"REVIEW ON DISCRIMINATION AND PREVENTION POLICIES OVER WEB DATA"

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ABSTRACT: *Data warehouse is emerging need of web users. Every user wants to store data in centralized location from where it can access the data. And data mining is the process of extracting the data which is most important or knowledgeable. Some time user access the data which is sensitive and on the basis of that discrimination can be occurred. According to the different area, state, country discrimination can be happened. Direct and indirect are the two most observable discrimination processes which are identified. This paper gives literature survey and identifies the some important facts that can consider.*

Keywords: discrimination, preprocessing, classification

1. INTRODUCTION

The aim of data mining is to extract useful information, such as patterns and trends, from large amounts of data. Many governments are gathering large amounts of data to gain insight into methods and activities of suspects and potential suspects. This can be very useful, but usually at least part of the data on which data mining is applied is confidential and privacy sensitive. Examples are race, religion, gender, nationality, disability, marital status, and age, etc. This raises the question how privacy. [1][2]

The information society services allows for automatic and routine collection of large amounts of data. Those automatic and routine collections of data are often used to train classification rules in view of making automated decisions, like loan granting/denial, insurance premium computation, personnel selection, etc. Firstly, automating decisions may give a sense of fairness: cataloguing rules do not guide themselves by personal preferences. However, at a closer look, one realizes that classification rules are actually learned by the system (e.g., loan granting) from the training data. [3] If the training data are fundamentally biased for or against a particular community, the learned model may show an unfair prejudiced behaviour. In other words, the system may infer that just being foreign is a legitimate reason for loan denial.

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 customer is to be recommended for a credit or a certain type of life insurance. Automating such decisions reduces the workload of the staff of banks and insurance companies, among other organizations. [4]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 automated decisions.

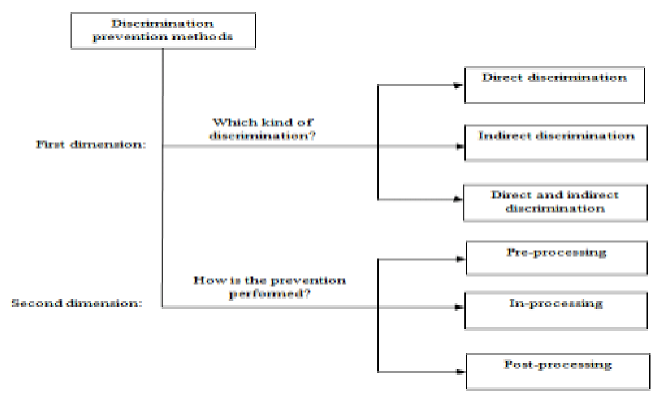

Figure1: Taxonomy for discrimination prevention methods [7]

Pre-processing: 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 and apply any of the standard data mining algorithms. It can be adapted from the privacy preservation literature. The existing systems perform a controlled distortion of the training data from which a classifier is learned by making minimally intrusive modifications leading to an unbiased data set. This approach is useful for applications in which a data set should be published and in which data mining needs to be performed.[8]

In-processing: Change the data mining algorithms in such a way that the resulting models do not contain unfair decision rules. 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.

Post-processing: Modify the resulting data mining models, instead of cleaning the original data set or changing the data mining algorithms.

In some of the paper there may be other attributes that are highly correlated with the sensitive ones and allow gathering discriminatory rules.

3. LITERATURE SURVEYS

Literature survey 1: Fast Algorithms for Mining Association Rules

They consider the problem of association rules discovery between items in a large database of sales transactions. For that they present two new algorithms for solving above mentioned problem that are fundamentally different from the known algorithms. Empirical evaluation shows that these algorithms outperform the known algorithms by factors ranging from three for small problems to more than an order of magnitude for large problems. [1]

They also show the best features of their two proposed algorithms can be combined into a hybrid algorithm, called AprioriHybrid. Scale-up experiments show that AprioriHybrid scales linearly with the number of transactions. AprioriHybrid also has excellent scale-up properties with respect to the transaction size and the number of items in the database.

The Apriori and AprioriTid algorithms they propose vary fundamentally from the AIS and SETM algorithms which was proposed in previous methods in terms of which candidate item sets are counted in a pass and in the way that those candidates are generated. In both the AIS and SETM algorithms, which was proposed by the existing methods, candidate item sets are generated on they during the pass as data is being read. Specially, after reading a transaction, it is determined which of the item sets found large in the previous pass are present in the transaction. New candidate item sets are generated by extending these large item sets with other items in the transaction.

The Apriori and AprioriTid algorithms generate the candidate item sets to be counted in a pass by using only the item sets found large in the previous pass without considering the transactions in the database. The AprioriTid algorithm has the additional property that the database is not used at all for counting the support of candidate item sets after the first pass.

Drawback:

The disadvantage is that this results in unnecessarily generating and counting too many candidate items sets that turn out to be small. They did not consider the quantities of the items bought in a transaction, which are useful for some applications. They did not find such rules.

Literature survey 2: Three Naive Bayes Approaches for Discrimination-Free Classification

They present three approaches for making the Naive Bayes classifier discrimination-free: i) modifying the probability of the decision being positive, ii) training one model for every sensitive attribute value and balancing them, and iii) adding a latent variable to the Bayesian model that represents the unbiased label and optimizing the model parameters for likelihood using expectation maximization. They present experiments for the three approaches on both artificial and real-life data.[11]

To tackle the problem of discrimination aware classification with Naive Bayes classifiers: Firstly, in a post-processing phase they modify the probability of the decision being positive by changing the probabilities in the model. Secondly, they train one model for every sensitive attribute value and balance them. Thirdly, they add a latent variable in the Bayesian model that represents an un-biased, discrimination free label and optimize the model parameters for likelihood using expectation maximization.

The proposed discrimination is quite brute force. No discrimination at all is allowed. So they lead to conditional discrimination; e.g., instead of requiring that there is no discrimination at all, they also could weaken this condition to no discrimination unless it can be explained by other attributes. Another one they didn't consider numerical attributes (e.g., income) as sensitive attribute. There are many other graphical models possible. They also could consider turning the arrows towards S, rejecting the idea that we can derive quite some information about the sensitive attribute S from the attributes Ai, but the attribute L should not help us any further for deriving S; i.e., S is condition-ally independent of L given the attributes Ai.

Drawback:

The problem of using their discrimination model is that it is based on assumptions that might not always hold in practice. They remove low frequency counts by pooling any bin that occurs less than 50 times which may lead problem.

One obvious drawback of such a method is that the number of parameters to describe the distribution of S is exponential in the number of attributes Ai. Therefore it would be beneficial to consider other models that could be \inserted" into the Bayesian model to replace the probability table, such as, e.g., a decision tree. Obviously they didn't explore why the convergence of Expectation maximization (EM) was relatively poor, even for the synthetic datasets where all conditions for a successful convergence were satisfied.

Literature survey 3: Discrimination Prevention in Data Mining for Intrusion and Crime Detection

In existing system, especially in computer science field, while considering anti-discrimination they elaborates on data mining models and related techniques. Some proposals are oriented to the discovery and measure of discrimination. Others deal with the prevention of discrimination. [13]

In other methods they consider removing discriminatory attributes from the dataset to handle discrimination prevention, there may be other attributes that are highly correlated with the sensitive one. Hence, one might decide to remove also those highly correlated attributes as well. Although this would solve the discrimination problem, in this process there is a chance of loss of much useful information. Some of them concentrated on discrimination discovery, by considering each rule individually for measuring discrimination without considering other rules or the relation between them.

In proposed system, they introduced anti-discrimination for cyber security applications based on data mining. The proposed solution is based on the fact that the dataset of decision rules would be free of discriminatory claim. The proposed solution in removing all evidence of discrimination from the original dataset is called as degree of discrimination prevention. The impact of the proposed solution on data quality is called as degree of information loss.

A discrimination prevention method should provide a good trade-off between both aspects above. The following is the evaluating their solution measures are proposed as:

Discrimination Prevention Degree (DPD), Discrimination Protection Preservation (DPP), Misses Cost (MC), Ghost Cost (GC). [14]

Their contribution concentrates on producing training data while saving their use to detect real intrusion or crime which are free or nearly free from discrimination. In order to control discrimination in a dataset, a first step consists in discovering whether there exists discrimination. If any discrimination is found, the dataset will be modified until discrimination is brought below a certain threshold or is entirely eliminated.

Drawback:

They didn't apply it real data set hence it is not evaluated for real scenario, and also they didn't consider the indirect discrimination by using the background knowledge.

Literature survey 4: Rule Protection for Indirect Discrimination Prevention in Data Mining

For discrimination prevention using pre-processing, they have to transform data by removing all evidence of discrimination in the form of α-discriminatory rules and redlining rules. In existing methods they concentrated on direct discrimination and considered α-discriminatory rules.[15]

Indirect discrimination consists of rules or procedures that, while not explicitly mentioning discriminatory attributes, impose the same disproportionate burdens, intentionally or unintentionally. In existing method, this effect and its exploitation is often referred to as redlining and indirectly discriminating rules can be called redlining rules.

The term "redlining" was invented in the late 1960s by community activists are mentioned in existing methods. They also support this claim: even after removing the discriminatory attributes from the dataset, discrimination persists because there may be other attributes that are highly correlated with the sensitive (discriminatory) ones or there may be background knowledge from publicly available data allowing inference of the discriminatory knowledge (rules). The existing literature on anti-discrimination in computer science mainly elaborates on data mining models and related techniques. Some of the existing methods are proposals are oriented to the discovery and measure of discrimination. Others deal with the prevention of discrimination. Although some methods have been proposed, discrimination prevention stays a largely unexplored research avenue. The straight forward way to handle discrimination prevention would consist of removing discriminatory attributes from the dataset. However in terms of indirect discrimination, some of the existing method have other attributes that are highly correlated with the sensitive ones or there may be background knowledge from publicly available data that allow for the inference of discrimination rules. Hence, one might decide to remove also those highly correlated attributes as well. Al-though this would solve the discrimination problem, in this process much useful information would be lost. Hence, one challenge regarding discrimination prevention is considering indirect discrimination other than direct discrimination and another challenge is to find an optimal trade-off between anti-discrimination and usefulness of the training data.

Drawback:

They didn't present a unified discrimination prevention approach based on the discrimination hiding idea that encompasses both direct and indirect discrimination.

Literature survey 5: Classification with No Discrimination by Preferential Sampling

In existing system, they introduced the concept of discrimination aware classification and proposed a solution to the problem based on changing the class labels. Preferential Sampling (PS) introduces a less intrusive technique to make the dataset unbiased than changing the class labels. In existing work also have similar motivation towards the solution of the discrimination problem. They concentrate on identifying discriminatory rules that are present in a dataset; hence they learn potential discriminatory guidelines that have been followed in the decision procedure.[13][14]

In the Proposed work they closely related to class imbalance problem. In existing system they introduced a synthetic minority over-sampling technique (SMOTE) for two class problems that over-sampled the minority class by creating synthetic examples rather than replicating examples. In contrast PS concentrates only on border regions. It changes the representation of data objects of each class according to the value of Sensitive Attribute (SA) and class attribute.

Classification with No Discrimination by Preferential Sampling is an excellent solution to the discrimination problem. It gives promising results with both stable and unstable classifiers. It reduces the discrimination level by maintaining a high accuracy level. It gives similar performance to “massaging” but without changing the dataset and always outperforms the “reweighing”.

In existing method, simply removing the discriminatory attribute from the training data in the learning of a classifier for the classification of future data objects is not enough to solve this problem, because often other attributes will still allow for the identification of the discriminated community.

Drawback:

They didn’t extending the discrimination model itself; in many cases, to have some discrimination and it is acceptable from an ethical and legal point of view, as long as it can be explained by other attributes. This extension of the model will help us to justify that the discrimination can be removed from those regions only where it is legally or ethically unacceptable. Therefore it would be interesting to refine our model to Classification with Conditional Discrimination.

4. PROBLEM IDENTFIED OF EXISTING SYSTEM

During the investigation of literature survey, some issues were identified and are summarized using the following points:

- The methods focus on the attempt to detect discrimination in the original data only for one discriminatory item and also based on a single measure
- They do not include any measure to evaluate how much discrimination has been removed and how much information loss has been incurred.
- It focuses either on direct discrimination or indirect discrimination or not on both together.
- The approaches do not shows any measure to evaluate how much discrimination has been removed, and thus do not concentrate on the amount of information loss generated.[12]

So the proposed work in data mining proposespre-processing methods which overcome the above limitations. And introduces new data transformation methods (rule protection and rule generalization (RG)) are based on measures for both direct and indirect discrimination and can deal with several discriminatory items.[17]

7. CONCLUSION

from the above literature survey it can be conclude that existing system has some drawbacks like some researcher works on single attribute, some researcher provide only direct discrimination. The system can be implemented which can be work on both for direct and indirect discrimination and use efficient preprocessing algorithm to overcomes the problems of in processing and post processing.

REFERENCE

[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] European Commission, “EU Directive 2004/113/EC on Anti-Discrimination,” http://eur-lex.europa.eu/ LexUriServ /LexUriServ.do?uri= OJ: L: 2004:373:0037:0043: EN: PDF, 2004.

[4] European Commission, “EU Directive 2006/54/EC on Anti-Discrimination,” http://eur-lex.europa.eu /LexUriServ /LexUriServ.do? Uri= OJ:L: 2006: 204 :0023: 0 036:en:PDF, 2006.

[5] 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.

[6] 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.

[7] F. Kamiran and T. Calders, “Classification without Discrimina-tion,” Proc. IEEE Second Int’l Conf. Computer, Control and Comm. (IC4 ’09),2009.

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

[9] 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.

[10] 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.

[11] D. Pedreschi, S. Ruggieri, and F. Turini, “Measuring Discrimina-tion in Socially-Sensitive Decision Records,”

Proc. Ninth SIAM Data Mining Conf. (SDM '09),pp. 581-592, 2009.

[12] D. Pedreschi, S. Ruggieri, and F. Turini, "Integrating Induction and Deduction for Finding Evidence of Discrimination,"Proc. 12th ACM Int'l Conf. Artificial Intelligence and Law (ICAIL '09),pp. 157-166, 2009.

[13] 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.

[14] S. Ruggieri, D. Pedreschi, and F. Turini, "DCUBE: Discrimination Discovery in Databases,"Proc. ACM Int'l Conf. Management of Data (SIGMOD '10), pp. 1127-1130, 2010.

[15] P.N. Tan, M. Steinbach, and V. Kumar,Introduction to Data Mining. Addison-Wesley, 2006.