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Data Transformation Method For Discrimination Prevention Along With Privacy Preserving

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Abstract—Datamining is mining useful information from huge dataset. We can classify a datamining system based on the type of knowledge mined. that is datamining system is classified based on the functionalities such as characterization, discrimination, association and correlation analysis, classification, Prediction. Discrimination is an important problem when considering legal and ethical aspects such unfairly treating based on their specific belonging group. discrimination means distinguishing, that is distinguishing the people based on their age, race, gender etc. Antidiscrimination techniques are used for preventing the dataset from discrimination. Discrimination can be classified into two direct and indirect discrimination. Direct discrimination means directly rejecting people on the basis of their age, gender etc. Indirect means rejecting people based on their background knowledge. In this paper, we discuss about how can prevent both direct and indirect discrimination on same time and α-protective Incognito.

Keywords- Antidiscrimination techniques, direct and indirect discrimination, privacy preserving.

I. INTRODUCTION

Discrimination is a very important issue when considering the legal and ethical aspects of data mining. It is more than obvious that most people do not want to be discriminated because of their gender, religion, nationality, age and so on, especially when those attributes are used for making decisions about them like giving them a job, loan, insurance, etc. It involves denying to members of one group opportunities that are available to other groups. There is a list of antidiscrimination acts, which are laws designed to prevent discrimination on the basis of a number of attributes (e.g., race, religion, gender, nationality, disability, marital status, and age) in various settings (e.g., employment and training, access to public. services, credit and insurance, etc.). At first sight, automating decisions may give a sense of fairness: 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 prejudiced behavior?. In other words, the system may infer that just being foreign is a legitimate reason for loan denial. Discovering such potential biases and eliminating them from the training data without harming their decision making utility is therefore highly desirable. One must prevent data mining from becoming itself a source of discrimination, due to data mining tasks generating discriminatory models from biased data sets as part of the automated decision making. it is demonstrated that data mining can be both a source of discrimination and a means for discovering discrimination. Discrimination can be either direct or indirect (also called systematic). Direct discrimination consists of rules or procedures that explicitly mention minority or disadvantaged groups based on sensitive discriminatory attributes related to group membership. Discriminatory (sensitive) attributes like gender, race, religion, etc. Indirect discrimination consists of rules or procedures that, while not explicitly mentioning discriminatory attributes, intentionally or unintentionally could generate discriminatory decisions. Redlining by financial institutions (refusing to grant mortgages or insurances in urban areas they consider as deteriorating) is an example of indirect discrimination, although certainly not the only one. With a slight abuse of language for the sake of compactness, in this paper indirect discrimination will also be referred to as redlining and rules causing indirect discrimination will be called redlining rules . In direct discrimination could happen because of the availability of some background knowledge (rules), for example, that a certain zip code corresponds to a deteriorating area or an area with mostly black population. The background knowledge might be accessible from publicly available data (e.g., census data) or might be obtained from the original data set itself because of the existence of nondiscriminatory attributes that are highly correlated with the sensitive ones in the original data set.

II. STATE OF ART

The discovery of discriminatory decisions was first proposed by Pedreschi. 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. There are two types of rules are used PND rule and PD rule. Potentially discriminatory rule A classification rule X -> C is potentially discriminatory (PD) when X = A, B with A is a discriminatory item set and B non discriminatory item set. For example, (Foreign worker = Yes, City = NYC->Hire = No). The word "potentially means that a PD rule could probably lead to discriminatory decisions. A classification rule X -> C is potentially nondiscriminatory (PND) when X = D, B is a nondiscriminatory item set. For example, {Zip =10451, City = NYC -> Hire = No} or {Experience = Low, City = NYC -> Hire = No} PND rule could lead to discriminatory decisions in combination with some background knowledge. e.g., if the premise of the PND rule contains the zip code as an attribute and one knows that zip code 10451 is mostly inhabited by foreign people.

A. *Classification With No Discrimination By Preferential Sampling[2]*

Preferential Sampling (PS) changes the distribution of different data objects for a given data to make it discrimination free. The idea is that the data objects close to the decision boundaries are more prone to the victim of discrimination. Then the distribution of this borderline objects is changed to make the dataset discrimination free. To know the least certain elements, use a ranking function, learned on original data, to identify the data objects close to the borderline. PS uses this ranker to class the data objects of DP (Discriminated community with Positive class labels) and PP (Privileged community with Positive class labels) in ascending order, and the objects of DN (Discriminated community with Negative class labels) and PN (Privileged community with Negative class labels) in descending order; both w.r.t the positive class probability. Such understanding of data objects makes sure that the higher the rank an element occupies, the closer it is to the borderline. PS starts from the original training dataset and iteratively duplicates (for the groups DP and PN) and removes objects (for the groups DN and PP) in the following way:

- Decreasing the size of a group is always done by removing the data objects closest to the borderline. Increasing the sample size is done by duplication of the data object closest to the borderline.
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Data points of the desired class and the negative class are represented by + and – symbols respectively. Then, based on the sanitized data, a nondiscriminatory model can be learned. Since the model is learned on non-discriminatory data, it reduces the prejudicial behavior for future classification. This approach gives similar performance to "massaging" but without changing the data set and always outperforms the

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"reweighing" scheme of previous method. Classification with No Discrimination by Preferential Sampling is an excellent solution to the discrimination problem. It gives promising results with both stable and unstable classifiers give more accurate results but do not reduce the discrimination. The drawbacks are low data utility rate and minimum discrimination removal. This PS is also not applicable for indirect discrimination.

B. RULE PROTECTION FOR INDIRECT DISCRIMINATION PREVENTION[2]

A method for indirect discrimination prevention based on data transformation that considers several discriminatory attributes and their combinations are introduced. The Pedreschi introduced some theorems based on that theorems the discrimination preventing. The rule protection method is used for preventing the indirect discrimination. The major drawback of this method is that only preliminary experiments are conducted and only the indirect discrimination is considered.

C. DATA MINING FOR INTRUSION AND CRIME DETECTION[3]

Automated data collection has encouraged the use of data mining for intrusion and crime detection. A new discrimination prevention method based on data transformation and the measures to evaluate the success in discrimination prevention and its impact on data quality are introduced. Antidiscrimination in the context of cyber security is considered. The drawback found is that only direct discrimination was addressed should be changed during data transformation are described. Extensive experimental results and utility measures are carried on Adult Data Sets and German Credit Data Sets. Both the values of direct discrimination removal and indirect discrimination removal measures shows high success in discrimination prevention. The data quality measures sound less information loss by implementing this method. The drawbacks addressed by this method are that non binary attributes are not considered and privacy preservation is not mentioned.

D. DCUBE: Discrimination Discovery In Databases[5]

DCUBE system which is based on existing approach of discrimination prevention. It is based on classification rule extraction and analysis, analyzing using an Oracle database. The intended users of DCUBE include:-owners of socially sensitive decision databases, anti-discrimination authorities and auditors, researches in social sciences. DCUBE tool helps in guiding the users about the legal issues about discrimination hidden in data. These tool helps in providing knowledge to users about discrimination facts in user friendly manner.

E. Methodology for direct and indirect discrimination prevention[1]

The rule generalization and rule protection is used for preventing the direct and indirect discrimination in the dataset. Here both direct and indirect can be find at the same time. Rule generalization means checking all relation between the rules. Any discrimination found it will change the rule. The rule protection means protecting the rule any discrimination found it will change that rule. Here no relation considering.

III.METHODOLOGY

The proposed method is for simultaneously prevent discrimination and privacy preserving. So we using I-diversity and k-anonymous privacy methods are used.The rule protection and generalization for preventing the direct and indirect discrimination simultaneously[1] and α-protective incognito for privacy preserving[6].The **K-anonymity** is k-anonymity is a property possessed by certain anonymized data. A release of data is said to have the k-anonymity property if the information for each person

contained in the release cannot be distinguished from at least k-1 individuals whose information also appear in the release. There are two common methods for achieving k-anonymity for some value of k. They are suppression and generalization. The suppression approach is attribute value are replaced by an asterisk '*'. All or some values of a column may be replaced by '*'.
The generalization approach is individual values of attributes are replaced by with a broader category. The **l-diversity** model handles some of the weaknesses in the k-anonymity model. The l-diversity is an extension of k-anonymity.The discrimination prevention and privacy preservation can be done by rule generalization method and α-protective incognito respectively is used.The methods gives high efficiency and provides utility measures.

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