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A UNIFIED APPROACH TO DIRECT AND INDIRECT DISCRIMINATION PREVENTION USING DATA RANSFORMATION

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ABSTRACT

In data mining, discrimination is a very important issue when considering the legal and ethical aspects of privacy preservation. It is more clear that most of the people do not have a wish to discriminated based on their race, nationality, religion, age and so on. This problem mainly arises when these kind of attributes are used for decision making purpose such as giving them a job and loan. For this reason discovering such attributes and eliminating them from the training data without affecting their decision-making utility is essential. So we introduce an antidiscrimination techniques which including discrimination discovery and prevention. Discrimination is two types. Direct ,indirect. Direct discrimination is occurs when decision making is based upon some sensitive attributes. Indirect discrimination is occurs when decision making is based upon non sensitive attributes which are correlated with sensitive attributes. There are many new techniques propose for solving discrimination prevention problems by applying direct or indirect discrimination prevention individually or both at the same time. New metrics to evaluate the utility were propose and are compare with approaches. The propose work discusses how privacy preservation and prevention between discrimination is implement with the help of post processing approach. The Classification based on predictive association rules(CPAR).

Keywords — CPAR,Direct discrimination, Indirect discrimination, RG etc

1. INTRODUCTION

D iscrimination is defined by the process of unfairly treating people on the basis of their belonging to a specific group, namely race, ideology etc. This involves denying opportunities to members of one group that are available to other group of people. Here some antidiscrimination acts are used , which are laws designed to prevent discrimination on the basis of a set of attributes (e.g., race, religion, gender, nationality, disability and marital status) in various settings (e.g. credit and insurance, employment and training, access to public services, etc.).Several decision-making tasks are there which lend themselves to discrimination, such as health insurances loan granting, education, and staff selection. In many applications, decision-making tasks are supported by information systems. Given a set of information items about a normal customer, an automated system decides whether the customer is to be recommended for a credit or a certain type of life insurance. This type of automated decisions reduces the workload of the staff of banks and insurance companies, among other organizations. The use of these information systems in data mining technology for decision making has attracted the attention of many persons in the field of computer applications. In consequence, automated data collection and data mining techniques such as association/classification rule mining have been designed and are currently widely used for making automated decisions. Automating decisions may give a sense of fairness classification rules (decision rules) do not guide themselves by personal preferences. However in a closer look, one realizes that classification rules are actually learned by the system based on training data. If this training data are inherently biased for or against a particular community (for example, foreign workers),then there is a chance of occurring discriminatory characteristics. Discrimination is two types. Direct and indirect. Direct discrimination consists of procedures or rules that explicitly mention minority or disadvantaged groups based on sensitive discriminatory attributes related to group membership. Indirect discrimination consists of procedures or rules that, not explicitly mentioning discriminatory attributes, directly or indirectly generate discriminatory decisions. An example of indirect discrimination is refusing to grant mortgages or insurances in urban areas they consider as deteriorating although certainly not the only one. In this paper indirect discrimination will also be referred to as redlining and rules causing indirect discrimination will be called redlining rules [1]. Indirect discrimination could need some background knowledge (rules).

Literature survey

In our earlier work [5], we introduced the initial idea of using rule protection and rule generalization for direct discrimination prevention, but we gave no experimental results. In [6], we introduced the use of rule protection in a different way for indirect discrimination prevention and we gave some preliminary experimental results. In this paper, we present a unified approach to direct and indirect discrimination prevention, with finalized algorithms and all possible data transformation methods based on rule protection and or rule generalization that could be applied for direct or indirect discrimination prevention.

2. RELATED WORK

PROBLEM STATEMENT

The existing system consist of preprocessing approach of just removing the discriminatory attributes from the data set. Although this would solve the direct discrimination problem, it would cause much information loss and it would not solve indirect discrimination.[1] The propose system uses post processing approach to solve the above problem using Classification based on predictive association rules(CPAR)which is a kind of association classification methods which combines the advantages of both associative classification and traditional rule-based classification used to prevent discrimination prevention in post processing. Solving approach and Efficiency issues: Here the objective is to minimize the information loss by maintaining data quality. For performing this, there are various algorithms like Direct Rule Protection, Direct Rule generalization and Rule Protection, Direct and Indirect Discrimination prevention and CPAR algorithm. Out of which CPAR is more efficient than remaining algorithms in terms of information loss and data quality.

EXISTING SYSTEM

In Existing system the initial idea of using rule protection and rule generalization for direct discrimination prevention, but we gave no experimental results. We introduced the use of rule protection in a different way for indirect discrimination prevention and we gave some preliminary experimental results. In this paper, we present a unified approach to direct and indirect discrimination prevention, with finalized algorithms and all possible data transformation methods based on rule protection and/ or rule generalization that could be applied for direct or indirect discrimination prevention. We specify the different features of each method. Since methods in our earlier papers could only deal with either direct or indirect discrimination, the methods described in this paper are new.

GOALS

Goal of the proposed system is to introduce a new algorithm for preventing discrimination in post processing approach using Classification based on predictive association rules(CPAR) algorithm. Objective is to reduce the information loss by maintaining data quality through the use of various data transformation methods like Direct Rule Protection ,Direct Rule Generalization, Direct and Indirect Discrimination Prevention and CPAR algorithm..

1. Misses cost(MC)
2. Ghost cost(GC)

Scope

Classification based on predictive association rules(CPAR)in data mining we can prevent discrimination prevention using post processing approach. In Postprocessing the resulting data mining model is modified instead of cleaning the original data set or changing the data mining algorithm. As it is a challenging approach we can prevent discrimination by removing discriminatory attributes from datasets.To obtain FR(frequent Result) the CPAR algorithm will be use,which uses association rule mining algorithm, such as Apriori or FP-growth, to generate the complete set of association rules and achieve higher classification accuracy than traditional classification approaches.It combines the advantages of both associative classification and traditional rule-based classification.

MOTIVATION

Discrimination is big issue in data mining.In order to tackle the discrimination problem various new techniques were proposed using direct and Indirect discrimination prevention. For solving direct and Indirect discrimination prevention preprocessing approach was proposed .Preprocessing approach consider to be more flexible one, it does not require changing the standard data mining algorithm. But this approach cannot guarantee that the transformed dataset is discrimination free.In order to make dataset discrimination free various other algorithms were proposed. One which is considering in this paper is post processing approach for removing direct and Indirect discrimination from the dataset.

PROPOSED SYSTEM

We propose new utility measures to evaluate the different proposed discrimination prevention methods in terms of data quality and discrimination removal for both direct and indirect discrimination. Based on the proposed measures, we present extensive experimental results for two well known data sets and compare the different possible methods for direct or indirect discrimination prevention to find out which methods could be more successful in terms of low information loss and high discrimination removal. The approach is based on mining classification rules (the inductive part) and reasoning on them (the deductive part) on the basis of quantitative measures of discrimination that formalize legal definitions of discrimination. Proposed work is focus on to develop a new preprocessing discrimination prevention methodology including different data transformation methods that can prevent direct discrimination, indirect discrimination or both of them at the same time. To attain this objective, the first step is to measure discrimination and identify categories and groups of individuals that have been directly and/or indirectly discriminated in the decision-making processes; the second step is to transform data in the proper way to remove all those discriminatory biases. Finally, discrimination- free data models can be produced from the transformed data set without seriously damaging data quality. The experimental results reported demonstrate that the proposed techniques are quite successful in both goals of removing discrimination and preserving data quality.

MODULE DESCRIPTION

1. Direct Discrimination Prevention Module.
2. Indirect Discrimination Prevention Module.
3. Rule Protection in Data Mining Module.
4. Rule Generalization in Data Mining Module.

3. DIRECT DISCRIMINATION PREVENTION MODULE

Direct discrimination occurs when decisions are made based on sensitive attributes. It consists of rules or procedures that explicitly mention minority or disadvantaged groups based on sensitive discriminatory attributes related to group membership. To prevent direct discrimination is based on the fact that the data set of decision rules would be free of direct discrimination if it only contained PD rules that are protective or are instances of at least one non redlining PND rule. In this we apply direct rule protection and direct rule generalization.

4. INDIRECT DISCRIMINATION PREVENTION MODULE

Indirect discrimination occurs when decisions are made based on non sensitive attributes which are strongly correlated with biased sensitive ones. It consists of rules or procedures that, while not explicitly mentioning discriminatory attributes, intentionally or unintentionally could generate discriminatory decisions. To prevent indirect discrimination is based on the fact that the data set of decision rules would be free of indirect discrimination if it contained no redlining rules. To achieve this, a suitable data transformation with minimum information loss should be applied in such a way that redlining rules are converted to non redlining rules. To overcome this we apply indirect rule protection and indirect rule generalization.

5.RULE PROTECTION IN DATA MINING MODULE

The data transformation is based on direct rule protection and indirect rule protection. Classification rules do not guide themselves by personal preferences. However, at a closer look, one realizes that classification rules are actually learned by the system (e.g., loan granting) from the training data. If the training data are inherently biased for or against a particular community (e.g., foreigners), the learned model may show a discriminatory pre judiced behavior. In other words, the system may infer that just being foreign is a legitimate reason for loan denial.

6. RULE GENERALIZATION IN DATA MINING MODULE

The data transformation is based on direct rule generalization and indirect rule generalization. In rule generalization, we consider the relation between rules instead of discrimination measures. Assume that a complainant claims discrimination against foreign workers among applicants for a job position. In other words, foreign workers are rejected because of their low experience, not just because they are foreign. The general rule rejecting low-experienced applicants is a legitimate one, because experience can be considered a genuine/legitimate requirement for some jobs.

PROPOSED WORK

In this paper, we propose pre processing methods which overcome the above limitations. Our new data transformation methods (i.e., rule protection and rule generalization (RG)) are based on measures for both direct and indirect discrimination and can deal with several discriminatory items.

Mathematical Model:

Given two attributes A1*A2 with domains {v11, v12…..v1d} And {V21, V22, V2dz} respectively. Their domain sizes are thus d1&d2. The mean square contingency coefficient between A1&A2 is defined as (A1, A2)=/min (d1, d2) $\sum^{d1}_{i=1} \sum^{d2}_{j=1}$ (fij-fifj)^2 /fi * fj Here fi*fj are fraction of occurrence of v1i, v2j in data respectively fij> fraction of co-occurrences of v1j&v2j in data. Therefore fi & fj are the marginal total of fij.Direct discrimination measure elift is given by Elift(A,B->C)=conf(A,B->C)/conf(b->c) Where A, B->C IS the class definition

Rule such that conf (B->C)>0. ………(eq^n 2)

1. A classification rule X → C is potentially discriminatory when X = A, B with A ⊆ DI a non-empty discriminatory item set and B a nondiscriminatory item set.
2. A classification rule X → C is potentially nondiscriminatory(PND) when X = D, B is a nondiscriminatory item set.
3. Direct Discrimination Measure elif t(A, B → C =
4. InDirect Discrimination Measure

conf (A, B → C)) (1.1)
conf (B → C)
elb(X, Y) = f (x)/yif f (x) > 0OR0otherwise

SYSTEM ARCHITECTURE

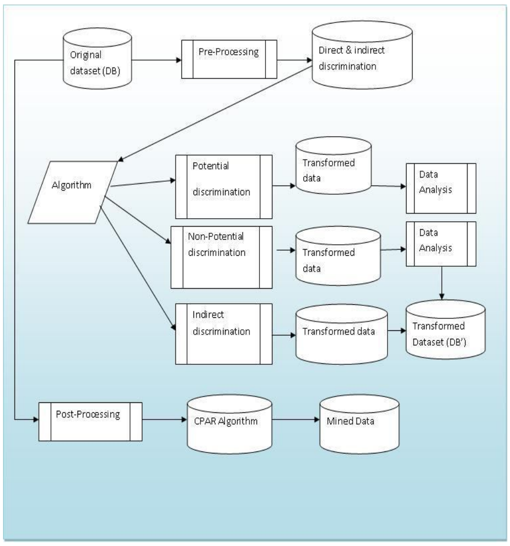

Figure 7.1: System Architecture

ALGORITHM

Algorithm 1. DIRECT RULE PROTECTION

Method 1

Step 1: Inputs: DB, F R, M R, α, DIs
Step 2: Output: DB0 (transformed data set) Step 3: for each r0 : A, B → C ∈ M R do
Step 4: F R ← F R − r0
Step 5: DBc ← All records completely supporting : + AB →+ C
Step 6: for each dbc ∈ DBc do
Step 7: Compute impact(dbc =| ra ∈ F R | dbc) supports the premise of ra |
Step 8: end for
Step 9: Sort DBc by ascending impact
Step 10: while conf (r0) ≥ α.conf (B → C) do
Step 11: Select first record in DBc
Step 12: Modify discriminatory item set of dbcfrom + A to A in DB
Step 13: Recompute conf(r') Step 14: end while
Step 15: end for
Step 16: Output: DB0 = DB

Method 2

Algorithm 2. DIRECT RULE PROTECTION (METHOD 2)
Step 1: Inputs: DB, F R, M R, α, DIs
Step 2: Output: DB0 (transformed data set)
Step 3: for each r0 : A, B → C ∈ M R do
Step 4: Steps 4-9 Algorithm 1
Step 5: while conf (B → C) ≤ conf (r0) do α
Step 6: Select first record in DBc
Step 7: Modify the class item of dbc from + C to C in DB Step 8: Recompute conf (B → C)
Step 9: end while
Step 10: end for
Step 11: Output: DB0 = DB

Method 3

Algorithm 3. DIRECT RULE PROTECTION AND RULE GENERAL- IZATION
Step 1: Inputs: DB, F R, T R, p ≥ 0 : 8, α, DI s
Step 2: Output: DB0(transformed data set)
Step 3: for each r0 : A, B → C ∈ T R do
Step 4: F R ← F R − r0

Step 5: if T Rr0 = RG then
Step 6: Rule Generalization
Step 7: DBc ← All records completely supporting A, B, + D → C
Step 8: Steps 6-9 Algorithm 1 conf (rb : D, B → C)
Step 9: while conf (r0) > do p
Step 10: Select first record in DBc
Step 11: Modify class item of DBc from C to + C in DB Step 12: Recompute conf (r0)
Step 13: end while
Step 14: end if
Step 15: if T Rr0 = DRP then
Step 16: Direct Rule Protection
Step 17: Steps 5-14 Algorithm 1 or Steps 4-9 Algorithm 2
Step 18: end if
Step 19: end for
Step 20: Output: DB0 = DB

Method 4

Algorithm 4. DIRECT AND INDIRECT DISCRIMINATION PREVEN- TION
Step 1: Inputs: DB, F R, RR, M R, α, DIs
Step 2: Output: DB0 (transformed data set)
Step 3: for each r : X →∈ RR, whereD, B ⊆ X do
Step 4: γ = conf (r)
Step 5: for each r0 : (A ⊆ DIs), (B ⊆ X) → C ∈ RR do
Step 6: β2 = conf (rb2 : X → A)
Step 7: ∆1 = supp(rb2 : X → A)
Step 8: δ = conf (B → C)
Step 9: ∆2 = supp(B → C)∆1
Step 10: β1 =2//conf (rb1 : A, B → D)
Step 11: Find DBc : all records in DB that completely support + A, B, + D →+ C
Step 12: Steps 6-9 Algorithm 1
Step 13: if r0 ∈ M R then
Step14: while (δ ≤ β1(β2 + γ − 1)β2.α) and δ ≤conf (r0)α
Step 15: Select first record dbcinDBc
Step 16: Modify the class item of dbcfrom toC in DB Step 17: Recompute δ = conf (B → C)
Step 18: end while
Step 19: else
Step 20: while (δ ≤β1(β2 + γ − 1)β2.α) do
Step 21: Steps 15-17 Algorithm 4
Step 22: end while Step 23: end if Step 24: end for Step 25: end for
Step 26: for each r0 : (A, B → C) ∈ M R RR do
Step 27: δ = conf (B → C)
Step 28: Find DBc : all records in DB that completely support, B →
Step 29: Step 12
Step 30: while (δ ≤conf (r0))do α
Step31 : Steps15 − 17Algorithm4
Step32 : endwhile
Step33 : endf or
Step34 : Output : DB' = DB

SOFTWARE REQUIREMENT

Operating System : Independence of Operating System
Application Libraries : Java
Language : Java
Front End : Java Swing

HARDWARE REQUIREMENT

Processor : Pentium IV. (onwards). Memory (RAM):256 MB RAM.

Output

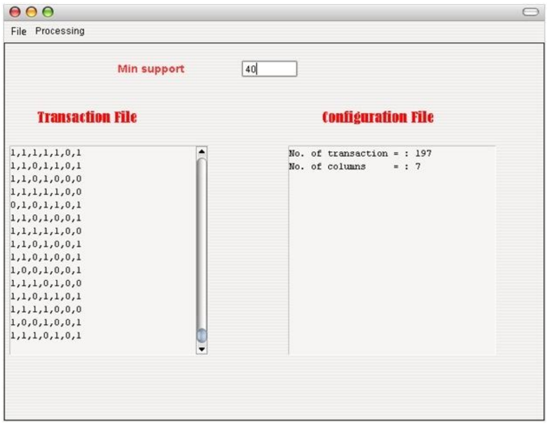

Figure 9.1: File Processing

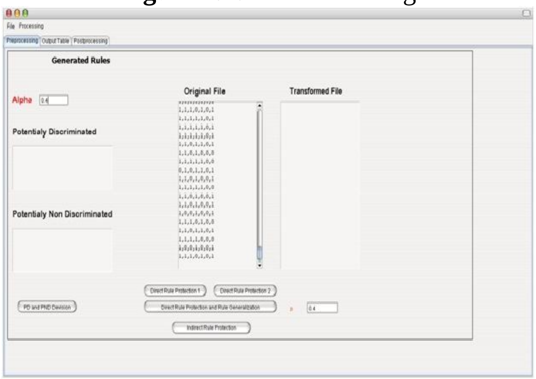

Figure 9.2: Preprocessing

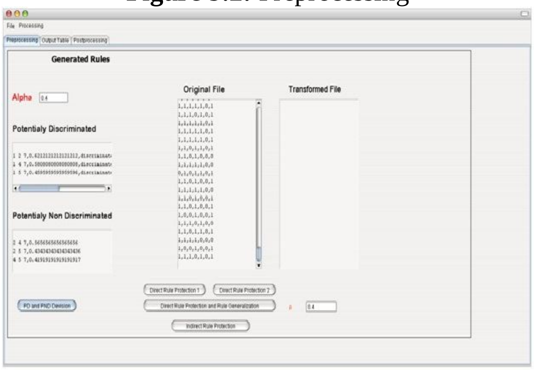

Figure 9.3: PO and PND Devision

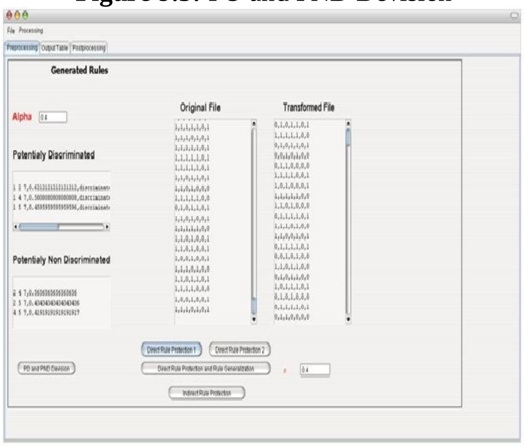

Figure 9.4: Direct Rule Prediction

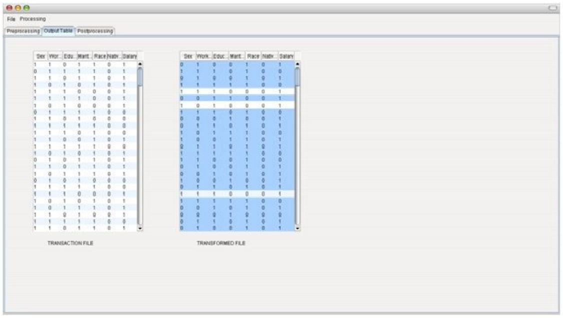

Figure 9.5: Output Table

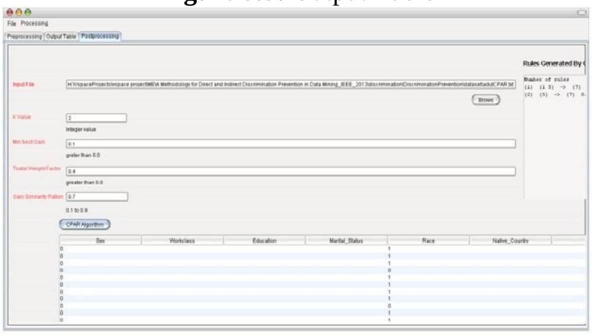

Figure 9.6: Postprocessing

7. CONCLUSION

The purpose of this paper was to develop a new preprocessing discrimination prevention methodology including different data transformation methods that can prove direct discrimination, indirect discrimination or both of them at the same time. To attain this objective, the first step is to measure discrimination and identify categories and groups of individuals that have been directly and/or indirectly discriminated in the decision-making processes .the second step is to transform data in the proper way to remove all those discriminatory biases. Finally, discrimination-free data models can be produced from the transformed data set without seriously damaging data quality.

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