# A METHODOLOGY FOR THE ASSESSMENT OF BUDDY-AGENTS

Ali R. Montazemi
Michael G. DeGroote School of Business
McMaster University
Hamilton, ON
Canada L8S 4M4
montazem@mcmaster.ca

Xiaoqing Li
Department of MIS
College of Business and Management
University of Illinois at Springfield
One University Plaza, MS-115
Springfield, Illinois 62703-5407
xli1@uis.edu

## ABSTRACT

Computer-based information systems connected to high-speed communication networks provide increasingly rapid access to a wide variety of data resources. However, this connectivity to data resources burdens decision-makers with the need to access and analyze large volumes of data to support their decision-making processes. Without effective guidance in decision-making, access to data resources provides only minor benefits. Intelligent agents are expected to act like human assistants and support complex decision processes, either by anticipating the information requirements of the decision makers or by autonomously performing a specific set of tasks. In this article, we provide a methodology based on fuzzy-set methodology for the assessment of buddy-agents in a distributed, multi-agent information system environment that supports complex decision problems. Our findings from an assessment of the methodology for the selection of common stocks support the viability of the methodology proposed.

Keywords: Multi-Agent Systems, Buddy-Agent, collaborative systems, P to P information sharing, Knowledge Management, Case-Based Reasoning System

## 1. Introduction

Information systems are being used more and more to help people deal with complex decision problems to such an extent that a user-friendly human-computer interface has become crucial to their success. *Intelligent agent*, an artificial intelligence (AI) technique, has been developed to support human-computer interface in order to implement a complementary style of interaction [Collins et al. 2002, Lieberman 1997, Karageorgos et al. 2002, Maes 1999 & 1994, Minsky 1994 and 2000, Montazemi and Gupta 1997a]. An intelligent agent is expected to reduce the complexity of dialog by understanding user goals and facilitating interaction with the system [Lewis 1998, Montazemi and Gupta 1996, Pilkington 1992]. We can identify applications of agent technology in diverse areas such as information retrieval systems to help users to retrieve relevant documents [Montazemi and Gupta 1997b, Shaw et al. 2002], and electronic commerce to help buying and selling [Turowski 2002]. More importantly, with the pricking of the Internet bubble, online retailers are under more pressure than ever to earn their keep, and as a result many companies are looking at intelligent agents as one of the sophisticated merchandising tools that can recommend products and build customer loyalty and boost sales [Kwak 2001].

The objective of this research is to present a methodology, based on fuzzy-set methodology, that will enable a group of distributed agents (i.e., multi-agent system "MAS") to plan their interaction, and to use learning techniques to improve their operational performance in complex decision-making processes where tacit-knowledge (e.g., selection of music or common stock) is needed. Table 1 presents the taxonomy of the proposed MAS methodology.

Table 1: Taxonomy of the proposed Buddy-Agent System

| |
|---|
| • Solve problems that are too large for a centralized agent to solve.<br>• Allow for the interconnection and interoperation of multiple existing systems.<br>• Provide solutions to problems that naturally can be regarded as a society of autonomous interacting component-agents.<br>• Provide solutions that efficiently use spatially distributed information sources (e.g., sources that gather information from the Internet).<br>• Provide solutions in situations where expertise (i.e., tacit-knowledge) is distributed (e.g., health care, stock market). |

We might have to sift through hundreds of music CDs, for example, to find one we have not heard before and that we like. A knowledgeable assistant in a music store may help us narrow our search by asking about our musical preferences (artist, composer, type, rhythm). As for selecting a common stock, many financial institutions (e.g., www.ETRADE.COM) enable investors to purchase common stocks on-line. However, the onus is on the investor to have complete knowledge of thousands of common stocks traded on different exchanges, before he or she can choose the most suitable one. This creates information overload, renders the on-line information market somewhat inefficient, and opens the door for information "intermediaries" in the market. In either case, we are faced with an extremely large database of possible selections that may or may not satisfy our taste or needs. In addition, the selection criteria are complex and usually not Boolean. In these situations, the information system must act intelligently, taking into account the knowledge of the user and the decision environment if it is going to provide suitably detailed information.

Intelligent agents are expected to embody some of the key capabilities of a human assistant -- observing and forming models of the decision environment; inferring the decision-maker's intentions from these observations, and formulating plans and taking action to support the decision-making processes. This is a challenging task, but there have been major breakthroughs in the design and development of agent-based information systems that can support complex decision problems [Bordetsky and Mark 2000, March et al. 2000, Montazemi 1999].

There are almost as many definitions of agents as there are agents themselves. This diversity of definitions can be attributed to the range of applications that can use this technology to enhance decision-making processes. In this paper, we use the terms "agents" and "intelligent agents" interchangeably. Section 2 of this paper elaborates on the characteristics of agents. Agents have to interact with each other as well as with environmental entities (e.g., human decision makers and databases) to achieve their goals. One of the basic problems facing designers of multi-agent systems for open and complex information environments such as the Internet is that of connection – finding decentralized buddy-agents who might have the needed information or other capabilities. With this in mind, Section 3 describes the characteristics of multi-agent systems. The objective of this research and the methodology proposed to assess buddy-agents membership is described in Section 4. Section 5 describes the procedures we followed to test the effectiveness of the proposed methodology, and Section 6 presents the test results.

## 2. Characteristics of Intelligent Agents

Intelligent agents are expected to work in open and complex information environments. The essential purpose of agents is that of delegation. The user delegates a task to the agent and the agent autonomously performs that task on behalf of the user. Researchers have described the characteristics of classified agents in numerous ways. Hayes-Roth [1995], for example, views intelligent agents as being capable of:

- perceiving dynamic conditions in the environment
- taking action to affect conditions in the environment
- reasoning in order to interpret perceptions, solve problems, draw inferences and determine actions.

Nwana [1996] provides a typology that defines different types of agents based on their abilities to cooperate, learn and act autonomously. By *autonomy* we mean the principle by which agents operate on their own without the need for human guidance. With cooperation capability, agents can interact with each other and possibly with humans via some communication language medium. The key attribute of any intelligent being is its ability to learn. Intelligent agents have to *learn* as they react to, or interact with, the environment in which they operate.

## 3. Characteristics of Multi-Agent Systems (MAS)

With the development of agent technology, the need for a system of multiple agents communicating in a peer-to-peer fashion is becoming apparent [Sycara et al. 1996]. Characteristics of MASs are as follows [Sycara 1998]:

- Each agent has incomplete information or ability to solve the decision problem.

- There is no global control system.
- Data are decentralized.
- Computation is asynchronous.

MAS is expected to solve problems that are beyond the capabilities of an individual agent as illustrated in Table 1. To communicate effectively, each agent in a multi-agent system needs to know the characteristics of the other agents that can best serve its requirements. A popular model to facilitate communication among agents is a middle-agent (also called "matchmaker" or "broker"). In this model all agents register with the middle-agent. For example, in figure 1, let us assume that agent A1 has a request (i.e., ASK(X)). To perform this request, the middle agent (M) can use one of the following two procedures:

(1) Recommend performative: A1 ask M to "recommend" an agent to whom it would be appropriate to send the performative ASK(X). Once M learns that A2 is willing to accept ASK(X) performatives, it replies to A1 with the name of agent A2. A1 is then free to initiate a dialog with A2 to answer this and similar queries (see Figure 1) [Finin et al. 1997].

(2) Broker-performative: A1 asks M to find an agent that can process an ASK(X) performative. A2 independently informs M that it is willing to accept performatives matching ASK(X). Once M has both of these messages, it sends A2 the query, gets a response and forwards it to A1 (See Figure 2) [Finin et al. 1994].

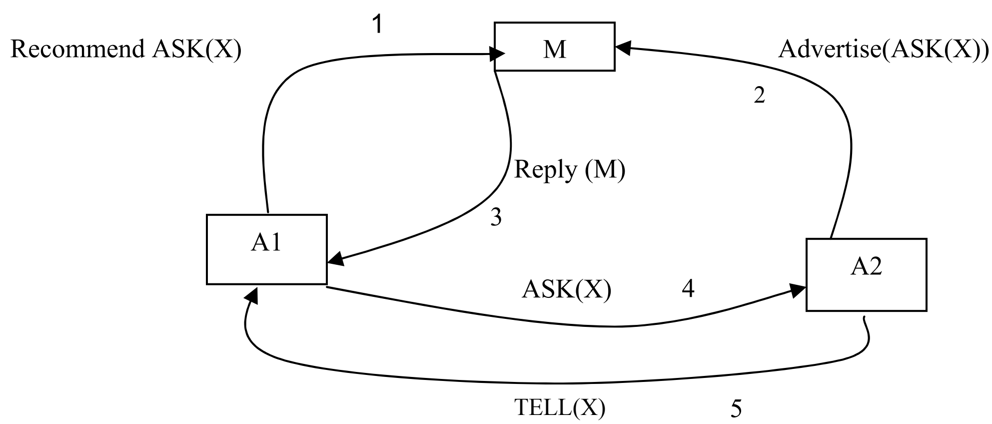


Figure 1: The recommend performative is used to ask the facilitator-agent to respond with the "name" of another agent to which it is appropriate to send a particular performative

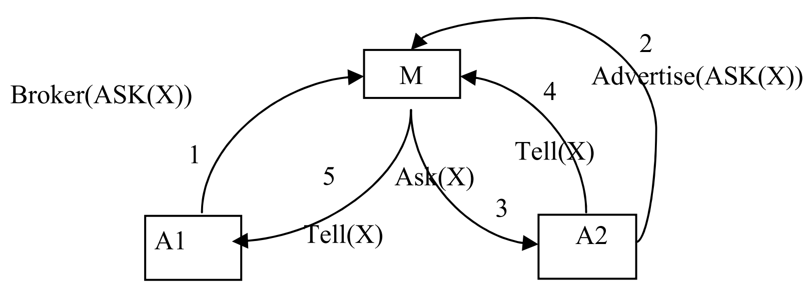


Figure 2: The broker-performative is used to ask a facilitator agent to find an agent who can process a given performative and forward the reply

The above methodology is applicable when the decision environment represented by each agent is simple, and the number of agents in need of cooperation is small. This structure becomes cumbersome, however, in complex decision environments such as common stock selection.

In an environment where decisions regarding stock selection are to be made, investors are distributed globally. This community is not controlled centrally, and each investor independently chooses his or her portfolio. Each investor has a local database storing a personal stock portfolio representing his or her personal knowledge and judgment of selected stocks. In addition, investors tend to share their knowledge to improve the quality of their decision processes in making portfolio selection (e.g., see investor community at www.ETRADE.COM). Thus, the environment where decisions regarding stock selection are to be made can be regarded as a society of autonomous investors who tend to share knowledge to improve decision-making. Let us assume that there are N agents (serving N investors), and that agent A1 wants to know if others could recommend a stock similar to IBM. Thus, A1 sends a message to other agents. Other Agents (A2 … An) search their own portfolio (case-base) and select similar stocks. These selections are sent back to agent A1. After receiving all the responses, A1 is in a position to assess them and select those that best match IBM stock. This is an acceptable process as long as there is no cost involved in sending, receiving and processing data. However, cost must be minimized in a "real world" business environment. Thus, to minimize cost, let us assume that A1 would like to send its message to a subset of agents which are most likely to give a good response within the shortest time. We call these agents "buddy-agents of A1." In the next section, we present a methodology for selecting buddy-agents.

## 4. Objective of this Research

In this research, we propose a methodology to assess buddy-agents in a distributed multi-agent system that supports ill-structured decision problems. Our basic premise is the desire of decision makers to understand and share knowledge [Bordetsky and Mark 2000]. This can be as simple as asking the address of a restaurant that is famous for its special Chinese seafood in Metropolitan Toronto. Another example could be tapping into a review of books such as those offered by Amazon.com. An equally complex task is sharing knowledge of our stock portfolio. Internet sites such as www.ETRADE.COM try to support this sharing through a chat group facility.

Our basic assumption is that a message sent by agent A1 to find stocks similar to IBM is best answered by agents of those investors whose portfolio (case-base) is "more" similar to the portfolio represented by agent A1. The objective of this research is to identify agents (buddies) who can best respond to the request of another agent. This is based on the assumption that in order to solve a new problem, one should first try using methods similar to those that have worked in similar problems. This is called the "reinforcement learning" model [Minsky 1995]. Reinforcement learning occurs when some aspects of the behavior of a system become more (or less) prominent as a consequence of the application of a "reinforcement operator" Z (See Figure 3). In response to a stimulus from the environment, the "reinforcement model" chooses one of several possible responses. It remembers what decisions were made in selecting this response. Shortly thereafter, the Trainer (decision-maker) sends the model positive or negative reinforcement signals.

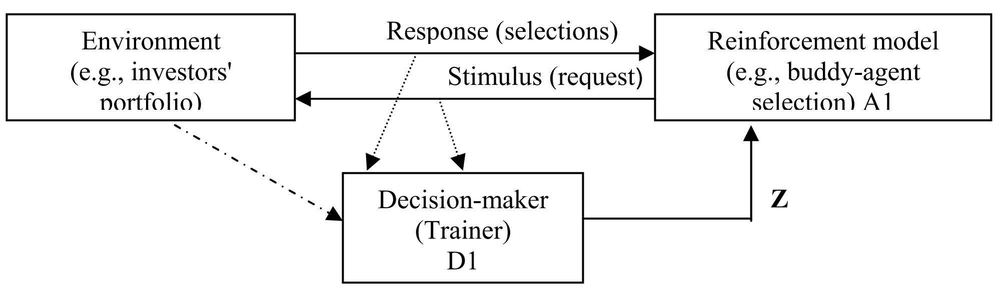


Figure 3: Reinforcement Learning Model

In response to a request from the decision-maker D1, and following the reinforcement learning model, agent A1 sends messages to a number of other agents seeking to satisfy the request from D1. Next, the responses of other agents are presented to decision-maker D1. The decision-maker D1 sends agent A1 his or her degree of satisfaction (i.e., positive or negative reinforcement signal) for each response received. The agent (reinforcement operator) does not initiate behavior, but merely selects from the responses received what the decision-maker likes.

Our proposed methodology, to assess the degree of membership of buddy-agent, is based on fuzzy-set modeling. The objective is to select a group of most similar agents (i.e., buddy-agents) that are expected to meet a set of criteria in responding to a request from an agent. The notion of being someone's "buddy" is rather vague. Someone could be classified as either a buddy or a non-buddy, depending on the degree of similarity of interests. Thus, we use Zadeh's *fuzzy set* theory to assess the degree of membership of buddy agents. Here, "a fuzzy set may be regarded as a class in which there is a gradual progression from membership to non-membership or, more precisely, in which an object may have a degree of membership lying somewhere between unity (full membership) and zero (non-membership)" [Zadeh 1965]. The buddy membership could be calculated on the basis of a set of criteria governing response to a request.

Let us assume that the two criteria governing a request for the selection of stock are as follows:

(1) Response time (T): Length of time it takes for each agent to respond to a request. Therefore, an agent tends to select buddies that respond quickly to its requests (i.e., T close to 0).

(2) Response quality (Q): The quality of the response (recommendation) received. This is the degree of match between the requested stock and the recommendations offered by an agent. We use a range 0-1, where 1 indicates a perfect match and 0 represents no match at all. Thus, the objective is to select agents as buddy-agents with Q close to 1. Response quality can be assessed directly by the decision-maker (using a variation of Likert-type scale), or by means of a closed-form model. In this research we used a closed-form model based on case-based reasoning techniques [Montazemi and Gupta 1997b] to assess the degree of match between the requested stock and the recommendations offered by an agent.

We used a variation of Yager fuzzy intersection [Cox 1999] to assess the value of goal attainment by each agent as follows:

- Identify goal attainment μ by agent x for each criterion using the following formula:

$$\mu\ (x) = \frac{1}{\left(1 + (x - a)^2\right)}$$

This formula is used to calculate the membership function of the vicinity ***x*** to its desired limit ***a*,** where ***x*** is a possible buddy-agent and ***a*** is the value of each criterion. Thus, the goal attainment for T (in which ***a*** is to take the lower limit of zero) and Q (in which ***a*** is to take the upper limit of 1) are derived as follows:

$$\mu\ (T) = \frac{1}{\left(1 + T^2\right)}$$

$$\mu\ (Q) = \frac{1}{\left(1 + (Q - 1)^2\right)}$$

Goal attainment j for all the agents is computed as follows:

$$(G_t\,(x_i))^{wt} = \{(x_1, \mu(t_1)), (x_2, \mu(t_2)), (x_3, \mu(t_3))\}^{wt}$$

$$(G_q\,(x_i))^{wq} = \{(x_1, \mu(q_1)), (x_2, \mu(q_2)), (x_3, \mu(q_3))\}^{wq}$$

where wt and wq are the weights assigned by the decision-maker with regard to the significance of the speed and quality of the buddy-agents' response. For example, a decision-maker may assign timeliness of response as wt=2.3, and quality of response as less significant, with a value of wq=1.2. The final membership value (D) for each agent is computed by the intersection of all the criteria that they should attain as follows:

$$D = \{[\ x_i, \min_j\ (\ G_j\ (x_i)^{wj})]\ \text{ where } i = 1,\ldots,n;\ j = t, q\}$$

Let us assume that the above decision-maker would like to identify two buddies out of four possible selections. Thus, the decision-maker's agent (Y) sends a request for information to all the other four agents (i.e., $x_i$ where i = 1, …,4). The response times of the four agents are as follows: $t_1$=5hours, $t_2$=2 hours, $t_3$=3 hours, and $t_4$=3 hours. The quality of information provided by each agent is assessed by the decision-maker on a nine-point Likert-type scale as follows: $q_1$=7, $q_2$=7, $q_3$=9, and $q_4$=6. After normalizing the value of t and q to be between 0 and 1, we get the following: $t_1$=1, $t_2$=0.4, $t_3$=0.6, $t_4$=0.6, $q_1$=0.8, $q_2$=0.8, $q_3$=1, and $q_4$=0.67. Next, based on the above formulae we can assess the degree of buddy-agent membership as follows:

$$\left(\tilde{G}_t(x_i)\right)^{2.3} = \{(x_1, 0.5^{2.3}), (x_2, 0.82^{2.3}), (x_3, 0.74^{2.3}), (x_4, 0.74^{2.3})\}$$
$$= \{(x_1, 0.20), (x_2, 0.63), (x_3, 0.50), (x_4, 0.50)\}$$

$$\left(\tilde{G}_q(x_i)\right)^{1.2} = \{(x_1, 0.96^{1.2}), (x_2, 0.96^{1.2}), (x_3, 0.50^{1.2})(x_4, 0.69^{1.2})\}$$
$$= \{(x_1, 0.95), (x_2, 0.95), (x_3, 0.44)(x_4, 0.64)\}$$

Then

$$D = \{(x_1, 0.20), (x_2, 0.63), (x_3, 0.44)(x_4, 0.50)\}$$

This indicates the degree of membership for $x_2 > x_4 > x_3 > x_1$. Thus, based on the limited number of four possible agents, the decision-maker may limit the choice to the top two selections as the preferred buddy-agents. This results in selecting $x_2$ and $x_4$ as buddies. Obviously, in a realistic peer-to-peer environment, such as music sharing, we have access to a large number of participants (agents), and that enables us to select a larger subset of them in the form of buddy agents

As the above formulae show, the goal attainment μ for all relatively unimportant goals (Wt, Wq <1) becomes larger, and for those goals with more important objectives (Wt, Wq >1) it becomes smaller. This has the effect of causing the membership function of the decision subset D (which is the minimum value of each X over all objectives) to be determined by the most important objectives. Our contention is that the proposed methodology can identify clusters of buddy-agents in a distributed environment. Thus, to assess its usefulness, the proposed methodology has to be compared with well-established cluster analysis, which is believed to be the most useful analytical tool available for organizing discrete units (e.g. consumers) into groups (i.e. segments) based on their similarities [Iacobucci at al. 2000, Knoke and Kuklinski 1982]. Cluster analysis organizes data with similar characteristics and identifies homogeneous clusters (groups) that are significantly different in a number of respects [Hyman and Shingler 1999].

Segmentation is key to marketing [Levin and Zahavi 2001]. Segmentation partitions the market into groups, or segments, of "like" people, with similar needs and characteristics [Levin and Zahavi 2001]. As a procedure that is appropriate for grouping objects (respondents) into groups (segments) [Gehrt and Shim 1998], cluster analysis is widely used to identify these like–minded customer segments [Gallagher and Mansour 2000, Gehrt and Shim 1998, Lin et al. 1999, March 1997]. The unsupervised classification of patterns (observations, data items, or features vectors) into groups (clusters) has wide applications in areas such as image segmentation, object and character recognition, document retrieval, and data mining [Jain et al. 1999, Kiang and Kumar 2001]. Cluster analysis organizes data with similar characteristics and identifies homogenous clusters or groups that are significantly different in various respects [Hyman and Shingler 1999]. As a well-established research method [Walsh et al. 2001], cluster analysis is the most useful analytical tool available for arranging discrete units (e.g., consumers) in groups (i.e., segments) according to their similarities [Iacobucci et al. 2000, Knoke and Kuklinski 1982].

Cluster analysis is a fundamental technique of unsupervised learning in machine learning and statistics [Duda and Hart 1973, Hartigan 1975]. In applying cluster analysis, the users have all the data in a database to measure the distance between data to form clusters with similar properties [Jain et al. 1999]. Therefore, we can use cluster analysis to find clusters of music lovers with similar music interests only if the music interests of the population are known in advance and are available in a database. However, complete availability of data in distributed and dynamic systems such as Internet is not possible. For example, music lovers use Napster in a distributed environment to share music with each other in a peer-to-peer mode. In this case, each individual music lover does not have access to the centralized data of all other music lovers. Therefore, a music lover cannot use cluster analysis to identify buddies (a cluster of other music lovers) with similar musical tastes. Our agent-based methodology is intended to help users find buddies even when there is no access to centralized data for clustering. Nonetheless, to use cluster analysis as a benchmark, we assume availability of a complete data set to test the following conjecture:

**There is no significant difference between the buddies (clusters) identified from the proposed methodology and the buddies derived from cluster analysis.**

## 5. Evaluation of the Methodology

The effectiveness of the methodologies for selecting the degree of membership of the buddy agents was assessed by means of two test scenarios. The first of these consisted of eight portfolios with different stocks. This test made it possible to measure our methodology under extreme conditions. Since different investors can carry the same stock in their portfolios, in our second test scenario of proposed methodology, we made sure that each portfolio had five stocks common to another portfolio closest to it (i.e., most similar to it). Section 5.1 describes the decision environment; Section 5.2 describes the tool developed for use in our investigation; Sections 5.3 and 5.4 present the experimental design used to assess the effectiveness of our proposed methodology.

### 5.1 Decision Environment

We developed a multi-agent system (MAS) to assist investors receiving (and providing) advice about stock market securities. The decision environment faced by an investor is ill-structured, so much so that security prices are posited to follow the random-walk hypothesis, which states that at any point in time the size and direction of the next price change is random with respect to the state of knowledge available at that time [Dyckman et al. 1975]. The major cause of this random behavior is caused by:

1. the large number of causal variables,
2. the fact that variables are highly stochastic, and
3. the unknown significance of causal relationships among the variables.

In addition, because of the very large number of stocks, an investor can cover only a small subset of stocks. This makes it highly desirable for investors to share their knowledge of specific stocks (see www.ETRADE.COM investor community). This decision environment resembles the society of minds as hypothesized by Minsky [1994], suitable for support by MAS because (1) decisions are distributed, (2) each decision-maker is autonomous, and (3) decision-makers need to share their knowledge to improve their own decision performance.

### 5.2 Tool

Using the methodology proposed in this research, we have developed an MAS which performs the following functions: (1) it enables the selection of buddy-agents, (2) it broadcasts the requirements of an investor for new stocks to other investors' agents, (3) it facilitates local comparison of stocks for selection of most similar stocks by means of distributed case-based reasoning systems (CBR), and (4) it ranks and presents stock information received from other agents. The procedures used in the development of the CBR systems was adopted from previous research [Gupta and Montazemi 1997, Montazemi & Gupta 1997b]. AGENTBUILDER software (see www.agentbuilder.com for details) was used in support of communication protocol among agents. An overview of the proposed system is provided in Figures 4 & 5.

### 5.3 Experimental Design for Test 1

The effectiveness of the methodologies used for selecting the degree of membership of the buddy-agents was assessed as follows:

I. Information about 5000 stocks was collected. Each stock was represented by the 17 financial attributes that are generally used to select stocks (See Table 2 below). Next, K-Means cluster analysis was used to identify eight groups of stocks with similar characteristics. K-Means cluster analysis attempts to identify relatively homogeneous groups of cases (e.g., stocks) based on selected characteristics (e.g., attributes used to represent a stock), using an algorithm that can handle large numbers of cases. However, the algorithm requires us to specify the number of clusters. Euclidean distances between the final cluster centers provide information about dissimilarities of the clusters: Greater distances between clusters correspond to greater dissimilarities (e.g., portfolio of stocks). This can be taken as the closeness of portfolios to each other or the degree of membership of one portfolio with others. Thus, we can use distance between clusters as a good benchmark for assessing the merits of our proposed assigning of buddy-agents membership.

   Stocks with the highest loading in each cluster were selected to represent the portfolio of an investor. We were limited to eight portfolios because there were eight microcomputers available to perform this experiment. Each microcomputer represented an investor with an assigned portfolio of stocks in the form of a case-base of a CBR system, and an agent to assist in the selection of stocks. Based on this, we selected eight clusters (portfolios), each with 48 stocks.

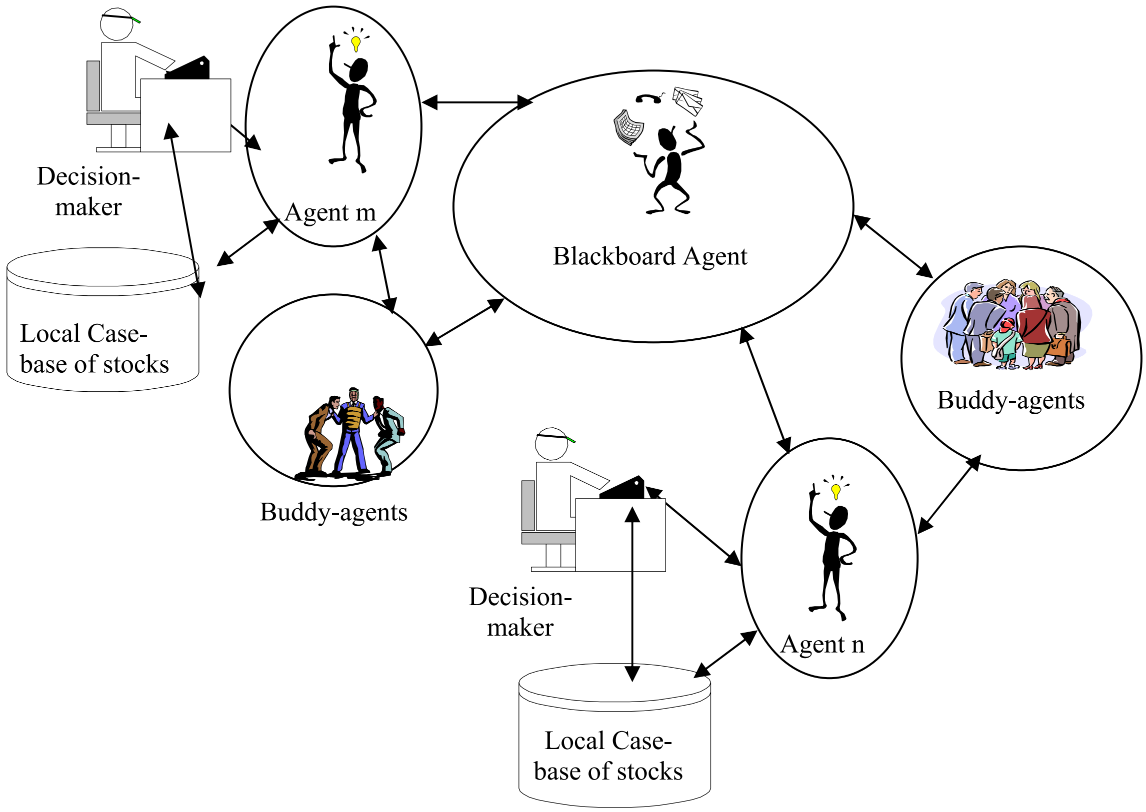


Figure 4: An Overview of the MAS using Buddy-Agents in Support of Common Stock Selection Blackboard agent's task is to identify the buddy-agents for each agent. A decision-maker's request for information is sent to by its agent to the buddy-agents, which then search their case-bases of stocks for best response.

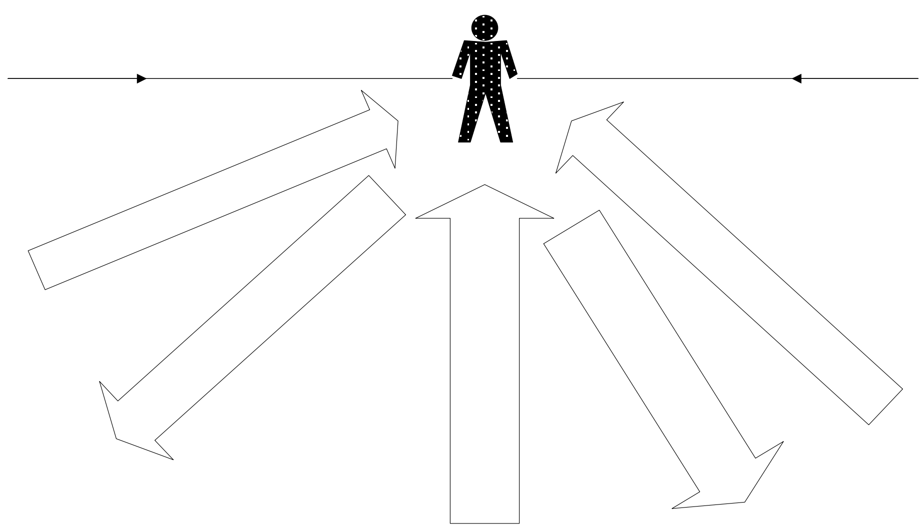

Figure 5: System Architecture of Blackboard Agent to Share Information among Buddy-Agents. Blackboard Agent acts as hub to Register a new Agent, identify its buddy-agents and enable communication among buddy agents.

Table 2: Attributes used to represent selected stocks

| Abbreviation | Definition |
|---|---|
| Ask | Latest asking price. |
| Bid | Latest bid price. |
| Dividend | Annual dividend payment representing either the latest fiscal year or indicated annual rate based on the most recently announced dividend payments. |
| Earning | Annual earnings per share representing either the latest fiscal year or indicated annual rate based on the most recent published earnings. |
| Last | Last trade price or value. |
| Net change | Difference between latest trading price or value, and the historic closing value or settlement price. |
| Opening Price | Today's opening price or value. |
| PE Ratio | Ratio of stock price to earnings per share. |
| Percent change | Percentage changes from the latest trade price or value from the historic close. |
| Today's high | Today's highest transaction value. |
| Today's low | Today's lowest transaction value. |
| Year high | Highest value of the year. |
| Year low | Lowest value of the year. |
| Yield | For equities, dividend per share expressed as a percentage of the price. |
| Last | Last trade price or value. |
| Historic close | Most recent non-zero closing value or settlement price. |
| Trade volume | Transactional volume of the trade price reported in the Last field. |

II. The multi-agents system was used to assess the degree of membership of agents. This was achieved by having each of the eight agents request recommendations about 48 stocks similar to those in its case-base. The “quality of the response” (computed by means of CBR methodology) received from agents was used to compute the degree of membership of remaining agents (i.e., seven buddies) for each agent.

III. Kendall’s Tau methodology was used to test the stated conjecture (i.e., that there is no significant difference between the buddies identified from the proposed methodology and buddies derived from cluster analysis).

5.4 Experimental Design for Test 2

The experimental design for this test was the same as for Test 1, except that we added five stocks from each portfolio to another one that was closest to it. For example, if the stocks of portfolio 1 were close to the stocks of portfolio 8, we added 5 of the stocks from portfolio 8 to portfolio 1. Our assumption was that the same stocks could be shared between two portfolios that were most similar to each other.

## 6. Analysis

The objective of testing the MAS was to determine the effectiveness of the proposed methodology in assessing the degree of membership of the buddy-agents. To this end, 5000 stocks were selected and financial data for each stock were collected. Cluster analysis identified eight stock-clusters among the 5000 stocks selected, based on the 17 financial attributes described in Table 2. The data for each cluster were saved in the case-base of a CBR system to represent the portfolio of an investor. Next, 48 requests were generated from each case-base. The MAS was responsible for sending the requests to other agents and returning the responses to the requesting agents. Here, we used the “quality of response” (computed here by our CBR methodology for each CBR portfolio) as our only criterion for assessing the degree of membership of the agents. The reason for ignoring other attributes, such as response time, is that our basis for assessing the merits of computed membership was its comparison with the distance between clusters. Our contention is that the merits of our proposed buddy-agents membership model can be assessed by comparing it with the distance between clusters. The correlation between the membership ranking of the two methods (the distance between clusters and our proposed method) shows that the two types of assessments are correlated (Kendall’s tau = 0.313) as shown in Table 3. Therefore, the stated conjecture cannot be rejected.

Table 3: Correlation Between the Agent Rank Order of Buddy-Agents and the Distance Between Clusters of Portfolios

| | | | Agent | Cluster |
|---|---|---|---|---|
| Kendall's tau_b | Agent | Correlation Coefficient | 1.00 | 0.313** |
| | | Sig. (2-tailed) | . | 0.002 |
| | | N | 56 | 56 |
| | Cluster | Correlation Coefficient | 0.313** | 1.00 |
| | | Sig. (2-tailed) | 0.002 | . |
| | | N | 56 | 56 |

** Correlation is significant at the 0.01 level (2-tailed)

The second test scenario was conducted in the same manner as the first one, except for the addition of five stocks from one portfolio to the portfolio closest to it. Therefore, we had 53 stocks in each portfolio after adding five stocks to the original 48-stock portfolio. We recomputed the distance matrix between these new sets of portfolios and used them as a proxy for the closeness of the portfolios.

Data about the characteristics of stocks for each new portfolio were also saved in a case-base of a CBR system to represent the portfolio of an investor. Next, 53 requests were generated from each case-base. Our MAS was responsible for sending the requests to other agents and returning the responses to the requesting agents.

The correlation between membership ranking of two methods (distance between new portfolios and our proposed method) shows that the two types of assessments are correlated (Kendall's tau = 0.601 ($p < 0.01$)). This indicates that our proposed model for assessing membership of the buddy agents works well when there are overlaps between portfolios of investors. This test also shows that our stated conjecture cannot be rejected. It should be noted that correlation between the buddy-agent methodology and cluster analysis is stronger for test 2. This is to be expected because test 1 was performed under an extreme condition in which all portfolios had different stocks. As stocks within portfolios become more similar to each other, the buddy agent membership gets closer to 1, and distance between clusters is reduced. Therefore, under another extreme condition in which all the portfolios are the same, the two methodologies of buddy agent and cluster analysis would correlate to 1.

## 7. Concluding Remarks

Agent technology is believed to be an effective way to reduce decision-makers' information overload. By delegating tasks to agent systems, decision-makers save not only time and energy, but also increase their opportunities to access valuable information and work on more complex and creative jobs. To communicate effectively, each agent in a multi-agent system needs to know the characteristics of the other agents that can best serve its requirements. In this paper, we proposed a methodology to assess the degree of membership of buddy-agents. This methodology is based on fuzzy-set modeling. The objective is to select buddy-agents that are expected to meet a set of criteria in responding to a request. The stated conjecture, based on our test results, could not be rejected: **There is no significant difference between the buddies (clusters) identified from the proposed methodology and the buddies derived from cluster analysis.** Nonetheless, we cannot use cluster analysis to assess the agent-membership in a large and dynamic decision environment because cluster analysis requires all the records (data) to be available prior to computation of the clusters. In reality, however, this is not possible because of the following conditions:

a. We do not know about all the records at once (i.e., records are distributed throughout the system), and agents (decision-makers) either join or leave the system without warning.
b. The nature of each portfolio (e.g., type of stocks) can change without warning.
c. The number of possible agents could be in the millions, thus making the complete portfolio too huge to perform cluster analysis as soon as a change is made to each local portfolio.

Our proposed methodology takes the dynamic nature of the decision environment into account. It is based on the following premises:

a. The degree of closeness between two portfolios is based on nature of records (e.g., stocks) at any point in time.
b. Assessment of the relationship between two portfolios does not require knowledge about all the portfolios in the system.
c. The degree of closeness among agents is based on interactions between pairs, thus making the assessment of degrees of closeness among agents computationally feasible.

d. We can use as many dimensions (e.g., quality of response time, response quality, cost of response, characteristics of decision-maker) as may be required to assess buddy-agent memberships by means of the proposed methodology. This is not easily possible with cluster analysis.

### 7.1 Implications for Practice

The Internet has created an enormous amount of business opportunities for electronic commerce. Web-based businesses are becoming increasingly popular and Internet users have become fast-growing groups that form a promising market [Liang and Huang 2000]. We can purchase a variety of goods and services such as flowers, books, and automobiles on-line. However, searching through thousands of possible sites is time-consuming and frustrating.

A popular research effort in helping to find like-minded people (buddies) in communities is collaborative filtering. Collaborative filtering provides computer-based support for the forwarding of information to others who might be interested in the information [Maltz and Ehrlich 1995]. Collaborative filtering is used in a large number of on-line companies, such as Amazon (www.amazon.com) and Moviecritic (www.moviecritic.com) [Good et al. 1999]. In collaborative filtering, the subjects are requested to evaluate different items. The highest level of overlap based on their evaluation of various items indicates that these subjects have similar interests (i.e., they are buddies) [Hayes et al. 2001, Maltz and Ehrlich 1995]. However, collaborative filtering has two major limitations. First, only users with the highest level of exact overlap would be considered as buddies [Hayes et al. 2001]. Thus, people who like similar songs are not considered buddies. Secondly, collaborative filtering is based on a centralized database, making it impractical for distributed systems.

The methodology presented in this paper represents a significant improvement over collaborative filtering by enabling us to identify buddies with similar tastes in a distributed decision-making environment.

### 7.2 Implications for Research

The contribution of our proposed methodology to literature is in the agent- coordination strategy in support of multi-agent systems. Since there is no middle agent in a decentralized control structure, agents use an acquaintance list and communicate only with a small subset of agents [Sikora and Shaw 1998]. Getting the right team of agents and controlling them is of prime importance in the decentralized control structure for a large number of users [Dignum et al. 2001]. As stated earlier, the existing acquaintance structure of agent coordination is fixed, which means the agent-system builders need to create the acquaintance list when they are implementing the multi-agent system. This constraint is relaxed in our proposed methodology. While the results of empirical tests of our proposed methodology are encouraging, there are still some limitations as follows:

One limitation of our methodology is that when the number of buddy-agents goes below a certain threshold, then a request has to be sent to all the other agents to recruit new buddy-agents. To elaborate on this, let us assume that a decision-maker D1 is interested in receiving common stock recommendations from at least 10 other like-minded investors. The decision-maker believes this minimum threshold is necessary to receive enough good recommendations on the kinds of stocks he or she likes. Furthermore, let us assume that it is possible to find 15 like-minded investors who are prepared to act as buddies. Over a period of time, however, the stock portfolio of seven of these buddies may diverge from D1 (i.e., their buddy-membership becomes too low for them to be considered as D1's buddies). At this point, decision maker D1 has to find at least two new like-minded investors to make sure that the minimum threshold of 10 is reached. These two new investors have to be selected from the pool of all other available investors. This could be inefficient, since computing workload increases proportionally as the number of agents increases. Future research should identify methodologies that utilize information about the buddy-agents of the requesting agents to assess new buddy-agents' membership.

Another issue in need of attention is selection procedures for responding to a request. We used a first-in-first-out (FIFO) procedure by a responding agent to serve the requesting agents in the queue. This was of no concern for our test environment in which there were only seven requesting agents. However, in the "real environment" of hundreds of requesting agents, FIFO can be an inefficient procedure since it is based on the assumption that is equally likely to give valuable recommendations to all requesting agents. Hence, we believe the Markov decision-process model [Sutton and Barto 1998] may provide a better procedure for serving requests from buddy-agents in the real world.

The issue of trust among buddy-agents to share information is another important research topic in need of further attention. Users in on-line communities build trust with each other mainly by cooperative interactions through message boards [Hoffman et al. 1999, Ridings et al. 2002]. However, when using our proposed buddy-finding methodology, the users would receive the recommended buddies directly from agents without interaction through a message board. Consequently, a lack of prior interactions between the users and the recommended buddies might influence the users' confidence in the usefulness of the recommended agent-found buddies. Research findings indicate that it is indeed possible to create trust between users without prior interactions [Ba and Pavlov 2002]. For example, in an on-line community, on-line feedback mechanisms help build trust among users by allowing them to rate the quality of the service [Ba and Pavlov 2002]. Developing a feedback mechanism to help users build trust in the agent- recommended buddies is another empirical research issue that we intend to pursue in the future.

Finally, our stated conjecture was tested in only one domain. There are hundreds of potential application domains for knowledge sharing that benefit greatly from using our multi-agent buddy-finding approach. Application of the proposed methodology needs to be assessed in other domains such as (1) sharing complex medical knowledge within the communities of common interest, (2) sharing problem-solving skills among software developers, and (3) sharing socio-political views among citizens with similar interests

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