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Sensitive Attribute Discrimination Prevention in Data Mining

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ABSTRACT: Today, Data mining is an increasingly important technology. It is a process of extracting useful knowledge from large collections of data. There are some negative view about data mining, among which potential privacy and potential discrimination. Discrimination means is the unequal or unfairly treating people on the basis of their specific belonging group. If the data sets are divided on the basis of sensitive attributes like gender, race, religion, etc., discriminatory decisions may ensue. For this reason, antidiscrimination laws for discrimination prevention have been introduced for data mining. Discrimination can be either direct or indirect. Direct discrimination occurs when decisions are made based on some sensitive attributes. It consists of rules or procedures that explicitly mention minority or disadvantaged groups based on sensitive discriminatory attributes related to group membership. Indirect discrimination occurs when decisions are made based on non-sensitive attributes which are strongly related with biased sensitive ones. It consists of rules or procedures that, which is not explicitly mentioning discriminatory attributes, intentionally or unintentionally, could generate decisions about discrimination.

KEYWORDS: -Antidiscrimination, data mining, direct and indirect discrimination prevention, rule protection, rule generalization, privacy

I. INTRODUCTION

In sociology, discrimination is the prejudicial treatment of an individual based on their membership in a certain group or category. 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.). For example, the European Union implements the principle of equal treatment between men and women in the access to and supply of goods and services in or in matters of employment and occupation. Although there are some laws against discrimination, all of them are reactive, not proactive. Technology can add proactively to legislation by contributing discrimination discovery and prevention techniques. Services in the information society allow for automatic and routine collection of large amounts of data. Those data are often used to train association/classification rules in view of making automated decisions, like loan granting/denial, insurance premium computation, personnel selection, Discrimination is a process of unfairly treating people on the basis of their belonging to some a specific group. For instance, individuals may be discriminated because of their race, gender , etc. or it is the treatment to an individual based on their membership in particular category or group. There are various slaws which are Prevent discrimination on basic of various attributes such as race, religion, nationality, disability and age. There are two types of discrimination i.e. Direct Discrimination and Indirect Discrimination. Direct Discrimination is direct discrimination which consists of procedure or some decided rule that mention minority or disadvantaged group based on sensitive attributes to they are related to membership of group. Indirect Discrimination is discrimination which consists of rules and procedures that are not mentioning attributes which causes discrimination and hence it generates discriminatory decision intentionally or unintentionally.

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II. RELATED WORK

The most important step in software development process is Literature survey. Before developing the tool it isnecessary to determine the time factor, economy and company strength. Once these things are satisfied, then next is to determine which operating system and language can be used for developing the tool. Once the programmers start building the tool the programmers need lot of experimental results. Introduced the use of rule protection in a different way for indirect discrimination prevention and gave some preliminary experimental results. In this survey, 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. Specify the different features of each method. Since methods in our earlier survey could only deal with either direct or indirect discrimination.

In the year 2000, Agrawal R. et al., [5] present an additive data perturbation method for building decision tree classifiers. Every data element is randomized by adding some noise. These random noise chosen independently by a known distribution like Gaussian distribution. The data miner rebuilds the distribution of the original data from its distorted version. They consider the concrete case of building a Decision-tree classifier from training data in which the values of individual records have been perturbed. These perturbed data records look very different from the original records and the distribution of data values is also very different from the original distribution. Agrawal R. et al. present a reconstruction method to exactly approximation the distribution of data values, present classifiers accuracy is comparable to the accuracy of classifiers built with the original data values by using these reconstructed distribution.

In the year 2002, Sweeney L. et al. [6] in this method the k-Anonymity model consider the problem that a data owner wants to share a collection of person-specific data without revealing the identity of an individual. This goal is achieve by data generalization and suppression methods are used to protect the confidential information. This technique also examines the re-identification attacks. In the year 2003 C. Clifton et al, they Discrimination prevention has been recognized as an issue in a tutorial [7] where the danger of building classifiers capable of racial discrimination in home loans has been put forward.

In the year 2005, Chen et al., present a rotation based perturbation method [8]. The method maintains zero loss of accuracy for many classifiers. Experimental results show that the rotation perturbation can greatly improve the privacy quality without sacrificing accuracy.

In the year 2006, Xu et al., present Singular value decomposition (SVD) based data distortion strategy for privacy protection [10]. In this work present a scarified Singular Value Decomposition (SVD) method for data distortion. They conducted experiment on synthetic and real world datasets and the experimental result show that t hesparsified SVD method is effective in preserving privacy as well as maintaining the performance of the datasets. In the year 2007, Xu et al., has used the Fast Fourier Transform (FFT) for data perturbation [12]. The dataset is distorted or perturbed by using Fast Fourier Transform (FFT) for privacy protection of data values.

In the year 2008, P Pedreschi et al, Discrimination prevention technique in [15] consists of inducing a classifier like Naive Bayes in which classification is done without any sensitive attribute. In this technique prevention need to modify probability of decision records. That does not lead to discriminatory decisions even if trained from a dataset containing these item set. Training model consist unwanted dependencies between attributes.In the year 2009, F Kamiran, et al, [20] had tackled the problem of impartial classification by introducing a new classification scheme for learning unbiased models on biased training data in 2009. The method is based on massaging the dataset by making the least intrusive modifications which lead to an unbiased dataset. Numerical attributes and group of attributes are not considered as sensitive attribute.

In the year 2010, T.Calders et al, [29] “Three Naive Bays Approaches for Discrimination-Free Classification,” Data Mining and Knowledge Discovery, in this method naive bayesis modify for discrimination classification. Discrimination laws do not allow the use of these rules of attributes such as gender, religion. Using d ecision rules that base their decision on these attributes in classifier. The approaches are used in this technique Navies bayes model,

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Latent variable model, and modified naive"sbayes. The naïvesbayes model is a bayes classifier is a simple possibility classifier based on applying bayes theorem with strong statistical independence assumption. Depending on precise nature of the probability model, naviebayes classifiers can be trained very efficiently in supervised learning.

In the year 2011, B Luong et al, [32] had modeled the discrimination discovery and prevention problems by a variant of k-NN classification that implements the legal methodology of situation testing in 2011. Major advancements over existing proposals consist in provide a stronger legal ground, overcoming the weaknesses of aggregate measures over undifferentiated groups a global description of who is discriminated and who is not inIn the year 2012 F. Kamiran et al [33] presented algorithmic solutions that preprocess the data to remove discrimination before a classifier is learned. They have present three preprocessing techniques i.e. Massaging, Reweighing and Sampling which applies on training dataset. These preprocessing techniques have been implemented in a modified version of Weak and presented the results of experiments on real-life data.

In the year 2013, Sara Hajian et al.,[38] they handle discrimination protection in data mining and present new techniques applicable for direct or indirect discrimination protection individually or both at the same time.The system clean training data sets and outsourced data sets in such a way that direct and indirect discriminatory decision rules are converted to legitimate (nondiscriminatory) classification rules. Also present new metrics to evaluate the utility of the present approaches and compare these approaches. The experimental evaluations demonstrate that the present techniques are effective at removing direct and indirect discrimination biases in the origina l data set while preserving data quality.

III.PROPOSED SYSTEM

Proposed 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) the basis of quantitative measures of discrimination that formalize legal definitions of discrimination.

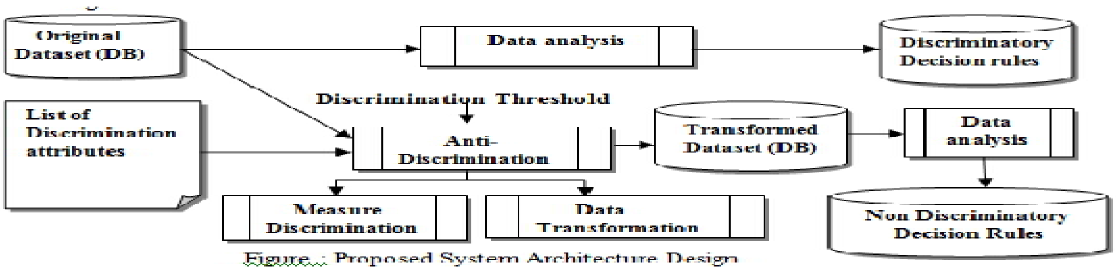
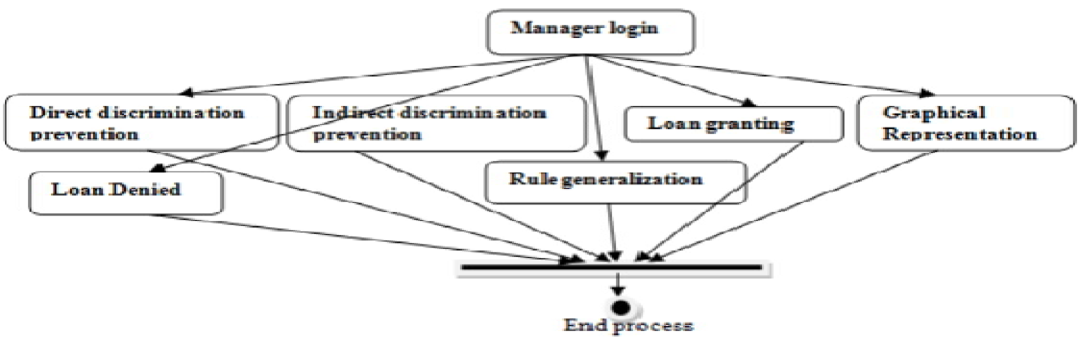


Figure.: Proposed System Architecture Design



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IMPLIMENTATION TECHNIQUE

(a) CLASSIFICATION BASED ON DISCRIMINATION PREVENTION USING DATA TRANSFORMATION TECHNIQUES

Classification is the task of generalizing known structures applies to new data. Classification is supervised learning. For example, classes are used to represent that a customer defaults on a loan decisions like „Yes" or" No". It is important that each record in the dataset used to represent the classifier already have a value for the attribute used to describe classes. Because each record has the attribute value used to define the classes. Classification is a machine learning technique used to predict group membership for data instances. It assigns items in a collection to target categories. The aim of classification is to accurately determine target class for each and every case in data. Direct discrimination restricts a particular community based on sensitive reasons. Indirect discrimination restricts certain number of peoples based on non-sensitive one.

(b) DATA TRANSFORMATION

Transform the original data DB in such a way to remove direct and indirect discriminatory biases, with minimum impact on the datasets. So there is no other negative impact can be discovered from transformed datasets. The data transformation method should increase or decrease the confidence of the rules to the target values with minimum impact on data quality, maximize the disclosure prevention measures and minimize the information loss measures. Data transformation includes rule protection and rule generalization methods for both f-direct and indirect discrimination.

VI. PROPOSED ALGORITHM

(a)RULE PROTECTION ALGORITHM FOR DIRECT AND INDIRECT DISCRIMINATION

In direct discrimination, rule protection algorithm is used to convert each α-discriminatory rule into a α- protective rule based on the direct discriminatory measure. There are two methods that could be applied for direct rule protection.

1. Method 1 modifies the discriminatory item set in some records.
2. Method 2 modifies the class item in some records from grant credit to deny credit in the records with male gender.

Indirect rule protection is used to turn a redlining rule into a non-redlining rule, based on the indirect discriminatory measure. Rules that are associated with some background knowledge indirectly called as redlining rules.

Input : Original data set DB
(b)RULE PROTECTION ALGORITHM
Output: Transformed data set DB'
1: For each r': A, B->C € MR do
2: FR<- FR-{r'}
// FR-database of indirect discriminatory rules
3: if MRr' = RG // then rule generalization
4: DBc<- All records completely supporting ¬A
5: B->¬C
6: For each dbc€ DBc do
7: Compute impact (dbc=|{ra € FR| dbc supports ra}|
8: Sort DBc by ascending impact

9: While conf(r') _ _.conf(B->C) do
10: Select first record in DBc
11: Modify discriminatory item set of dbc from ¬A to A in DB
12: Recomputeconf(r')

For each direct α -discriminatory rule in MR, after finding the subset, records in DBc should be changed until direct rule protection requirement met for each respective rule. For each record, the number of rules whose premise is supported is taken as the impact. If conf(r') α _.conf (B->C), confidence of rule is greater than the discriminatory threshold can be considered as minimum impact. Then the records in dbc with minimum impact are selected for change.

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(c) RULE GENERALIZATION

Rule generalization is based on the fact that if each discriminatory rule r‟: A, B -> C in the database of decision rules was an instance of at least one non redlining PND rule r: D, B -> C, the data set would be free of direct discrimination. In rule generalization, it considers the relation between rules instead of discrimination measures. A classification rule {Foreign worker = Yes, City = NYC} -> Hire = No with high elift supports the complainant‟s claim. The decision maker could argue that this rule is an instance of a general rule {Experience= Low, City=NYC} -> Hire =No. Usually foreign workers are rejected because of their low experience, not only they are foreign.

(d)BIRCH ALGORITHM

BIRCH (Balanced Iterative Reducing and Clustering using Hierarchies) is an unsupervised data mining algorithm used to perform clustering in discrimination environment. It can be used in multidimensional datasets and it has minimized I/O cost than Apriori algorithm (1 or 2 scans). BIRCH has two concepts: CF and CF tree. CF (Clustering Feature) is represented as a triple CF = (N, LS, SS) N defines the number of points, LS represents linear sum of points and SS defines the square sum of points in cluster. First, it scans the data set and construct clustering feature tree in its memory as described in Figure 4.9.1. Then it condenses large clustering feature tree into smaller one and performs global clustering by using its cancroids points. Finally it does cluster refining one more time for removing outliers. BIRCH algorithm can be divided into two phases: It scans the transformed data set in memory and generate model based on eligible and not eligible criteria.

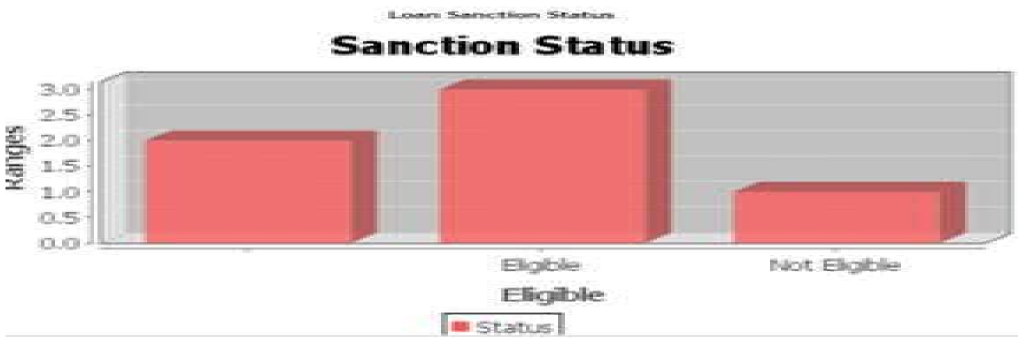
V. RESULTS

Net Beans is an integrated development environment (IDE) for developing primarily with Java. It is also an application platform framework for Java desktop applications. Net Beans IDE is an open-source integrated development environment. Net Beans IDE supports development of all Java application types (Java SE(including Java FX), Java ME, web and Enterprise Java Beans (EJB).

ADULT DATA SET

System used the Adult data set also known as Annual Income, in our experiments. Fig describes adult data set consists of 48,842 records, split into a "train" part with 32,561 records and a "test" part with 16,281 records as shown in Figure4.. The data set has 13 attributes. The support and confidence value measure with associated rule. the Adult

data set is to determine whether a person makes less than 60,000 Annual Income and Sensitive Attribute (Age ,Gender, Marital Status) information about people.



TABLE

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Direct and Indirect Rule Protection Methods

	Method1	Method2
DirectRuleProtection	A,B->C >A,B-> C ¬	A,B->C >A,B-> C ¬ ¬
IndirectRuleProtection	A,B,D ->>CA,B D->C	A,B,D ->>CA,B D->C

VI.CONCLUSION

The techniques of this method was to develop a new preprocessing discrimination prevention technique that consists of various data transformation methods includes rule protection and rule generalization used to prevent direct discrimination and indirect discrimination To obtain this goal, the first step is to measure discrimination and identify the groups of individuals that have been directly and indirectly discriminated in the automated decisions processes; the second step is to transform data in the proper way to eliminate all those legitimate biases. Finally, discrimination-free data models can be produced from the transformed data set without damaging data quality.

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