

A Trust and Reputation Model for Supply Chain Management

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 contributes to the field of multi-agent systems by proposing a novel trust-based decision model for supply chain management.

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.

Related Work: Lin et al. [2003] build a trust model based on experiences with suppliers; trust is measured in terms of product quality, order-cycle time, and price. They generalize these factors to the abstract concepts of ability, integrity, and benevolence. This model is not probabilistic. Other SCM trust factors have been studied as well, although many of them are focused on specific SCM industries.

Several trust models have been proposed in the multi-agent literature; the Harsanyi Agents Pursuing Trust in Integrity and Competence (HAPTIC), a trust-based decision framework, is among the few existing models with a strong theoretical basis

[Smith and desJardins, 2009]. HAPTIC is grounded in game theory and probabilistic modeling. It has been proved that HAPTIC agents learn other agents' behaviors reliably using direct observations. One shortcoming of HAPTIC is that it does not support reported observations.

Various probabilistic trust models have been developed to consider both reported and direct observations. However, most of these models discount or discard biased information received from the reputation providers, including BRS [Whitby *et al.*, 2004], TRAVOS [Teacy *et al.*, 2005] and Vogiatzis's model [2010]. Moreover, Vogiatzis's model and TRAVOS both assume that there has been a history of interactions between the agent (who is looking for reputation information) and a service provider, so they are not appropriate when agents are relatively new to a society.

2 Approach

I propose a novel trust model for SCM [Haghpanah and desJardins, 2010]. This model incorporates multiple trust factors specific to SCM, and considers 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.

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 to adjacent downstream agents, and downstream agents ask for services or send requests for quotes to the adjacent upstream agents. Agents 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) direct observations and (2) reported observations from other agents. In this model, trust by downstream agents in upstream agents (or by upstream agents in downstream agents) is maximized when certain criteria have been met, for example, when the upstream 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 can be affected by the number of times that the downstream agent has accepted the upstream agent's offer, the payoff level for each interaction, and/or the frequency of on-time payments. My proposed trust

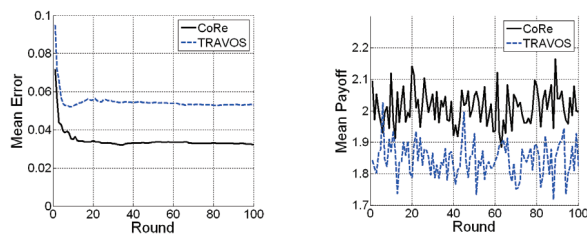


Figure 1: Core vs. TRAVOS (a) mean error (b) mean payoff.

framework is generic and not restricted to these factors. The combination of the trust factors will yield an overall trust level of an agent from one layer to an agent from the other layer. 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. To complement my model and benefit from direct observations as well as reported observations, I augmented CoRe with one of the existing trust models from the multi-agent literature, HAPTIC. As mentioned before, in real-world scenarios, a reporter may not always provide correct information about a reportee. To address this issue, in CoRe, agents first gather information through reported observations, then model their trust level in reporters' behaviors by learning an agent's characteristic behavior in reporting observations. Then, a CoRe agent interprets the given information, using it effectively even if the reporters are not honest and their 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 reports.

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 *Reportees*. *RepSeeker* first starts to interact with a Reportee directly, then asks Reporter for some information about that Reportee.

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 when direct interaction begins. I show experimentally that CoRe identifies other agents' behaviors faster and more accurately than other state-of-the-art trust and reputation models, even when reported information is incorrect.

Results: In my current experiments, CoRe is compared with TRAVOS, a state-of-the-art trust and reputation model that outperforms many other models including BRS. I used an IPD game platform for my experiment, where RepSeeker is gaining information from different Reporters to learn the

behavior of a Reportee with a randomly selected behavior; RepSeeker plays with a Reportee; and few Reporters play with the same Reportee. The population of these Reporters consists of honest and biased reporters (pessimistic and optimistic). Each Reporter changes the outcome of its play based on its type behavior and then reports the changed results to RepSeeker, which updates RepSeeker's belief about the Reportee. The results show that CoRe outperforms TRAVOS in identifying the Reportee's behavior, in terms of the mean error (i.e., the difference between the identified type and the correct type). In Figure 1 (a), the mean error for TRAVOS has converged to 0.057 and for CoRe to 0.037 (a 35% improvement over TRAVOS). The reason is that TRAVOS heavily discounts the biased reports, while CoRe interprets and uses that data to learn more about the behavior of the Reportee. As a result of correctly identifying the behavior of the Reporter correctly, the average payoff per round is increased from 1.84 to 2.01, which is a 9% improvement (Figure 1 (b)). The results also pass a t-test.

3 Future Work

My plan is to develop the proposed trust framework for SCM and to investigate the benefits of such a framework for SCM applications. I plan to explore the use of context-dependent Reporter types that can cause agents to behave differently in different situations (e.g., when reporting to a competitor versus a collaborator). I will also investigate multi-dimensional trust models that can be applied when a Reporter agent can have varying degrees of trust for different aspects of a second agent's behavior (e.g., quality, price, and on-time delivery in a supply chain management context). 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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