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APPLYING ANTI-DISCRIMINATION TECHNIQUES IN BANKING SERVICES

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***Abstract*: Data mining is the useful technology for extracting knowledge buried in large storage of data. Discrimination is one of the negative effects of data mining. Automatic collection of data and data mining techniques such as classification have cleared the way to make automatic decisions, like loan granting/denial, insurance premium computation, giving job etc. In classification, if the banking training datasets are discriminated towards any sensitive attributes like gender, age, religion, etc., then the resulting decisions will have discrimination like loan rejection. Discrimination discovery and discrimination prevention are the two anti-discrimination techniques introduced in data mining. Gender discrimination, age discrimination, racial discrimination are some of the examples of discrimination. But all these discriminations come under the two class namely, direct and indirect discrimination. If the resulting decision depends directly on sensitive attributes, it comes under direct discrimination. If it depends on background knowledge like census data, other than the sensitive attributes it is indirect. The discrimination problems in banking services like loan grant/deny are resolved with the help of anti-discrimination technique. Also the measures of discrimination are identified. The training data related to banking services are transformed in the correct way to remove the discriminatory biases, while maintaining data quality.**

***Keywords*: Anti-discrimination, Classification, Pre-processing, Rule protection, Rule generalization.**

I. INTRODUCTION

In social life, discrimination is the problem of treating people irregularly based on their sex, period, faith etc. Almost everyone do not wish them to distinguish. Nowadays all techniques like data collection, classification, prediction etc are automated. Those data will be helpful in training classification algorithm to make automated decisions, like loan grant/deny, computing insurance premium, selection of personnel, etc.

With the first glance, automated decisions seem to be quiet fair. The classification rules will not teach them by personal preferences. When looking into deeper, one can realize the truth that classification rules are of-course learned by the algorithm with the help of training data. If those training data are biased towards or against a particular attribute (e.g., female), then the resulting model may reveal a discriminatory behaviour. In other words, the algorithm may learn that just being female is an ultimate reason for rejecting loan those discriminatory attributes should be identified and eliminated from the training data without affecting the decision making factor. Data mining becomes both a source of discrimination and also helps to discover discrimination.

Discrimination may come under one of the following class, either direct or indirect. Gender discrimination, age discrimination, racial discrimination, pregnant discrimination are some of the examples of discrimination.

Direct discrimination contains rules which directly express the discriminated group based on sensitive attributes. While indirect discrimination contains rule that, cannot explicitly express discriminatory attributes, but it purposely or unknowingly may generate discriminatory decisions. Refusing to give loan because of his belonging to certain community can be an example for direct discrimination in bank. Redlining by financial institutions is the typical example of indirect discrimination.

The following circumstance may reveal the fact that how discrimination may look like. Moreover it's important to keep in mind that, while discrimination may take place in many forms, there can also be proper reasons for the other people's behaviour in most of these situations. Swarna, aged 46, just found out that she didn't get a job that she was perfectly qualified for. Instead, the firm hired Manju, a man aged 25, just out of college with far less experience and fewer qualifications. It's possible that Swarna could be a victim of age or gender discrimination.

II. RELATED WORK

1) Discrimination discovery

In the perspective of civil rights law, discrimination refers to iniquitous or unequal treatment of people based on their belonging to a community or a minority, without considering individual pro. Researchers in human science have been analysing discrimination in various fields like credit, mortgage, insurance, labour market, and learning.

With the emergent of automatic decision support systems, such as credit scoring systems, the simpler data collection proposes several problems to data analysts to fight against discrimination. The discrimination discovery is introduced in data mining in a dataset of historical decision records, collected by humans or by automated systems. The process of discovering both direct and indirect discrimination is analysed by modelling protected-by-law groups and contexts.

In both the case discrimination occurs in a classification rule based on grammar. Normally, classification rules extracted from the dataset allow us to remove covering from context of unlawful discrimination, where the degree of saddle over protected-by-law groups is legalized by extending lift measure of a classification rule. In case of direct discrimination, mining extracted rules can be done by probing the discriminatory contexts.

While in case of indirect discrimination, the mining process further requires some background knowledge further input, e.g., census data, which may get combined with the extracted rules that allows for unveiling contexts of discriminatory decisions. Inference model is the adopted tactic which combines the extracted classification rules with background knowledge.

2) Discrimination Aware Decision Tree Learning

The problem of discrimination-aware classification can be identified by constructing a decision tree classifier without discrimination. The new idea of constructing the decision trees with non-discriminatory constraints is a divergent to the earlier approaches. As they aims in “removing” undesired dependencies from the training data and thus can be considered as “pre-processors”. Particularly, relabeling, for which an algorithm, based on KNAPSACK, is proposed, which is proved to show good results in evaluated experiments.

Instead of learning a discrimination aware classifier for future predictions, the theme of discrimination in data mining concentrates mainly on identification of the discriminatory rules that could present in a dataset, and the specific subset of the data where they hold. Before applying traditional algorithms, the discrimination that are present in the dataset should be “cleaned away”.

To triumph over this, discrimination-aware classification and its extensions to independence were introduced. Two approaches namely, **Massaging** and **Reweighing** are used to clean away the data.

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a) In massaging method, in order to achieve a discrimination free dataset, the class labels of preferred objects in training set needs to be altered.
b) The subjective sample is selected in order to counterbalance the impact of discrimination.

Dependency-Aware Tree Construction

While evaluating the splitting criterion for a tree node, not only its payment to the accuracy, but also the level of dependency caused by this split needs to be evaluated.

Leaf Relabeling

Normally, in a decision tree, the label of a leaf is determined by the class that occurs frequently in the tuples that belong to this node in the training set. But, in leaf relabeling, only the label of selected leaves require changes so that the dependency is reduced with minimal loss in accuracy.

3) Classification with No Discrimination

One of the emergent research area is the concept of classification without discrimination. The idea of Classification with No Discrimination (CND) finds a key based on "massaging", in which the data should be massaged to remove the discrimination and to have least possible changes. As an alternative to relabeling the dataset, sampling scheme is the new solution proposed to the CND problem, where the data is prepared to be discrimination-free.

A new classifier is learned, from the resulting non-discriminatory dataset. This method is both less interfering as compared to the "massaging" and also outperforms the "reweighing" approach.

An admirable solution to the discrimination problem is "Classification with No Discrimination by Preferential Sampling". It guarantees hopeful results with both stable and unstable classifiers. Reducing discrimination by maintaining high accuracy level is one of the leading features of this approach. It provides analogous performance to "massaging" but without varying the dataset and always outstands the "reweighing" idea.

For massaging the data, a ranker needs to be learned first for predicting the class attribute, without making an allowance for the discrimination. This ranker is then often used to sort the data objects based on their likelihood of being in the desired class, (e.g., job = yes). The class labels of the sufferers and profiteers should be changed. This modified data is then used for additional learning of classifier with no discrimination which helps in making future decisions.

Preferential Sampling (PS)

The foremost inspiration behind the Preferential Sampling (PS) is that the data objects which are close to the borderline have more promise to get discriminated and those data will get high inclination while sampling. For recognizing the borderline objects, PS starts by learning a ranker from the training data.

It then consumes this ranker to regulate the data objects with respect to the positive class probability. This arrangement of data objects ensures that if the rank of the element is high, then it is more close to the borderline. PS starts from the original training dataset and iteratively duplicates and removes objects in the following way:

a) To **reduce** the size of a group**,** the data objects closest to the borderline should be removed. i.e., the top element
b) To **increase** the size of the group, the data object closest to the borderline should gets duplicated. The object after duplication is moved to the bottom of ranking , along with its replica.

4) Rule Protection

Services available in the information society permits habitual and custom compilation of large amounts of data. For preparing classification rules to make automated decisions, like loan grant/deny, computing insurance premium, etc. If the training datasets are prejudiced towards sensitive attributes like gender, race, religion, etc., then the resulting decisions may encompass discrimination. Direct discrimination contains rules which openly convey the discriminated group based on sensitive attributes. Whereas indirect discrimination contains rule that, cannot openly express discriminatory attributes, but it knowingly or unknowingly may generate discriminatory decisions. The training datasets and outsourced datasets are cleaned in an appropriate manner, so that only lawful classification can be extracted without including indirect discrimination rules.

Rule protection is the first scheme which has been projected to avert indirect discrimination in data mining due to biased training datasets. It aims to produce training data which are absolutely free or roughly free from indirect discrimination. At the same time, their helpfulness to data mining algorithms remains unchanged. In order to get rid of indirect discrimination in a dataset, the primary step is to identify the existence of indirect discrimination. If such a discrimination is identified, then the data set requires adjustment until the entire discrimination is eliminated or comes under a specified threshold.

By now, some methods are practical for discrimination prevention, which focus only on direct discrimination. Those existing approaches cannot make sure that the transformed dataset is really discrimination-free, because some discriminatory behaviours generally hidden behind non-discriminatory items.

This method attempts to alter the source data by eliminating indirect discriminatory biases with the aim that unreasonable decision rule should not be indirectly extracted from the transformed data. It reveals the concept that if the dataset of decision rules contain no redlining rule, then it is free of indirect discrimination. The data should be transformed in such a way that no proof of discrimination such as α-discriminatory rules and redlining rules can be found, which is the key perception of discrimination prevention using pre-processing.

Indirect discrimination focus on and aims to resolve redlining rules. To accomplish this, a appropriate data transformation which converts redlining rules into non-redlining rules are anticipated, with least information loss named as “Rule protection”.

5) Data Mining For Intrusion and Crime Detection

Automated data collection in data mining seems to be a reason for intrusion and crime detection. Furthermore, banks, large corporations, insurance companies, casinos, etc, used to mine data about their customers or employees with the intention of detecting potential intrusion, fraud or even crime. Mining algorithms are trained from the datasets which may be influenced by sex, race, faith or any other sensitive attributes.

Since mining carried out in collaboration by several entities, discrimination problem begin. Potential intrusion, fraud or crime which ought to be identified from objective misbehaviour, rather than from sensitive attributes like gender, race or religion.

The training datasets and outsourced datasets are cleaned in a proper manner, so that only justifiable classification can be extracted without including indirect discrimination rules. The discrimination which has its force on cyber security applications, especially Intrusion Detection Systems has been examined. Intrusion Detection Systems in general use computational intelligence technologies such as data mining. There is no uncertainty that the training data of these systems could be discriminatory, which would cause them to make discriminatory decisions when predicting invasion or, more generally, offense.

Anti-discrimination also plays a foremost role in cyber security, in which the computational intelligence technologies such as data mining may be used for different decision making scenarios. It is the former work that applies anti-discrimination in cyber security. The main concern here is to deal the problem without corrupting the efficacy of data for cyber security applications that rely upon data mining, *e.g.* intrusion detection systems . The main offerings of this method are as follows:

- It introduces anti-discrimination in the perspective of cyber-security.
- It analyzes a new discrimination prevention method based on data transformation that can consider numerous discriminatory attributes and their combinations.

III. PROPOSED SYSTEM

Data mining is the valuable technology for extracting knowledge underlying in large storage of data. Discrimination is one of the destructive effects of data mining. The intention of this system was to enlarge a new pre-processing discrimination prevention methodology including different data transformation methods that can stop direct discrimination, indirect discrimination or together at the same time.

To accomplish this idea,

- measure discrimination
- individuals which have been directly and/or indirectly discriminated in the decision-making processes ought be identified.
- data are transformed in the proper way to take out all those discriminatory attributes.

Advantages

Even though there exists more than a few methods for each of the above mentioned approaches, discrimination prevention still remains a largely unexplored research avenue. It aim principally on discrimination prevention based on pre-processing. The following serves the virtues of the proposed system:

- The pre-processing approach seems the most flexible one.
- No need to modify the benchmark data mining algorithms.
- Not only knowledge publishing, but also data publishing.
- To overcome direct and indirect discrimination based on anti-discrimination techniques.
- Resolving direct and indirect discrimination either independently or together at the same time.
- The transformed data is in fact discrimination free.

Discrimination Measurement

Direct discrimination contains rules which directly articulate the discriminated group based on sensitive attributes. While indirect discrimination contains rule that, cannot explicitly articulate discriminatory attributes, but it knowingly or unknowingly may generate discriminatory decisions. Direct and indirect discrimination discovery includes identifying both α-discriminatory rules and redlining rules respectively.

Data Transformation

The original data is supposed to transform in such a way that both direct and/or indirect discriminatory biases should be eliminated. This must be done with minimum impact on the data and on legitimate decision rules, so that the transformed data is free of unfair decision rules.

Direct Rule Protection

In order to convert each α-discriminatory rule into an α-protective rule, based on the direct discriminatory measure the two methods could be applied for direct rule protection. In the first method, the discriminatory item set in some records need to be changed (e.g., religion changed from xxx to yyy in the records with granted credits). In the second method , the class items in some records require proper changes (e.g., from grant credit to deny credit in the records with xxx).

Rule Generalization

Rule generalization is one more data transformation method for direct discrimination prevention. Instead of considering the discrimination measures, it takes into account the relation between rules.

The instance given below illustrates this principle. Consider that a accuser claims discrimination against religion=xxx among applicants for a loan application. A classification rule {Religion = xxx; City = TN} → Loan = deny, with high elift supports the accuser's claim. However, the decision maker could disagree that this rule is an instance of a more general rule {Income = low; City = TN}→Loan = deny. In other words, applicant belonging to religion xxx are rejected because of their low income, not just because they belong to particular religion. The general rule rejecting low-income applicants is a legitimate one, because low income can be considered a genuine/legitimate requirement for loan approval.

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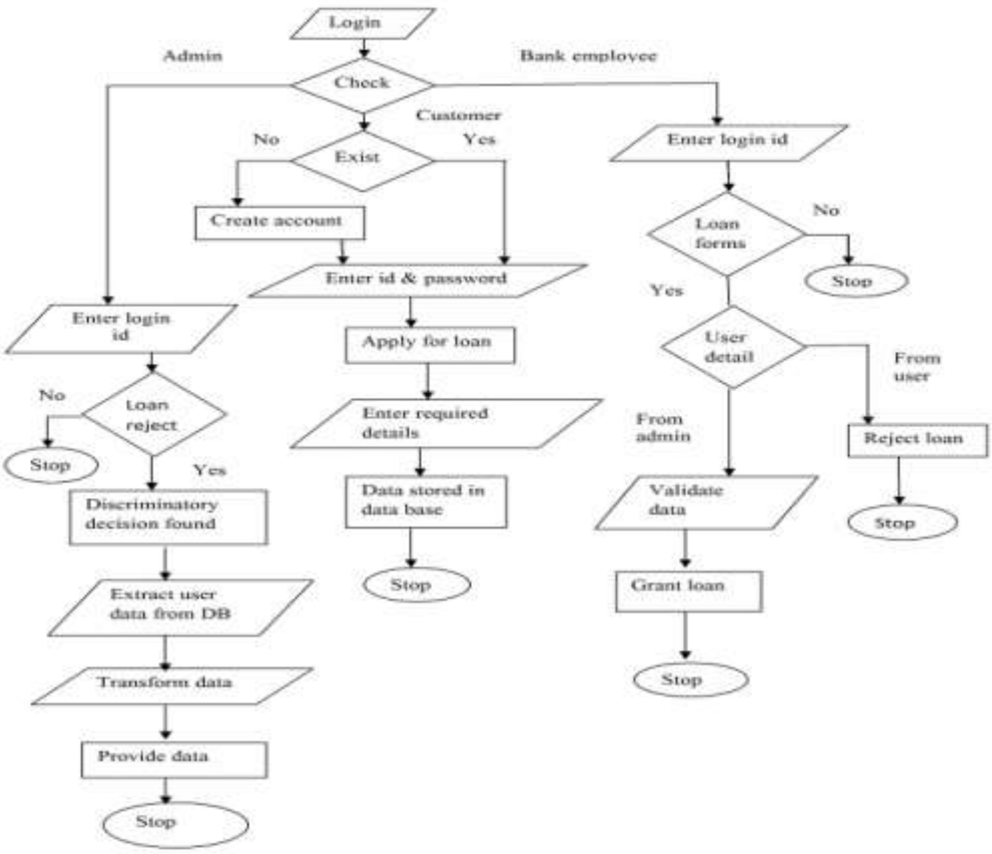

Fig. 1. Flow Diagram

Direct and Indirect Discrimination Classification Rule

Direct discrimination algorithm is based on sensitive attributes. Direct discrimination contains rules which directly express the discriminated group based on sensitive attributes. Whereas indirect discrimination contains rule that, cannot explicitly express discriminatory attributes, but it knowingly or unknowingly may generate discriminatory decisions.

Borrower Information and Loan Sanction Module

In communal life, discrimination is the problem of treating people unevenly based on their sex, period, faith etc. Approximately citizens do not wish them to distinguish. In this day and age all techniques like data collection, classification, prediction etc are programmed. Those data will be helpful in training classification algorithm to make automated decisions, like loan grant/deny, computing insurance premium, selection of personnel, etc.

Data Alteration for Direct Discrimination

The original data should be transformed in such a way that both direct and/or indirect discriminatory biases should be eliminated. This must be done with minimum impact on the data and on legitimate decision rules, so that the transformed data is liberated from unfair decision rules.

The proposed solution to prevent direct discrimination can promise that, if the data set of decision rules contains potentially discriminatory (PD) rules that are α-protective of decision rules, then it would be free of direct discrimination.

Therefore, a appropriate data transformation with minimum information loss should be applied in such a way that each α-discriminatory rule either becomes α-protective or an instance of a non-redlining potentially non-discriminatory(PND) rule. This procedure is known as direct rule protection (DRP).

Data Alteration for Indirect Discrimination

The proposed solution to prevent indirect discrimination can promise that if the data set contains no redlining rules, then it would be free of indirect discrimination. To achieve this, a appropriate data transformation with minimum information loss should be applied in such a way that redlining rules are converted to non-redlining rules. This procedure is known as indirect rule protection (IRP).

IV. CONCLUSION AND FUTURE WORK

In communal life, discrimination is the problem of treating people unevenly based on their gender, age, religion etc. Almost people do not want them to discriminate. In this day and age all techniques like data collection, classification, prediction etc are programmed. Those data will be helpful in training classification algorithm to make automated decisions, like loan grant/deny, computing insurance premium, selection of personnel, etc.

The objective of this methodology was to develop a new pre-processing discrimination prevention tactic including different data transformation methods that can prevent both direct and indirect discrimination in banking services like loan approval, computing insurance premium, etc.

As a future work the supplementary measures of discrimination should be taken into consideration. The further study of legal writing on discrimination in several countries would help to find different measures of discrimination. The new different data transformation methods should be projected to eliminate entire discrimination in banking services.

REFERENCES

[1] R. Agrawal and R. Srikant, "Fast Algorithms for Mining Association Rules in Large Databases," Proc. 20th Int'l Conf. Very Large Data Bases, pp. 487 -499, 1994.

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

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

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

[5] F. Kamiran and T. Calders, "Classification with no Discrimination by Preferential Sampling," Proc. 19th Machine Learning Conf. Belgium and The Netherlands, 2010.

[6] F. Kamiran, T. Calders, and M. Pechenizkiy, "Discrimination Aware Decision Tree Learning," Proc. IEEE Int'l Conf. Data Mining (ICDM '10), pp. 869-874, 2010.

[7] R. Kohavi and B. Becker, "UCI Repository of Machine Learning Databases," http://archive.ics.uci.edu/ml/datasets/Adult, 1996.

[8] D.J. Newman, S. Hettich, C.L. Blake, and C.J. Merz, "UCI Repository of Machine Learning Databases," http://archive.ics.uci.edu/ml, 1998.

[9] D. Pedreschi, S. Ruggieri, and F. Turini, "Discrimination-Aware Data Mining," Proc. 14th ACM Int'l Conf. Knowledge Discovery and Data Mining (KDD '08), pp. 560-568, 2008.

[10] D. Pedreschi, S. Ruggieri, and F. Turini, "Measuring Discrimination in Socially-Sensitive Decision Records," Proc. Ninth SIAM Data Mining Conf. (SDM '09), pp. 581-592, 2009.

[11] S. Ruggieri, D. Pedreschi, and F. Turini, "Data Mining for Discrimination Discovery," ACM Trans. Knowledge Discovery from Data, vol. 4, no. 2, article 9, 2010.