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DISCRIMINATION INVENTION AND PRECLUSION IN ONLINE EDIFICATION STRUCTURE FOR INFORMATION TECHNOLOGY STUDIES

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ABSTRACT

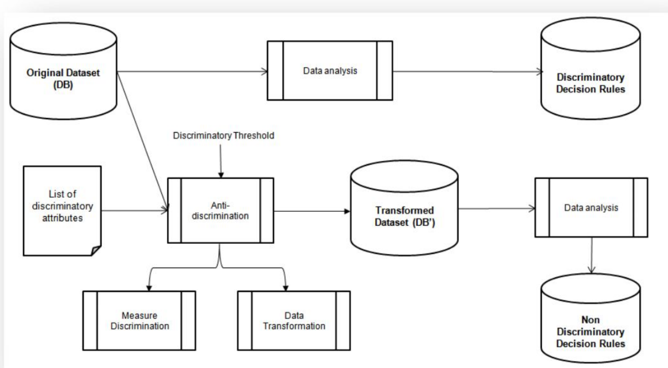
This paper describes to examine the discovery of discrimination and prevention in a fully online Education program in Information Technology of the same courses at a Traditional Educationin Information Technology. Vast efforts were taken to make sure that the online program is as not similar as possible to the Traditional Education in Information Technology may include Bachelor or Master of Science in Information Technology program. Discrimination refers to unjust or uneven dealing of people based on attachment to a category. Discrimination in education, employee, corporate, and recruitment board. For this reason, In this paper, anti-discrimination techniques including discrimination discovery and prevention have been introduced in data mining. Discrimination prevention consists of inducing patterns that do not lead to discriminatory decisions even if the original training datasets are inherently biased. In this chapter, by focusing on the discrimination prevention, we present a taxonomy for classifying and examining discrimination prevention methods. Then, we introduce a group of pre-processing discrimination prevention methods and specify the different features of each approach and howthese approaches deal with direct or indirect discrimination. A presentation of metrics used to evaluate the performance of those approaches is also given. Finally, we conclude our study by enumerating interesting future directions in this research body. In direct discrimination, the extract system can be in a straight line mined in search of discriminatory contexts. In indirect discrimination, the mining method needs some background knowledge as an additional contribution, e.g., online student data, that combine with the extracted system might permit for presentation contexts of discriminatory decisions.

Keywords: Online learning, fully online education, information technology, discrimination discovery, discrimination prevention.

1. INTRODUCTION

The focal point of the paper is to resolve the discrimination in online education in Information Technology and an evaluation with a traditional college educational program in Information Technology. The paper was able to bring to a close that there was not a resemblance to a student success in the fully online program and traditional program. There are many disadvantages of online education. Students are interested in professional and personal networking, socializing and sharing with others of similar interests might prefer on-campus classes. Enchanting the online class's make restrictions to the sum of individual interface to a student may have and requires a great contract of self-discipline. Procrastination can make it hard to grasping up if a student falls at the back. Computer problems or an unpredictable Internet connection can basis a student to neglect the assignment deadlines. A student who is not well-known with Web browsers, Email and newsgroups will not be successful online courses. Because online education is quite innovative, the excellence of online classes can differ considerably, even from the same institution. It is not always easy to tell if an online course offers a good return on your investment before you begin. Through there were no major difference between the two programs. One possible clarification for the irrelevant difference between the traditional and fully online program is the implementation of online courses policies designed to ensure organization of online courses and that students enrolled in the online environment are continuously engaged. Course organization and planning are critical in the process of teaching effective courses, particularly courses taught online explained that the process of course organization should go far beyond simply choosing a textbook and developing the syllabus. Instead, it is essential to include detailed planning, including developing specific objectives for the entire course as well as for each individual lesson, specifying assignments in detail, and describing specific deliverables. Reported a significant correlation between student engagement and course organization as well as a relationship between course organization, student engagement, and active learning. There are several decision-making tasks which lend themselves to discrimination, e.g. loan granting, education, health insurances and staff selection. In many scenarios, decision-making tasks are supported by information systems. Given a set of information items on a potential student, an automated system decides whether the student is to be recommended for a online classes. The use of information systems based on data mining technology for decision making has attracted the attention of many researchers in the field of computer science. In consequence, automated data collection and an excess of data mining techniques such as association/classification rule mining have been designed and are currently widely used for making automated decisions. At first sight, automating decisions may give a sense of fairness: classification rules (decision rules) do not guide themselves by personal preferences. However, at a closer look, one realizes that classification rules are actually learned by the system based on training data. If the training data are inherently biased for or against a particular community (for example, teaching scenario), the learned model may show a discriminatory prejudiced behavior. For example, in a certain student lacking to grasp presentation through online. If this biased historical dataset is used as training data to learn classification rules for an automated student information granting system, the learned rules will also show biased behavior toward traditional learning people Figure I illustrates the process of discriminatory and non-discriminatory decision rule extraction. If the original biased dataset *DB* is used for data analysis without any anti-discrimination process (i.e. discrimination discovery and prevention), the discriminatory rules extracted could lead to automated unfair decisions. On the contrary, *DB* can go through an anti-discrimination process so that the learned rules are free of discrimination, given a list of discriminatory attributes (*e.g.* gender, race, age, etc.). As a result, fair and legitimate automated decisions are enabled.

Figure.1. The process of extracting biased and unbiased decision rules



2. PLAN OF THE PAPER

This paper is present a scenario for the analysis of direct and indirect discrimination. In this paper we are used some standard notions on association and classification rules are recalled, and the measure of extended lift is introduced. In this paper we formalize the scenario of discrimination prediction by introducing the notions of α- protective and α -discriminatory classification rules, where αis a user threshold on the acceptable level of discrimination. The two notions are refined for binary classes to strong α-protection and strong α-discrimination. Direct discrimination checking is presented, with experimentation on the student and online course dataset. Indirect discrimination is considered in this same section, where background knowledge is adopted in two inference models. Experimentation on the online student dataset is reported as well. Further experimentation on online education dataset is presented later .

3. SEVERAL DISADVANTAGES IN ONLINE EDUCATION

Chances of distraction high: With no faculty around for face-to-face interaction and no classmates who can help with constant reminders about pending assignments, the chances of getting distracted and losing track of deadlines are high. You need to keep yourself motivated and focused if you want to successfully complete your distance learning course. Distance education is not a good idea if you tend to procrastinate and can't stick to deadlines.

Hidden costs: Although the cost of a distance education program is usually cheaper than a regular program, there can be hidden costs involved. For example, if your distance learning course is offered online, you might have to incur some initial expenses like installing a computer and getting a reliable Internet connection. You may need to buy additional resources such as a printer, a web camera and so forth.

Complicated technology: Overdependence on technology can be a major drawback in distance learning mode of education, especially when the learning takes place in an online environment. Any malfunctioning software or hardware can bring an ongoing class to a standstill and interrupt the learning process. Similarly, if a student is not computer and tech savvy, his learning experience can be dissatisfactory.

Quality of faculty compromised: Often considered to be the lesser cousin of regular education, distance education is often plagued by lack of enough good quality faculty members. In other cases, even if the instructor is good, he or she may not be comfortable with teaching in an online environment. Sometimes the technology might not do full justice to the delivery and design of the course. A student loses out in all these scenarios. Distance education providers should realize that it is not the technology, but good and effective teachers that teach students.

Questionable credibility of degrees: Even though distance and online education is starting to get Recognition, there are still a lot of fraudulent and non-accredited degrees being offered. With the increase in the number of distance/online programs, the number of scam operators is also rising. This affects the credibility of recognised distance learning degrees among prospective employers.

Lose out on networking: The advantages of pursuing a regular programme go beyond just interaction with teachers and good course content. MBA graduates from premier business schools (B-schools) in India would vouch for the fact that the opportunities to network with established alumni, renowned faculty and industry heads go a long way in paving a secure career. A distance learning program loses out on this very important aspect.

Reduced Opportunity for Networking: Attending class in an online environment also reduces the opportunity for planned or chance professional networking. When students interact in an environment with only one objective, usually an assignment or reading, there is a great potential to miss opportunities to interact with other future professionals. Professional networking and making professional contacts is essential for students who are looking to enter the workforce. Having the opportunity to directly interact with others may not only help students understand the working world of their chosen profession, it may also provide a jump start to the task of job hunting.

Lack of Academic Collaboration and Interaction: A great disadvantage of attending online certification classes is the lack of opportunity for academic collaboration and interaction. While it is true that online classes afford students the chance to interact with one another, create personal connections, and exchange ideas, interaction in an online environment can reduce the opportunity for collaboration. Asynchronous online classes can also eliminate the opportunity for a continuous, sustained class discussion among a potentially diverse student population. Learning from others and being exposed to different ways of thinking can be considered a large part of the educational process.

Demand a Specific Skill Set: Online classes and education carry an implied requirement. In order to be successful in an online environment, a student must possess a skill set that includes above-average time management and strong self-discipline. Students in an online program must be motivated to study, attend class when necessary and avoid the urge to postpone assignments. Additionally, students must possess time-management skills in order to complete online work while not neglecting other personal and family obligations.

Social Isolation: Attending certification classes online has the potential to be socially isolating since students attend class alone through their computer. Students in online classes attend class after work or during free time in their schedule, which may be in place of social activities. This isolation can prevent students from being able to develop and maintain social skills that may be useful in their personal or professional lives. It is important for students to find a balance between school and social engagements to find success in an online program. Possible Challenges: Recent high school graduates may lack the self-discipline to keep up with the workload in online classes. Doing simulated laboratory activities in online classes can be more difficult than conducting experiments in a supervised campus laboratory. Employers also expect a job applicant to have people skills in addition to occupational knowledge, and students in online courses have fewer opportunities to practice interpersonal and public speaking skills

Lack of Interaction: A disadvantage to pursuing your education in a distance learning environment is the lack of face-to-face interaction with your classmates and instructor. While instructors use learning-platform tools such as wiki blogs and group sessions to encourage students to share ideas and communicate, it is not the same as the social interaction available in a traditional environment. Technology features such as email, voicemail and podcasts limit the amount of face-to-face communication that can take place, and if you require hands-on learning, you may find that pursuing your education in a distance learning environment is more difficult.

Self-Motivation: Pursuing your education in a distance learning environment can be challenging unless you have a great deal of motivation. It is easy to be unrealistic about the amount of time the class will take or to procrastinate by thinking that you'll log in later. While many online programs have required log-in times and the instructor schedules office hours, it is easy to postpone attendance. Only the most independent and self-motivated students should take online courses.

Cost: Students in online programs may save money on housing and transportation, but distance learning programs can cost just as much as -- or more than -- traditional programs and may have additional costs, such as technology fees. Online students need access to a computer and internet service. Some distance learning courses require expensive video-conferencing equipment. However, remember that you are paying for a quality education: Online universities that boast extremely low price tags are usually diploma mills and are designed specifically to rob you of funds. Be sure to check the accreditation of any distance learning program you're considering.

4. MEASURING DISCRIMINATION

Unfairly treating students on the basis of their knowledge to a specific group, namely online students, indirect observation, distance mode, unknown peoples,etc., is known as discrimination. In law, economics and social sciences, discrimination has been studied over the last decades and antidiscrimination laws have been adopted by many democratic governments.

There are several decision-making tasks which lend themselves to discrimination,e.g. loan granting, education, health insurances and staff selection. In many scenarios, decision-making tasks are supported by information systems. Given a set of information items on a potential customer, an automated system decides whether the student is to be recommended for an online education or a Traditional classroom education. Automating such decisions reduces the workload of the student's off-line complexity and among other education systems.

The use of information systems based on data mining technology for decision making has attracted the attention of many researchers in the field of computer science. In consequence, automated data collection and a plethora of data mining techniques such as association/classification rule mining have been designed and are currently widely used for making automateddecisions.At first sight, automating decisions may give a sense of fairness: classification rules (decision rules) do not guide themselves by personal preferences. However, at a closer look, one realizes that classification rules are actually learned by the system based on training data. If the training data are inherently biased for or against a particular community (for example, student-lack of knowledge), the learned model may show a discriminatory prejudiced behavior. For example, in an online classroom students are not able to understand the presentation due to various reasons and also student availability and attention is not compulsion. If this biased historical dataset is used as training data to learn classification rules for an automated teaching method and presentation system, the learned rules will also show biased behavior toward student or faculty. Figure illustrates the process of discriminatory and non-discriminatory decision rule extraction. If the original biased dataset *DB* is used for data analysis without any anti-discrimination process (i.e. discrimination discovery and prevention),the discriminatory rules extracted could lead to automated unfair decisions. On the contrary, *DB* can go through an anti-discrimination process so that the learned rules are free of discrimination, given a list of discriminatory attributes (*e.g.* gender, race, age, etc.). As a result, fair and legitimate automated decisions are enabled.

Despite the wide deployment of information systems based on data mining technology in decision making, the issue of anti-discrimination in data mining did not receive much attention. After that, some proposals have addressed the discovery and measure of discrimination. Others deal with the prevention of discrimination. The discovery of discriminatory decisions was first proposed by Pedreschi and Ruggieri. 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.

Discrimination can be either direct or indirect. Direct discriminatory rules indicate biased rules that are directly inferred from discriminatory items (*e.g. online student* = Yes). Indirect discriminatory rules (redlining rules) indicate biased rules that are indirectly inferred from non-discriminatory items (*e.g. teaching mode* = distance(virtual) because of their correlation with discriminatory ones. Indirect discrimination could happen because of the availability of some background knowledge (rules), for example, indicating that a certain teaching mode corresponds to a deteriorating area or an area with a mostly black population.

The background knowledge might be accessible from publicly available data(*e.g.* no. of student's lac in knowledge) or might be obtained from the original dataset itself because of the existence of non-discriminatory attributes that are highly correlated with the sensitive ones in the original dataset. One might conceive that, for direct discrimination prevention, removing discriminatory attributes from the dataset and, for indirect discrimination prevention, removing on-discriminatory attributes that are highly correlated with the sensitive ones could be a basic way to handle discrimination. However, in practice this is not advisable because in this process much useful information would be lost and the quality/utility of the resulting training datasets and data mining models would substantially decrease. The rest of this chapter contains notation and background on direct and indirect discriminatory rules. It gives taxonomy of discrimination prevention methods. That describes several preprocessing discrimination prevention methods we have proposed in recent papers. Metrics to measure the success at removing discriminatory rules are given in Section Data quality metrics are listed in below. This paper contains experimental results for the direct discrimination prevention methods proposed. Conclusions and suggestions for future work are summarized later.

5. PRELIMINARIES

In this section we briefly recall some basic concepts which are useful to better understand the study presented in this chapter.

Basic Notions

I. A dataset is a collection of data objects (records) and their attributes. Let DB Bethe original dataset.
II. An item is an attribute along with its value, e.g. {Race=black}.
III. An item set, i.e. X, is a collection of one or more items, e.g. {Foreign worker=Yes, City=NYC}.
IV. A classification rule is an expression X→C, where C is a class item (a yes/no decision), and X is an item set containing no class item, e.g. {Foreign worker=Yes, City=NYC} →{hire=no}. X is called the premise of the rule.

The support of an item set, sup(X), is the fraction of records that contain theitemset X. We say that a rule X→C is completely supported by a record if bothX and C appear in the record.

· The confidence of a classification rule, conf(X→C), measures how often the class item C appears in records that contain X. Hence, if supp(X)> 0supp(x,c)onf(x-.c)= ------------ [1]

supp(x).

Support and confidence range over [0,1].

I. A frequent classification rule is a classification rule with a support or confidence greater than a specified lower bound. Let FR be the database of frequent classification rules extracted from DB.

II. Discriminatory attributes and item sets (protected by law): Attributes are classified as discriminatory according to the applicable anti-discrimination acts(laws). Hence these attributes are regarded as discriminatory and the itemsets corresponding to them are called discriminatory itemsets. {Student=Online, Exposure=Nil} is just an example of a discriminatoryitemset. Let DAs be the set of predetermined discriminatory attributes in DB and DIs be the set of predetermined discriminatory itemsets in DB.

III. Non-discriminatory attributes and itemsets: If As is the set of all the attributes in DB and Is the set of all the itemsets in DB, then nDAs (i.e. set of nondiscriminatoryattributes) is As-DAs and nDIs (i.e. set of non-discriminatory itemsets) is Is-DIs. An example of non-discriminatory itemset could be{Mode=Online, Practical Knowledge=Nil}.

IV. The negated itemset, i.e. ~X is an itemset with the same attributes as X, butsuch that the attributes in ~X take any value except those taken by attributes inX. In this chapter, we use the ~ notation for itemsets with binary or categoricalattributes. For a binary attribute, e.g. {Mode of Student =distance/virtual class}, if X is {mode=distance}, then ~X is {distance=No}. Then, if X is binary, itcan be converted to ~X and vice versa. However, for acategorical (non-binary)attribute, e.g. {method=virtul/online/distance}, if X is {mode=distance}, then ~X is{mode=trational} or {exposure=good}. In this case, ~X can be converted to X with out ambiguity, but the conversion of X into ~X is not uniquely defined, whichwe denote by ~X X. In this chapter, we use only non-ambiguous negations.

6. DIRECT AND INDIRECT DISCRIMINATORY RULES

As more precisely discussed, frequent classification rules fall intoone of the following two classes:

A classification rule (r: X→ C) with negativedecision (e.g. denying credit or hiring) is potentially discriminatory (PD) if X ∩DIs ¹ Ø, otherwise r is potentially non-discriminatory (PND). For example, if DIs= {Foreign worker=Yes}, a classification rule {Foreign worker=Yes;City=NYC}→Hire=No is PD, whereas {Zip=10451, City=NYC} → Hire=No, or{Experience=Low; City=NYC} → Hire=No are PND.

The word ``potentially'' means that a PD rule could probably lead to discriminatorydecisions; hence some measures are needed to quantify the direct discriminationpotential. Also, a PND rule could lead to discriminatory decisions in combinationwith some background knowledge; e.g., if the premise of the PND rule containsthe zip code as attribute and one knows that zip code 10451 is mostly inhabited byforeign people. Hence, measures are needed to quantify the indirect discriminationpotential as well.

As mentioned before, translatedqualitative discrimination statements in existing laws, regulations and legalcases into quantitative formal counterparts over classification rules and they introduceda family of measures over PD rules (for example elift) for direct discriminationdiscovery and over PND rules (for example elb) for indirect discriminationdiscovery. Then, by thresholding elift it can be assessed whether the PD rule hasdirect discrimination potential. Based on this measure (elift), a PD rule (r: X →C)is said to be discriminatory if elift(r) ≥ α1 or protective if elift(r) <α. In addition,whether the PND rule has indirect discrimination potential can be assessed bythresholding elb. Based on this measure (elb), a PND rule (r': X →C) is said to beredlining if elb(r') ≥ α or non-redlining (legitimate) if elb(r') <α. For more detailedinformation and definitions of these measures.

7. A CLASSIFICATION OF DISCRIMINATION PREVENTION METHODS

Beyond discrimination discovery, preventing knowledge-based decision supportsystems from making discriminatory decisions (discrimination prevention) is amore challenging issue. The challenge increases if we want to prevent not only direct discrimination but also indirect discrimination or both at the same time. In this section, we present taxonomy of discrimination prevention methods after having reviewed a collection of independent works in the area. Figure 13.2 shows this taxonomy. In order to be able to classify the various approaches, we consider two orthogonal dimensions based on which we present the existing approaches. As a first dimension, we consider whether the approach deals with direct discrimination, indirect discrimination, or both at the same time. In this way, we separate the discrimination prevention approaches into three groups: direct discrimination prevention methods, indirect discrimination prevention methods, and direct and indirect discrimination prevention methods. The second dimension in the classification relates to the phase of the data mining process in which discrimination prevention is done. Based on this second dimension, discrimination prevention methods fall into three groups pre-processing, inprocessingand post-processing approaches. We next describe these groups:· Pre-processing. Methods in this group transform the source data in such a way that the discriminatory biases contained in the original data are removed so that no unfair decision rule can be mined from the transformed data; any of the standard data mining algorithms can then be applied. The pre-processing approaches of data transformation and hierarchy-based generalization can be adapted from the privacy preservation literature.

In-processing. Methods in this group change the data mining algorithms in such a way that the resulting models do not contain unfair decision rules. For example, an alternative approach to cleaning the discrimination from the original dataset is proposed inCalders and Verwer whereby the non-discriminatory constraint is embedded into a decision tree learner by changing its splitting criterion and pruning strategy through a novel leaf re-labeling approach. However, it is obvious that in-processing discrimination prevention methods must rely on new special purpose data mining algorithms; standard data mining algorithms cannot be used because they ought to be adapted to satisfy the non-discrimination requirement.· Post-processing. These methods modify the resulting data mining models, instead of cleaning the original dataset or changing the data mining algorithms. For example, a confidence-altering approach is proposed for classification rules inferred by the rule-based classifier: CPAR (classification based on predictive association rules).

8. TYPES OF PRE-PROCESSING DISCRIMINATION PREVENTION METHODS

Although some methods have already been proposed for each of the above mentioned approaches (pre-processing, in-processing, post-processing), discrimination prevention stays a largely unexplored research avenue. In this section, we concentrate on a group of discrimination prevention methods based on pre-processing (first dimension) that could deal with direct or indirect discrimination (second dimension), because pre-processing has the attractive feature of being independent of the data mining algorithms and models. The purpose of all these methods is to transform the original data *DB* in such a way as to remove direct or indirect discriminatory biases, with minimum impact on the data and on legitimate decision rules, so that no unfair decision rule can be mined from the transformed data. As part of this effort, the metrics that specify which records should be changed, how many records should be changed and how those records should be changed during data transformation are developed. There are some assumptions common to all methods in this section

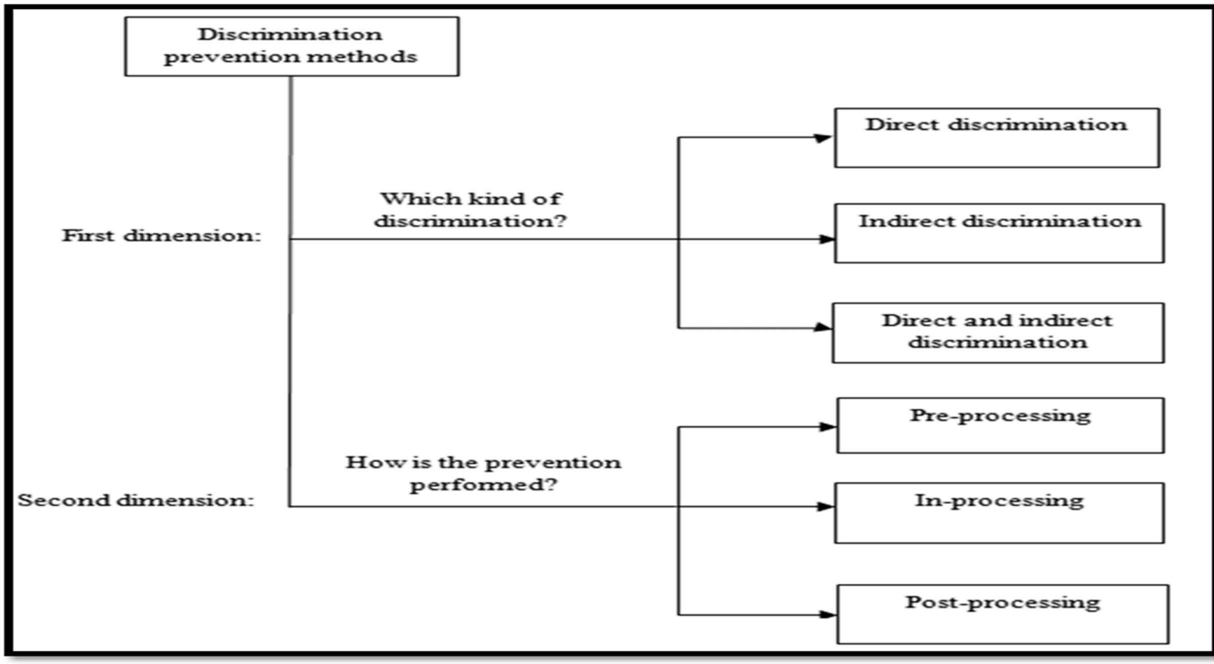


Figure. 2Discrimination Prevention Methods

. First, we assume the class attribute in the original dataset DB to be binary (e.g. denying or granting credit). Second, we obtain the database of discriminatory and redlining rules as output of a discrimination measurement (discovery) phase based on measures, discrimination measurement is performed to identify discriminatory and redlining rules then a data transformation phase is needed to transform the data in order to remove all evidence of direct or indirect discriminatory biases associated to discriminatory or redlining rules. Third, we assume the discriminatory itemsets (i.e. A) and the non-discriminatory itemsets (i.e. D) to be categorical.

Direct Discrimination Prevention Methods

The proposed solution to prevent direct discrimination is based on the fact that the dataset of decision rules would be free of direct discrimination if it only contained rules that are *protective* or PD rules that are instances of at least one *no redlining(legitimate)* PND rule. Therefore, a suitable data transformation with minimum information loss should be applied in such a way that each *discriminatory* rule either becomes *protective* or an instance of a *non-redlining* PND rule.
We call the first procedure direct rule protection and the second one rule generalization.

Direct Rule Protection (DRP)

In order to convert each discriminatory rule r’: A, B →C, where A is a discriminatoryitemset and B is non-discriminatory itemset, into protective rule, two data transformation methods (DTM) could be applied. One method (DTM 1) changes the discriminatory itemset in some records (e.g. gender changed from male to female in the records with granted credits) and the other method (DTM 2)changes the class item in some records (e.g. student not interested or can’t keep track the presentation

Indirect Discrimination Prevention Methods

To prevent indirect discrimination is based on the fact that the dataset 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. We call this procedure indirect rule protection (IRP).

In order to turn a redlining rule :□ : D,B → C, where D is a non-discriminatoryitemset that is highly correlated to the discriminatory itemset A, into a nonredlinin gruel based on the indirect discriminatory measure (elb), two data transformationmethods could be applied, similar to the ones for direct rule protection.One method (DTM 1) changes the discriminatory itemset in some records and the other method (DTM 2) changes the class item insome records.

Measuring Discrimination Removal

Discrimination prevention methods should be evaluated based on two aspects: discrimination removal and data quality. We deal with the first aspect in this section: how successful the method is at removing all evidence of direct and/or indirect discrimination from the original dataset.

Direct Discrimination Prevention Degree (DDPD).

This measure quantifies the percentage of discriminatory rules that are no longer discriminatory in the transformed dataset.

Direct Discrimination Protection Preservation (DDPP).

This measure quantifies the percentage of the protective rules in the original dataset that remain protective in the transformed dataset.

Indirect Discrimination Prevention Degree (IDPD).

This measure quantifies the percentage of redlining rules that are no longer redlining in the transformed dataset.

Indirect Discrimination Protection Preservation (IDPP).

This measure quantifies the percentage of non-redlining rules in the original dataset that remain on-redlining in the transformed dataset. Since the above measures are used to evaluate the success of the proposed methods in direct and indirect discrimination prevention, ideally their value should be 100%.

Measuring Data Quality.

The second aspect to evaluate discrimination prevention methods is how much information loss (*i.e.* data quality loss) they cause.

Misses Cost (MC).

This measure quantifies the percentage of rules among those extractable from the original dataset that cannot be extracted from the transformed dataset (side-effect of the transformation process).

9. CONCLUSIONS

In 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. Like privacy, discrimination could have negative social impact on acceptance and dissemination of data mining technology. Discrimination prevention in data mining is a new body of research focusing on this issue. One of the research questions here is whether we can adapt and use the pre-processing approaches of data transformation and hierarchy-based generalization from the privacy preservation literature for discrimination prevention. In response to this question, we try to inspire on the data transformation methods for knowledge (rule) hiding in privacy preserving data mining and we devise new data transformation methods (*i.e.* direct and indirect rule protection, rule generalization) for converting direct and/or indirect discriminatory decision rules to legitimate (nondiscriminatory)classification rules; our current results are convincing in terms of discrimination removal and information loss. However, there are many other challenges regarding discrimination prevention that could be considered in the rest of this research. For example, the perception of discrimination, just like the perception of privacy, strongly depends on the legal and cultural conventions of a society. Although we argued that discrimination measures based on *elift* and *elb* are reasonable, if substantially different discrimination definitions and/or measures were to be found, new data transformation methods would need to be designed. Another challenge is the relationship between discrimination prevention and privacy preservation in data mining. It would be extremely interesting to find synergies between rule hiding for privacy-preserving data mining and rule hiding for discrimination removal. Just as we were able to show that indirect discrimination removal can help direct discrimination removal, it remains to see whether privacy protection can help anti-discrimination or vice versa.

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