A Rough Set Approach to Agent Trust Management

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Abstract—Trust management in Multi Agent Systems plays a key role in today's growing need for such systems. Methods of trust management try to approximate a set of best agents, in terms of some pre-defined measures. The theory of Rough Sets deals with the approximation of classifying objects in an environment for which we do not have a certain definition. In this research, we propose a new trust management approach based on the concepts of the theory of rough sets. We apply this approach on an Information Retrieval (IR) MAS. This application includes defining the attribute and their domain of values, discretizing the attribute values, collecting these values, and employing a rough set tool for analyzing them. The results of this application are presented.

I. INTRODUCTION

Multi Agent Systems (MAS) define a new perspective for developing systems that operate in distributed and open environments. A MAS is a society of intelligent agents which act autonomously in a goal oriented manner. Together, the agents try to achieve the final goal of the system by combining all the sub-goals. Each agent is responsible for satisfying one sub-goal. In some cases, there are several agents which can satisfy a particular sub-goal. The problem here is selecting one, or a set, of the best agent(s), with respect to pre-defined measures, amongst those agents who are able to perform that specific task. The measures can vary from the time it takes for an agent to respond to the degree of its reputation [1]. This problem is known as trust management in MAS [1, 2]. As an example, we consider the eBay web site (www.eBay.com) as a MAS where agents are human who want to trade. The trust model of eBay is based on the reputation each agent acquires based on its previous interactions with other agents [3, 4]. Thus if agent A wants to start an interaction with agent B, then A will first check the reputation of B.

In this paper, we are interested in formalizing agent trust management for an Agent-based Information Retrieval (IR) system using The theory of Rough Sets. Consider the case in which there are several IR agents and the user has to choose one to submit his/her query to. The final goal of this research is to guide the user to select an IR system with the highest precision for retrieved documents based on the attributes of both the user's query and the system itself. To this end, we employ a rough set tool to extract rules according to the evidences collected during the operation time or training phase of the system.

The theory of rough sets has been successfully applied on different domains, such as information retrieval [1-3], intelligent data analysis and prediction [4], intelligent control system [5]. Our work differs from the work reported in [6-11] where they propose a very general model for trust management in multi agent systems based on different approaches like rough sets [6], fuzzy sets [8, 9], Bayesian Network [10], and graph theory [11]. However, our work, firstly, uses rough set for analyzing the trust evidences and secondly, it is applied in a specific-domain application which is agent-based IR.

The rest of this paper is structured as follows. Section II presents a background of ATM and Rough Sets. In Section III, we formalize the trust attributes of RS-ATM. Section IV describes the architecture of RS-ATM. Section V defines the test case of RS-ATM in an agent-based IR system. Section VI concludes the paper with some future directions.

II. BACKGROUND

A. Agent Trust Management

Trust management in a MAS can be modeled as shown in Figure 1. This model contains two main components: Multi-Agent System consists of several agents trying to achieve the final goal of the system. Amongst these agents, there are two agents responsible for collecting the trust evidences, the Agent Management System (AMS) and the Evidence Agent. More description about how these two agents act in the society will be covered in Section IV.

Analyzing Tool employs different mathematical tools to convert the trust evidences into trust information. Samples of these methods are fuzzy sets [12, 13], graph theory [11], etc.

The output of the analyzing tool will be the trust information. The type of the resulting information varies based on the mathematical model employed by the analyzing tool. For example, set of trust rules if the rough sets approach is used.
B. The Theory of Rough Sets

The theory of Rough Sets introduced by Pawlak [14] can be used as a formal tool for manipulating and processing information in an environment in which there may be no certain definition for objects. It deals with vague concepts which are caused by incomplete information and knowledge. The knowledge is represented by some equivalence relations to define the indiscernibility of individual objects in the universe of discourse. In Table I, we summarize some of the concepts in the theory of rough sets.

### Table I – Rough Sets Concepts

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Concept</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>U</td>
<td>Universe of Discourse</td>
<td>Set of all objects in the System</td>
</tr>
<tr>
<td>A</td>
<td>Set of all Attributes</td>
<td>Attributes of each object A=C∪D</td>
</tr>
<tr>
<td>C</td>
<td>Set of Condition Attributes</td>
<td>C ⊆ A</td>
</tr>
<tr>
<td>D</td>
<td>Set of Decision Attributes</td>
<td>D ⊆ A</td>
</tr>
<tr>
<td>Ind</td>
<td>Indiscernibility Relation</td>
<td>Ind(P) = ∩{P, P ⊆ R and P ≠ φ}</td>
</tr>
<tr>
<td>( \underline{R} )</td>
<td>Lower Approximation</td>
<td>( \underline{R}(X) = \bigcup{Y \in U \mid \text{Ind}(R); Y \subseteq X} )</td>
</tr>
<tr>
<td>( \overline{R} )</td>
<td>Upper Approximation</td>
<td>( \overline{R}(X) = \bigcup{Y \in U \mid \text{Ind}(R); Y \cap X \neq \phi} )</td>
</tr>
</tbody>
</table>

III. Defining Trust Attributes

The goal of this Section is to formalize agent trust management for IR systems based on the theory of Rough Sets. As illustrated in Table II, we first identify the universe of discourse and the set of condition and decision attributes. Below we define each attribute and its domain of possible values.

Moreover, for those which have continuous values, we discretize the values by defining proper intervals. These intervals may have either overlaps which will lead us to have fuzzy values or they may be totally separated in boundaries.

A. Condition Attributes

InfoType defines the type of information of each query entered by the user (cf. Table III).

### Table III - Discretizing InfoType Attribute Values

<table>
<thead>
<tr>
<th>Actual Value</th>
<th>Discretized Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sports</td>
<td>1</td>
</tr>
<tr>
<td>Science</td>
<td>2</td>
</tr>
<tr>
<td>Politics</td>
<td>3</td>
</tr>
<tr>
<td>Economics</td>
<td>4</td>
</tr>
<tr>
<td>Entertainment</td>
<td>5</td>
</tr>
<tr>
<td>General</td>
<td>6</td>
</tr>
</tbody>
</table>

UpdatingTime indicates how often the collection in an IR system is updated (Table IV).

Language states if the IR system supports the language of the query or not (Table V).

HasArchive indicates if the corresponding IR system has an archive or not (Table VI).


Reputation is an aggregation of two of four measures defined in the FIRE system [7] and which are:

Direct Interaction consists of information gained from previous direct interactions between two agents.

Witness Information are those information that other agents in the society provide about the target agent.

Table VII shows the discretized values for this attribute.

### Table VII - Discretizing Reputation Attribute Values

<table>
<thead>
<tr>
<th>Actual Value</th>
<th>Discretized Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>[0, 0.35)</td>
<td>LOW = 1</td>
</tr>
<tr>
<td>[0.35, 0.65]</td>
<td>MEDIUM = 2</td>
</tr>
<tr>
<td>[0.65, 1]</td>
<td>HIGH = 3</td>
</tr>
</tbody>
</table>

As mentioned in [13], in order to prevent the “Cold Start” problem, we initialize the reputation value of newly joined IR agents to 0.5. The cold start problem concerns the case in which the system cannot infer because there is not enough information collected about the user or any other individual part of the system[15].

Regarding the aggregation, we simply use the average of these two values. For example, if the value for Direct Interaction is 0.73 and value for Witness Information is 0.49, then the value of Reputation is 0.61. In this case, the discretized value for reputation will be “MEDIUM” or “2”.

B. Decision Attribute

We define the decision attribute in terms of higher precision, i.e. the higher the precision of the retrieval process, the more trustworthy the agent. It should be mentioned that we consider our system as a high precision IR system in which gaining a higher precision is the goal of the system and it doesn’t try to increase the recall. Precision measure is defined as the fraction of the documents retrieved that are relevant to the user’s information need. However, the recall measure is defined as the fraction of the documents that are relevant to the query that are successfully retrieved[16].

\[
\text{Precision} = \frac{|\text{Relevant Docs} \cap \text{Retrieved Docs}|}{|\text{Retrieved Docs}|}
\]

\[
\text{Recall} = \frac{|\text{Retrieved Docs} \cap \text{Relevant Docs}|}{|\text{Relevant Docs}|}
\]

Table VIII shows how we discretized the values of the precision attribute.

### Table VIII - Discretizing Precision Attribute Values

<table>
<thead>
<tr>
<th>Actual Value</th>
<th>Discretized Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>[0, 0.25)</td>
<td>LOW</td>
</tr>
<tr>
<td>[0.25, 0.5)</td>
<td>MEDIUM</td>
</tr>
<tr>
<td>[0.5, 1]</td>
<td>HIGH</td>
</tr>
</tbody>
</table>

IV. FORMALIZATION

Figure 2 illustrates the architecture of our agent-based IR system which is composed of four major parts:

**IR Systems.** We have several IR systems for retrieving documents. Each IR system is considered as an agent in our system. It has its own collection and matching algorithm (or retrieval model) such as Language Modeling [17], Vector Space[18], LSI[19], etc. All the IR agents process each user’s query independently and in parallel.

**Agent Management System (AMS).** AMS[20] is responsible for managing the life-cycle of agents in our society. Each agent upon the time of joining the system registers itself in AMS. All the agents can send a request to AMS to find out details about other agents currently registered in the society. In this paper, we also employ AMS to manage the reputation of each IR agent.

To this end, each IR agent on the time of joining the society gets a reputation value of 0.5 in order to prevent the cold start problem as described in Section III.A. Then, after the user entered his/her query, the IR agent returns a list of relevant documents. The user judges these documents and provides a positive, neutral, or negative feedback for each IR system he/she judging. The values of these feedbacks are +1, 0, or -1. By providing this feedback, the user expresses his/her overall evaluation of each agent in terms of how well that agent could satisfy his/her information need. Finally, the system calculates the direct interaction measure by using the following equation:

\[
\text{Direct Interaction} = \frac{\text{Current Reputation} + \sum \text{All feedbacks}}{\text{Number of all feedbacks} + 1}
\]

We add 1 to the denominator in order to normalize the result of Equation 2 in the interval of 0 and 1. For example, consider the first feedback by a user for a recently joined IR agent. The value of current reputation is 0.5, as defined in Section III.A. If the user provides a positive feedback, the new value for Direct Interaction measure will be:

\[
\text{Direct Interaction} = \frac{0.5 + 1}{1 + 1} = 0.75
\]

**Trust Evidence Agent.** This agent is responsible for collecting information of all the trust attributes which are sent from different components in the system. The Evidence agent gathers all these attributes in a single file called trust evidences and sends it to the analyzing tool.

**Analysis System.** This tool extracts trust rules from the trust evidences sent by evidence agent. The analyzing tool can employ different theories and methods, such as fuzzy sets [12, 13], graph theory [11], etc, to produce trust rules.
Firstly, the user enters a query. Then, each IR agent processes the query and sends proper information about the condition attributes to the Evidence agent. However, the value of “Reputation” attribute is provided by the AMS agent. Secondly, each IR agent returns a list of documents with respect to the issued query. Then the user judges the results of the retrieval process. More precisely, he judges top N documents returned by each IR system. We use these judgments to calculate the precision of retrieval for each query and for each IR system. The decision attribute is then sent to the Evidence Agent.

V. A CASE STUDY

In this experimentation, we employed the open search API for the three most famous search engines on the web: Google, Yahoo, and Bing and used them as our retrieval agents. The Open Search API of these search engines allows us to submit the queries and get the results back. To be able to use this system, we implemented a website accessible from the address: http://thesis.sadra.info/.

In this website, the user can simply submit his/her query to the underlying MAS. The underlying MAS is capable of querying the three search engines mentioned above and responds to user’s information need, and will return the top N documents retrieved by each of them. The parameter N can be simply changed by entering the desired value in the “Count” field. The results will be shown in a grid after being sent back.

Finally, as shown in Figure 3, the user can judge the retrieved item and set it as either “Relevant” or “Irrelevant” by clicking on the proper button on each result. The background color of each item will change to Green, if it is judged as Relevant, and it will turn into Red if it is judged Irrelevant. The results of the judgments are being stored in a SQL Server 2005 database on the server.

We used the set of sixty queries used in [21] as our training query set. These sixty queries are generated by a number of students. For each of these queries, the person who has generated it includes the English translation of the query to state his/her information need both in Persian and English. In this experiment, we chose forty queries out of these sixty and for each of these forty queries, and for each of three search engines, we judged the first 20 documents.

To analyze the trust attributes, we used a rough set tool called RSES ver. 2.2 [22] to analyze the trust evidences. However we needed to change the format of information produced by our retrieval system to a text file readable by RSES. Then, we employed RSES functionalities to extract rules.

The values for UpdatingTime, Language, and HasArchive attributes were the same for all three search engines, and for all queries. These values were 0, 1, 1 respectively. The values for InfoType attribute are determined according to each query. The precision of retrieval for each query, and for each search engine, was calculated after judging all 60 results for each query.

Moreover, the values for feedback attribute were calculated using the function $F : [0, 1]^2 \rightarrow [-1, 0, 1]$. These values were sent back to the AMS to evaluate the value for Reputation attribute for each agent as defined in Section III.A
Where $p$ is the precision of retrieval from each search engine for each query, and $ap$ is the average precision for that specific search engine. The $ap$ is calculated simply as the average of all forty precision values. Table IX shows the average precisions in our experiment:

<table>
<thead>
<tr>
<th>Search Engine</th>
<th>Average Precision</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yahoo!</td>
<td>0.44375</td>
</tr>
<tr>
<td>Google</td>
<td>0.50625</td>
</tr>
<tr>
<td>Bing</td>
<td>0.54625</td>
</tr>
</tbody>
</table>

Figure 5 shows a number of rows representing the trust evidences in our experiment. In order to generate the trust rules, we first utilized RSES to get the Minimal Reduct set for attributes. Later, using this Minimal Reduct set, the Global Rules were generated (Figure 6). Global Rules are one of the ways to generate rules in the RSES tool. Finally, we used the “Shorten” function of the generated rule set to get the trust rules. The flow of generating the Minimal Reduct set and the trust rules is shown in Figure 4. The RSES tools asks for the “Shortening Ratio” parameter, a parameter of real values in the interval of $[0, 1]$, which determines how aggressive the shorten function will be performed. The values of 1 means that there would be no shortening, and the values close to 0 forces the tool to maximally shorten the rules. In this experiment, we set this ratio to two different values: 0.3, 0.5.

\[ F(p, ap) = \begin{cases} 
-1 & p < 0.9 \times ap \\
0 & p \in ap \pm 0.1ap \\
1 & p > 1.1 \times ap 
\end{cases} \] (1)

The resulting rules for setting each of two shortening ratios are presented as shown in Figure 7 and Figure 8 respectively. These rules are Boolean expressions defining how the decision attribute is related to condition attributes.

A. Analyzing the Results

The trust rules shown in figures above are Boolean expressions that show how the decision attribute, precision in this case, is related to condition attributes. The first rule in Figure 6 reveals the fact that when the user’s information needs are satisfied, i.e. the reputation value is 1, the precision of retrieval will be high. This rule might be considered as an evident property of IR systems. However, considering the fourth rule which is defined as:
It can be obtained that sometimes, it happened 11 times in our experience, the higher reputation doesn’t result in higher precision. This rule indicates although the “Bing” IR system did not fully satisfied the user’s information need, it could return relevant documents with a high precision. The reason is the fact that for a number of queries in our experience, the “Bing” IR system was returning relevant information from only one relevant website. In other words, the precision of retrieval process was high, but the results were not exhaustive and, as a result, could not satisfy user’s information need. For example, for the query “Persian Gulf Pollution”, the Bing IR agent returned 11 relevant documents. Out of these 11 relevant documents, five of them were in the http://www.atmos-chem-phys.net, and two others in http://www.american.edu website.

Moreover, consider the rules in Figure 7. Comparing rule 1 and rule 4, it can be revealed that, according to our forty test queries, Bing returns more relevant documents comparing to Yahoo. Also, rule 6 depicts that when the query is in the domain of sports, the precision of retrieval is high.

Furthermore, the rule 8 in both Figure 8 indicates the fact that Bing returns relevant documents with lower precision when the domain of the query is Economics.

VI. RELATED WORK

Trust Management in MAS has attracted a lot of attention in the past couple of years. Different methods and models have been introduced. The FIRE system introduced in [7] is a system for managing trust and reputation between agents. In this system, four different sources of trust information are used to evaluate the trust.

Another work is reported in [12, 13] in which authors introduce a fuzzy trust model in the domain of E-Commerce. They provide an algorithm to calculate the degree of trust between two agents. This algorithm handles trust in different time slots. The evidences in different time slots are aggregated to calculate the final degree of trust.

Meta-Search Engines (MSE) can aggregate the results sent back from several web-based search engines into a single list. For example, DogPile (http://www.DogPile.com), and SavvySearch [23], are two industrial MSE that can aggregate results returned from different search engines into groups.

Moreover, some other approaches like [24] try to improve the results by using other knowledge available to the system, including user’s current context and propagation of services proved to return high quality results.

Another work is presented in [25]. The authors merge the results of four different language modeling methods using different variations of Fuzzy OWA operator. They show that the result are marginally improved comparing to the case where no aggregation method is being used.

Information filtering can be considered as the same problem as trust. For example, in [26], Clarke et al. mention that for a given query, there will be several answers returned and the system should choose one of them. Although it is not categorized as trust, choosing one answer can be defined as which answer to trust.

VII. CONCLUSION AND FUTURE WORKS

We have formalized the agent trust management for a multi agent IR system using the theory of rough sets. Based on the proposed architecture of our system, we conducted an experiment for a specific agent-based IR system.

This work can be extended by employing the extensions of Rough Sets, like fuzzy[27] and variable precision[28] in order to generate probabilistic trust rules. As used in this research, the basic theory of rough sets results in Boolean rules. However, a better way of stating these rules would be the case in which the rules are expressed by a probability of correctness. This goal can be achieved by employing the extensions of basic rough sets.

Agent trust management has been applied widely in the field of E-Commerce. The goal of these systems is to employ a number of intelligent agents who are able to negotiate, and trade instead of users. The next step of this research can be a comparison between our proposed method and the works already done in this field. This work can be extended by employing the extensions of Rough Sets, like fuzzy[27] and variable precision[28] in order to generate probabilistic trust rules. As used in this research, the basic theory of rough sets results in Boolean rules. However, a better way of stating these rules would be the case in which the rules are expressed by a probability of correctness. This goal can be achieved by employing the extensions of basic rough sets.
REFERENCES


