments show an aggregate trend across datasets where privileged groups were disproportionately misclassified with unfavorable outcomes and unprivileged groups were disproportionately misclassified with favorable outcomes (see Figure 10). These observations highlight how interventions can negatively impact the privileged group. Future interventions should be more considerate towards their possible negative impact on the different population groups.

4.4 Comparison between Interventions (R4)

So far, we have focused on the aggregate trends which might or might not apply for a given intervention. In this section, we focus on specific interventions and how they compare against different evaluation metrics. For each evaluation metric, we ranked all interventions from the best performing to the worst performing based on their respective mean score across datasets. For the accuracy, F1 score and consistency metric, higher values are desirable so we sorted interventions based on descending order of their corresponding values. For all other metrics, we used ascending order. Moreover, we used absolute values for all group fairness metrics as we are primarily concerned with the magnitude of bias.

Table 2 contains the 10 best and worst performing interventions for different evaluation metrics (given limited space, we have only shown 7 evaluation metrics.). From this table, we can make a few important observations. Logistic regression (by which we mean ‘No intervention’) tops the list for the accuracy metric. As all interventions optimize for some aspect of fairness, they might sacrifice a bit on accuracy. So, one should not use any intervention for achieving the best accuracy. For the F1 score, we observe that a few interventions rank higher than Logistic Regression, such as DIR + EGR + ROC. However, the difference between them was quite slim (0.3%) which might be attributed to imbalanced output class distribution. The broader point is that applying more interventions does not always lead to a significant loss in utility. In the case of DIR + EGR + ROC, we observe the best performance for the F1 score and the 4th best for accuracy. Among the 10 bottom ranked interventions across all fairness metrics, Logistic Regression occurs only twice. This shows that there are several individual and cascaded interventions that perform worse than the baseline case for at least some fairness metric. Hence, it is important to choose interventions wisely. ML practitioners/researchers can leverage resources like Table 2 and prioritize interventions that have worked well for other datasets while designing their own fair ML pipeline(s).

For the fairness metrics, we observe that the best performing intervention is mostly unique for each one of them. In other words, there is no silver bullet for all fairness metrics. This observation is in line with the existing literature which proves that no intervention can simultaneously optimize for all fairness metrics [28].

representation. Under this viewpoint, cascaded interventions are desirable as they help bridge the gap in base rates (see Figure 11).
Table 2: Ranking of 10 best and worst performing interventions for different evaluation metrics across datasets.

| Rank | Metric       | Interventions                                                                 |
|------|--------------|-------------------------------------------------------------------------------|
| 1    | Accuracy     | Logistic Regression + GSR + ROC + EOP                                        |
| 2    | F1 Score     | Logistic Regression + GSR + ROC                                              |
| 3    | Theil Index  | Logistic Regression + GSR + ROC                                              |
| 4    | Consistency  | Logistic Regression + GSR + ROC                                              |
| 5    | FPR Diff     | Logistic Regression + GSR + ROC                                              |
| 6    | FNR Diff     | Logistic Regression + GSR + ROC                                              |
| 7    | Accuracy Diff| Logistic Regression + GSR + ROC                                              |
| 8    | Logistic Regression |          |
| 9    | Logistic Regression |          |
| 10   | Logistic Regression |          |

From a practical standpoint, this implies that ML practitioners need to prioritize which metrics are more important to them and then choose interventions accordingly. It is also worth noting that the best performing intervention for any metric is either Logistic Regression (No Intervention) or a combination of two or more interventions. Apart from the top performing interventions, we also observe that the top 10 interventions for all fairness metrics are predominantly cascaded interventions. For example, 9 out of the top 10 interventions for the Consistency metric are cascaded interventions. These observations further motivate the efficacy of cascaded interventions over individual interventions. Among the top 10 interventions across all metrics, OP + GFC + ROC occurs the most number of times. Similarly, OP + GFC + EOP occurs the most number of times among the worst 10 interventions across metrics. It is interesting to see that both of these interventions have much in common (OP and GFC). This shows that certain intervention are more compatible/incompatible with another. Changing an ingredient can drastically impact the outcome. For instance, swapping ROC with EOP resulted in the entire combination (OP + GFC + ROC) to change from being one of the top ranked to one of the worst ranked interventions. It should be noted that ranking abstracts the real difference in magnitude. For brevity, we have used ranking in the table. We encourage the readers to refer to the source code/experimental data for more details.

5 DISCUSSION

This work explores the realm of cascaded debiasing by asking basic research questions and then answering them via a large empirical study. To conduct such a study, we chose IBM’s AIF 360 toolkit as it supports one of the largest collection of interventions, fairness metrics and datasets. On the flip side, we were limited to the different options it supported and faced runtime issues executing a certain intervention (Optimized Preprocessing) for a particular dataset (Bank Marketing dataset). It is important to note that all insights and analyses presented in this paper are empirical in nature, and so, they may or may not generalize to other datasets, interventions or metrics. Having said that, our study covers a wide range of popular fairness metrics and state-of-the-art interventions. The insights reported in this paper can serve as a good starting point or heuristic to assist ML practitioners design fair ML pipelines and inform the design of fair ML tools. Moreover, these insights can help guide further research into this area. For e.g., why do certain combinations of interventions work better than others?

This work suggests multiple venues for future research. One research direction can be to conduct even larger studies which include more datasets [10], ML models, fairness metrics like counterfactual fairness [29], statistical equity [31], etc., other stages of intervention like the data curation stage [20], and multiple hyperparameters for different interventions [37]. Such a study will paint a more comprehensive picture and its results will be more generalizable to different contexts. Another interesting research direction will be to conduct similar studies for other data types like text, images, etc., and consider other problem types such as regression, clustering, etc. This work deals with fairness at a group level (say males and females) and at an individual level (through the individual fairness metrics). It will be interesting to study the effect of cascaded interventions on different subgroups say black females, high-earning white males, etc. Future work might also take a deep dive into the underpinnings of the different trends/patterns reported in this paper. Lastly, the source code and experimental data can be accessed at github.com/bhavyaghai/Cascaded-Debiasing for anyone to reproduce/extend this study as they see fit.

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