Discrimination detection by causal effect estimation

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***Abstract*—With more and more decisions being made by learnt algorithms from data, algorithmic discriminations have become a risk for civil rights. The detection of discrimination is a process of counterfactual reasoning. This paper proposes a general detection framework by combining a data mining method with a well established counterfactual reasoning framework, potential outcome model. The potential outcome model supports operational definitions of global and local discriminations and discriminations by combined factors, while a data mining method makes the detection efficient. The proposed method, instantiated by association rule mining with potential outcome model based causal effect estimation, is evaluated with four real world data sets and is compared with a Bayesian network (BN) based detection method. It is able to detect not only global discriminations that are detected by the BN based method, but also local and combined discriminations that the BN based method cannot find. The proposed method is efficient, and scales well with the data set size and the number of attributes.**

***Index Terms*—Discrimination detection; potential outcome model; association rules; causal effect**

I. INTRODUCTION

While big data technologies have transformed every aspect of our society, data driven technologies potentially cause social harms [1]. More and more decisions, such as those in health care, employment, housing, insurance, and education, have been made by computer models learnt from data to maximise a utility measure. The decisions made by these models may be discriminatory. We use an example to illustrate this. Assume that in a call centre, the queue for the service (e.g, for Internet connection) is maintained by an algorithm learnt from historical data to prioritise the most profitable customers, and that one of the rules embedded in the algorithm is that the customers with phone numbers starting with a certain pattern (e.g. 833*) are of the least profit. When a customer with a phone number starting with 833 calls the centre for help, he/she will be predicted least profitable by the algorithm and his/her request will be put in the back of the queue so other more profitable callers will be served first. As a result, the customer may not receive a service if the centre receives a large number of calls on the day. The deprival of the service from a less profitable customer by the algorithm is discriminatory.

Some data mining methods for detecting discriminations from data have been proposed. Most of them are correlation based, such as extended lift [2], selection and contrast lift [3], olift [3], η-neutrality [4], balanced error rate [5], and the direct use of contingency tables [6]. However, legally acceptable evidence of discrimination is based on counterfactual reasoning: if the person had belonged to a different group, would the outcome have changed? Answering such a counterfactual question is a process of causal inference. For example, when we assess whether females are discriminated in their payment, we will need to find out if being a female is a cause of a lower salary by unbiasedly estimating the causal effect of gender on salary.

Causal methods for discrimination detection head towards a right direction since they answer the counterfactual questions. Currently emerging works using causal methods for discrimination detection [7, 8, 9, 10] are causal Bayesian network based methods. A causal Bayesian network is very good for visualising causal relationships, and helps define various types of discrimination cases.

A causal Bayesian network (Bayesian network or BN for short in this paper) is structured as a directed acyclic graph where nodes denote variables and edges denote dependency relationships between nodes. A BN graphically represents the joint distribution of variables under the Markov assumption [11]. When the causal sufficiency assumption and the faithfulness assumption [11] are made, an edge of a BN learnt from data is potentially a causal relationship between two variables. A fair decision system represented by a BN should not contain an edge from a protected attributes (e.g. gender or age) to the outcome variable. In the case where such an edge exists, potential discrimination appears, and the degree of the discrimination is evaluated by estimating the causal effect of the protected attribute on the edge [12, 13].

The BN based discrimination detection approach has some limitations although it is a major step forward in discrimination detection.

Firstly, causal effect estimation using BNs has uncertainties because of the equivalent classes of BNs learnt from a data set. As the same joint distribution of a variable set can be represented by multiple BNs of the same equivalent class [11], the causal effect of the same pair of variables in different BNs can be different. In addition, because of the high complexity of BN learning, many heuristics to improve efficiency for constructing BNs also result in uncertainties in learnt BNs.

Secondly, the definition of local discrimination using BNs is not succinct and does not lead to efficient discovery. The local discrimination in [9] is defined on a sub data set of a context using a BN. In the discovery, constructing a BN is difficult, and constructing a number of BNs in context specific data sets is very difficult since a data set often has many possible contexts.

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In [9], authors did not show how to find local discriminations except for presenting a conceptual definition.

Thirdly, it is very inefficient to find combined causes in a BN. Combined causes mean that two or more variables jointly cause an outcome. Naively, combined causes can be modelled directly by combining multiple variables to construct a new variable in BN construction and detecting the causal effect of the newly constructed variables on the outcome variable. However this will increase the number of variables exponentially, making constructing BNs impossible. Other solutions presented in [14] are still quite expensive.

This is why we propose a combination of the potential outcome model [15], a main framework for causal effect estimation, and a data mining method, i.e. an association rule mining method in our instantiation, to discover discriminations in data. Our contributions are outlined as the following.

1) We propose a sound method for discrimination detection. It uses causal effect to measure discrimination. The method provides unified and succinct operational definitions for global and local discriminations by single or combined attributes. There are no other causality based methods detecting local discriminations or discriminations by combined attributes.

2) The method is efficient. The efficiency is from the use of an association rule mining algorithm for discovering candidate discrimination rules. The experimental results show that it is multiple orders of magnitude faster than a BN based detection method for high dimensional and large data sets.

II. Problem definition

A. Notations

Given a data set $\mathbf{R}$ containing all historical decision records of a system. Each record of the data set represents an individual and contains three types of attributes, *protected*, *explanatory*, and *other* attributes, in addition to the *decision* attribute D. The set of protected attributes $\mathbf{P^c} = \{P_1, P_2, \ldots\}$, such as a Gender, Age, Race, Religion, and etc., are defined by the law and they cannot be used in decision making. The set of explanatory attributes $\mathbf{E^c} = \{E_1, E_2, \ldots\}$ are supposed to be used for making decisions. The other attributes $\mathbf{O^c} = \{O_1, O_2, \ldots\} = \mathbf{R} - \mathbf{P^c} - \mathbf{E^c} - \{D\}$ are the remaining attributes that are not protected and not used in decision making. The explanatory attributes and other attributes are disjoint. Users know which attributes have been used for making decisions. For example, home loan or insurance companies are required to explain to the regulatory authority the information used in decision making. For government organisations, policy transparency also requires that the factors for decision making are publicly known. Explanatory attributes may not be all used in building a decision system as in supervised learning, but they are claimed and legally allowed attributes used for making decisions. We use $\mathbf{P}$ and $\mathbf{O}$ to mean subsets of $\mathbf{P^c}$ and $\mathbf{O^c}$ respectively, including the empty set. $\mathbf{PO}$ is a shorthand notation for $\{\mathbf{P} \cup \mathbf{O}\}$. The decision attribute D takes a value of 1 or 0 where 1 means the unfavourable decision.

For the simplicity of presentation, we assume that all attributes are binary. This assumption does not restrict the generality of the proposed approach and the assumption affects only the matching methods [15] used in causal effect estimation of the potential outcome model [16].

B. Risk difference and bias in its estimation

Risk difference is a commonly used measure for discrimination detection. Risk difference in a population or a sub population is presented as the following: $\mathrm{prob}(D = 1|P = 1) - \mathrm{prob}(D = 1|P = 0)$, where P is a protected attribute.

If a group of people with $P = 1$ have a higher chance receiving an unfavourable decision than the other people in the population, this group is discriminated. British legislation for sex discrimination sets a threshold difference of 5% [17].

A major drawback of this criterion is the Simpson's paradox. When we observe a high risk difference in a group of people, the same high risk difference may not be observed in its subsets or supersets. For example, University of California, Berkeley was accused of discrimination against females since the admission rate of males was significantly higher than that of females in 1973. However, when examining the admission rates of all departments, the majority of departments showed a bias in favour of females [18]. Which statistics should readers believe?

We see that causal inference is a better way for detecting discriminations. Causal effect will give a unbiased estimation of the effect of a protected variable on the outcome. For example, to estimate whether the females are discriminated in their payment, a fair comparison should compare the payments of females and males given the same education level, the same type of positions, and the same experience in the same location, and so on. This is in contrast to the risk difference, which is based on the whole population and may compare payments of people with different education levels and positions.

C. Definitions in the potential outcome framework

To detect discriminations in data, the fundamental question to answer is whether the decision will be changed if the value of a protected attribute changes. The average causal effect estimated in Rubin's potential outcome model [15] is a suitable measure to provide a quantitative answer to this question. We use a discrimination scenario to explain average causal effect.

Let P be a protected variable. Each individual has two potential outcomes corresponding to the two values of P (known as a treatment variable in the potential outcome model). Let Y_i^1 be the potential outcome of individual i assuming $P = 1$ and Y_i^0 be the potential outcome of individual i assuming $P = 0$. Our decision variable D_i equals to Y_i^1 or Y_i^0 depending on the observed P value. For each individual, we are only able to observe one of the potential outcomes. For example, if P be the gender, we are able to observe $D_i = Y_i^1|P = 1$, the potential outcome of male when the individual is male, or $D_i = Y_i^0|P = 0$, the potential outcome of female when the individual is female. We are not able to

observe $Y_i^1|P=0$ and $Y_i^0|P=1$. Readers may then ask why we need two potential outcomes when one is unobservable. In a legal discrimination case, a judge will infer whether the victim in the opposite sex will receive a different decision, or formally whether $Y_i^1 = Y_i^0$? Since we only observe one potential outcome, and the other will need to be inferred. The inference is also called counterfactual reasoning, e.g. whether Mary will obtain that job if she were a male (when Mary is in fact a female).

Let us assume that we could observe both potential outcomes, Y_i^0 and Y_i^1. The causal effect of P on the decision of individual i is quantified as $CE_i(P) = Y_i^1 - Y_i^0$. If $CE_i(P)$ is zero, this means that P does not cause a difference in the decisions. If $CE_i(P)$ is larger than 0, this means that P causes a difference in the decisions and there is a potential discrimination since the same person receives different decisions just because of the difference in P.

When we aggregate the causal effects of all individuals in a target population, we obtain the average causal effect as the following:

$$ACE(P) = E[Y_i^1 - Y_i^0] = E[Y_i^1] - E[Y_i^0]$$

where $E[.]$ is the expectation of a random variable.

Since only one potential outcome is observed for an individual, the average causal effect in the above above equation needs to be estimated.

We consider a group (a stratum) of indistinguishable individuals, sharing the same vector value $\mathbf{e}$ of the set of explanatory attributes $\mathbf{E^c}$. Let us assume q proportion of individuals having $P=1$. The average causal effect over the group then is: (In the following, we omit i since this does not cause an ambiguity.)

$$\begin{aligned} &ACE_e(P) = E[Y^1|\mathbf{E^c}=\mathbf{e}] - E[Y^0|\mathbf{E^c}=\mathbf{e}] = \\ &qE(Y^1|P=1,\mathbf{E^c}=\mathbf{e}) + (1-q)E(Y^1|P=0,\mathbf{E^c}=\mathbf{e}) - \\ &(qE(Y^0|P=1,\mathbf{E^c}=\mathbf{e}) + (1-q)E(Y^0|P=0,\mathbf{E^c}=\mathbf{e})) \quad (1) \end{aligned}$$

In the above equation, both $Y^1|P=0$ and $Y^0|P=1$ are unobservable and need to be estimated. When a decision is made by an algorithm, input $\{P, \mathbf{E^c}\}$ determines the output (Y^1, Y^0). A potential outcome takes an assumed P value not the real P value. Therefore, $E(Y^1|P=0,\mathbf{E^c}=\mathbf{e}) = E(Y^1|P=1,\mathbf{E^c}=\mathbf{e})$ given the same $\mathbf{E^c}$ value for the treated ($P=1$) and untreated ($P=0$). For example, if Mary and John are identical except for gender, the outcome for Mary is the same as that for John when Mary is assumed as a male. In the same way, we have $E(Y^0|P=1,\mathbf{E^c}=\mathbf{e}) = E(Y^0|P=0,\mathbf{E^c}=\mathbf{e})$. Therefore,

$$ACE_e(P) = E(Y^1|P=1,\mathbf{E^c}=\mathbf{e}) - E(Y^0|P=0,\mathbf{E^c}=\mathbf{e})$$

The causal effect of the whole population is the weighted sum of the average causal effects of all strata:

$$ACE(P) = E[ACE_e(P)]$$

The above estimation is a standard and statistically sound solution for estimating causal effect by perfect stratification [19] or exact matching [16].

In a fair decision system, as long as the values for the explanatory attributes are the same, the decision should be the same regardless of the values of P. So, the expectation of $ACE(P)$ is zero.

Definition 1 (Global discrimination) *Attribute P is discriminatory if $|ACE(P)| > \alpha$ where α is a discrimination threshold.*

The global discrimination is defined on all strata of all explanatory variables. It is relatively easy to observe. In contrast, many other discriminations are local and hidden. For example, females in rural areas may be discriminated even though overall females are not discriminated.

Before defining local discrimination, let us define the context based causal effect as the following:

$$\begin{aligned} ACE(P|O=o) &= E[ACE_e(P|O=o)], where \\ ACE_e(P|O=o) &= E[Y^1|P=1,O=o,\mathbf{E^c}=\mathbf{e}] - \\ &\quad E[Y^0|P=0,O=o,\mathbf{E^c}=\mathbf{e}] \end{aligned}$$

Definition 2 (Local discrimination) *Given a context $O=o$, an attribute P is discriminatory if $|ACE(P|O=o)| > \alpha$ where α is a discrimination threshold.*

In the above discussions, discriminations are defined on a single protected attribute. In some cases, the combined protected attributes cause discriminations, for example, old females are discriminated although either females or old people are not discriminated.

We define a combined protected attribute $\mathbf{P} = (P_1, P_2, \ldots, P_l)$ to consist of l attributes. Given $\mathbf{p} = (p_1, p_2, \ldots p_l)$ where $p_1, p_2, \ldots p_l$ are either 1 or 0, then the value of $\mathbf{P}$ is defined as:

$$\mathbf{P} = \begin{cases} 1 & \text{if } \mathbf{P}=\mathbf{p} \\ 0 & \text{otherwise} \end{cases}$$

$\mathbf{P}$ is also called a l-pattern.

Definition 3 (Discrimination of a combined attribute) *Let $\mathbf{P} = (P_1, P_2, \ldots P_l)$. The combined attribute $\mathbf{P}$ is discriminatory if $|ACE(\mathbf{P}|O=o)| > \alpha$ where α is a discrimination threshold. When $O=\emptyset$, the discrimination is global and otherwise local.*

Note that, the context in Definitions 2 and 3 can be a l-pattern $\mathbf{O} = (O_1, O_2, \ldots O_l) = \mathbf{o}$.

D. Causal effect adjustment

When there are more than one global discriminatory attributes, there might be an interaction between the attributes. For example, gender discrimination and race discrimination occur frequently together. The causal effect of gender on the decision may include some effect from race on the decision. It is good to know how the change of a discriminatory attribute P directly affects D.

In order to find direct causal effect of a single protected attribute (or a combined attribute) P, we need to screen off the causal effect from other discriminatory attributes. The set of attributes for stratification in this case becomes $\mathbf{E}' = \mathbf{E}^c \cup \mathbf{P}'$ where $\mathbf{P}'$ is the set of discriminatory attributes. The calculation of adjusted causal effect $ACE(P)$ uses attribute set $\mathbf{E}'\backslash\{P\}$ for stratification and this estimation excludes the effects of other discriminatory attributes. For the direct effect of a set $\mathbf{P}$ of discriminatory attributes, the stratification set is $\mathbf{E}'\backslash\mathbf{P}$.

The above discussed method for causal effect estimation employs perfect stratification or exact matching of samples [16, 19]. Matching is to balance the distributions of co-variates in the treatment group and control group in a data set and to make them have similar distributions to reduce bias in causal effect estimation. A number of measures are commonly used for assessing the similarity of samples for matching. Examples are exact matching (samples having exactly same values for co-variates), Mahalanobis distance, and propensity score. There are also different techniques or procedures for matching samples based on the measures [16], and some typical examples are k : 1-nearest neighbourhood matching and subclassification (stratification).

III. Algorithm

The mathematical models in the previous section are not complex. However, computing them is still challenging as the possible combination of all sorts of attributes. In this section, we describe our framework of solutions. Our framework for discrimination detection from data consists of two steps. Firstly for a given data set, an association rule mining method is used to detect the signals of discriminations in it. Then the causal effects of the detected signals are estimated using the potential outcome model.

A. Candidate discriminatory rules

Definition 4 (Candidate discriminatory rules) $\mathbf{PO} = 1 \rightarrow D = 1$ *is a candidate discriminatory rule if* $corr(\mathbf{PO}, D) > \beta$ *and* $\text{prob}(\mathbf{PO} = 1, D = 1) > \gamma$ *where* β *and* γ *are user defined parameters,* $corr(\mathbf{PO}, D)$ *stands for correlation between the combined attribute* $\mathbf{PO}$ *and attribute* D*, and* $\text{prob}(\mathbf{PO} = 1, D = 1)$ *is called the support of the association rule.*

We use odds ratio [20] as a measure for $corr(\mathbf{PO}, D)$. $\mathbf{PO}$ is called a pattern, and a pattern is frequent if its support is higher than γ. Note that a subset of $\mathbf{PO}$ is also a pattern.

For the candidate discriminatory rule $\mathbf{PO} = 1 \rightarrow D = 1$, we test the following discriminatory cases:

1) When $\mathbf{O} = \emptyset$, $\mathbf{P}$ is a global single (or combined) discriminatory attribute if $ACE(\mathbf{P}) > \alpha$.
2) When $\mathbf{O} \neq \emptyset$, $\mathbf{P}$ is a local single (or combined) discriminatory attribute given $\mathbf{O} = 1$ when $ACE(\mathbf{P}|\mathbf{O} = 1) > \alpha$.

Definition 5 (Redundant candidate discriminatory rules) *Candidate discriminatory rule* $\mathbf{P_2Q_2} = 1 \rightarrow D = 1$ *is redundant if* $\mathbf{P_1Q_1} = 1 \rightarrow D = 1$ *is discriminatory, and* $\mathbf{P_1} \subseteq \mathbf{P_2}$ *and* $\mathbf{Q_1} \subseteq \mathbf{Q_2}$.

Redundancy means that the testing of $\mathbf{P_2Q_2} = 1 \rightarrow D = 1$ is not necessary if $\mathbf{P_1Q_1} = 1 \rightarrow D = 1$ is true. This is true because of the nature of itemset supports. This property will help prune the search space in a level-wise search and evaluation process.

B. Forming strata

In Equation (1), exact matching [16] is used to unbiasely estimate the average causal effect. The data set is firstly stratified according to values of the explanatory attributes. That is, the data records are sorted by the values of explanatory attributes $\mathbf{E}^c$. The average causal effect is calculated in each stratum. The overall average causal effect is the weighted average over all strata.

C. Algorithm – DDCR

Our proposed algorithm, called Discrimination Discovery by Causal Rules (DDCR), is listed in Algorithm 1. It contains mainly two modules, global discrimination discovery and local discrimination discovery.

Lines 1 - 3 initiate variables and generate strata using explanatory variables by a quick sort algorithm (Line 3).

Lines 4 - 8 discover global discriminations for each protected attribute. It firstly tests the correlation between each protected attribute P and the decision attribute D. If the correlation is high enough, ACE is calculated. If the ACE is high enough, the attribute is a discriminatory attribute. $\emptyset$ (Line 7) means that P's discrimination does not have a context attribute.

Lines 9 - 18 discover combined discriminatory attributes and local discriminations. Firstly, frequent patterns are generated from itemised attribute sets $\mathbf{P}'$ (the discovered global discriminatory attributes will be excluded) and $\mathbf{O}^c$. An itemset is like $\{P_1 = p_1, O_1 = o_1\}$ where P_1 and O_1 are attributes and p_1 and o_1 are respective values of the attributes. A pattern is an itemset. FP-growth [21] is used for the discovery of frequent patterns.

The frequent pattern set will be tested for local discriminations including those combined attributes from 2-patterns to k_0-patterns level by level. The test is based on Definition 4. The candidates for redundant discriminatory attributes will be removed before the test.

Lines 19- 21 calculate the causal effect of each discriminatory attribute by removing the contribution from other discriminatory attributes. The discriminatory attributes are organised into the context. If each group has only one discriminatory attribute, this can be skipped.

Line 22 outputs the discovered discriminatory attributes.

D. Analysis of the algorithm

The algorithm is correct. It follows the well established potential outcome model to estimate causal effect as discussed in Section II without a heuristic or approximation. The search for combined discriminatory attributes and contexts of local

Algorithm 1 Discrimination Discovery by Causal Rules (DDCR)

Input: Data set $\mathbf{R}$ with decision attribute D, protected attributes $\mathbf{P^c}$, explanatory attributes $\mathbf{E^c}$, and other attribute $\mathbf{O^c}$, discrimination threshold α, minimum odds ratio β, minimum support γ, maximum length of candidate rules k_0.
Output: A set of discriminatory attributes (global and local, and single and combined) $\mathbf{Z}$

1: let discriminatory attribute set $\mathbf{Z} = \emptyset$
2: let candidate attribute set $\mathbf{C} = \mathbf{P^c}$
3: sort data set by values of $\mathbf{E^c}$ to generate strata
4: **for** each protected attribute $P \in \mathbf{C}$ **do**
5: **if** $\mathrm{OR}(P, D) \leq \beta$: next attribute
6: **if** $ACE(P) > \alpha$:
7: add $(P, \emptyset)$ to $\mathbf{Z}$; remove P from $\mathbf{C}$
8: **end for**
9: itemise $\mathbf{P}^c$ and $\mathbf{O}^c$ for pattern mining
10: find frequent l-patterns using the minimum support γ which include at least one attribute in $\mathbf{P}$ where $l \leq k_0$.
11: let $\mathbf{F}$ contain the discovered patterns sorted from the shortest to the longest
12: **for** each pattern $\mathbf{PO}$ in $\mathbf{F}$ (the shortest first) **do**
13: **if** $\mathbf{PO}$ is redundant:
14: remove $\mathbf{PO}$ and move to the next pattern
15: **if** $\mathrm{OR}(\mathbf{PO}, D) \leq \beta$:
16: remove $\mathbf{PO}$ and move to the next pattern
17: **if** $ACE(\mathbf{P}|\mathbf{O}) > \alpha$: add $(\mathbf{P}, \mathbf{O})$ to $\mathbf{Z}$
18: **end for**
19: **for** each group of discriminations organised by the same context **do**
20: recalculate ACE when there are more than one discriminatory attribute as in Section II-D
21: **end for**
22: output $\mathbf{Z}$

discriminations is exhaustive given a minimum support constraint. It does not miss any signals of discriminations in a data set.

We analyse the complexity of the algorithm in three phases. In Phase I (Lines 1 - 3), the complexity is that of quick sort: $O(n \log n)$ where n is the number of records of a data set. In Phrase II (Lines 4-8), the discovery of global discriminatory attributes involves the calculation of correlations and causal effects, and each calculation scans the data set once to count respective contingency table. The overall complexity is $O(n)$. In Phase III (lines 12-18), the most expensive part is finding the k_0-frequent patterns. The time complexity is $O((|\mathbf{P}| + |\mathbf{O}|)^{k_0})$. The FP growth algorithm for frequent pattern discovery scans the data set once. For each pattern, there is a need to scan the data set once more to work out correlation and the average causal effect. The overall complexity in this process is $O(n(|\mathbf{P}| + |\mathbf{O}|)^{k_0})$. This is also the overall complexity of the complete algorithm since the complexity of Phrases I + II is multiple orders of magnitude smaller than this.

TABLE I
DATA SETS USED IN EXPERIMENTS

Name	#Records	#attrs	Distributions
Adult	48842	14	23.9% & 76.1%
Census-income	299285	13	6.2% & 93.8%
Dutch census	60420	11	47.6% & 52.4%
Titanic	2201	6	32.3% & 67.7%

IV. EXPERIMENTS

As discussed in the Introduction, discrimination detection is fundamentally a process of counterfactual reasoning. Causality based approaches are principled methods for this problem. In causal inference research, causal Bayesian network [12, 13] and potential outcome model [15, 22] have been widely used in various applications. Therefore, we compare the proposed method which uses the potential outcome model with a recent work based on causal Bayesian network [9].

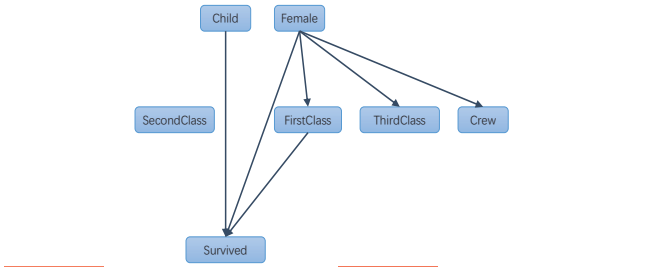
A. Data sets and settings

To evaluate DDCR, the proposed discrimination detection method, we apply DDCR to four data sets used in previous discrimination detection research: the Adult, Census Income (KDD), Dutch Census, and Titanic data sets. The Adult and the Census-Income data sets contain the USA census data in 1994 (both available at https://archive.ics.uci.edu/ml/datasets, UCI Machine Learning Repository). The Dutch census data set contains the Dutch census data in 2001 [9]. The easily understandable data set, Titanic (https://www.kaggle.com/c/titanic/data), is used to illustrate our comparisons. A summary of the data sets is given in Table I. We leave interesting readers to read the attribute description following the link to our software package web page (http://nugget.unisa.edu.au/jiuyong/DDCR/).

B. A case study on the Titanic data set

Discriminations are difficult to validate since we do not have labeled data sets as for classification. We use a data set that has known discriminations to show the power of our algorithm. We know that in the last few hours on the Titanic ship, females and children were preferably treated, and there existed discriminations against males.

We firstly show the results of the BN based method [9]. The BN based method takes two steps to identify discriminations. Firstly, it builds a Bayesian network. A candidate discriminatory attribute must be a parent node of the decision attribute. It then calculates direct causal effect of the candidate discriminatory attribute on the decision attribute. To find the direct causal effect, "path block" technique [13] has been employed to screen off causal effect of other attributes. The work in [9] shows that the set of all parents except the candidate discriminatory attribute are sufficient to form a block



0.647	FirstClass=1 Child=0 count:319 (144)
0.438	FirstClass=0 Child=0 count:1773 (281)
0.207	FirstClass=0 Child=1 count:103 (44)
0.000	FirstClass=1 Child=1 count:6 (1)

0.674	FirstClass=1 Female=0 count:180 (5)
0.218	FirstClass=0 Female=0 count:1551 (59)
0.028	FirstClass=1 Female=1 count:145 (1)
-0.013	FirstClass=0 Female=1 count:325 (44)

Fig. 1. Results of the causal BN based approach [9] on Titanic data set. Top: the BN learnt from the data set. Edges between the modes in the same tier are omitted for clarity. Bottom: data strata for causal effect estimation. Values indicate risk differences in strata, and counts are represented as: strata size (the number of protected individuals in the strata). Left for attribute Female. Right for attribute Child.

0.777	FirstClass=0 SecondClass=1 ThirdClass=0 Crew=0 Child=0 count:261 (93)
0.647	FirstClass=0 SecondClass=0 ThirdClass=0 Crew=1 Child=0 count:885 (23)
0.647	FirstClass=1 SecondClass=0 ThirdClass=0 Crew=0 Child=0 count:319 (144)
0.298	FirstClass=0 SecondClass=0 ThirdClass=1 Crew=0 Child=0 count:627 (165)
0.181	FirstClass=0 SecondClass=0 ThirdClass=1 Crew=0 Child=1 count:79 (31)
0.000	FirstClass=1 SecondClass=0 ThirdClass=0 Crew=0 Child=1 count:6 (1)
0.000	FirstClass=0 SecondClass=1 ThirdClass=0 Crew=0 Child=1 count:24 (13)

0.917	FirstClass=0 SecondClass=1 ThirdClass=0 Crew=0 Female=0 count:179 (11)
0.674	FirstClass=1 SecondClass=0 ThirdClass=0 Crew=0 Female=0 count:180 (5)
0.140	FirstClass=0 SecondClass=1 ThirdClass=0 Crew=0 Female=1 count:106 (13)
0.108	FirstClass=0 SecondClass=0 ThirdClass=1 Crew=0 Female=0 count:510 (48)
0.028	FirstClass=1 SecondClass=0 ThirdClass=0 Crew=0 Female=1 count:145 (1)
-0.009	FirstClass=0 SecondClass=0 ThirdClass=1 Crew=0 Female=1 count:196 (31)

Fig. 2. Results from DDCR on Titanic data set. Top: data strata for causal effect estimation for attribute Female. Bottom: data strata for causal effect estimation for attribute Child. Values indicate risk differences in strata, and counts are represented as: strata size (the number of protected individuals in the strata).

set for estimating direct causal effect. Then, the block set is used for stratification, and risk differences in the strata are examined to determine discrimination.

The results of the BN based approach [9] on the Titanic data set is shown in Figure 1, where we see that both the Female node and the Child node are candidates for discrimination since they are both parents of the Survival node. Another parent node is FirstClass. To test whether adults are discriminated, the data records are stratified by the FirstClass and Child attributes. They form four strata and their risk differences are listed in Figure 1 (left bottom). The first two strata show that the adults are discriminated. To test whether males are discriminated, the data records are stratified by the FirstClass and Female attributes. They form four strata and their risk differences are listed in Figure 1 (right bottom). The first two strata show that males are discriminated. Note that in the last two strata where Female is true, the risk differences are very close to zero and this is understandable since children and females have the same priority.

With DDCR, to test whether males are discriminated, the data records are stratified by cabin classes and crew status for causal effect estimation. The causal effect is estimated as 0.546. Similarly, the average causal effect of Child on Survival is estimated as 0.287. Since both protected attributes are discriminatory, we rectify the causal effect of Female on Survival by adding the Child attribute into the stratification attribute set. The rectified causal effect is 0.537. The rectified causal effect of Child on Survival is 0.272. To compare with the BN based approach, we list the strata after the correction and their risk differences in Figure 2. Both methods give the same conclusions.

The causal effects estimated by DDCR are higher than the causal effects by the Bayesian network based approach. In this data set, we believe that our estimation is more accurate. The cabin classes and crew status are all possible information for situation that we can use for the detection and we have used them all. Note that the risk differences in the first, second and fourth strata in the upper table of Figure 2 have quite different causal effects. In the causal Bayesian network based approach, the causal effect is estimated in a single stratum (the second stratum in the bottom left table in Figure 1). When a stratum contains such heterogeneous subgroups, its average causal effect estimation likely contains a bias. This is a reason that we assert that our estimation is more accurate.

C. Compare the Bayesian network approach and DDCR

We continue comparing the DDCR method with the Bayesian network method [9] on the Adult, the Census income and the Dutch data sets.

The Bayesian networks are learned from the three data sets, where both protected attributes Gender and Race (or Marital status in Dutch data set) are candidates for discrimination since they have edges into the decision nodes. To test whether a candidate protected attribute is discriminatory, the set of other parent nodes of the decision node is used as a block set for calculating causal effect.

Both methods detect the same discriminatory attributes. The block sets for stratification in the BN approach are different from the explanatory attribute sets in DDCR. Even with the differences, the causal effects obtained from both methods are quite similar as shown in Figure 3. Gender in data sets Adult and Dutch is discriminatory, and other attributes are not dsicrminatory.

It is interesting to observe the close similarity of causal effect estimation of both methods although the stratification attributes are different. This makes DDCR practical since the explanatory attributes do not have to be precise. One exception is that any effect attribute of the decision attribute should not be included in the explanatory attribute set (and a block set). Such an inclusion will incur bias in causal effect

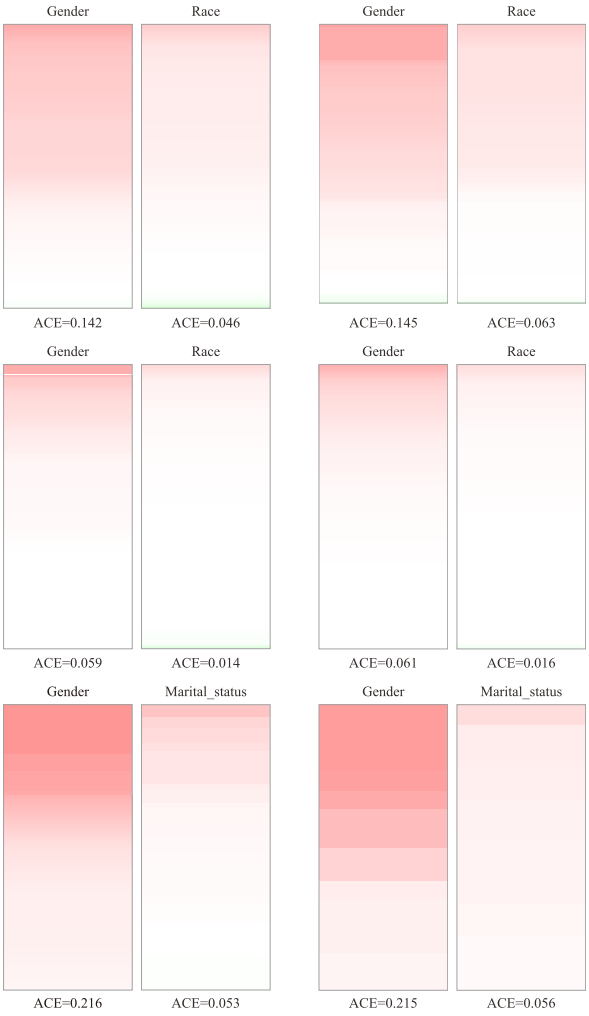


Fig. 3. Results from causal BN approach and DDCR. Left Two: results by the BN approach. Right two: results by DDCR. From the top to the bottom, Adult data set, Census income data set, and Dutch data set. Each block indicates a stratum, with a darker shade standing for a larger risk difference. The overall causal effect estimations of both methods are quite consistent.

estimation. We will have to rely on domain experts to sift effect attributes from causal attributes. Note that a Bayesian network could not separate causal and effect attributes either since edge orientation based on data is largely impossible. In our experiments, when we do not set tier for attributes in Bayesian network learning, most edges are undirected or bi-directed. This means that we do not know whether a node is a parent or a child of the decision node either.

D. Local discrimination and discrimination by combined attributes

DDCR can find local discriminations and discriminations by combined attributes. In the Census data set, females are not discriminated globally since the average causal effect is 0.061. However, in private sector (context: work.Private=1), females are discriminated since the causal effect is 0.092, close to 0.1. Since we have only two protected attributes in each data set, we did not find discriminations of combined attributes. However, the following discovery shows the potential for such a finding. In the Dutch data set, Gender=1 and Marital status=2 have a significant higher causal effect than that of either Gender or Marital Status alone.

E. Efficiency

We compare the scalability of DDCR and the BN based approach with data set size and the number of attributes. We randomly sampled the Census Income data set into 50K, 100K, 150K, 200K and 250K for scalability study on data set size. We use the original Census Income data set, and take each value as a binary attribute and obtain data set with 495 attributes. We randomly sampled 100K records, and 15, 20, 40, 60, 80 and 100 attributes including Gender attribute. Gender is the protected attribute for both methods. For DDCR, 10 randomly selected attributes are set as explanatory attributes. The comparisons were carried out using a desktop computer (Quad core CPU 3.4 GHz and 16 GB of memory).

DDCR is significantly faster than the BN based approach and is up to multiple orders of magnitude faster as shown in the left figure of Figure 4. This observation is consistent to their computational complexities.

BN based approach does not scale well with the number of attributes while DDCR does as shown in the middle figure of Figure 4. When the number of variables is 40, the BN based approach did not return results in two hours. The complexity of learning a Bayesian network is exponential to the number of attributes. Although some works reported building Bayesian networks with hundreds of variables, the networks are very sparse. DDCR scales well with the number of attributes.

DDCR scales well with the minimum support as shown in the right diagram of Figure 4.

V. Conclusion

Discrimination detection is crucial to advance civil rights in the big data era. The detection of discriminations is a process of counterfactual reasoning. Bayesian network (BN) based methods have been proposed for the detection by counterfactual reasoning, but they are inefficient and not effective for local and combined discriminatory detection. This paper proposes a detection method by combining association rule mining with potential outcome model. The potential outcome model supports unified and succinct operational definitions for global and local discriminations and discrimination by combined attributes. The proposed method, DDCR, detects global discriminations as effectively as a BN based method and is also able to discover local and combined discriminations that a BN based method could not find. The method is very fast, and scales well with the data size and the number of attributes.

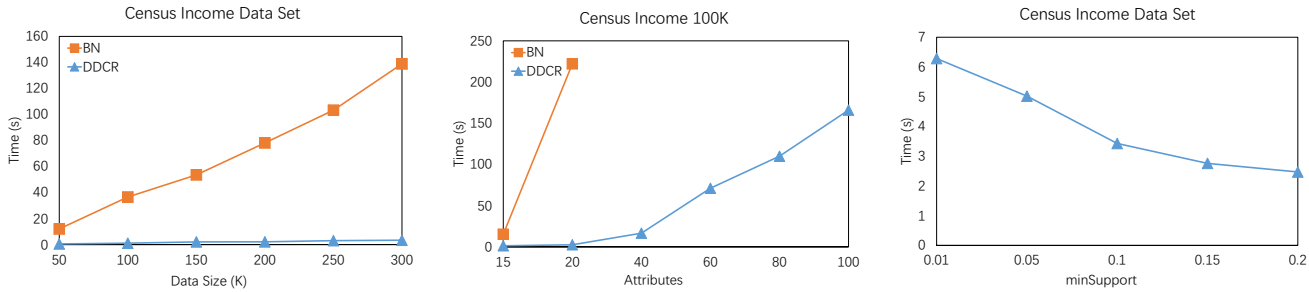


Fig. 4. Running time of DDCR with the data set size, the number of attributes and the minimum supports. The first two are compared with Bayesian network based approach.

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