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Anil Gurung
University of Texas at Arlington, gurung@uta.edu

Riyaz T. Sikora
University of Texas at Arlington, rsikora@uta.edu

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Anil Gurung
Dept. of Information Systems
Univ. of Texas at Arlington
P.O. Box 19437, Arlington, TX 76019
gurung@uta.edu

Riyaz T. Sikora
Dept. of Information Systems
Univ. of Texas at Arlington
P.O. Box 19437, Arlington, TX 76019
rsikora@uta.edu

ABSTRACT
Multiagent systems (MAS), long studied in artificial intelligence, have recently become popular in mainstream IS research. This resurgence in MAS research can be attributed to two phenomena: the spread of concurrent and distributed computing with the advent of the web; and a deeper integration of computing into organizations and the lives of people, which has led to increasing collaborations among large collections of interacting people and large groups of interacting machines. However, it is next to impossible to correctly and completely specify these systems a priori, especially in complex environments. The only feasible way of coping with this problem is to endow the agents with learning, i.e., an ability to improve their individual and/or system performance with time. Learning in MAS has therefore become one of the important areas of research within MAS. In this paper we present a survey of important contributions made by IS researchers to the field of learning in MAS, and present directions for future research in this area.

Keywords
Multiagent systems, Multiagent learning, Coordination.

INTRODUCTION
Multi-Agent Systems (MAS) can typically become very complex and their behaviors can be hard to specify. Since, by definition, a MAS consists of a group of autonomous agents, one of the key challenges in designing a MAS is coordinating the actions of the agents. In a dynamic environment where the actions of the agents are also interdependent on each other, it is especially critical that the agents learn to adapt their actions to the actions of other agents. This dependence makes learning in MAS more difficult than single agent learning (Banerjee et al., 2004). Furthermore, when designing agent systems it is impossible to foresee all the potential situations an agent may encounter and define behavioral repertoires and activities optimally in advance. Agents therefore have to learn from, and adapt to, their environment, especially in a multi-agent setting.

Until recently, research in the field of machine learning (ML) mainly concentrated on learning techniques and methods in single-agent or isolated-system settings. More and more, ML is being explored as a vital component to address challenges in multi-agent systems (Weiss and Sen, 1996). For example, many application domains are envisioned in which teams of software agents or robots learn to cooperate amongst each other and with human beings to achieve global objectives. Learning may also be essential in many non-cooperative domains such as economics and finance, where classical game-theoretic solutions are either infeasible or inappropriate. Today the area of learning in MAS receives broad and steadily increasing attention. This is also reflected by the growing number of publications in this area; see (Huhns and Weiss, 1998; Imam, 1996; Sen, 1998; Weiss, 1998)for collections of papers related to learning in MAS.

At the same time, multi-agent learning poses significant theoretical challenges, particularly in understanding how agents can learn and adapt in the presence of other agents that are simultaneously learning and adapting. This is a fertile area of research that seems ripe for progress: the numerous and significant theoretical developments of the 1990s, in fields such as Bayesian, game-theoretic, decision-theoretic, and evolutionary learning, can now be extended to more challenging multi-agent scenarios (Weiss, 1999).

The importance of learning for multiagent systems is inherent for two reasons. Multiagent are located in distributed environments where they have limited information. In such environments, it is difficult to predict what conditions will prevail in the future, which agents will be available at the desired time, and how the agents need to interact on those emerging conditions (Sen and Weiss, 1999). The second reason is that the learning in multiagent systems implies both the individual learning and the group learning as a system. For e.g., Ho and Kamel (1998) investigate how individual and group learning can be combined to achieve coordination among multiple agents.

Learning in MAS has therefore become one of the important areas of research within MAS. In this paper we present a survey of important contributions made by IS researchers to the field of learning in MAS, and present directions for future research in this area. We are mainly interested in applications of learning in multi-agent information systems to realistic business problems. While computer science related research has been focused on developing algorithmic capabilities, the IS related research on MAS is explicitly focused on business problems. We hope to achieve two main objectives with this exercise. First, this paper will systematically collate the past IS literature in multi-agent learning into different research streams that will contribute to the body of knowledge. Second, the issues within each research stream will be discussed so as to provide researchers with guidelines and directions for future work.

LEARNING THEORIES

Learning has long been studied in psychology, anthropology and biology. Most of the prior work in psychology defines learning as a change in behavior based on the works of Pavlov, Skinner, Thorndike, Watson, Guthrie, Hull and Tolman (Smith, 1999). This definition suggests learning as an outcome or the end result of some process. Other orientations to learning are Cognitivist (i.e. Lewin, Bruner, Koffka, Kohler), Humanist (i.e. Maslow, Rogers), Social and Situational (i.e. Bandura, Lave and Wenger, Salomon). Merriam and Caffarella (1999) provide a good overview of learning theories. Psychologists consider learning as a social activity involving other agents. There has been an increased interest in developing agents and learning algorithms that consider social issues and learning in social environments (Alonso et al., 2001; Conte and Paolucci, 2001). In social learning the learning agent updates its own knowledge base (adding to, or removing from it a given information, or modifying an existing representation) by perceiving the positive or negative effects of any given event undergone or actively produced by another agent on a state of the world in which the learning agent has as a goal (Conte and Paolucci, 2001). In other words, the agents can learn by observing the behavior of other agents. An elementary type of social learning known as social facilitation is a mechanism that allows agents to update their knowledge by observing others, their behaviors, and possibly by inferring their mental states. This implies that agents can learn by creating mental models of other agents. To enact social learning in multiagent systems the agents need to possess mechanisms by which they can construct new decision functions, modify existing ones in order to satisfy new or modified goals or adapt to changing conditions in their environment (Morikawa et al., 2001). This suggests that agents can learn by adapting to their environment as well as learning new knowledge regarding the decision functions or goals. Prior work on learning in multiagent systems considers communication and coordination as essential part of learning. Communication in agents is required for the development of "common and shared meanings of symbols" that is considered an essential task in multiagent learning (Sen and Weiss, 1999). Based on the above discussion, we classify learning in multi-agent systems into the following categories: learning to model other agents, learning for communication and coordination, learning a behavior or strategy, learning to adapt and learning new knowledge. In the next section we present a literature survey of MAS learning and classify the articles based on the above categories.

RESEARCH STREAMS ON LEARNING IN MULTIAGENT SYSTEMS

After doing an extensive literature search, we created a short list of 35 relevant articles published in the last decade on learning in MAS. The articles came from various IS related journals such as Decision Support Systems, Journal of Management Information Systems, Decision Sciences, Management Science, Journal of Experimental & Theoretical Artificial Intelligence, Machine Learning, International Journal of Human-Computer Studies, and Intl Journal of Cooperative Information Systems. Articles were selected based on their IS orientation which essentially meant focusing on articles that have practical implications in terms of solving business problems. The journals were selected for being popular outlets of IS researchers working on multi-agent systems. Non-IS journals were selected for their orientation towards dealing with business problems. 11 out of 35 articles were obtained from Decision Support Systems. These articles were published from 1995 to 2005. Table 1 presents the break down of the number of articles by journal name. These articles on multiagent learning can be broadly classified into the five categories mentioned earlier.

The first category involves the learning in modeling other agents. Modeling other agents becomes crucial in complex environments where there are many attributes and very little information available to predict the actions of agents (Tambe et al., 1998). We have observed that modeling of other agents is done for the following reasons: for keeping track of other agents' mental states such as goals beliefs and intentions (Tambe et al., 1998); coordinate multiple agents by creating models of other agents (Ramos et al., 2003); and forming a strategic learning strategy which requires building a model of responses of other agents (Wellman and Hu, 1998).

Journal	Articles count
Decision Support Systems	11
Journal of Management Information Systems	1
Decision Sciences	1
Management Science	1
Journal of Experimental & Theoretical Artificial Intelligence	5
Machine Learning	6
International Journal of Human Computer Studies	7
International Journal of Cooperative Information Systems	3
Total	35

Table 1. Sources of Survey Articles

The second category relates to learning in communication and coordination of agents. Most of the articles in this section are concerned with agent interactions in ecommerce. One way of facilitating coordination in distributed environment with limited information is developing proper communication protocols for agent interaction. Some of the related work involves developing communication protocols in auctions (Iwasaki et al., 2005) and using communication to reduce locality of the agents (Mataric, 1998). Communication may not be the suitable method for agent coordination if the communications cost run high. Bui et al (1999) added a Bayesian classifier as a learning module in the negotiation agent architecture and showed the use of learning to complement communication in acquiring knowledge about other agents.

The third category describes the learning that takes place in choosing a strategy for multiagent interactions. The papers included in this category fall into two distinct domains – ecommerce and games. Various strategies are adopted when agents buy and sell in market interactions (Cheng et al 2005; Valluri and Crosnan 2005; Cai and Wurman 2005; Oliver 1998). In game playing domain multiagent researchers have shown how agents learn to adopt different strategies (Sałustowicz et al., 1998; Sheppard, 1998; Stone and Veloso, 1998).

The fourth category discusses multiagent learning that is needed to adapt to complex environment. Adaptation is one of the key concerns in multiagent learning. Surprisingly, only few papers (Natter, 2001; Sen et al., 1998) were found in this category in spite of its importance.

The last category of multiagent learning includes agent enhanced search engines and decision support systems (DSS). Multi-agent based search engines are used to learn new knowledge about customer preferences and retrieve information that is relevant to user queries (Menczer, 2003; Yuan, 2003). Researchers in the field of DSS have adopted multiagent paradigm where group of agents work collaboratively to solve problems (Chi and Turban, 1995; Prasad et al., 1998).

Table 2 presents the categorization of the literature on multi-agent learning studied in this paper. The following sections present briefly describe the papers included in each category. We focus primarily on research issues on each category and the related research work that has been carried out. We then chart out future directions to be explored in multiagent research.

Category	Relevant articles
Learning to model	Wellman & Junling (1998), Vidal & Durfee (1998), Haynes & Sen (1998), Tambe et al (1998), Ramos et al (2003)
Learning for communication and coordination	Mataric (1998), Crites & Barto (1998), Sugawara & Lesser (1998), Ho & Kamel (1998), Sen & Sekaran (1998), Carmel & Markovitch (1998), Bhattacharya & Koehler (1998), Bui et al (1999), Wu & Sun (2002), Kimbrough et al (2002), Iwasaki et al (2005)
Learning a behavior or strategy	Oliver (1996), Sheppard (1998), Salustowicz et al (1998), Bichhieri et al (1998), Stone & Veloso (1998), Zeng & Sycara (1998), Banerjee et al (2004), Bandyopadhyay et al (2005), Cheng et al (2005), Cai & Wurman (2005), Valluri & Crosnan (2005)
Learning to adapt	Sen et al (1998), Natter et al (2001)
Learning new knowledge	Chi & Turban (1995), Prasad et al (1998), Delgado & Ishii (2001), (2001)), Menczer (2003), Yuan (2003)

Table 2. Categorization of MAS literature on learning

Learning to Model

The question of whether to model other agents is an important issue in multiagent research. Agents can be differentiated based on their modeling of other agents (Vidal and Durfee, 1998). The 0-level agents learn everything from their own observations and interactions with the environment. Agents with 1-level models recognize the existence of other agents in the environment but they do not know the mental processes of the other agents. Such agents model others by observing the past behavior of other agents and trying to predict their future actions. Agents with 2-level models use intentional models that correspond to the functions used by agents that use 1-level models.

Vidal and Durfee (1998) examine the relationship between strategic behavior and learning in multiagent economies. They describe an approach by which an agent can achieve strategic behavior by learning and using other agents' models. Modeling other agents incurs a cost and the choice of doing so depends upon the amount of expected benefits from modeling. Conflicting situations in the dynamic world of ecommerce pose problems in negotiation. Issues that arise are how to model the agents so as to form strategies to improve the system performance. Ramos et al (2003) suggests using modeling collaborative strategies in a soccer match to resolve disputes in B2B negotiation. The agents described in this paper are using 1-level models. They use Q-learning model to evaluate the risk and utility of a given action in any situation. Using this model, each agent would assess the contribution of other agents involved in the action.

Multiple agent coordination can be enhanced if there is some mechanism to keep track of the agents in the environment. Interactions in multiagent domain requires an agent to track other agents' mental states such as their goals, beliefs and intentions (Tambe et al., 1998). As such, the accuracy of the agent's model of the tracked agent is critical. When learning takes place in agents the environment changes as one agent can not know what the other agent has learned. Adaptive agent tracking (i.e. 1-level model) attempts to deal with this problem by adapting the model of the tracked agent. Authors introduce an approach based on discrimination-based learning known as discrimination-based explanation focused (DEFT) tracking. The learning activity of an agent affects other agents because it requires them to constantly update their knowledge. Question one may ask is: how do multiagent systems reach a position where all the agents have knowledge about all other agents? A concept of conjectural equilibrium, as proposed by Wellman and Hu (1998), is the condition where the expectations of all agents are realized and each agent responds optimally to its expectations.

Some of the research issues that need to be addressed in this stream are: how do agents decide whether to take strategic action or follow market mechanism; how to model other agents in complex environment; does modeling strategies differ in long and short term interaction between agents; in long term interaction what sort of implications does trust-building between agents have. As the environment changes, the roles of the agents may change. How do dynamic evolving equilibriums affect agent modeling? How do modeling agents keep their models of other agents current?

Learning for Communication and Coordination

The multiagent environment has inherent problem of hidden state and credit assignment distribution. In distributed environment it is hard for agents to sense out all the information necessary to complete a given task. When agents positively affect the system their actions should be rewarded as a part of reinforcement learning.

Mataric (1998) describes how agents in a MAS with only local knowledge use communication by applying local undirected broadcast communication in a dual role of sensing and reinforcement. Crites and Bartow (1998) show that cooperation can be learned indirectly on the basis of the global reinforcement signal that is provided to the overall team. The emerging markets of ecommerce pose designing problems to promote cooperation and coordination among bidding agents. Some of the important issues here are: how to enhance cooperation among independent agents; and what kind of coordination mechanism to implement. Iwasaki et al (2005) propose a new ascending-price multi unit auction protocol. Wu and Sun (2002) examine the behavior of a learning agent in the framework of social trust and demonstrates that the agent learning helps to cooperate over time.

A coordination strategy for a context may not be suitable for other contexts. Sugawara and Lesser (1998) focus on how agents in multiagent systems can learn to identify the information that is needed to improve coordination in specific problem-solving contexts. They discuss an approach to learning situation-specific control rules that helps the agents to identify and avoid uncoordinated situations. Various authors have investigated the problem of coordination in multiagent systems (Bhattacharyya and Koehler, 1998; Bui et al., 1999; Crites and Barto, 1998; Kimbrough et al., 2002; Sen et al., 1998; Sugawara and Lesser, 1998; Wellman and Hu, 1998; Wu and Sun, 2002; Zeng and Sycara, 1998). Carmel and Markovitch (1998) present a game and automata theoretic approach to improve the coordination on the basis of model based and experience based learning. Sen and Sekaran (1998) demonstrated that agents can consistently develop effective policies to coordinate their actions without explicit information sharing.

Some of the important research issues that need to be addressed are: how to deal with the problem of credit assignment distribution when it is difficult to provide the reward locally to the agents based on their impact at global level; what kind of coordination problems may arise as the number of agents increase in multi-agent systems; what mechanisms can be used in auction protocols for making combinatorial bidding; how to learn behavior of other agents using effective communication.

Learning a Behavior or Strategy

Learning in contexts of strategic interaction has also received a lot of attention. Bandyopadhyay et al (2005) present a two seller game where agents use a reinforcement learning algorithm to change their pricing strategy over time. Cheng et al (2005) present decision-analytic strategy for bidding where each action is based on an explicit optimization with respect to its model assumptions. Valluri and Crosnan (2005) use reinforcement learning with q-learning to select from a group of suppliers. Cai and Wurman (2005) describe a multi-agent system where the agents bid strategically using learning about other bidders' previous valuations.

Most of the multiagent learning considers learning in one agent or group of agents which are pitted against another agent or group of agents. Sheppard (1998) develops algorithms for co-learning in which all agents attempt to learn their optimal strategies simultaneously. Two approaches to co-learning are taken – memory based reinforcement learning agent and a tree based reinforcement learning agent.

Predicting what type of behavior will emerge amongst agents in MAS is hard to determine. Therefore, it is always challenging for system designers to determine optimal strategies for multi-agent interactions. Bichhieri et al (1998) concentrate on the use of genetic algorithms to generate preferred strategy. Using genetic algorithms, Oliver (1996) show that multiple agents can learn strategies that enable them to take part in business negotiations. Multi-agent learning can also take place at different levels. Stone and Veloso (1998) propose a layered learning paradigm using neural network based learning scheme where lower level learned behaviors are used to learn higher level behaviors and strategies.

Learning to Adapt

The dynamism of the environment implies that agents in MAS must exhibit some sort of adaptive behavior. The changes in the environment may be due to limited resources, reinforcement learning, new agents joining the system, and changing goals.

Having access to too much information or having a wider global view may not always be desirable for multiagent coordination. Sen et al (1998) found that the agents with a limited global view converged faster to optimal states. This suggests that agents adapt themselves in the limited information scenario to reach a state of equilibrium. Learning to adapt to new behavior, new environment has connotations of a longer term period rather than a short time period. While simulating the behavior of real world with artificial agents more realistic results can be obtained if the artificial agents are modeled in the realistic view of the real agents. It is pertinent to the goal of agent based simulation that the agents should be modeled as bounded rational agents. Natter et al (2001) demonstrate how connectionist models can be used to simulate the adaptive nature of agents' learning that is similar to experienced learning curves.

Important research questions that arise in this area are: how do agents adapt to the changing environment; does increased communication that result in more information help for adaptation; what kind of agent modeling is needed to represent real world scenarios; can business simulations be designed realistically by the use of advanced adaptive mechanisms such as genetic algorithms?

Learning New Knowledge

Multiagent systems provide an effective means to learn new knowledge. We are observing the growth of multiagent systems for searching for information on the web and for complementing decision support systems. Menczer (2003) proposes a multiagent system that supports web mining by using reinforcement learning to compare the relevance of information. Yuan (2003) uses reinforcement learning with value approximation in their personalized comparison-shopping engine to get a better understanding of user preferences.

Recommender systems provide suggestions about relevant information that the users are searching based on their previous stored preferences. Agent based recommender systems with multiagent systems have been developed which calculates their predictive function based on preferences of its users and that of other agents' users. Delgado and Ishii (2001) propose a compound algorithm for each learning agent by combining memory-based individual prediction and online weighted-majority voting.

The research work on agent based decision support systems illustrate how a group of cooperative agents are organized to learn to play different roles to work together effectively. Prasad et al (1998) show how agents can learn situation-specific roles to facilitate group problem solving. They use reinforcement learning where agents learn from their experience to choose appropriate roles in contributing to an evolving design. Chi and Turban (1995) present a framework for distributed intelligent executive information system where various agents work together for collaborative information processing. Their framework includes learning agents that are capable to learn new knowledge by various methods such as induction, deduction and similarity-based techniques.

Some important issues to deal with are as follows: how to incorporate feedback mechanisms in multiagent based search engines to enhance the quality of information retrieved; how to improve environment scanning in agent based executive information systems; how do agents determine the relevancy of the search results; how to coordinate the actions of independent search agents.

CONCLUSION

Learning in multiagent systems is an interesting and fertile area of research. The growing popularity of multiagent systems fueled by the rise of distributed computing has presented new vistas for MAS research. In this paper, we have categorized the literature on multiagent learning into five streams. The important findings within each research stream were summarized and issues for future work were identified.

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