PERFORMANCE ANALYSIS OF MULTI AGENT SYSTEMS FOR DIRECT DISCRIMINATION IN DATA MINING

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Abstract : Data Mining provides many techniques for extracting invaluable hidden information from the datasets. The extracted valuable information can be used in the process of decision making by the administrators of the organization or business. The words Discrimination Discovery in the field of Data Mining and Multi-Agent Systems in the field of agent programming and these both unique technologies become popular in the fields of data analysis and in the information technology. In social sciences the word discrimination refers, specifically to an action based on biased or prejudice resulting 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. Fundamentally Agent Programming models an application as a collection of core elements called agents and all these agents are characterized by the properties such as autonomy, pro-activity and these agents has the capability to communicate with fellow agents. 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 be able to start communication with any other agents by receiving and sending of messages. Our proposed algorithms are designed based on agent programming environment and all the algorithms are implemented by using java programming environment. Classification Rules Mining is one of the most important techniques used for extracting hidden information from the datasets. In this technique an algorithm is trained by huge dataset and the trained algorithm generates the classification rules as its output. Based on these generated classification rules, decision making can be made by the administrators of the organization.

Index Terms **– Data mining, Multi-Agent Systems, Agent programming and** JADE

I. INTRODUCTION

Data Mining (DM) is a novel technology in the field of computer science, which plays an important role in processing massive amounts of data, the massive amounts of data are generated by the business organizations used by their Information systems. By using this bulk data we can be able to mine huge valuable information hidden in the datasets. DM provides many techniques for extracting invaluable hidden information from the datasets. The extracted valuable information can be used in the process of decision making by the administrators of the organization or business.

The words Discrimination Discovery in the field of Data Mining and Multi-Agent Systems (MAS) in the field of agent programming and these both unique technologies become popular in the fields of data analysis and in the information technology. Whereas In Social sciences the word discrimination can be treated as the act of unfairly treating people based on their identity to a specific or minority group. All the civilized country's civil rights laws prohibits discrimination based on race, caste, color, religion, nationality, gender, marital status, age, region etc.,. The name or word "discrimination" is originally originated from the Latin word "dis" and "criminare", which means to "distinguish between". In social sciences the word discrimination refers, specifically to an action based on biased or prejudice resulting 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.

Agent Programming (AP) or Multi Agent Systems (MAS) programming is a moderately a new model of programming. Fundamentally Agent Programming models an application as a collection of core elements called agents and all these agents are characterized by the properties such as autonomy, pro-activity and these agents has the capability to communicate with fellow agents. 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 be 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. In the domains such as system diagnostics, process control, manufacturing, transportation logistics and network management, where MAS are successfully used.

Classification Rules (CR) or Classification Rule Mining is one of the most important techniques used for extracting hidden information from the datasets. In this technique an algorithm is trained by huge dataset and the trained algorithm generates the classification rules as its output. Based on these generated classification rules, decision making can be made by the administrators of the organization. If these generated classification rules are fair and not biased to any group of people then the administrator's decisions will be fair. If not the administrator's decision is biased. The concept of discrimination comes into the picture, if the generated decision rules are biased to a particular group of people then the decision rules generated by the algorithm

are of waste. In this context identification of discriminated rules has highest significance in the field of discrimination discovery in data mining.

II ESSENCE OF DISCOVERY OF DISCRIMINATION IN THE DATA SET

In the Human societies discrimination can be evidenced in each and every corner of the world. In order to protect the dis-advantaged or minority group of masses from discrimination, the Governments have designed many laws or legislations. The study of discrimination is being done over a hundreds of years and the struggle of noble people for decades led to the formulation of new laws against discrimination. Currently we have many laws in United States Equal Pay Act [1], United Kingdom Sex Discrimination Act [2], European Union Directive 2000/43/EC on Anti-Discrimination[3], etc.,Currently in the organizations all the decisions are automated by using their decision making systems and its applications, The following fields uses their Decision Making Systems for decision making they are (i) Banking, (ii) credit scoring, (iii) employment and training, (iv) accessing the public services, (v) insurance and so on.

In the beginning the researchers think that automation of making decisions can prevent discrimination. To make the automated decisions, they used classification rules technique in the DM. 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 biased.

It is very sad that the concept discrimination discovery in the Information processing sector has not given much importance or attention till 2008[4]. The topic of discrimination classification was first introduced in the research paper [5] and motivated by the observation that often training data consisting of unwanted dependences between the attributes. Coming to the research, the issue of discrimination in the fields of credit management systems, mortgage adviser, insurance sector, education was not addressed. Where a sin human activities attracted the interest of researchers in economics and social sciences in late 1950s. Information scientist's has to prevent data mining from becoming itself a source of discrimination. From the existing works on anti-discrimination, the concept Discrimination can be broadly categorized as (a) Discrimination Discovery and (b) Discrimination Prevention. Discrimination discovery can be done based on the legal definitions of discrimination laws and proposing quantitative measures for it, whereas Discrimination Prevention consists of methods that do not lead to discriminatory decisions even though trained dataset is biased.

Discrimination can be of Direct or Indirect whereas in this research work we concentrated on finding of direct discrimination from the generated decision rules by using the classifier. The process for finding Direct Discrimination (DD) rules are time consuming and it is iterative process in nature. In this context, we focused on direct discrimination discovery with multiple agents and each agent concentrates on a discrimination measure and the proposed ranking algorithms under the Multi Agent Systems (MAS) environment also concentrates on assigning a rank to each and every discriminated rule for better removal of discrimination from the decision rules.

III RELATED WORKS

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 2008 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 they proposed a measure called elift and they also proposed methods for preventing both direct, indirect discrimination. Elaborate Experiments have been made to find discrimination by using Extended Lift (elift) measure in their experiments[8].

IV CONTRIBUTIONS TO THE EXISTING WORK

The main objective of this evaluation is to prove the performance of MAS will be high i.e time complexity will be less, when compared with stand-alone systems (SAS). For which, in this work we compared the discrimination measure algorithms of elift, slift, odds, olift, eliftD, sliftD, eslift, oolift and esliftD in SAS environment with MAS environment. The algorithms designed in this research are best suitable for finding Direct Discrimination from the decision rules with minimized time complexity and the ranking algorithms are proposed in this work such aseslift, oolift and esliftD. These ranking algorithms assigns a rank to each and every decision rule generated for decision making in the field of Data Mining. Using a single measure in finding discrimination leads to further problems hence, in this work we used multiple measures in finding discrimination discovery in Data Mining.

V JAVA AGENT DEVELOPMENT ENVIRONMENT (JADE)

Agent based Programming is a new field and be thought of as a evolution of object oriented programming[9]. Agent programming provides a means to effectively solve the problems, in almost all the fields with an exception of some fields. There are so many development platforms for Agent Programming such as GIGA[10], MESSAGE [11], Cassiopeia[12], JADE etc.,

This section is mainly focused on JADE Environment or Platform. The popular framework Java Agent Development framework was developed by the Telecom Italia lab (TILAB) in Italy, in compliance with FIPA(Foundation for Intelligent Physical Agents) Specifications [13]. JADE is a middleware which facilitates the development of Multi Agent Systems. Now it is a community project and distributed as open source under the LGPL license. Agent-Oriented Programming (AOP) or Agent Programming is a moderately new software paradigm from which we can construct distributed systems.

As JADE is written completely in Java, it benefits from the huge set of language features and third-party libraries on offer, and thus offers a rich set of programming abstractions allowing developers to construct JADE multi-agent systems with

relatively minimal expertise in agent theory. In this research work, we used JADE version 4.3.3 to implement the agents which are designed to find direct discrimination discovery.

VI ALGORITHMS

The proposed Algorithms specified in this research work 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" is used to represent 'positive' decision and "no" for 'negative' decision of the rule. Classification Rules (CR) are generated with predefined support and confidence using 'R' Programming language. Among the generated classification rules, we extracted only the rules with negative decision i.e class=no by using a dedicated agent and they are 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 6.1: FINDING DISCRIMINATED RULES BY USING "ELIFT" MEASURE

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

ALGORITHM 6.2: FINDING DISCRIMINATED RULES BY USING ELIFT MEASURE

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

ALGORITHM 6.3: FINDING DISCRIMINATED RULES BY USING ESLIFT MEASURE

```
Step 1 :   Input eliftD, sliftD, α
Step 2 :   Output Generates High, moderate, none Discriminated rules and Stores in the
```

```
        file esliftD file
Step 3 : Copy rwdi to esliftD and Sort on rule number
Step 4 : Sort eliftD ascending on rule number
Step 5 : Sort sliftD ascending on rule number
Step 6 : for each row in esliftD of test do
Step 7 :     Get elift value from eliftD on  esliftD(rule number)
Step 8 :     If found
Step 9 :         Add 1 to esliftD(dis_level)
Step 10 :    end if
Step 11 :    Get slift value from sliftD on
             esliftD(rule number)
Step 12 :    If found
Step 13 :       Add 1 to esliftD(dis_level)
Step 14 :    end if
Step 15 : end for
Step 16 : for each row in  esliftD of test do
Step 17 :    if dis_level = = 2
Step 18 :       Add 1 to high
Step 19 :    end if
Step 20 :    if dis_level = = 1
Step 21 :       Add 1 to moderate
Step 22 :    end if
Step 23 :   If dis_level = = 0
Step 24 :       Add 1 to nondiscriminated
Step 25 :    end if
Step 26 : end for
Step 27 : Display high, moderate and nondiscriminated count
Step 28 : Output high, moderate, nondis
```

Till-now Multi Agent Systems (MAS) are implemented in mission critical systems to solve the complex problems. In terms of Agent programming terminology the work to be done is divided into Agents and these agents can be executed in one or more containers with different platforms. In this research, we implemented the Direct Discrimination process for Multi Agent Systems and implemented every measure as an Agent.

In this work, we created the agents namely AgentElift, AgentSlift and AgentESlift, AgentSupp, AgentConf, AgentDIA, Agent SepDiandNDi in a container or they can be created in multiple containers. The "AgentElift" agent and "AgentSlift" agent are executed in parallel whereas the agent "AgentESlift" is executed after the execution of "AgentElift" and "AgentSlift". All these three agents are controlled by a Main Agent.

ALGORITHM 6.4: IMPLEMENTING DIRECT DISCRIMINATION DISCOVERY 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 :  Load Agent "AgentSupp" in the container
7 :  Load Agent "AgentConf" in the container
8 :  Start Agent "AgentElift" to Compute Elift values
9 :  Start Agent "AgentSlift" to Compute Slift values
10 : If AgentElift and AgentSlift are completed
11 :    Start AgentEslift to compute ESlift values
12 : End if
13 : Stop all the Agents
```

VII RESULTS AND DISCUSSION

We implemented all the discriminated discovery algorithms on a stand-alone systems environment as well as on a Multi Agent platform i.eJADE agent platform. For the given algorithms, we have given the threshold values as 1.0, 1.1, 1.2, 1.3, 1.4, 1.5 for the measures elift (Extended Lift) and slift (Selection Lift) for the odds and olift the threshold values are given with the class frequency 1-5, 6-10, 11-15, 16-20, 21-25 and for the measures eliftD and sliftD threshold values are given as 0.01, 0.02, 0.03, 0.04, 0.05, 0.06. For ranking algorithms we used the terms as Highly, Moderate, None.

For all the algorithms the time taken to generate discriminated rules are measured in terms of seconds and every algorithm implemented in multi agent system is taking less time to generate discrimination rules when compared with the existing discrimination discovery system. Total number of discriminated rules generated with negative decision, having discriminated item as its precise are 1062.

Table7.1: Number of Direct Discriminated Rules by elift and elift Measures

Threshold	Existing elift	Proposed elift
1.0	524	438
1.1	140	138
1.2	73	94
1.3	35	56
1.4	25	40
1.5	7	6

Based on the above table 6.1, we conducted t-test for statically significance in which we attained 95% of significance on the rules generated by elift measure proposed in the chapter 4 of this research work. Based on this, result we conclude that the method proposed in the existing work is statically significant with the proposed elift measure for multi agent systems environment. Hence, the proposed elift measure for multi agent environment can be used for finding direct discrimination in MAS environment.

With regard to selection of the threshold value, the discrimination analyst can choose the threshold based on the literature of law, which is to be imposed in the process of dissemination discovery. If no threshold value is defined in the legal literature, then discrimination analyst can calculate the mean and choose the threshold i.e 1.1. When we see the number of rules and threshold values we can clearly observe that as the threshold value is increasing the number of discriminated rules are decreasing. In this context selection of the middle threshold value balances the number of discriminated rules. Where it is too high at the threshold 1.0 i.e 438 in case of elift and 524 in case of elift*, whereas the number of rules are very low in case of proposed elift it is 6 and existing elift is 7.

Table 7.2: Number of Direct Discriminated Rules by elift and slift Measure

Threshold	Existing elift	Proposed slift
1	524	289
1.1	140	159
1.2	73	93
1.3	35	68
1.4	25	57
1.5	7	104

Based on the above table 6.2, we conducted t-test for existing elift and proposed slift measure for statically significance in which we attained 95% of significance on the direct discriminated rules generated by proposed slift measure proposed in the chapter 4 of this research work. Based on this result we conclude that the existing elift method proposed in the existing work is statically significant with the proposed slift measure and can be used for multi agent systems environment for finding direct discrimination from the generated decision rules. Hence, the proposed slift measure for multi agent environment can be used for finding direct discrimination.

With regard to selection of the threshold value, the discrimination analyst can choose the threshold based on the literature of law which is to be imposed on the decision rules. If no threshold value is defined the legal literature then discrimination analyst can calculate the mean value and can choose the threshold i.e 1.2.

When we observe the number of discriminated rules generated by the slift measure and its threshold values it is clearly witnessed that as the threshold value is increasing the number of rules is decreasing. In this context selection of the middle threshold balances the number of discriminated rules. Where it is too high at the threshold 1.0 i.e 289 in case of existing eliftand 289 in case of proposed slift, whereas the number of rules are very low at the threshold 1.5 in case of existing elift it is 6 and proposed slift it is 104.

Table 7.3: Time Taken to Generate Direct Discrimination Rules by elift and slift Measure

Measure	Stand-Alone System	Individual Agent in MAS
elift	227	211
slift	289	222

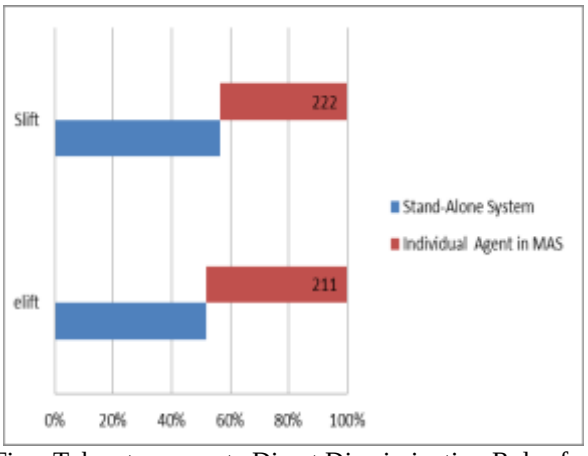

Figure 7.1 : Time Taken to compute Direct Discrimination Rules for slift and elift

From the table 7.3 and graph shown in the figure 7.1, we can clearly say that when the measures elift and slift are executed in the stand-alone system environment to generate direct discrimination measures for which they taken 227 and 289 seconds of time respectively. Whereas the same measures are executed in the Multi agent systems environment the measures elift and slift proposed in the chapter 4 has taken 211 and 222 seconds respectively. Hence, the measures proposed elift and slift in the chapter 4 of this thesis performed well in terms of time complexity. It is observed that both the methods elift and slift require 516 seconds to generate direct discrimination rules in the stand-alone systems environment, whereas the same measures have taken 443 seconds in the multi agent systems environment.

Table 7.4: Time Taken to Generate Direct Discrimination Rules by odds and oliftMeasure

Threshold	odds	olift
1-5	372	473
6-10	48	180
11-15	121	17
16-20	63	06
21-25	41	02

Based on the above table7.4, we conducted t-test for odds and proposed olift measure for statically significance in which we attained 95% of significance on the direct discriminated rules generated by proposed research work. Based on this result, we conclude that the odds method proposed in the existing work is statically significant with the proposed olift measure and can be used for multi agent systems environment for finding direct discrimination from the generated decision rules. Hence the proposed olift measure for multi agent environment can be used for finding direct discrimination.

With regard to selection of the threshold value, the discrimination analyst can choose the threshold based on the literature of law which is to be imposed on the decision rules. If no threshold value is defined the legal literature then discrimination analyst can choose the mean value of the threshold i.e 6-10 in case of odds and in case of lift it should be 1-5.

When we observe the number of discriminated rules generated by the olift measure and its threshold values, it is clearly witnessed that as the threshold value is increasing the number of rules are decreasing. In this context selection of the middle threshold balances the number of discriminated rules. Where it is too high at the threshold 11-15 i.e 121 in case of odds and 180 in case of olift, whereas the number of rules are very low at the threshold 21-25 in case of odds it is 41 and olift it is 2.

Table 7.5: Time Taken to Generate Direct Discrimination Rules by odds and olift Measure

Measure	Stand-Alone System	Individual Agent in MAS
odds	170	161
olift	390	330

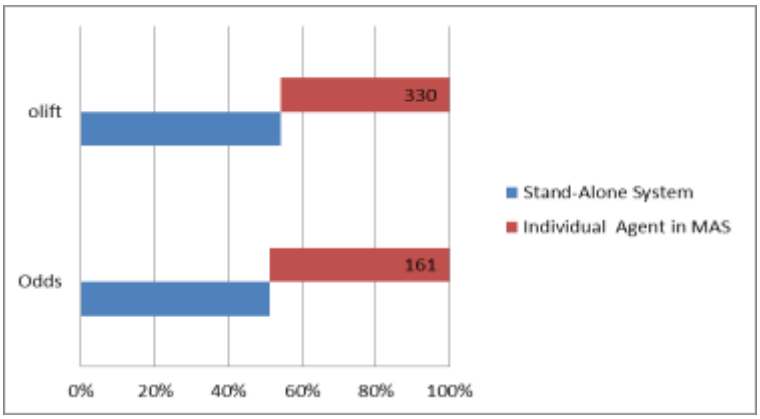

Figure 7.2 : Time Taken to Compute Direct Discrimination Rules for olift and odds

From the above table 7.5 and graph shown in figure 7.2 we can clearly say that when the measures odds and olift are executed in the stand-alone system environment to generate direct discrimination measures for which they have taken 170 and 390 seconds of time respectively. Whereas, the same measures are executed in the Multi agent systems environment the measures odds and olift has taken 161 and 330 seconds respectively. Hence the measures proposed odds and oliftperformed well in terms of time complexity. It is observed that both the methods odds and olift require 560 seconds to generate direct discrimination rules in the stand-alone systems environment, whereas the same measures have taken 491 seconds in the multi agent systems environment.

Table 7.6: Time Taken to Generate Direct Discrimination Rules by eliftd and sliftd Measure

Measure	Stand-Alone System	IndividualAgent in MAS
eliftD	156	143
sliftD	166	154.5

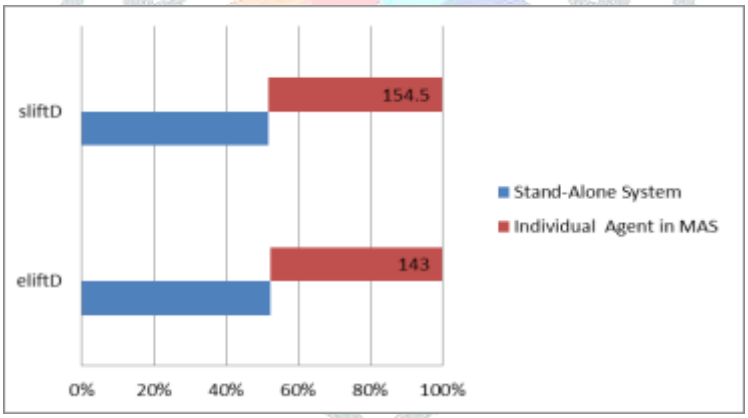

Figure 7.3 : Time Taken to Compute Direct Discrimination Rules of sliftD and eliftD

From the table 7.6 and graph shown in figure 7.3 we can clearly say that the measures eliftD and sliftD are executed in the stand-alone system environment to generate direct discrimination measures for which they have taken 156 and 166 seconds of time respectively, whereas, the same measures are executed in the Multi agent systems environment the measures eliftd and sliftD proposed in the chapter 5 has taken 143 and 154.5 seconds respectively. Hence, the measures proposed eliftD and sliftD in the chapter 5 of this thesis performed well in terms of time complexity. It is observed that both the methods eliftD and sliftD require 322 seconds to generate direct discrimination rules in the stand-alone systems environment, whereas, the same measures have taken 298.5 seconds in the multi agent systems environment.

VIII CONCLUSION

In this work we present the empirical analysis of stand-alone systems with Multi Agent Systems and use of multiple discrimination measures. Multiple discrimination measures can be used for better identification of direct discrimination from the decision making rules and the proposed research work assigns a rank to each and every negative decision rule having sensitive attributes as its premise. With the usage of Multi Agent systems framework in finding direct discrimination process it reduced the time complexity for generating the direct discriminated rules. Our proposed algorithms are designed based on agent programming environment and all the algorithms are implemented by using java programming environment. All the proposed algorithms outer performs well on multi agent environment when compared to stand-alone systems. With the usage of multiple measures for finding direct discrimination paves a way to find better identification of discriminated rules among the decision rules.

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