International Journal of
Emerging Research in Management &Technology
ISSN: 2278-9359 (Volume-4, Issue-7)

Research Article

July 2015

Review of a Methodology for Indirect Discrimination Prevention in Data Mining Using Indirect Rule Protection

Shubhangi R. Khade, **Y. B. Gurav**
Dept. of Computer Engineering
PVPIT, Bavdhan, Pune,
Maharashtra, India

Abstract:

Data mining is the most necessary technology for extracting useful data in giant collections of information. There are some negative social aspects about data processing, like, potential privacy invasion and potential discrimination. The latter comprises of discrimination among people on the basis of their origin from some specific group. automaticknowledgecollection and data processing techniques like classification rule mining have paved the block to creating automatic selections,vizloan granting/denial, premium computation, etc. If the given data sets are biased withdiscriminatory (sensitive) attributes like gender, race, religion, etc., discriminatory decisions might result. For this purpose, antidiscriminatry techniques like discrimination discovery and prevention are introduced in data processing. Discrimination either direct or indirect. Direct discrimination happens when decisions are based on sensitive attributes. Indirect discrimination happens when decisions are based on non sensitive attributes that powerfully correlative with sensitive ones. Here, we tried toseek solution to prevent discrimination in data processing and will try to bring new techniques applicable for direct or indirect discrimination preventionseparately or severally at the same time. we discussed a way to clean training data sets and outsourced data sets as such the way that direct and/or indirect discriminatory decision rules changed to form a legitimate (nondiscriminatory) classification rules. We also bring new metrics to gauge the utility of the planned approaches and moreovercompare these approaches. The experimental outputs shows that the said techniques are capable of at removing direct and/or indirect discrimination biases within the original data setkeeping quality at the same time.

Index Term: Antidiscrimination, data mining, direct and indirect discrimination prevention, rule protection, rule generalization, Privacy

I. INTRODUCTION

In study of society, discrimination is the detrimental treatement of an individual based on their membership in a particular group or category. it involves not to allow members of 1 cluster opportunities that are available to different teams.Here,is an list of antidiscrimination acts, these are laws designed to prevent discrimination on the idea of variety of attributes (e.g., race, religion, gender, position, disability, legal status, and age) in numerous settings (e.g., employment and coaching, access to public services, credit and insurance, etc.). The example, the UK Union implements the principle of equal treatment between men and girls within the access to and supplier of products and services in [3] or in matters of employment and occupation in [4]. If there are some laws against discrimination,thesearc reactive, not proactive. Technology will add proactively to legislation by contributory discrimination discovery and prevention techniques.

Services in the information society allow for automatic and routine collection of big amounts of data. Which data are often used to train association/classification rules in view of making automated decision, like loan granting/denial, insurance premium computation,personnelselection.Discriminationmay be either direct or indirect (also called systematic). Direct discrimination involves rules or procedures that clearly mention minority or demerits teams supported sensitive discriminatory attributes associated with team membership. Indirect discrimination includes rules or procedures that, where it is not specially mentioning discriminatory attributes, purpose or accidentally might generate discriminatory selections. Redlining by financial establishments (refusing to grant mortgages or insurances in urban areas they supposed as deteriorating) is an example of indirect discrimination, which is not the sole one. With small abuse of language for the sake of compactness, into this paper indirect discrimination also will be referred as redlining and rules inflicting indirect discrimination is going to be known as redlining rules. Indirect discrimination may happen cause of some background information (rules), example that an explicit postal code corresponds to a deteriorating space or an area with largely black population. The background information can be accessible from in publicly available data (e.g., census knowledge) or it can be obtained from the initial data set itself cause of the existence of nondiscriminatory attributes that are extremely correlate with the sensitive ones within the initial data set.

II. RELATED WORK

Preprocessing. This transform the source data in such away that the discriminatory biases contained in theinitial data are removed so that no unfair decisionrule can be mined from the transformed data andapply any of the standard data mining algorithm.

In-processing. In this change the data mining algorithms insuch a way that the resulting models do not containunfair decision rules. The example, an alternativeapproach to cleaning the discrimination from theinitial data set is proposed in

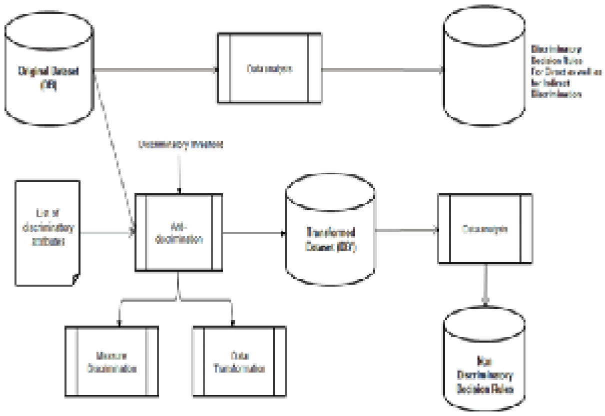
[2] whereby thenon-discriminatory constraint is embedded into adecision tree learner by changing its splittingcriterion and pruning strategy through a novel leaf rrelabeling approach.

Postprocessing. Its modify the output data models, instead of cleaning initial data set or changing the data mining algorithms.Its not allowed the data set to publish. onlymodified data can be published, so we can say that the data mining can be performed by the data holder only.

III. BACKGROUND

In this section, we just review the background information required in the remainder of this paper. First we see some basic definition related to data mining.

A. System Architecture



B. Basic Definitions

- A data set is a collection of data objects (records) andtheir attributes. Let DB be the original data set. An item is an attribute along with its value, e.g.,Race= black.
- .An item set, i.e., X, is a collection of one or more items, e.g., {Foreign worker =Yes, City = NYC}.
- A classification rule is an expression X → C, where Cis a class item (a yes/no decision), and X is an itemset containing no class item, e.g., {Foreign worker = Yes; City = NYC} →Hire = no. X is called the premiseof the rule.
- The support of an item set, supp(X), is the fraction ofrecords that contain the item set X. We say that arule 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 inrecords that contain X. Hence, if supp(X)→ 0 then

$$conf(X \rightarrow C) = \frac{supp(X, C)}{supp(X)}.$$

Support and confidence range over [0,1].

IV. APROPOSAL FOR DIRECT AND INDIRECT

A. The Approach

Our approach for direct and indirect discriminationprevention can be described in terms of two phases:

. **Discrimination measurement.** Identification of direct and indirect-discriminatory rules and redlining rules. To thisend, first, based on predetermined discriminatoryitems in DB, frequent classification rules in FRare divided in two groups: PD and PND rules. Second, direct discrimination is measured byidentifying _-discriminatory rules among the PDrules using a direct discrimination measure (elite)and a discriminatory threshold. Third, indirectdiscrimination is measured by identifying redliningrules among the PND rules combined with backgroundknowledge, using an indirect discriminatorymeasure (elb), and a discriminatory threshold(_). Let MR be the database of direct _-discriminatoryrules obtained with the above process. Inaddition, let RR be the database of redlining rulesand their respective indirect _-discriminatory rulesobtained with the above process.

Data transformation.

Transform the original dataDB in such a way to remove direct and/or indirectdiscriminatory biases, with minimum impact on thedata and on legitimate decision rules, so that nounfair decision rule can be mined from the transformeddata. In the following sections, we presentthe data transformation methods that can be used forthis purpose.

B. Data Transformation for Indirect Discrimination

In order to turn a redlining rule into a nonredlining rule, based on the indirect discriminatory measure (i.e., elb in Theorem 1), we should enforce the following inequality for each redlining rule r : D,B --→ C in RR. The discriminatory item set (i.e., A) is not removed from the original database DB and the rules rb1 :A,B → D and rb2 : D,B → A are obtained from DB, so that their confidences might change as a result of data transformation for indirect discrimination prevention. Clearly, in this case Inequality (12) can be satisfied by decreasing the confidence of rule rb1 : A,B → D to values less than the right-hand side of Inequality (14) without affecting either the confidence of the redlining rule or theconfidence of the B →C and rb2 rules. Since the values of both inequality sides are dependent, a transformation is required that decreases the left-hand side of the inequality without any impact on the right-hand side. A possible solution for decreasing.

V. ALGORITHMS

We describe in this section our algorithms based on thedirect and indirect discrimination preventions methods.There are someassumptions common to all algorithms in this section. First,we assume the class attribute in the original data set DB to be binary (e.g., denying or granting credit). Second, weconsider classification rules with ergative decision (e.g.,denying credit) to be in FR. Third, we assume thediscriminatory item sets (i.e., A) and the non-discriminatory item sets (i.e., D) to be binary or no binary categorical.

Direct discrimination prevention algorithms, we start with direct rule protection. Algorithm 1 detailsMethod 1 for DRP. For each direct _-discriminatory rule r0in MR (Step 3), after finding the subset DBc (Step 5),records in DBc should be changed until the direct ruleprotection requirement (Step 10) is met for each respective rule (Steps 10-14).

Direct And Indirect rule protection (Asocissiative generalization)

Inputs:DB, FR, TR, p>=0.8,∝ , Dis

Output:DB' (transformed data set)

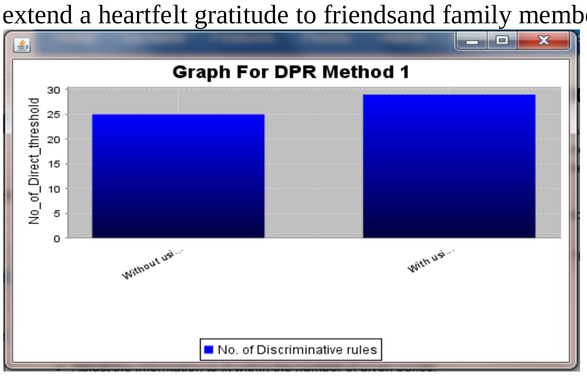
1. for each r':A,B⟶ C ϵ TR do
2. FR ⟵FR-{r'}
3. if $Tr_{r'}$=RG then
4. // Rule Generalization
   DBc ⟵All records completely supporting A,B,¬D→C
5. Steps 6-9 Algorithm 1
6. while conf(r')>conf(($r_{b:D,B}$→C)/p) do
7. Select first record in Dbc
8. Modify class item fdbc from C to ¬C in DB
9. Recompute conf(r')
10. end while
11. end if
12. if Tr=DRP then
13. // InDirect Rule Protection
14. Steps 5-14 Algorithm 1 or Steps 4-9 Algorithm 2
15. end i
16. end for
17. Output: Transformed DB

VI. CONCLUSION AND FUTURE WORK

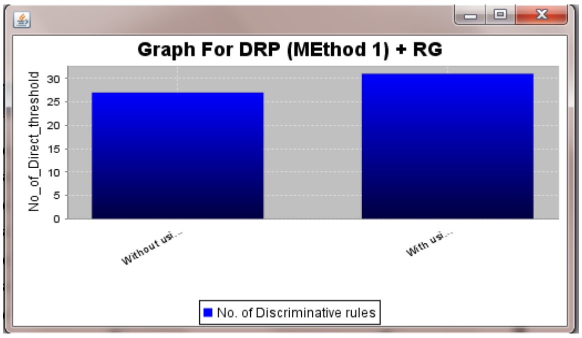
We obviously knows that most of the people do notwant to be discriminated only because of their gender, religion,nationality, age, race condition and so on, And its very especially when those attributesare used for making decisions about them when giving thema job, loan, insurance, etc.The purpose of this paper was to build a new pre-processingdiscrimination prevention methodology includingdifferent data transformation methods that can preventdirect and indirect discrimination or both ofthemsimultaneously.

ACKNOWLEDGMENT

The authors would like to thank the researchers as well aspublishers for making their resources available and teachersfor their guidance. We are thankful to the authorities ofSavitribaiPhule University of Pune and concern membersof cPGCON2015 conference, organized by, for their constantguidelines and support. We are also thankful to the reviewerfor their valuable suggestions. We also thank the college authoritiesfor providing the required infrastructure and support.Finally, we would like to extend a heartfelt gratitude to friendsand family members.



Direct Protection of Rules



Direct Rule Protection with Rule Genaralization

REFERENCES

[1] S. Hajian, J. Domingo-Ferrer, "A Methodology for Direct And Indirect Discrimination Prevention in Data Mining,"IEEE Transaction on knowledge And Data Engineering, VOL.25,NO.7,2013.

[2] T. Calders and S. Verwer, "Three Naive Bayes Approaches forDiscrimination-Free Classification," Data Mining and KnowledgeDiscovery, vol. 21, no. 2, pp. 277-292, 2010.

[3] S. Hajian, J. Domingo-Ferrer, and A. Martı´nez-Balleste´, "DiscriminationPrevention in Data Mining for Intrusion and CrimeDetection," Proc. IEEE Symp. Computational Intelligence in CyberSecurity (CICS '11), pp. 47-54, 2011.

[4] S. Hajian, J. Domingo-Ferrer, and A. Martı´nez-Balleste´, "RuleProtection for Indirect Discrimination Prevention in DataMining," Proc. Eighth Int'l Conf. Modeling Decisions for ArtificialIntelligence (MDAI '11), pp. 211-222, 2011.

[5] F. Kamiran and T. Calders, "Classification without Discrimination,"Proc. IEEE Second Int'l Conf. Computer, Control and Comm.(IC4 '09), 2009.

[6] D. Pedreschi, S. Ruggieri, and F. Turini, "Discrimination-AwareData Mining," Proc. 14thACM Int'l Conf. Knowledge Discovery andData Mining (KDD '08), pp. 560-568, 2008.

[7] D. Pedreschi, S. Ruggieri, and F. Turini, "Measuring Discriminationin Socially-Sensitive Decision Records," Proc. Ninth SIAMData Mining Conf. (SDM '09), pp. 581-592, 2009.

[8] S. Ruggieri, D. Pedreschi, and F. Turini, "Data Mining forDiscrimination Discovery," ACM Trans. Knowledge Discovery fromData, vol. 4, no. 2, article 9, 2010.

[9] V. Verykios and A. Gkoulalas-Divanis, "A Survey of AssociationRule Hiding Methods for Privacy," Privacy-Preserving DataMining: Models and Algorithms, C.C. Aggarwal and P.S. Yu, eds.,Springer, 2008.