Direct Discrimination Discovery through Multi Agent Systems in Data Mining

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Abstract: ***In the modern society no human being is allowed to discriminate by means of gender, race, place, caste etc., the field of Discrimination Discovery in Data Mining is a novel and it is attracting many researchers. Discrimination is the prejudicial treatment of a certain group of people. Discrimination is an important issue in the field of Data Mining. Mining Algorithms are trained from datasets if these datasets are biased based on sensitive attributes like caste, color, place, country etc., then the rules extracted become biased, resulting Discrimination in the decisions. Many laws are made to avoid Discrimination but inherently discrimination is finding in the automated decisions. Multi-Agent Programming or Multi Agent System is also another vital field in the research. By using Multi Agent Systems we can able to develop complex machine critical systems. This paper discourses the possibilities of Combining Discrimination Discovery and Multi-agent programming or Multi-Agent Systems (MAS) which leads to way for finding new technologies and frameworks and MAS reduces the time to find Discriminated rules generated by using Data Mining algorithms.***

Keywords: Discrimination, Direct Discrimination, Multi Agent Systems, Multi Agent Platform, Discrimination Discovery.

1. Introduction

Currently Discrimination Discovery in the field of Data Mining and Multi-Agent systems (MAS) are two unique technologies, becoming popular in the fields of data analysis and information technology. In Social science, discrimination can be treated as the act of unfairly treating people on the basis of their identity to a specific group or minority group. Civil right laws prohibits discrimination on the basis of caste, color, religion, nationality, gender, marital status, age, region etc.,. The name “discrimination” is originated from Latin word “dis-criminare”, which means to “distinguish between”. Discrimination results in denial of opportunity(s), or unfair treatment of people on the basis of their membership to a category, without giving regard to the individual merit.

Data mining is the procedure of selecting, exploring, and exhibiting large amounts of data to discover new trends and patterns from huge databases or large amounts of data. This huge amount of Data contains invaluable information and knowledge. For the past many years researchers in the field of data mining developed many algorithms and methodologies to mine valuable information and hidden knowledge by using classification methods, association rules, clustering techniques etc.,

On the other hand Agent Programming or Multi Agent Systems (MAS) programming is a moderately a new model of programming. Agent Programming fundamentally models an application as a group of core elements called agents that are characterized by, among other things like autonomy, pro-activity and agent has capability to communicate with other fellow agents in the same environment or in other environments. The basic programming model of Multi-Agent-oriented application is peer-to-peer means ability to execute agents in many machine‟s, at any period of time an agent can able to start communication with any other agents by receiving and sending of messages. MAS are being used in different types of applications ranges from small systems used for personal assistance to open, mission-critical and complex systems for industrial applications.

1.1 Need of Discrimination Discovery in Datasets

In the human societies discrimination can be viewed in every corner of the world. The study of discrimination is being done over a hundreds of years. In order to protect the disadvantaged or minatory group of masses from discrimination, many laws have been designed by the governments with the efforts of noble people for decades led to the formulation of new laws against discrimination. Currently many laws are enforced to avoid discrimination such as United States Equal Pay Act [1], United Kingdom Sex Discrimination Act [2], European Union Directive 2000/43/EC on Anti-Discrimination[3], etc.,

Currently all the decisions are automated by using information systems and its associated applications, in the field of Banking for granting credit to people, providing employment and training, accessing the public services, insurance etc.,. In the beginning researchers think that automation of making decisions can avoid discrimination and started to use. To make the automated decisions, so may methods are used in which classification rules plays an important role. In fact classification rules are generated by using past data and these rules are used to train the system. If this past data and classification rules are biased or discriminated then the automated decisions are also biased.

Shockingly, discrimination discovery in the field of Data mining and Information systems processing has not given much attention till 2008[4]. The topic of discrimination classification was first introduced in the paper [5] and motivated by the observation that often training data consisting of unwanted dependences between the attributes. Concerning to the research side, the issue of discrimination in the field of credit management, mortgage, insurance, education and in human activities has attracted much interest of researchers in economics and social sciences in late „50s. Information scientist"s has to prevent data mining from becoming itself a source of discrimination. The available literature on anti-discrimination can broadly categorized as

a) Discrimination Discovery
b) Discrimination prevention

a) Discrimination Discovery:- Discrimination discovery can be performed based on the legal definitions of discrimination laws and proposing quantitative measures for it. Some of the measures are proposed by pedreschi in 2008. Discrimination can be of Direct or Indirect. Direct Discrimination consists of rules or procedure that explicitly mention minority group based on sensitive discriminatory attributes related to the group of membership. Indirect discrimination consists of rules or procedures that, which are not explicitly mentioning discriminatory attributes purposefully or by mistake could generate discriminatory decisions.

b) Discrimination Prevention:- prevention consists of methods that do not lead to discriminatory decisions even though trained dataset is biased, and this can be implemented in the preprocessing, In-processing and post processing in the field of Data mining.

1.2 Related Work

With the widespread usage of Information Technology in decision making with the use of technologies such as Data Mining, the issue of anti-discrimination comes into picture. From the year 2008 so many methods were proposed to find discrimination and as well as to prevent discrimination in datasets defined in [6],[7] in the paper "Methodology for both Direct, Indirect Discrimination Prevention in Data Mining" [8] Discrimination Discovery has been made on both direct as well as indirect and proposed a measure called "elift" and proposed methods for preventing both direct, indirect discrimination. Experiments have been made to find discrimination by using "elift" measure.

1.3 Contributions

Previous works cited in this paper concentrated only on discovery of Direct Discrimination using a single measure i.e elift, and all the above papers used single thread to find Discrimination in the generated rules, where as in this paper we concentrated to find Direct Discrimination based on various measures and we implemented "elift" , "slift" and "eslift" and categorized discriminated rues based on ranking from high to low as *High*, *Moderate* and *Nil* and till-now Discrimination Discovery was implemented on Single threaded platform and in this research paper we propose to implement Direct Discrimination Discovery using Multiple Agent Systems Platform with multiple measures.

1.3 Organization of the Paper

The rest of the paper is organized in the following format. Section 2 is reserved for knowing basic definitions and concepts which are essential for understanding Anti-Discrimination Analysis. Section 3 reserved for our proposal to find direct discrimination using Multi-Agent Systems (MAS) platform. Section 4 is meant to discuss about the experiments conducted to find discrimination and to compare results with the existing methods. Section 5 briefs about conclusions and discussed the scope of the future research in the field of discrimination discovery through Multi-Agent platform.

2. Basic Definitions and Concepts

In this section, we would like to brief the fundamental definitions related to Data Mining [9] and Discrimination terminology and Multi-Agent Systems Platform. Further this section is subdivided into two parts a) Data Mining and b) Multi-Agent Platform

a) Data Mining and Discrimination terminology

1) A *dataset* is a set or collection of data objects popularly known as records and their associated attributes. Let „DB" is referred as original dataset.
2) An *item* is an attribute along with its value or property defined to the attribute. e.g gender=female, age=young, race=black, caste=kuruba.
3) An *item-set* is a set of or collection of one or more items in the original dataset. e.g {age=young, gender=female, race=white, caste=kuruba}.
4) A *Class Item* is an item consists of an attribute along with its value either yes/no or true/false.
5) A *Classification rule* is an expression defined in the form of „X → C", where „C" is a class item and „X" is an item set without class item. Where X is called premise of the rule and C is called consequence of the rule. e.g {gender=female, age=young} → class=no
6) The *Support* of an itemset defined as sup (X) is a fraction of records which contain item set X. We say that a rule X → C is completely supported by a record if both premise (X) and consequence (C) appear in the record.
7) The *Confidence* of a classification rule can be defined as conf (X → C), measures how often the class item C appears in the records of dataset that contain X. Hence, if sup(X) > 0 then the confidence can be calculated as

$$sup(X \rightarrow C)=Supp(X,C)/Supp(X)$$

Support and Confidence ranges over 0 and 1.

8) A *Frequent classification* rule is a classification rule with support and confidence greater than respective specified lower bounds. Support is a measure of statistical significance, whereas Confidence is a measure of strength of the rule. Let „FR" be the database of frequent classification rules extracted from the DB (Dataset).
9) The *Negated Item i.e* X is an attribute with the same attribute as X, but the attributes in X takes any value

except those taken by the attribute in X. In this paper we use notation for binary attributes.

10) Discriminatory Attribute is an attribute which are classified or protected by law as discriminatory according to the applicable anti-discriminatory laws.

b) Multi-Agent Programming

Agent based Programming is a relatively new field and be thought of as evolution of object oriented programming [10]. Agent programming terminology provides a means to effectively solve problems, in almost all the fields with an exception of some fields. There are so many development platforms for Agent Programming such as GIGA [11], MESSAGE [12], Cassiopeia[13], JADE etc.,

This section we mainly focused on JADE Environment Platform. Java Agent Development frame work has been developed by the Telecom Italia lab (TILAB) in Italy, in compliance with FIPA (Foundation for Intelligent Physical Agents) Specifications [14] JADE is a middleware that facilitates the development of Multi Agent Systems.

1) *Agent* is a collection of Programs that are implemented on a platform and have sensors to react to the environment.
2) A *Runtime Environment* where JADE agents are can "Live" and that must be active on a given host.
3) A *Library* is a set of classes that programmers use to develop their agents.
4) *Graphical tools* are a suite of tools that allows administrating and monitoring the activity of running agent.
5) A *Container* is an instance of JADE environment, and a container can have more than one agent.
6) *Platform* is a set of active containers.
7) *AMS* (*Agent Management System*) provides naming service to agents.
8) *DF* (*Directory Facilitator*) provides yellow pages service by means of which an agent can find another agent.

3. Direct Discrimination Discovery (DDD) using Multi Agent Systems (MAS)

In this section we present a new method for finding Direct Discrimination Discovery Process using Multi Agent Systems (MAS). Till now may works done on finding DDD using popular measure called "elift". The proposed method is to find DDD based on the fact that dataset will contain discriminatory attributes and which leads to discriminatory rules. DDD process starts with the preparation of datasets for mining Association rules with predefined support and confidence. The rest of the section organizes as 3.1 describe the measures used for finding the DD. Section 3.2 explains the algorithms used in this paper and section 3.3 describe about the implementation of DDD in MAS.

3.1 Measures for finding Direct Discrimination

In the process of finding DD rules, popularly used measure is "elift". In many works "elift" measure is used to find DD rules. In this paper we use "elift", "slift" and "eslift" measures to find DD rules. The mined classification rules from a dataset can have either positive decision or negative decision. Further the rules with negative decision i.e class=no and having discriminatory items such as {age=young}, {gender=female} are defined as rules with discriminated items. These discriminated item rules can be classified as discriminated rule (DR) and non-discriminated rule (NDR). A rule X → C is DR when X=A,B in which „A" consists of discriminatory attribute and „B" consists of non-discriminatory items. Pedreshi et al [15] translated the quantitative statements in existing laws, regulations and legal cases into quantitative formal counter parts over classification rules and they used a measure called "extended lift" or "elift".

Extended lift[16] : Let A, B → C is a classification rule with discriminated item at „A" and with negative class decision and conf(B→C) >0 then elift can be defined as

$$elift(A,B\rightarrow C) = conf(A,B\rightarrow C) \,/\, conf(B\rightarrow C)$$

A rule sex=female, car=own → credit=no with an elift of value 3 means that being a female increases three times probability of having refused credit with respect to the average confidence of people owning a car.

Let α is fixed threshold and in classification rule „A" may be a discriminated item with negative decision then elift(A,B→C) > α then rule is discriminated or rule is not discriminated.

Selection lift (slift) :-Selection lift measures the contrast between disadvantaged group i.e „A" and the rest of the records ¬A. From which we can able to calculate the denial rate of rule having discriminated attribute. Let A,B→C be a rule with discriminated item set at „A" and „B" has non discriminated items and „C" is having negative decision then

$$slift(A,B\rightarrow C) = conf(A,B\rightarrow C) \,/\, conf(\neg A,B\rightarrow C)$$

Selection lift occurs when contrasting or binary attributes such as A={sex = female} and ¬ A={sex=male}. Slift measures how much attribute value „A" increases the chance of denying the rule when comparing with the people with ¬A in the context of B.

Let α is the fixed threshold value and A may be discriminatory value. A rule A,B→C is non-discriminatory if slift(A,B→C) < α else the rule A,B→C is discriminatory.

eslift :-eslift is the measure defined based on the measures elift and slift. Elift measure evaluates the discrimination of the rule by gaining of confidence due to the presence of the discriminatory item in the premise of the rule with negative decision. Whereas elift can be defined as ratio of the confidence of the two items that is with having discriminated item and without non-discriminated item. The selection lift deals with the denial rate of a rule with discriminated item. By using both the measures on a single classification rule we can classify the rule as Highly, Moderately and not-discriminated.

- *If a rule is said to be Highly discriminated if elift(A,B→C) > α and slift(A,B→C) > α*
- *If a rule is said to be moderately discriminated if elift(A,B→C) > α or slift(A,B→C) > α*
- *If a rule is said to be not-discriminated if elift(A,B→C) < α and slift(A,B→C) < α*

If a rule is having eslift measure as 2 then we can say that the rule is discriminated by elift and as well as slift. Hence the rule is "Highly" discriminated. If a rule is having a elift measure as 1 then the rule is discriminated by either elift or slift. If a rule is having a zero measure then the rule is not discriminated by any measure hence the rule is not discriminated and it can be used for decision making.

3.2 Algorithms

Algorithms in this section are drafted based on the assumptions on the following. The class attribute in the dataset (DB) are of binary in nature i.e "yes" or "no", the value "yes" for positive decision and "no" for negative decision of the rule. Classification rules(CR) are generated with predefined support and confidence. Among the generated classification rules, we extracted only the rules with negative decision i.e class=no and termed as "rule with negative decision" (rnd). A discriminated rule consists of Discriminatory Items and they are referred as DI. The Discriminated Item consists of binary valued attribute with the values as gender=female/male and age=young/old. A discriminated item has the value gender=female or age=young. The rows with discriminated items are referred as rwdi.

Algorithm 1: Finding Discriminated Rules by using "elift" measure

1 : Input CR, α, DI : age=young, gender=female
2 : Output Generates rnd, rwdi database and the file eliftD
3 : Sort CR ascending on rule number
4 : for each row in CR of test do
5 : if class=no in CR rule then
6 : add the rule to rnd list
7 : if premise consists DI
8 : add the rule to rwdi
9 : end if
10 : end if
11 : end for
12 : Sort rnd ascending on rule number
13 : for each row in rwdi of test do
14 : compute elift(rule)
15 : if elift(rule) > α
16 : store rule into eliftD
17 : end if
18 : end for
19 : Output rnd, rwdi, eliftD

Algorithm 2: Finding Discriminated Rules by using elift measure

1. Input CR, α, DI : age=young, gender=female
2. Output Generates rnd, rwdi database and the file sliftD
3. Sort CR ascending on rule number
4. for each row in CR of test do
5. if class=no in CR rule then
6. add the rule to rnd list
7. if premise consists DI
8. add the rule to rwdi
9. end if
10. end if
11. end for
12. Sort rnd ascending on rule number
13. for each row in rwdi of test do
14. compute slift(rule)
15. if slift(rule) > α
16. store rule into sliftD
17. end if
18. end for
19. Output rnd, rwdi, sliftD

Algorithm 3: Finding Discriminated Rules by using eslift measure

1. Input eliftD, sliftD, α
2. Output Generates High, moderate, none Discriminated rules and Stores in the file esliftD file
3. Copy rwdi to esliftD and Sort on rule number
4. Sort eliftD ascending on rule number
5. Sort sliftD ascending on rule number
6. for each row in esliftD of test do
7. Get elift value from eliftD on esliftD(rule number)
8. If found
9. Add 1 to esliftD(dis_level)
10. end if
11. Get slift value from sliftD on esliftD(rule number)
12. If found
13. Add 1 to esliftD(dis_level)
14. end if
15. end for
16. for each row in esliftD of test do
17. if dis_level = = 2
18. Add 1 to high
19. end if
20. if dis_level = = 1
21. Add 1 to moderate
22. end if
23. If dis_level = = 0
24. Add 1 to nondiscriminated
25. end if
26. end for
27. Display high, moderate and nondiscriminated count
28. Output high, moderate, nondis

3.3 Implementation of Direct Discrimination Discovery through Multi Agent Systems

Till now Multi Agent Systems are implemented in mission critical systems to solve complex problems. In Agent terminology the work to be done is divided into Agents, which can be executed in one or more containers with different platforms. In this paper we implemented the Direct Discrimination process through Multi Agent Systems and implemented every measure as an Agent. In this paper we created three agents namely AgentElift, AgentSlift and AgentESlift. The agents "AgentElift" and "AgentSlift" are exceuted in parallel where as "AgentESlift" is executed after the execution of "AgentElift" and "AgentSlift". All these three agents are controlled by a Main Agent.

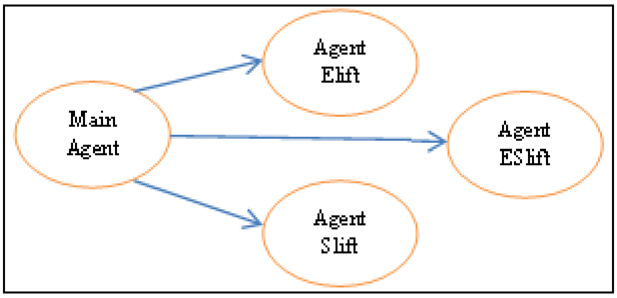


Figure 1 : DDD process in MAS

Algorithm 4: Implementing DDD process through MAS
1 : Start Multi Agent Environment
2 : Create a container in the Agent Environment
3 : Load Agent "AgentElift" in the container
4 : Load Agent "AgentSlift" in the container
5 : Load Agent "AgentESlift" in the container
6 : Start Agent "AgentElift" to Compute Elift values
7 : Start Agent "AgentSlift" to Compute Slift values
8 : If AgentElift and AgentSlift are completed
9 : Start AgentEslift to compute ESlift values
0 : End if
1 : Stop all the Agents

4. Experiments

This section reserves to discuss on the experiments conducted on the proposed algorithms. Firstly the association rules were generated by using „R" Language[17] by Arules algorithm[18] with minimum support 2 and confidence as 10 percent by a script written in „R" Language. All the proposed algorithms were implemented by using the Java Programming language and JADE (Multi Agent Programming Platform). The proposed tests were performed on an 2.10 Ghz Intel Core i3 processor machine, with 8 GB Ram equipped and running under Windows 7 Ultimate.

4.1 Data Set

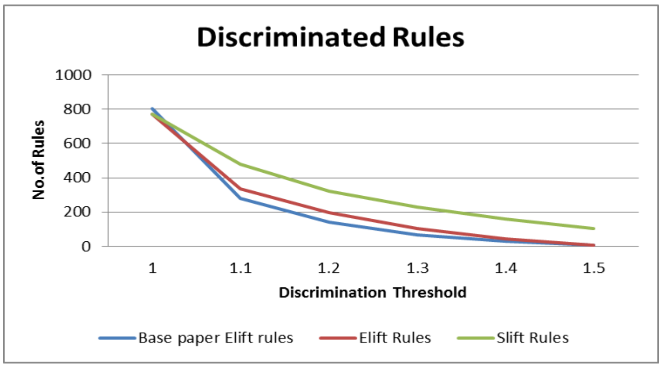
We used Adult Dataset, also popularly known as Census Income dataset. This dataset consists of 48,842 records, split into a train part with 35,561 records and a test part with 16,281 records. The dataset has 14 attributes (without class attribute). We used the train part in our experiments. The predication task associated with the adult dataset is to determine whether a person makes more than 50K$ a year based on census and demographic information about people.

The dataset contains both categorical and numerical attributes. In our conducted experiments, we set DI={Sex=female, age=young}. Although the age attribute in the Adult dataset is numerical, we converted the attribute in to categorical by partitioning its domain into two fixed intervals: Age <= 30 renamed as "Young" and Age >30 was renamed as "Old".

We will report some analyses based on tables and graphs as defined below. Table 1 and its associated graph shows the discriminated rules generated and time taken by using elift and slift measure on a single threaded environment. Table 2 shows eslift ranking measure. Table 3 shows the time taken to generate discriminated rules by elift and slift measure.

Table 1: elift and slift measures on a single thread environment and time taken to generate proposed results are 227 Sec and 289 sec

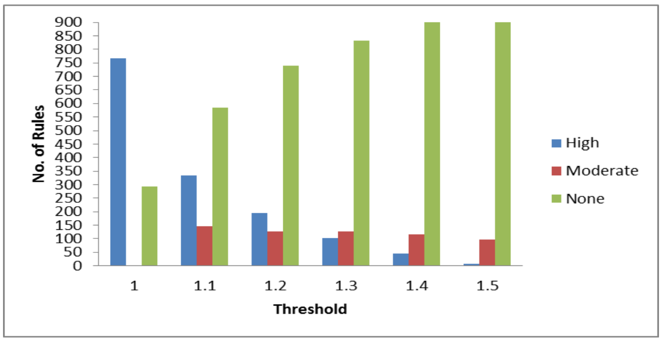
α (Threshold)	*1.0*	*1.1*	*1.2*	*1.3*	*1.4*	*1.5*
Base paper Elift rules	804	280	140	67	32	7
Elift Rules	772	334	196	102	46	6
Slift Rules	770	481	322	229	161	104



Graph 1: No.of elift and slift rules with Threshold values

Table 2: Eslift Ranking Measure

α	**1.0**	**1.1**	**1.2**	**1.3**	**1.4**	**1.5**
High	767	334	196	102	46	6
Moderate	2	147	126	127	115	98
None	293	584	740	833	901	958

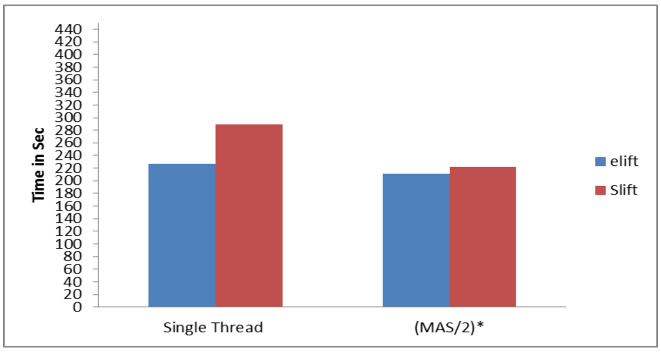


Graph 2: Graph showing Ranking measure

Table 3: Time taken to generate discriminated rules by measures elift and slift

Measure	Single Thread	MAS	(MAS/2)*
elift	227	423	211
Slift	289	444	222

* *calculated time for single agent*



Graph 1: Time taken to generate Discriminated Rules

5. Conclusion and Future Research

As per our knowledge, we have presented a novel approach for finding discrimination in the given classification rules. The purpose of this paper is to develop a new method to find Direct Discriminated rules based on Multi Agent Systems using elift, slift, and eslift measures. The conducted results attained satisfactory results when compared with previous results. In future, we want to present more discrimination measures to find discrimination in generated rules through Multi Agent Systems.

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