A PROTOPTYPE TO RECOMMEND TRUSTWORTHY KNOWLEDGE IN COMMUNITIES OF PRACTICE

Juan Pablo Soto, Aurora Vizcaíno, Javier Portillo-Rodríguez, Mario Piattini
University of Castilla-La Mancha, Alarcos Research Group – Institute of Information Technologies & Systems
Department of Information Technologies & Systems - Escuela Superior de Informática, Ciudad Real, Spain

Oscar M. Rodríguez-Elias
University of Sonora, Department of Mathematics, Hermosillo, Mexico

Keywords: Knowledge Management, Recommendation, multi-agent Systems.

Abstract: Knowledge Management is a key factor in companies which have, therefore, started using strategies and systems to take advantage of its intellectual capital. However, employees frequently do not take advantage of the means to manage knowledge that companies offer them. For instance, employees often complain that knowledge management systems overload them with more work since they have to introduce information into these systems, or that this kind of tools floods them with too much knowledge which is not always relevant to them. In order to avoid these problems we have implemented a tool to recommend trustworthy knowledge sources in communities of practice. This tool is based on a multi-agent architecture in which agents attempt to help users to find the information which is most relevant to them. In order to do this, the agents use a trust model to evaluate how trustworthy a knowledge source (which may even be another agent) is.

1 INTRODUCTION

In recent years Knowledge Management (KM) has become an important success factor for companies. The purpose of knowledge management is to help companies to create, share and use knowledge more effectively (Davenport and Prusak, 1997). Information technologies play a key role in achieving these goals but are only a small component of an overall system that must integrate the supporting technology with people-based business processes. KM is not a technology solution but rather is primarily about people oriented process, such as leadership, culture, expertise and learning, with technology playing a supporting role. Based on this idea we have studied how people obtain and increase their knowledge in their daily work. From this study we have realized that frequently, employees exchange knowledge with people who work on similar topics and consequently, either formally or informally, communities are created which can be called "communities of practice", by which we mean groups of people with a common interest where each member contributes knowledge about a common domain (Wenger, 1998).

Communities of practice (CoPs) enable their members to benefit from each other's knowledge. This knowledge resides not only in people's minds but also in the interaction between people and documents. CoPs share values, beliefs, and ways of doing things. Many companies report that such communities help reduce problems due to lack of communication, and save time by "working smarter" (Wenger et al, 2002). An interesting fact is that members of a community are frequently more likely to use knowledge built by their community team members than those created by members outside their group (Desouza et al, 2006). Because of this, as is claimed in (Desouza et al, 2006), knowledge reuse tends to be restricted within groups. Therefore, people, in real life in general and in companies in particular, prefer to exchange knowledge with "trustworthy people" by which we mean people they trust. For these reasons we consider important the implementation of mechanism in charge of

Pablo Soto J., Vizcaíno A., Portillo-Rodríguez J., Piattini M. and M. Rodríguez-Elias O. (2008).
A PROTOPTYPE TO RECOMMEND TRUSTWORTHY KNOWLEDGE IN COMMUNITIES OF PRACTICE.
In *Proceedings of the Third International Conference on Software and Data Technologies - PL/DPS/KE*, pages 321-326
DOI: 10.5220/0001887103210326

measuring and controlling the confidence level in a community where the members sharing information.

Bearing in mind that people exchange information with “trustworthy knowledge sources” we have designed a prototype in which software agents try to emulate humans evaluating knowledge sources with the goal of fostering the use of knowledge bases in companies where agents provide “trustworthy knowledge” to the employees.

The remainder of this work is organized as follows: Section 2 describes the design of a multi-agent system to recommend CoPs’ members trustworthy knowledge sources. Then in Section 3 the prototype of the system is presented, in this section the trust model that we propose to be used in CoPs is also explained. After that in Section 4 the preliminary evaluation of the prototype is shown. Section 5 outlined related works and finally in Section 6 conclusions are future work are summarized.

2 DESIGN OF THE MULTI-AGENT SYSTEM

Due to the importance of knowledge management, tools which support some of the tasks related to KM have been developed. Different techniques are used to implement these tools. One of them, which is proving to be quite useful, is that of intelligent agents (van-Elst et al., 2003). Software agent technology can monitor and coordinate events, meetings and disseminate information (Balasubramanian et al., 2001). Furthermore, agents are proactive in the sense that they can take the initiative and achieve their own goals. The autonomous behaviour of these agents is critical to the goal of this research since agents can act on behalf of their users by carrying out difficult and often time-consuming tasks that employees have to perform when using a KM system. Most agents today employ some type of artificial intelligence technique to assist the users with their computer-related tasks, such as reading e-mails, maintaining a calendar, and filtering information. The advantages that agent technology has shown in the area of information management have encouraged us to consider agents as a suitable technique by which to develop a multi-agent system with the goal of supporting CoPs. To do this, we need to emulate people’s behavior when they interact with the other members of a community. For this reason, we have grouped the agents into communities, thus attempting to emulate CoPs. Figure 1 represents the distribution of the multi-agent system where there are two kinds of agent and where there are different roles to play.

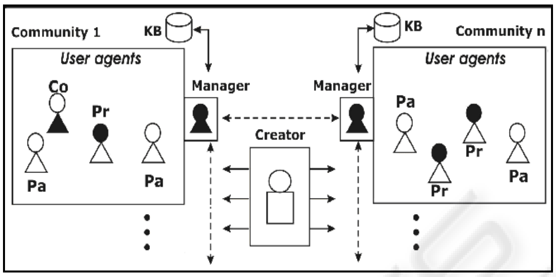

Figure 1: Multi-Agent System.

One type of agent is the User Agent which is in charge of representing each person that may consult or introduce knowledge in a community. The *User Agent* can assume three types of behavior or roles similar to the tasks that a person may carry out in his/her community. Therefore, the User Agent plays one role or another depending upon whether the person that it represents carries out one of the following actions:

- The person contributes new knowledge to the communities in which s/he is registered. In this case the User Agent plays the role of **Provider**.
- The person uses knowledge previously stored in the community. Then, the User Agent will be considered as a **Consumer**.
- The person helps other users to achieve their goals, for instance by giving an evaluation of certain knowledge. In this case the role is that of a **Partner**. So, Figure 1 shows that in Community 1 there are two User Agents playing the role of Partner (Pa), one User Agent playing the role of Consumer (Co) and another being a Provider (Pr).

The second type of agent within a community is called the *Manager Agent* (represented in black in Figure 1) which is in charge of managing and controlling its community.

Every user agent has been constructed by following the multi-agent architecture explained in (Soto et al, 2007), in which the authors present a three level architecture to support CoPs.

The multi-agent system has been designed by using the INGENIAS (Pavón and Gómez-Sanz, 2003) methodology because this is considered by many authors to be one of the most up to date and complete methodologies.

3 THE PROTOTYPE

In order to test our multi-agent system, we have developed a prototype system into which CoPs members can introduce documents and where these documents can also be consulted by other people. The goal of software agents is that of helping members to discover the information that may be useful to the CoPs members, thus decreasing the overload of information which, for instance, employees often have and strengthening the use of knowledge in enterprises. This prototype also helps to discover experts in a community and permits the detection of fraud when users insert non-valuable knowledge into the community.

One feature of this system is that when a person searches for knowledge in a community, and after having used the knowledge obtained, that person then has to evaluate the knowledge in order to indicate whether:

- The knowledge was useful.
- How it was related to the topic of the search.

In this paper, due to space limitations, we shall only explain how agents recommend documents when a person is searching for information about a topic.

In order to make it easier to search for documents in a community, users can choose one topic from those which are available in the community and the user agent will attempt to find documents about this topic.

The general idea is to consider those documents which come from trustworthy knowledge sources according to the user's opinion or needs. User agents use a trust model to discover which knowledge sources are trustworthy. As this trust model will be used in CoPs then the factors that arise in this kind of community should be considered, such as:

The number of interactions that an agent will have with other agents in the community will be low in comparison with other scenarios such as auctions. This is very important because we cannot use trust models which need a lot of interactions to obtain a reliable trust value; it is more important to obtain a reliable initial trust value. We use four factors (see Figure 2) to obtain a trust value:

- **Position:** employees often consider information that comes from a boss as being more reliable than that which comes from another employee in the same (or a lower) position as him/her (Wasserman and Glaskiewics, 1994). However, this is not a universal truth and depends on the situation. For instance in a collaborative learning setting collaboration is more likely to occur between people of a similar status than between a boss and his/her employee or between a teacher and pupils (Dillenbourg, 1999). Such different positions inevitably influence the way in which knowledge is acquired, diffused and eventually transformed within the local area. Because of this, as will later be explained, this factor will be calculated in our research by taking into account a weight that can strengthen this factor to a greater or to a lesser degree.
- **Expertise:** This term can be briefly defined as the skill or knowledge that a person who knows a great deal about a specific thing has. This is an important factor since people often trust experts more than novice employees. In addition, "individual" level knowledge is embedded in the skills and competencies of the researchers, experts, and professionals working in the organization (Nonaka and Takeuchi, 1995). The level of expertise that a person has in a company or in a CoP could be calculated from his/her CV or by considering the amount of time that a person has been working on a topic. This is data that most companies are presumed to have.
- **Previous Experience:** This is a critical factor in rating a trust value since, as was mentioned in the definitions of trust and reputation, previous experience is the key value through which to obtain a precise trust value. However, when previous experience is scarce or it does not exist humans use other factors to decide whether or not to trust in a person or a knowledge source. One of these factors is intuition.
- **Intuition:** This is a subjective factor which, according to our study of the state of the art, has not been considered in previous trust models. However, this concept is very important because when people do not have any previous experience they often use their "intuition" to decide whether or not they are going to trust something. We have tried to model intuition according to the similarity between personal profiles: the greater the similarity between one person and another, the greater the level of trust in this person as a result of intuition.

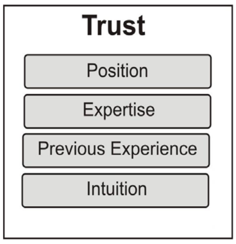

Figure 2: Trust Model.

We have classified these four factors into two groups: objective factors (position and expertise) and subjective factors (intuition and previous experience). The former is given by the company or community and the latter depends on the agent itself and the agent's experience in time. There are four different ways of using these factors, which depend upon the agent's situation.

- If the agent has no previous experience, for instance because it is a new user in the community, then the agent uses position, expertise and intuition to obtain an initial trust value and this value is used to discover which other agents it can trust.
- When the agent has previous experience obtained through interactions with other agents but this previous experience is low (low number of interactions), the agent calculates the trust value by considering the intuition value and the experience value. For instance, if an agent A has a high experience value for agent B but agent A has a low intuition value for agent B (profiles are not very similar), then agent A reduces the value obtained through experience. In this case the agent does not use position and expertise factors (objective factors) because the agent has its own experience and this experience is adjusted with its intuition which is subjective and more personalized.
- When the agent has enough previous experience to consider that the trust value it has obtained is reliable, then the agent only considers this value.

The way to translate the trust model to trust values is by using the following formula:

$$\mathbf{T_{ij}= \quad w_e{*}E_j{+}w_p{*}P_j{+}w_I{*}I_{ij}{+} \quad (\sum_{j=1}^{n} QC_{ij})/n}$$

where $\mathbf{T}_{ij}$ is the value of trust of j in the eyes of i, E_j is the value of expertise which is calculated according to the degree of experience that the person upon whose behalf the agent acts has in a domain.

P_j is the value assigned to a person's position.

I_{ij} denotes the intuition value that agent i has in the agent j which is calculated by comparing each of the users' profiles.

In addition, previous experience should also be calculated. When an agent i consults information from another agent j, the agent i should evaluate how useful this information was. This value is called QC_{ij} (Quality of *j*'s Contribution in the opinion of i). To attain the average value of an agent's contribution, we calculate the sum of all the values assigned to these contributions and we divide it between their total. In the expression n represents the total number of evaluated contributions.

Finally, w_e, w_p and w_I are weights with which the trust value can be adjusted according to the degree of knowledge that one agent has about another. Therefore, if an agent i has had frequent interactions with another agent j, then agent i will give a low weight (or even zero) to w_i since, in this case, previous experience is more important than intuition. The same may occur with w_e, $w_{p.}$ So the weights may have the value of 0 or 1 depending on the previous experience that an agent has.

In order to illustrate how the prototype works, let us look at an example. If a user selects a topic and wants to search for documents related to this topic his/her user agent will contact other user agents which have documents about the topic, and the user agent will then calculate the trust value for each agent, which means that these agents are considered to be knowledge sources and the user agent needs to calculate which "knowledge source" is more trustworthy. Once these values have been calculated, the user agent only shows his/her user the documents which have come from the most trustworthy agents. In Figure 3 we can see the results of a search sorted by the trust values, that is, the first documents on the list come from the most trustworthy knowledge sources (in this case the most trustworthy agents with the highest trust values). There are other possibilities, depending on user preferences. For instance, as we can see in Figure 3, the results of the request (sorted by reputation) show a large amount of results, and the first one on the list has five stars in the reputation level and four shields in the position level.

This method of rating trust helps to detect an increasing problem in companies or communities in which employees are rewarded if they contribute with knowledge in the community. Thus, if a person introduces non-valuable documents with the sole aim of obtaining rewards, the situation can be detected since these documents will have low values and the person will also be considered to be less

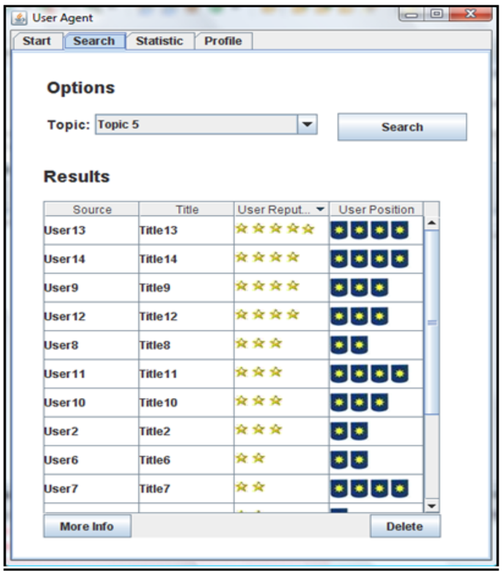

Figure 3: Showing and sorting results.

trustworthy. The agent will, therefore, not recommend those documents. Moreover, this model implies the reduction of users' overload when they use knowledge management systems, since with this model the user agent only recommends the most adequate and trustworthy knowledge.

4 EVALUATION OF THE PROTOTYPE

Once the prototype has been finished we have evaluated it. To do this, different approaches can be followed, from a multi-agent point of view or from a social one. First of all we have focused on the former and we are testing the most suitable number of agents advisable for a community. Therefore, several simulations have been performed. As result of them we found that:

The maximum number of agents supported by the Community Manager Agent when it receives User Agents' evaluations is approximately 800. When we tried to work with 1000 agents for instance, the messages were not managed conveniently. However, we could see that the Manager Agent could support a high number of petitions, at least, using simpler behavior.

All these results are being used to detect whether the exchange of messages between the agents is suitable, and to see if the information that we propose to be taken into account to obtain a trustworthy value of the reputation of each agent is enough, or if more parameters should be considered.

5 RELATED WORKS

This research can be compared with other proposals that use agents and trust in knowledge exchange.

With regard to Trust, in models such as eBay (1995) and Amazon (1996), which were proposed to resolve specific situations in online commerce, the ratings are stored centrally and the reputation value is computed as the sum of those ratings over six months. Thus, reputation in these models is a single global value. However, these models are too simple (in terms of their trust values and the way in which they are aggregated) to be applied in open multi-agent systems. For instance, in (Zachaira et al, 1999) the authors present the Sporas model, a reputation mechanism for loosely connected online communities where, among other features, new users start with a minimum reputation value, the reputation value of a user never falls below the reputation of a new user and users with very high reputation values experience much smaller rating changes after each update. The problem with this approach is that when somebody has a high reputation value it is difficult to change this reputation, or the system needs a high amount of interactions. A further approach of the Sporas authors is Histos which is a more personalized system than Sporas and is orientated towards highly connected online communities. In (Sabater and Sierra, 2002) the authors present another reputation model called REGRET in which the reputation values depend on time: the most recent rates are more important than previous rates. Carbó et al (2003) presents the AFRAS model, which is based on Sporas but uses fuzzy logic. The authors present a complex computing reputation mechanism which handles reputation as a fuzzy set while decision making is inspired in a cognitive human-like approach. In (Caballero et al, 2006) the authors present a trust and reputation model that considers trust and reputation as emergent properties of direct interactions between agents, based on multiple interactions between two parties. In this model, trust is a belief an agent has about the performance of the other party to solve a given task, according to own knowledge.

The main differences between these reputation models and our approach are that these models need an initial number of interactions to obtain a good reputation value and it is not possible to use them to discover whether or not a new user can be trusted. A further difference is that our approach is orientated towards collaboration between users in CoPs. Other approaches are more orientated towards competition, and most of them are tested in auctions.

6 CONCLUSIONS AND FUTURE WORK

This paper describes a multi-agent prototype to support CoPs in which knowledge source are rated by using a trust model developed to be used solely in CoPS. In this prototype CoPs members can introduce documents and the software agents must decide how trustworthy those documents are for the user that they represent.

One important contribution of this paper is the trust model, as it helps to detect experts in a community, since those knowledge sources with high trust values are supposed to be people who contribute with valuable knowledge. The trust model also helps to detect fraud when users contribute with non-valuable knowledge. Another important feature of our trust model, and that which makes it different from previous models, is that even when a user is new to the community and other agents do not have any previous experience of working with him/her, the trust model allows agents to obtain a preliminary trust value by considering other factors such as the new agent's position, and level of expertise, along with the intuition that each agent has about the new member. In this way we attempt to model human features, since when a person has to evaluate something and s/he has no previous experience this person uses other aspects such as his/her intuition in order to decide whether or not to trust in it.

As future work, we are performing different tests with the prototype and the trust model in order to see how they might be improved according to different domains.

ACKNOWLEDGEMENTS

This work is partially supported by the MELISA project (PAC08-0142-3315), Junta de Comunidades de Castilla-La Mancha, Consejería de Educación y Ciencia, in Spain, partially supported by MECENAS (PBI06-0024) and ESFINGE project (TIN2006-15175-C05-05) Ministerio de Educación y Ciencia (Dirección General de Investigación)/Fondos Europeos de Desarrollo Regional (FEDER) in Spain and CONACYT (México) under grant of the scholarship 206147 provided to the first author.

REFERENCES

Amazon (1996). URL: www.amazon.com

Balasubramanian, S., Brennan, R., Norrie, D., 2001, An Architecture for Metamorphic Control of Holonic Manufacturing Systems. *Computers in Industry*, Vol. 46, No. 1, pp: 13-31.

Caballero, A., Botía, J., Skarmeta, A., 2006, A New Model for Trust and Reputation Management with an Ontology Based Approach for Similarity Between Tasks. In: *Fischer, K., Timm, I. J., André, E., Zhong, N. (eds.) MATES.* LNCS 4196, pp: 172-183.

Carbó, J., Molina, M., Davila, J, 2003, Trust Management through Fuzzy Reputation. *International Journal of Cooperative Information Systems*. Vol. 12, No. 1, pp: 135-155.

Davenport, T., Prusak, L., 1997, Working Knowledge: How Organizations Manage What They Know. *Project Management Institute*. Harvard Business School Press, Boston, Massachusetts.

Desouza, K., Awazu, Y., Baloh, P., 2006, Managing Knowledge in Global Software Development Efforts: Issues and Practices. *IEEE Software*, pp: 30-37.

Dillenbourg, P., 1999, Introduction: What Do You Mean By "Collaborative Learning"?, *Collaborative Learning Cognitive and Computational Approaches*. Dillenbourg (Ed.). Elsevier Science.

ebay (1995). URL: www.ebay.com

Nonaka, I., Takeuchi, H., 1995, The Knowledge Creation Company: How Japanese Companies Create the Dynamics of Innovation, *Oxford University Press*.

Pavón, J., Gómez-Sanz, J., 2003, Agent Oriented Software Engineering with INGENIAS. *Multi-Agent Systems and Applications III: CEEMAS 2003, LNCS 2691,* pp. 394-403

Sabater, J., Sierra, C., 2002, Social REGRET, a Reputation Model based on social relations. *Proceedings of the Fifth International Conference on Autonomous Agents*, Vol. 3, No. 1, pp: 44-56.

Soto, J. P.,Vizcaíno, A., Portillo-Rodríguez, J., Piattini, M., 2007, A Three Level Multi-agent Architecture to Foster Knowledge Exchange. In *19th International Conference on Software Engineering and Knowledge Engineering (SEKE)*, Boston, USA. pp. 565-569.

van-Elst, L., Dignum, V., Abecker, A., 2003, Agent-Mediated Knowledge Management. *International Symposium AMKM*, Stanford, CA, USA, Springer. pp. 1-30

Wasserman, S., Glaskiewics, J., 1994, Advances in Social Networks Analysis, *Sage Publications*.

Wenger, E., 1998, Communities of Practice: Learning Meaning, and Identity, *Cambridge University Press*.

Wenger, E., McDermott, R., Snyder, W., 2002, Cultivating Communities of Practice, *Harvard Business School Press*.

Zacharia, G., Moukas, A., Maes, P., 1999, Collaborative Reputation Mechanisms in Electronic Marketplaces. In *32nd Hawaii International Conference on System Sciences (HICSS)*.