Fair Data Integration

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Abstract

The use of machine learning (ML) in high-stakes societal decisions has encouraged the consideration of fairness throughout the ML lifecycle. Although data integration is one of the primary steps to generate high quality training data, most of the fairness literature ignores this stage. In this work, we consider fairness in the integration component of data management, aiming to identify features that improve prediction without adding any bias to the dataset. We work under the \textit{causal interventional fairness} paradigm. Without requiring the underlying structural causal model a priori, we propose an approach to identify a sub-collection of features that ensure the fairness of the dataset by performing conditional independence tests between different subsets of features. We use group testing to improve the complexity of the approach. We theoretically prove the correctness of the proposed algorithm to identify features that ensure interventional fairness and show that sub-linear conditional independence tests are sufficient to identify these variables. A detailed empirical evaluation is performed on real-world datasets to demonstrate the efficacy and efficiency of our technique.

1 Introduction

Algorithmic fairness is of great societal concern when supervised classification models are used to support allocation decisions in high-stake applications. There have been numerous recent advances in statistically and causally defining group fairness between populations delineated by protected attributes and in the development of algorithms to mitigate unwanted bias \cite{Feller2018}.\textsuperscript{1} Bias mitigation algorithms are often categorized into pre-processing, in-processing, and post-processing approaches. Pre-processing modifies the distribution of the training data, in-processing modifies the objectives or constraints of the learning algorithm, and post-processing

\textsuperscript{1}We use the terms \textit{sensitive attribute} and \textit{protected attribute} interchangeably.
modifies the output predictions — all in service of increasing group fairness metrics while upholding classification accuracy [7].

However, this categorization of algorithmic fairness misses an important stage in the lifecycle of machine learning (ML) practice: data collection, engineering and management [34, 18]. Holstein et al. report that practitioners “typically look to their training datasets, not their ML models, as the most important place to intervene to improve fairness in their products” [13]. Data integration, one of the first components of data management, aims to join together information from different sources that captures rich context and improves predictive ability. With the phenomenal growth of digital data, ML practitioners may procure features from millions of sources spanning data lakes, knowledge graphs, etc. [27, 10]. Practitioners typically generate exhaustive sets of features from all different sources and then perform feature subset selection [37, 23, 10]. Some may argue that data integration is a part of pre-processing but we make this distinction as data integration does not involve modification of the data distribution and is considered as the task of a data engineer as opposed to data modeler.

Filtering methods for feature selection exploit the correlation or information gain of features with the target variable to identify a subset [12]. However, these techniques are ignorant of sensitive attributes and fairness concerns. For example, consider a dataset with features $F_1$ and $F_2$ such that $F_1$ provides slightly more improvement in accuracy than $F_2$; however, incorporating $F_1$ yields a classifier that reinforces discrimination against protected groups whereas incorporating $F_2$ yields a classifier with similar outcomes for different groups. Feature selection techniques that are not discrimination-aware will prefer $F_1$ to $F_2$, but $F_2$ is a better feature to select from a societal perspective.

To overcome the fairness limitations of standard feature selection methods, we study the problem of fair feature selection, specifically in the context of data integration when we are integrating new tables of features with an existing training dataset, i.e., the join operation in databases. Our goal is to identify a subset of new features that can be integrated with the original dataset without worsening its biases against protected groups. We assume access to some sensitive and admissible attributes that help to identify the feature subset that obeys fairness. The identification of features that do not induce additional bias is tricky because of relationships between non-protected attributes and protected ones that allow the reconstruction of information in the protected attributes from one or more non-protected ones. For example, zip code can reconstruct race information [15] and choice of vocabulary in a resume can reconstruct gender [8].

There has been recent interest in studying causal frameworks [5, 36, 25, 17, 6, 22, 39, 38, 19, 20, 32] to achieve fairness. Due to their ability to distinguish different discrimination mechanisms, we use causal fairness [33, 26] as our fairness framework, with a specific focus on interventional fairness in which the effect of protected attributes on the target is characterized using do-calculus [33]. Importantly, we do not make the assumption that we are given the complete causal graph (formally, the structure of the causal bayesian network that generates the data) a priori.

We propose an algorithm SeqSel to identify all new features that when added to the original dataset still ensure interventional fairness. Our algorithm takes as input a dataset $D$ comprising an outcome variable, some sensitive features, admissible features, and a collection
of features that are neither admissible nor sensitive. A feature is considered *admissible* if the protected variables are allowed to affect the outcome through it. For example, consider a credit card application system that contains gender and race as sensitive attributes, expected monthly usage as an admissible attribute (it may have a sensitive attribute as one of its parent but it is permissible for the sensitive attribute to influence the outcome through this variable), and age and education level as variables which are neither sensitive nor admissible. A set of features $\mathcal{X}$ is considered to ensure interventional fairness if after adding these features one could increase accuracy of a subsequently trained classifier on this new dataset without worrying about interventional fairness metrics, i.e. in effect the subset of features when added does not introduce any tradeoff between fairness and accuracy and they are safe to subsequent attempts at building a purely predictive classifier. We assume that the original dataset with just sensitive attributes and admissible attributes has no fairness tradeoff to start with. Our approach operates in two phases focused towards performing conditional independence tests with respect to sensitive features and the target variable. These tests help identify variables that (1) do not capture information about sensitive attributes, or (2) ensure fairness even if they capture some information about sensitive attributes. We theoretically prove that both types of these variables ensure causal fairness and analyze the conditions to identify all such variables.

The naïve *SeqSel* algorithm performs a number of conditional independence tests that grows linearly in the number of features. One of the major shortcomings of extant conditional independence testing methods is that they generate spurious correlations between variables if too many tests are performed [35]. To overcome this limitation and reduce the chances of getting spurious results, we propose a more efficient algorithm, *GrpSel*, that uses *group testing* to reduce the number of tests to the logarithm of the number of features and additionally improves the overall efficiency of the pipeline.

Our primary contributions are:

- We formalize the problem of fairness in data integration using causal interventional fairness.
- We provide an algorithm that performs conditional independence tests to identify the variables that do not worsen the fairness of the dataset.
- We prove theoretical guarantees that the variables identified by our algorithm ensure fairness and identify a closed form expression for variables that cannot be added.
- We propose an improved algorithm that leverages ideas of *group testing* to reduce the chances of getting spurious correlations and has sub-linear complexity.
- We show empirical benefits of our techniques on synthetic and real-world datasets.

The paper represents a principled use of causal reasoning to address an important problem that has not been addressed before: fair data integration.
2 Related Work

To the best of our knowledge, there is very little related work on discrimination-aware or fair feature selection. Grgič-Hlača et al. [11] use human moral judgements of different properties of features (volitionality, reliability, privacy, and relevance) as the starting point for feature selection. Although they cite causal fairness definitions as the basis for feature relevance, they do not use the data to quantify this relevance. Salimi et al. [33] consider causal fairness to change the input data distribution as opposed to identification of a small set of features that ensure causal fairness. Dutta et al. [9] start with the causal fairness perspective as well and also use tools from information theory, but use partial information decomposition to partition the information contained in the features into exempt and non-exempt portions; the goal is not feature subset selection, but gaining insight into different types of discrimination. Nabi and Shpitser [29] considered causal pathways to identify discrimination and then train a fair classifier assuming full knowledge of the underlying causal graph. Zhang et al. [40] consider causal definitions of fairness and devise algorithms that repair the dataset to ensure fairness. The work [30] and its followup [3] examine an active feature acquisition paradigm from the perspective of fairness. That work is a completely different paradigm for a few reasons. First, statistical notions of group fairness rather than causal notions are considered. Second, active feature acquisition implies training on the entire feature set and then ordering the inclusion of different features at inference time for different groups and individuals, whereas in our approach, we are attempting a global feature subset selection for everyone prior to training.

3 Causal Fairness

Consider a dataset $D$, comprising of a disjoint set of two types of features (i) Sensitive $S = \{S_1, \ldots, S_{|S|}\}$ and (ii) Admissible $A = \{A_1, \ldots, A_{|A|}\}$ along with a target variable $Y$. Let $X = \{X_1, \ldots, X_n\}$ denote the collection of $n$ features that are neither admissible nor sensitive and can be added to $D$ by performing a join between the input dataset and different datasets from different sources. Let $V = A \cup S \cup X \cup Y$ denote the exhaustive list of available variables and $Y'$ denote the learnt target variable using a subset of these variables. The goal is to identify the largest subset of $T \subseteq V$ such that the variable $Y'$, trained using these variables is fair.

We assume the existence of a causal graph over the set of variables $V$, where the target $Y$ has no descendants. We consider the do operator as an intervention on the causal graph (or the causal bayesian network) that generates the various features. An intervention to a causal graph is where a variable (or a collection of variables) $X$ is set to some specific value, say $x$, and its effect on the distribution of the learnt target variable $Y'$ is observed. According to [31], the do operator helps to evaluate this effect of fixing the value of $X$ on the target variable, $Pr(Y' | \text{do}(X = x))$. Using this operator, we consider the following definition of causal fairness [33] that does not allow the sensitive variables to affect the target through any variable which is not admissible.
Definition 1 (Causal Interventional Fairness\textsuperscript{2}). For a given set of admissible variables, $A$, a classifier is considered fair if for any collection of values $a$ of $A$ and output $Y'$, the following holds: $Pr(Y' = y | do(S) = s, do(A = a)) = Pr(Y' = y | do(S) = s', do(A = a))$ for all values of $A$, $S$ and $Y'$.

This definition is generic enough to capture group level statistics as the sensitive attributes do not impose any influence on the target variable in any configuration \cite{33}. We use $\perp$ to denote independence.

4 Problem Statement

The goal of our problem is to identify the features that can be considered for training a classifier without worsening the fairness of the dataset $D$. Please note that $D$ contains only features $S \cup A$ to begin with, so there is no fairness violation as sensitive attributes are allowed to influence $Y$ through $A$. We make the following assumptions:

Assumption 1 (Faithfulness assumption). The causal graph $G$ on $V$ is faithful to the observational distribution on $V$.

This implies, that if two variables $A$ and $B$ are connected in the causal graph, the data cannot result in any spurious conditional independency of the form $(A \perp B | C)$ for any subset $C \subset V \setminus \{A, B\}$.

A new variable $Y'$ is generated by learning a predictor over the selected subset of features $(A \cup \mathcal{T})$, and this predictor is the Bayes optimal classifier with $Pr[Y'|A \cup \mathcal{T}]$ derived from the observational distribution $P(V)$. In our work, we do not need this generation to actually happen. Our fairness criterion is evaluated on random $Y'$ samples from such an optimal predictor. We make the Assumption 2 to ensure that one would apply the Bayes optimal predictor (learnt from observational data) to all future datasets. This assumption is crucial to decouple fairness of feature selection from the training procedure and to theoretically analyze the quality of bias removal in feature selection. In practice, the classifier can be trained after a complex feature engineering pipeline on the identified features. Our work focuses on identifying all the features that ensure causal fairness and not training the best classifier using those features.

Assumption 2. For evaluating the fairness criterion in Definition 2 using hypothetical interventional distributions, we assume that the mechanism generating $Y'$ is the same as $P[Y'|A \cup \mathcal{T}]$ where $P(\cdot)$ is the observational distribution.

Now, we present the definition of causally fair features that can be added to the original dataset.

Definition 2 (Causally Fair Features). For a given set of admissible variables, $A$, we say a collection of features $D = A \cup \mathcal{T}$ is causally fair if the bayes optimal predictor $Y'$, trained on $D$ satisfies causal fairness with respect to sensitive attributes $S$.

\textsuperscript{2}In this work, we consider causal interventional fairness paradigm and any future reference to causal fairness refer to this definition.
Using this definition, we define our formal problem statement as follows.

**Problem 1.** Given a dataset $D = \{A, S, Y\}$ and a collection of variables $\mathcal{X}$, identify the largest subset $T \subseteq \mathcal{X}$ such that the features $D' = A \cup T$ is causally-fair.

**Problem intuition:** According to the definition of causal fairness, the output distribution of the prediction algorithm, say $f$ should not change when the value of sensitive variables is changed whenever we intervene on $A$. According to do-calculus, intervention on $(A)$ is equivalent to removal of its incoming edges and conditioning on $A$. The learned variable $Y'$ is constructed by applying the function $f$ on the considered features. The goal of the classifier is to learn $Y'$ that mimics the target $Y$ using the selected features.

If all paths from the sensitive variables to the learnt target $Y'$ that go through the variables considered by $f$ are blocked after an intervention on the admissible variables, then the features considered by $f$ are causally-fair. Suppose there exists a path from the sensitive variables to the target through one of the features that is not blocked. In this case, the change in values of $S$ will impact the learnt variable $Y'$ and the algorithm will be causally-unfair. The following section builds on this intuition to devise an algorithm to identify the largest subset of $\mathcal{X}$ which ensures that all paths from sensitive to the target variable are blocked, even when the causal graph is not known a priori.

## 5 Solution Approach

One na"ive solution to ensure fairness is to consider only the admissible variables $A$ for prediction and not add anything to the dataset $D$. This would satisfy the fairness condition but achieve poor prediction performance as there may be a variable $X \in \mathcal{X}$ that is highly correlated with the target variable $Y$. Another extreme solution is to consider all the variables of $\mathcal{X}$ for prediction. This approach would yield high predictive performance but can have arbitrarily poor fairness, for example when there exists a variable $X$ which is highly correlated with one of the protected variables. To this end, we propose **SeqSel** (Algorithm 1) which considers the collection of variables $A, S$ and $\mathcal{X}$ to identify the largest subset of $\mathcal{X}$ which when considered along with $A$ ensure causal fairness of the learnt variable $Y'$. **SeqSel** algorithm operates by performing conditional independence tests over the observed data without explicit knowledge of the underlying causal graph. We use causal graphs only to illustrate the intuition behind the different components of our algorithm.

Figure 1 presents different example causal graphs, to understand the solution approach and identify conditional independence tests that can be performed without inferring the complete causal graph. These graphs contain sensitive variables $S$, admissible variables $A$, target variable $Y$ along with other subsidiary variables $X_i$’s.

1. Variables like $X_1$ that have paths from the sensitive attributes to $X_1$ blocked by the admissible set do not capture any new information about the protected variables. Such variables can be identified by checking their conditional independence with $S$ given $A$.

2. Variables like $X_3$ in Figure 1(b) are independent of the sensitive attributes and do not capture any sensitive information.
Figure 1: Example causal graphs to demonstrate different types of variables and paths from sensitive variables to the target variable. Note: These examples demonstrate different behaviors of our algorithm for different scenarios and do not capture all possible configurations.

3. Variable like $X_3$ in Figure 1(c) is not independent of $S_1$ but is independent of $S_1$ given $A_2$.

4. $X_2$ in Figure 1(b) and 1(c) is not independent of $S_1$ even with an intervention on $A$ and captures sensitive information. However, $X_2$ is independent of $Y$ given $A$.

The different types of variables considered in points 1-3 above do not capture any sensitive information after intervening on $A$. We denote these variables by $C_1$, identified by testing conditional independence of $X$ with $S$ given any subset of $A$. Therefore, all paths from $S \rightarrow X \rightarrow Y$ are blocked for all these variables. The variables that capture sensitive information but are independent of $Y$ given all the selected features $C_1 \cup A$ also do not impact the bayes optimal classifier. This shows that all the variables discussed above ensure causal fairness. Any variable that is not independent of $S$ and $Y$ even after intervening on $A$ is biased and is not safe to be added. $X_2$ in Figure 1(a) is one such example.

Remark 1. In Figure 1(a), there is no edge from $X_2 \rightarrow X_1$ because there does not exist any path from $S$ to $X_1$ which is unblocked given $A$.

Remark 2. If $C_2$ is conditionally independent of $Y$ given $A$, $C_1$, it may not contribute towards
the predictive power of the Bayes optimal classifier trained on these variables. However, for most practical purposes the classifier trained can leverage $C_2$ for better prediction.

Algorithm 1 captures these intuitions to perform conditional independence tests in two phases. The first phase aims at identifying all variables that do not get affected by sensitive attributes, in the presence of admissible attributes $A$ or any subset of $A$. All these variables do not capture any extra information about sensitive attributes and are safe to be added to the dataset $D$. The rest of the variables, $X\backslash C_1$, capture information about sensitive attributes which can worsen fairness of the dataset. However, the second phase identifies the subset of these variables such that the target variable is not affected by their sensitive information in the presence of admissible attributes. We call this algorithm SeqSel as it sequentially performs independence tests to select features.

5.1 Theoretical Analysis

In this section, we show that the variables identified by SeqSel ensure causal fairness. For this analysis, we assume that the target variable $Y$ does not have a child.

We consider the original causal graph comprising all variables in the dataset along with a new variable $Y'$ that refers to the prediction variable trained using the variables $A$ along with the variables returned by Algorithm 1. Given this causal graph comprising $A, S, X, Y, Y'$, we analyze the counterfactual scenario of intervention on $S$ and $A$ to understand the effect on $Y'$. We first show that the variables $C_1$ and $C_2$ identified by Algorithm 1 maintain causal fairness. Please refer to Appendix for the proofs.

**Lemma 1.** Consider a dataset $D$ with admissible variables $A$ and sensitive $S$ and a collection of variables $C_1$, if $\exists A \subseteq A$ such that $(C_1 \perp S |A)$ then $A \cup C_1$ is causally fair.

The following lemma justifies the addition of $C_2$ to the dataset $D$ without affecting its causal fairness.

**Lemma 2.** Consider a dataset $D$ with admissible variables $A$ and sensitive $S$, a set of variables $C_1$ satisfying $(C_1 \perp S |A)$ and a collection of variables $C_2$ with $(C_2 \not\perp S |A)$, if $(C_2 \perp Y |A, C_1)$ then $A \cup C_2 \cup C_1$ is causally fair.

This shows that the features $C_1$ and $C_2$ ensure causal fairness of the dataset. Using these results, we identify a closed form expression to identify all variables that ensure causal fairness.

**Theorem 1.** Consider a dataset $D$ with admissible variables $A$, sensitive $S$, a set of variables $X$ with a target $Y$. A variable $X \in X$ is safe to be added along with $T \cup A$, where $T \subseteq C_1 \cup C_2 \cup A$ without violating causal fairness iff (i) $(X \perp S |A)$ for some $A \subseteq A$ or (ii) $(X \perp Y |C', A)$, where $(C' \perp S |A)$ or (iii) $X$ is not a descendant of $S$ in $G_A$, where $G_A$ is same as $G$ with incoming edges of $A$ removed.

SeqSel captures all variables that can be identified by performing these tests with $S$ and $Y$. However, the last condition of Theorem 1 requires intervention to identify other variables. Devising a set of conditional independence tests to identify these variables is an interesting question for future work.
Complexity: Algorithm 1 tests conditional independence (CI) of each variable with $S$ and $Y$. In the worst case, it requires a total of $O(2^{|A|} n)$ conditional independence tests to identify all the variables that do not worsen the fairness of $D$. In most realistic scenarios, $|A|$ is a small constant, yielding overall complexity of $O(n)$. Existing CI testing techniques can generate spurious correlations between independent variables for large values of $n$. In the next section, we propose a group testing formulation that reduces this complexity to $O(p \log n)$ tests, thereby improving its accuracy.

5.2 Group Testing

Group testing is an old technique that efficiently performs tests on a logarithmic number of groups of items rather than testing each item separately. To the best of our knowledge, it has not been used in causal inference to identify independent variables. We show the following two results for any collection of variables $X$ and $Z$ justifying the correctness of group testing in causal inference.

Lemma 3. If $\exists X_i \in X$ such that $X_1 \not\perp X_i | Z$ then $(X_1 \not\perp X \setminus\{X_1\} | Z)$ for some variable $X_1$ and $Z$.

Lemma 4. If $(X_1 \not\perp X \setminus\{X_1\} | Z)$ then $\exists X_i \in X \setminus\{X_1\}$ such that $(X_1 \not\perp X_i | Z)$ for some $Z$.

These results yield the following two properties that make Algorithm 1 more efficient.

- If $(X_1 \perp X_2, X_3 | Z)$ then $X_1 \perp X_2 | Z$ or $X_1 \perp X_3 | Z$
- If $(X_1 \perp X_2, X_3 | Z)$ then $X_1 \perp X_2 | Z$ and $X_2 \perp X_3 | Z$

Algorithm 2 GrpSel

**Input:** Variables $A, S, X, Y$

$C_1 \leftarrow \text{first\_phase}(A, S, X, Y)$

$C_2 \leftarrow \text{final\_candidates}(A, S, X, Y, C_1)$

return $C_1 \cup C_2$

Algorithm 2 presents an improved version of SeqSel that uses group testing to remove all the variables that do not satisfy the conditional independence statements shown in Theorem 1. We call this approach GrpSel as it performs group testing for feature selection. GrpSel operates in two phases, aiming to capture variables $C_1$ and $C_2$, respectively. The first phase (Algorithm 3) identifies the variables which do not capture any new information about sensitive variables given $A \subseteq A$. It tests the conditional independence between $S$ and $X$ given $A \subseteq A$. If the variables are conditionally independent, then all the variables $X$ are identified to maintain causal fairness. On the other hand, if the variables are conditionally dependent, the set $X$ is partitioned into two equal partitions and first\_phase algorithm is called recursively for both the partitions. Algorithm 4, performs the second phase to identify the variables which are independent of the target variable $Y$ given $A$ and $C_1$. This algorithm operates similarly to first\_phase with a different conditional independence test.

Complexity. Algorithm 3 requires a total of $2^{|A|} k \log n$ tests to identify all the variables $X$ that satisfy $(S \perp X | A)$, where $k$ is the number of variables that do not satisfy the condition.
The second phase requires \(k' \log k\) tests to identify the variables that satisfy conditional independence with \(Y\) where \(k'\) is the number of variables that do not satisfy the condition. This shows that the \texttt{GrpSel}\(^1\) has better complexity when the total number of biased variables \(k\) is \(o(n/\log n)\).

6 Experiments

In this section, we empirically evaluate our technique along with baselines on real-world and synthetic datasets. We show that (a) identified features ensure causal fairness, (b) the classifier that relies on fair features has comparable quality, (c) group testing is efficient on high-dimensional data. We present additional experiments in the Appendix.

Datasets. We consider the following datasets.

- **Medical Expenditure** (MEPS) \cite{2}: predict total number of hospital visits from patient medical information. (Healthcare utilization is sometimes used as a proxy for allocating home care.) We consider two variations denoted by MEPS(1) and MEPS(2). MEPS(1) considers ‘Arthritis diagnosis’ as admissible and MEPS(2) considers ‘Arthritis diagnosis’ and ‘Mental health’ as admissible. Race is considered sensitive. Contains 7915 training and 3100 test records.

- **German Credit** \cite{1} dataset from UCI repository contains attributes of various applicants and the goal is to classify them based on credit risk. The account status is taken as admissible and whether the person is below the mean age is taken as sensitive. Contains 800 training and 200 test records.

- **Compas\(^3\)** \cite{16} : predict criminal recidivism from features such as the severity of the original crime. This dataset contains features like age, race, prior conviction, etc. The time of moving out of jail is taken as admissible and race as sensitive. Contains 7200 samples.

- **Synthetic**: a synthetically-constructed dataset where a feature is constructed to be highly correlated to a sensitive feature with probability \(p\). This dataset is used for understanding

\(^1\)https://github.com/propublica/compas-analysis
the effect of number of features and the fraction of noisy features on the complexity of our techniques.

In addition to the default set of features, we use techniques from [21] to generate new features, constructed by composition of already present features.

**Baselines.** We consider the following baselines to identify a subset of features for the training task. (i) **A** – uses the variables in the admissible set. (ii) **ALL** – uses all features present in the dataset. (iii) **Hamlet** [24] – uses statistics-based heuristics to identify features which do not add additional value to the data set and can be ignored. (iv) **SPred** – learn a classifier using exhaustive set of features to predict the sensitive attribute. Based on feature importance, we remove the highly predictive features.

![Graph showing classifier fairness and accuracy on MEPS, German, and Compas datasets.](image)

**Figure 2:** Classifier fairness and accuracy on MEPS, German, and Compas datasets.

**Experiment Setup.** We evaluate the accuracy and fairness of the trained classifier on the test set. To evaluate fairness, we measure conditional mutual information and absolute odds difference calculated as the difference in false positive rate and true positive rate between the privileged and unprivileged groups. We consider a group fairness metric as a proxy because causal fairness implies group fairness and can be easily evaluated from observed data [33].

We use RCIT [35] package in R for conditional independence (CI) tests, logistic regression as the classifier and report average of 5 runs. We considered the default threshold of p-value to be 0.01 and default settings of sklearn’s logistic regression classifier. **GrpSel** and **SeqSel** were implemented in R and the classifier training and testing in Python. The code was run on a laptop with 16GB RAM running MAC OS.

### 6.1 Solution Quality

Figure 2 compares the accuracy of the classifier trained with the features identified by our baselines along with its fairness. **ALL** learns the most accurate classifier as compared to all other techniques. However, it achieves the highest odds difference and hence worst fairness with respect to the sensitive attribute of the dataset. **A** maintains high fairness but achieves quite low accuracy as compared to **SeqSel** and **GrpSel**. **Hamlet** is not able to identify features that are highly correlated with sensitive attributes and does not improve its fairness. **SPred** is able to identify a few features that capture sensitive information but is unable to identify all such features. Hence, it does not improve the fairness of the classifier as compared to **GrpSel**. **SeqSel** and **GrpSel** maintain high fairness with respect to various metrics of fairness without much loss in accuracy.
For MEPS and German datasets, \texttt{GrpSel} and \texttt{SeqSel} are able to identify features that reduce the bias and do not lose much in classifier accuracy. However, all techniques have higher bias against the protected attribute on Compas. In this case, we observe that the admissible feature is correlated to the sensitive attribute, affecting the fairness of the trained classifier.

We observed similar behavior on changing p-value thresholds of CI tests and the classifier from logistic regression to random forest.

**Table 1:** Conditional Mutual Information \cite{28}

| Dataset    | CMI(S, Y'|A) | CMI(S, Y|A) |
|------------|-------------|------------|
| MEPS(1)    | 0.0         | 0.015      |
| MEPS(2)    | 0.0         | 0.014      |
| German     | 0.002       | 0.018      |
| Compas     | 0.0         | 0.01       |

**Table 2:** Total number of tests.

| Dataset   | \texttt{SeqSel} | \texttt{GrpSel} |
|-----------|----------------|----------------|
| MEPS(1)   | 343            | 247            |
| MEPS(2)   | 420            | 390            |
| German    | 525            | 81             |
| Compas    | 257            | 83             |

Complexity. The total number of CI tests required by \texttt{SeqSel} and \texttt{GrpSel} are shown in Table 2. The total number of tests required by \texttt{GrpSel} is better than \texttt{SeqSel} across all datasets. Since all these datasets contain fewer than 1000 features, the improvement is not very significant. To understand the difference in complexity of the two techniques, we perform an extensive simulation study by varying the total number of features and the fraction of biased variables.

Figure 4 plots the total number of CI tests required to identify variables that ensure causal fairness. With the increase in total number of features (n), the number of tests required by \texttt{SeqSel} grows linearly. However, the growth of \texttt{GrpSel} is sub-linear and requires fewer tests than \texttt{SeqSel} for larger n. This result is coherent with our theoretical analysis of $O(n)$ tests for \texttt{SeqSel} and $O(k \log n)$ for \texttt{GrpSel}, where k is the number of biased variables.

\footnote{Some mutual information values were slightly negative and were truncated to 0 as suggested by \cite{28}.}
**Effect of $p$.** Figure 3 compares `GrpSel` and `SeqSel` as a function of the total fraction of biased variables in the dataset. `SeqSel`’s complexity is driven by the total number of features but the tests required by `GrpSel` are dependent linearly on $p$. This experiment confirms the benefit of using group testing when the total number of biased variables are fewer than the variables that ensure fairness.

**Efficiency.** Among all the techniques considered, we observe that `GrpSel` and `SeqSel` are able to identify all the variables in less than 110 seconds on all real-world datasets. The time taken to train a classifier on these data sets is less than 1 minute. Our feature selection pipeline is able to learn a fair classifier in less than 3 minutes across all datasets.

7 Conclusion

In this paper, we have tackled the problem of data integration — joining additional features to an initially given dataset — while not introducing additional unwanted bias against protected groups. We have utilized the formalism of causal fairness and do-calculus to develop an algorithm for adding variables that is theoretically-guaranteed not to make fairness worse. We have enhanced this algorithm using group testing to make it more efficient (the first use of group testing in such a setting) and shown its efficacy on several datasets.

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A Proofs

First, we show the following property of do-calculus.

**Lemma 5.** Given a disjoint collection of variables $X, Y$ and $Z$ in a causal graph $G$, such that $(X \perp Y|Z')$, where $Z' \subseteq Z$, then $P_r[X|do(Y), do(Z)] = P_r[X|do(Z)]$

**Proof.** Using the third rule of do-calculus (Equation 10, [14]), $P_r[X|do(Y), do(Z)] = P_r[X|do(Z)]$ when $X$ is independent of $Y$ given $Z$ in the graph where incoming edges of $Z$ have been removed. Since, $X \perp Y|Z'$ in $G$ where $Z' \subseteq Z$, removing additional incoming edges will ensure that none of the variables in $Z$ are a collider and conditioning on $Z\setminus Z'$ additionally will still maintain conditional independence.

**Lemma 6.** Given a dataset $D$ comprising of variables $A \cup S \cup X$, target variable $Y$ and let $Y'$ be the variable learnt using the feature subset $T \cup A$, then $P_r(Y'|do(A), do(S), T) = P_r(Y'|do(A), T)$, where $T \subseteq X$

**Proof.** Based on the assumption about the construction of $Y'$ (Assumption 2), the variable $Y'$ is only dependent on the variables in $A \cup T$ in all environments. Given $A \cup T$, the variable $Y'$ is independent of $S$. The same condition holds even when incoming edges of $A$ are removed. Also, $S$ nodes do not have any incoming edges. Therefore, on applying the third rule of do-calculus, since $Y'$ is independent of $S$ in the modified graph where incoming edges of $A$ and $S$ nodes that are ancestors of $T$ are removed. Therefore, $P_r(Y'|do(A), do(S), T) = P_r(Y'|do(A), T)$

**A.1 Proof of Lemma 1**

**Proof.** Given $(C_1 \perp S|A)$ for some $A \subseteq$, the variable $X$ does not capture any information about the sensitive variables. Hence all paths from $S$ to the target $Y$ that pass through $X$ are blocked. To show this mathematically, we consider a causal graph along with $Y'$ and evaluate the distribution under the intervention of $A$ and $S$ as follows.

\[
P_r[Y'|do(S), do(A)] = \sum_{C_1} P_r[Y'|C_1, do(S), do(A)]P_r[C_1|do(S), do(A)]
\]

Using Lemma 5 as $C_1$ is independent of $S$, given $A$

\[
= \sum_{C_1} P_r[Y'|C_1, do(S), do(A)]P_r[C_1|do(A)]
\]

Using Lemma 6

\[
= \sum_{C_1} P_r[Y'|C_1, do(A)]P_r[C_1|do(A)] = P_r[Y'|do(A)]
\]

This shows that any intervention on $S$ does not affect the variable $Y'$, thereby ensuring causal fairness of the considered features.
A.2 Proof of Lemma 2

Proof. We consider the original causal graph along with $Y'$ and simplify the causal fairness condition as follows:

$$Pr[Y'|do(S), do(A)] = \sum_{C_1, C_2} Pr[Y'|C_1, C_2, do(S), do(A)] \times Pr[C_1, C_2|do(S), do(A)]$$

Using Lemma 6

$$= \sum_{C_1, C_2} Pr[Y'|C_1, C_2, do(A)] \times Pr[C_2|C_1, do(S), do(A)] Pr[C_1|do(S), do(A)]$$

Since $Y'$ is independent of $C_2$ given $A$ and $C_1$

$$= \sum_{C_1, C_2} Pr[Y'|C_1, do(A)] Pr[C_2|C_1, do(S), do(A)] \times Pr[C_1|do(S), do(A)]$$

Summing $Pr[C_2|C_1, do(S), do(A)]$ over $C_2$

$$= \sum_{C_1} Pr[Y'|C_1, do(A)] Pr[C_1|do(S), do(A)]$$

Using Lemma 5 as $C_1$ is independent of $S$, given $A$

$$= \sum_{C_1} Pr[Y'|C_1, do(A)] Pr[C_1|do(A)] = Pr[Y'|do(A)]$$

This condition shows that the variable $Y'$ learned using $A \cup C_1 \cup C_2$ is causally-fair. \qed

A.3 Proof of Theorem 1

Proof. First we show: if either of the conditions are satisfied then $\mathcal{C}$ ensures causal fairness. Using Lemma 1 and 2, we can observe that all the variables $C_1 \cup C_2$ such that $(C_1 \perp S|A)$, where $A \subseteq A$ and $(C_2 \perp Y|C_1, A)$ are safe to be added without worsening the fairness of the dataset. Now consider a variable $X$, which is not a descendant of $S$ in $G_\mathcal{A}$. All paths from $S$ to $X$ are blocked when we intervene on $A$ as all incoming edges of $A$ are removed. Therefore it is safe to add $X$ without affecting causal fairness of the dataset.

To show the converse, when $X \not\perp S|A$, $\forall A \subseteq A$ and $X \not\perp Y|C'$, $A$ and $X$ is a descendant of $S$ in $G_\mathcal{A}$, then we show that $X$ can worsen the fairness. We can observe the following properties about $X$:

- $(S \not\perp X|A)$ implies there exists a path from $S$ to $X$ that is unblocked given $A$.
- $(X \not\perp Y|A, C')$ implies that $X$ is predictive of $Y$ given the features $\mathcal{T} \subseteq C_1 \cup C_2$. Therefore, there will be a direct edge from $X$ to the learned variable $Y'$.

If the paths from $S$ to $X$ are unblocked in $G_\mathcal{A}$ then $S$ to $X$ is unblocked when we intervene on $A$. In this case, the path from $S \rightarrow X \rightarrow \hat{Y}'$ is unblocked and therefore $X$ is a biased variable that violates causal fairness of the dataset. \qed
Figure 5: Example graph where $X_2$ is not identified as causally fair by GrpSel. We omit other nodes for the sake of clarity.

A.4 Proof of Lemma 3

We denote conditional mutual information between two variables $X$ and $Y$ given $Z$ as $I(X,Y|Z)$.

Proof. Using chain rule, $I(X_1, X|Z) = I(X_1, X|Z) + I(X_1, Z|X) \geq I(X_1, X|Z) > 0 \square$

A.5 Proof of Lemma 4

Proof. $X_1 \not\in \mathcal{X}\backslash X_1|Z$ means that path from $X_1$ to $\mathcal{X}$ is not blocked. Using assumption 1, that the path to atleast one of $X_i \in \mathcal{X}\backslash X_1$ is not blocked. Hence, $\exists i$ such that $X_1 \not\in X_i|Z$. \square

B Additional Experiments

Our experiments on real-world datasets that compare group fairness metric (absolute odds difference) and conditional mutual information (CMI) correspond two ends of the spectrum. Since causal fairness implies group fairness, Figure 2 provides some evidence that our algorithms can potentially ensure fairness. On the other hand, since GrpSel has low CMI with the target variable given $\mathcal{A}$ (Table 1), the CMI of $S$ and $Y'$ will be low even after intervening on $\mathcal{A}$. This experiment guarantees the effectiveness of our techniques to ensure causal fairness.

To further analyze the ability of our algorithms to ensure causal fairness, we evaluate GrpSel and SeqSel on multiple synthetic datasets generated using causal graphs of varied sizes (1000, 3000 and 5000) along with the examples shown in Figure 1 a-c.
In this experiment, we validated the effectiveness of \texttt{SeqSel} and \texttt{GrpSel} to identify the variables that ensure causal fairness. Across all datasets, we observed that \texttt{SeqSel} and \texttt{GrpSel} identified all the variables that ensure causal fairness. One of the variables in 1000 node dataset was not detected by our algorithm. We show a small subgraph of this dataset in Figure 5. In this dataset, variable $X_2$ is not identified by \texttt{GrpSel} and \texttt{SeqSel} because $X_2 \not\perp S_1$ and $X_2 \not\perp S_1|A_1$. This is an example scenario where interventional data is required to identify such variables.