A Trust Model for Supply Chain Management (Extended Abstract)

Yasaman Haghpanah
Department of Computer Science and Electrical Engineering
University of Maryland Baltimore County
1000 Hilltop Circle, Baltimore MD 21250
yasamanhj@umbc.edu

ABSTRACT

My thesis will contribute to the field of multi-agent systems by proposing a novel and formal trust-based decision model for supply chain management.

Categories and Subject Descriptors

I.2.11 [**Artificial Intelligence**]: Distributed Artificial Intelligence - *multiagent systems*

General Terms

Algorithms, Economics, Experimentation

Keywords

Trust, Reputation, Learning, Game theory, Bayesian updating

1. INTRODUCTION

Almost all societies need measures of trust in order for the individuals – agents or humans – within them to establish successful relationships with their partners. In Supply Chain Management (SCM), establishing trust improves the chances of a successful supply chain relationship, and increases the overall benefit to the agents involved.

There are two important sources of information in modeling trust: direct observations and reported observations. In general, direct observations are more reliable but can be expensive and time-consuming to obtain, while reported observations are cheaper and more readily available but are often less reliable. One problem with using reported observations is that when people are asked for their opinions about other people, they reply based on their own perceptions of those behaviors. Some people are realistic and honest, truthfully providing all of the information they have gained in their relationships with other people. Others tend to hide people's defects, or to report their observations with pessimism.

There are several factors or criteria at play in decision making in a supply chain. For example, in a simple buyer-seller relationship, product delivery, quality, and price can all be important criteria in the decision making of a buyer when trading an item. Therefore, trust can be defined not only for one factor but for multiple context-dependent factors. Current SCM trust models considering multiple factors are typically focused on specific industries or are ad hoc [2].

The Harsanyi Agents Pursuing Trust in Integrity and Competence (HAPTIC) model [4], a trust-based decision framework grounded in game theory is among the few existing trust models with a strong theoretical basis. HAPTIC models two key aspects of trust: *competence* (an agent's ability to carry out its intentions) and *integrity* (an agent's commitment to long-term cooperation) using direct observations. HAPTIC has been applied to the two-player Iterated Prisoner's Dilemma (IPD) setting, but has modified the classic IPD by scaling the payoff matrix using a random variable *multiplier*. As a result, the payoffs differ from one round to another. It has been proved that HAPTIC agents learn other agents' behaviors reliably, perform well in cooperating with a wide variety of players. One shortcoming of HAPTIC is that it does not support reported observations.

Various models have been developed that use reported observations, including BRS [6] and TRAVOS [5]. Both approaches construct Bayesian models; however, a drawback of these approaches is that a significant amount of information may be considered unreliable, and therefore is discarded or discounted. In contrast, BLADE [3], a Bayesian reputation framework, uses an approach for interpreting unfair ratings. However, this model relies heavily on reported observations.

2. APPROACH

I proposed a novel trust model for SCM [1]. This model incorporates multiple trust factors specific to SCM, and uses both direct and reported observations. My model is represented in probabilistic and utility-based terms. Using game theory, I build cooperative agents for SCM applications with uncertainties and dynamics.

My proposed SCM model consists of several layers in a supply network, where each layer contains a number of agents, which may correspond to suppliers, producers, distributors, or retailers. In general, upstream agents provide services (or offers) to adjacent downstream agents, and downstream agents ask for services or send requests for quotes to the adjacent upstream agents. In this model, I use variable payoffs for different services in different environments. Agents in this framework use a utility function to estimate the future reward that would result from working with a potential partner. This utility function is calculated based on the amount of benefit minus the cost of the transaction.

My trust model incorporates two components: (1) di-

Cite as: A Trust Model for Supply Chain Management (Extended Abstract), Yasaman Haghpanah, *Proc. of 10th Int. Conf. on Autonomous Agents and Multiagent Systems (AAMAS 2011)*, Tumer, Yolum, Sonenberg and Stone (eds.), May, 2–6, 2011, Taipei, Taiwan, pp. 1375-1376.

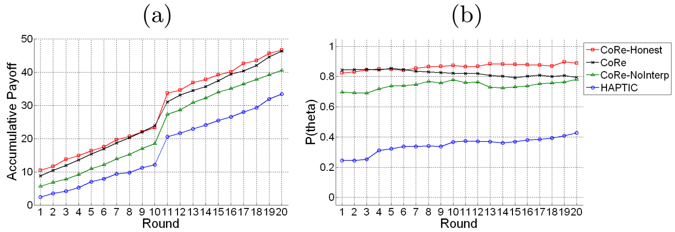

Figure 1: (a) Cumulative payoffs and (b) growth of true type probability over a series of rounds.

rect observations and (2) reported observations from other agents. In this model, trust by downstream agents in upstream agents is maximized when the latter agents provide goods and services with low prices and good quality in a timely manner. Similarly, the trust of an upstream agent to a downstream agent is affected by the number of times that the downstream agent has accepted the upstream agent's offer, the payoff level for each interaction, and the frequency of on-time payments. I define the two components of competence and integrity for each factor (e.g., quality, price, time, on-time payment, and acceptance rate). The combination of these factors will yield an overall trust level of an agent from one layer to an agent from the other layer. My proposed trust framework is generic and not restricted to these factors. I claim that my model will help to increase (or maximize) the overall profit of the supply chain over time.

Completed Work: So far, I have presented the Cognitive Reputation (CoRe) model as the reputation mechanism that will be incorporated into SCM in my future work. CoRe augments HAPTIC with a reputation framework that allows agents to gather information through reported observations. As mentioned before, in real-world scenarios, a reporter may not always provide correct information about a reportee. To address this issue, I also proposed a method for agents to model their trust level in reporters' behaviors by learning an agent's characteristic behavior in reporting observations. Then, I showed how the learning agent can correctly interpret the given information, even if the reports are based on faulty perceptions or on dishonest reporting. The key benefit of CoRe's interpretation is in the ability to use all of the reported information efficiently, even for biased or unfair reports. I combine direct and reported observations in a game-theoretic framework using probabilistic modeling.

CoRe helps agents who are relatively new to a society to learn the characteristic behavior of reporter agents, in order to acquire and interpret more reported observations about other agents. For example, suppose that *Reporter* has been in a society for some time and has had direct interactions with several *Reportee*s. *RepSeeker* first starts to interact with a Reportee directly, then asks Reporter for some information about that Reportee. Reportee makes its decisions based on its competence and integrity and the payoff multiplier of each game, as modeled in HAPTIC [4]. I define three types of reporters: honest, optimistic, and pessimistic. An honest reporter always reports truthful information. A pessimistic reporter underestimates other agents' behavior, and an optimistic reporter overestimates other agents' behavior. I use Bayesian model averaging over all possible Reportee types, in order to find the probability of each type of Reporter, given the biased results and direct observations.

After learning Reporter's type, RepSeeker asks Reporter for information about other agents, and uses its learned knowledge of Reporter's type to interpret the reported results. As a result, RepSeeker will have more information about other Reportees when direct interaction begins, and this knowledge will increase its payoffs.

I used IPD platform in my experiments. Since HAPTIC has been shown to outperform many common strategies in the IPD literature, I used it as a baseline. CoRe without interpretation (CoRe-NoInterp) is used to show the importance of interpretation of information. A third baseline shows the upper limit of the benefits of reported observations when the reporter is honest (CoRe-Honest). I ran two experiments: Exp1 and Exp2. In Exp1, the reporter's type is pessimistic. The cumulative payoffs and the learned probability of the reportee's true type over 20 rounds are shown in Figure 1(a) and (b). In this experiment, CoRe-Honest achieves the highest payoff, as expected. The next best performance is given by the CoRe model, which always outperforms HAPTIC, our baseline. To verify the effectiveness of CoRe, Exp2 uses randomly selected reporter types. The cumulative and mean payoffs for this experiment are averaged over 100 runs. CoRe achieves 19% improvement in this experiment over the HAPTIC baseline, confirmed by a t-test.

3. FUTURE WORK

My plan is to implement and investigate the benefits of a trust and reputation framework for SCM.I plan to migrate CoRe from IPD to SCM application and to integrate it with a multi-factor trust model. The initial proposed reputation mechanism, CoRe, is based on certain assumptions that I plan to remove in order to improve the CoRe model and generalize it to the SCM framework. One key improvement is to model the context-dependent reporter types, which can cause agents to behave differently when reporting in different situations (e.g., when reporting to a competitor versus a collaborator). In my preliminary experiments, I have tackled complete, relevant, but incorrect reported observations. In future work, I plan to deal with reported observations being incomplete and irrelevant as well.

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