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Congrats: a Configurable Granular Trust Scheme for Effective Seller Selection in an E-marketplace

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ABSTRACT

CONGRATS: A CONFIGURABLE GRANULAR TRUST SCHEME FOR EFFECTIVE SELLER SELECTION IN AN E-MARKETPLACE

by

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ABSTRACT OF GRADUATE STUDENT RESEARCH

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Problem

The e-marketplace of today, with millions of buyers and sellers who never get to meet face to face, is susceptible to the presence of dishonest and fraudulent participants, prowling on unsuspecting trading partners to cheat in transactions, thereby increasing their profit to the detriment of their victims. There is also the multiplicity of goods and services with varying prices and quality, offered by a mix of honest and dishonest vendors. In order to participate in trade without incurring substantial loss, participants rely on intelligent agents using a trust evaluation scheme for partner selection. Making good deals thus depends on the ability of the intelligent agents to evaluate trading partners and picking only trustworthy ones. However, the existing trust evaluation
schemes do not adequately protect buyers in the e-marketplace; hence, this study focused on designing a new trust evaluation scheme for buyer agents to use to effectively select sellers.

Method

To increase the overall performance of intelligent agents and to limit loss for buyers in an e-marketplace, I propose CONGRATS—a configurable granular trust estimation scheme for effective seller selection. The proposed model used historical feedback ratings from multiple sources to estimate trust along multiple dimensions. I simulated a mini e-marketplace to generate the data needed for performance evaluation of the proposed model alongside two existing trust estimation schemes—FIRE and MDT.

Results

At the peak of performance of CONGRATS, T1 sellers with the highest trust level accounted for about 45% of the total sales as against less than 10% recorded by the least trustworthy (T5) sellers. Compared to FIRE and MDT, CONGRATS had a performance gain of 15% and 30%, respectively, as well as an average earning of 0.89 (out of 1.0) per transaction in contrast to 0.70 and 0.62 per transaction respectively. Cumulative utility gain among buyer groups stood at 612.35 as contrasted to 518.96 and 421.28 for the FIRE and MDT models respectively.

Conclusions

Modeling trust along multiple dimensions and gathering trust information from many different sources can significantly enhance the trust estimation scheme used by intelligent agents in an e-marketplace. This means that more transactions will occur
between buyers and sellers that are more trustworthy. Inarguably, this will reduce loss to an infinitesimal level and consequently boost buyer confidence.
CONGRATS: A CONFIGURABLE GRANULAR TRUST SCHEME FOR EFFECTIVE SELLER SELECTION IN AN E-MARKETPLACE

A Thesis
Presented in Partial Fulfillment of the Requirements for the Degree
Master of Science

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CHAPTER 1

INTRODUCTION

E-commerce

E-commerce is the use of electronic communications and digital information processing technology in business transactions to create, transform, and redefine relationships for value creation between or among organizations, and between organizations and individuals (Andam, 2003). It includes all aspects of buying and selling electronically and happens through a variety of technologies, including electronic data interchange (EDI), electronic mail, electronic funds transfer, and Web-based applications (Innovation & Information Consultants, 2004).

According to Stair and Reynolds (2006), e-commerce is a useful tool for connecting business partners in a virtual supply chain, which helps to reduce costs and cut time, and as You (2007) stresses, it offers new, effective, and efficient business models, business opportunities, and channels for buyers and sellers to conduct business over the Internet. E-commerce has become a necessary component of business strategy and a strong catalyst for economic development in the emerging global economy as the integration of information and communications technology (ICT) in business has revolutionized relationships within organizations and those between and among organizations and individuals (Andam, 2003). Business models have changed across the world with the introduction of e-commerce. Along with the United States, various other
countries are contributing to the growth of e-commerce. For example, the United Kingdom is the largest e-commerce market in the world when measured in terms of per capita spending. E-commerce is growing in Brazil because of the tax reductions and the interest in the consumers, and China with 384 million Internet users had an online market share of $36.6 billion in 2009. The reasons for this growth in e-commerce include improved trust level for shoppers, increased speed of the broadband Internet, advanced home delivery methods, and the use of mobile phones for the online shopping and the payment of bills (Big Trend, 2011).

In a March 2010 survey by the Nielson Company involving more than 27,000 Internet users in 55 markets to look at how consumers shop online, only 16% of respondents indicated they never shopped online. Of these respondents, one-third say their online shopping primarily happens at retailers that have only online presence (such as Amazon.com), while about 20% say they prefer sites that also have traditional “brick and mortar” stores. Another 20% prefer those that allow you to select products from many different online stores. The promise of a continued growth of e-commerce in years ahead comes from the finding that a huge 44% of online consumers spend less than 5% of their online spending online while 29% spend between 6% and 10% (The Nielson Company, 2010).

**E-marketplace**

An e-marketplace is a virtual market where buyers and sellers meet just like in a traditional market but all interactions are done virtually (Business Link, 2011). Participants in an e-marketplace register as buyers and/or sellers in order to conduct
e-commerce over the Internet. Sellers utilize a combination of pictures, videos, and literal descriptions to introduce the quality and details of the traded commodities.

Hagel and Armstrong (1997) used the concept of “reverse market” to explain the power reversal in the vendor-customer relationship existent in the e-marketplace. They described a market with unconventional dynamics in which the customer wields more power by utilizing the large amount of information at his disposal to search out vendors offering the best combination of quality and price, thereby extracting more value from vendors than would have been the case in a traditional market. This perfectly plays out in today’s electronic marketplaces (a virtual representative of physical markets) operated by e-commerce giants like Amazon and eBay. Consumers are able to compare the price of the same product from different merchants, are also able to read others’ reviews of a product, be they experts or simply fellow shoppers, and use them to make purchasing decisions satisfactorily (The Nielson Company, 2010).

Vendors also benefit from e-marketplaces. You (2007) identifies these benefits to include greater access by consumers online, avoidance of brick-and-mortar stores, thereby saving on rentals, and speedy maintenance of inventory and pricing. One joint advantage to both consumers and vendors as identified by Bolton, Katok, and Ockenfels (2004) is the opportunity to trade with a larger set of trading partners. This large pool of available trading partners in the e-marketplace increases trading risks and makes it imperative for participants to utilize automated help in order to maximize the attendant benefits. This is where the use of intelligent agents comes in.

According to You (2007), for the e-marketplace to flourish, transactions have to be fulfilled successfully, which implies that the buyer receives exactly what he is
promised and the seller receives the due payment. Conversely, the e-marketplace suffers a setback when either or both participants cheat, as the disappointed participant may opt out and/or choose another means of doing business. This makes trust a significantly important component of the e-marketplace since buyers and sellers may never see each other and may do business only once with each other.

Many e-marketplace platforms, including Amazon and eBay, have instituted online reputation mechanisms, known as "feedback" systems, to promote the exchange of information on the reliability of individual traders. Amazon, for example, requests buyers to post comments on the transaction which future buyers can view when deciding whether to make a purchase. In spite of these “feedback” systems used to promote trust in transactions, online markets have more problems with fraud. Bolton et al. (2004) record that the GartnerG2 report of 2002 concludes that Internet transaction fraud is 12 times higher than in-store fraud. They go further to state that a U.S. Department of Justice survey of 2002 cites high levels of online fraud. Chief among these are frauds common on auction sites (many with online feedback systems) that “induce their victims to send money for the promised items, but then deliver nothing or only an item far less valuable than what was promised (e.g., counterfeit or altered goods)” (p. 1587).

**Agents, Intelligent Agents, and Multi-agent Systems**

An agent is a computer system embodied in some environment, which is capable of sensing its environment and has a repertoire of possible actions that it can autonomously perform in order to modify its environment to meet its design objectives (Wooldridge, 2000). This is not a universally accepted definition of what an agent is as
there are many definitions in extant literature, but it captures in simple terms the main essence of agents in computational domains.

An intelligent agent is a specific type of agent that, in addition to autonomy, is capable of perceiving and reacting to its environment, shows proactive behavior, and is able to interact with other agents or with humans (Mosqueira-Rey, Alonso-Ríos, Vázquez-García, del Río, & Moret-Bonillo, 2009). Being autonomous, agents decide independently for themselves what actions they need to take in order to achieve their goals. Reactivity enables the agent to respond to changes in its environment in real-time. Being proactive makes the agent goal-directed and enables it to take the initiative in its actions. The social behavior allows the agent to interact with other agents and even humans, to satisfy its design objectives. These behaviors distinguish intelligent agents from passive agents, who never try to do anything (Wooldridge, 2000).

Considering that humans achieve most of their goals by interacting and cooperating with other people, intelligent agents designed to act on behalf of humans, who individually may be limited in amount of available information as well as computing resources, must also interact and cooperate. This cooperation among agents gives rise to the multi-agent system (MAS) formed when the intelligent agents are able to interoperate and coordinate with each other. According to Sycara (1998), in a MAS, each agent’s information or capacities for solving the problem is incomplete, there is no global control system, data are decentralized, and computation is asynchronous. The e-marketplace environment is perfect for the application of multi-agents.
Intelligent Agents in E-commerce

Despite the numerous benefits of trading in e-marketplaces rather than the traditional marketplace, online consumers still have to do much to conduct an e-commerce transaction. Some of the burdens faced by buyers in today’s e-commerce transaction include:

1. To make a good deal, buyers have to spend a lot of effort and time searching.
2. To learn about their transaction partner’s trustworthiness, they must read feedback and check diverse scores all without any guarantee.
3. In order to bid on an auction, buyers continue to monitor the entire process of the auction.

The use of intelligent agents in the e-marketplace will definitely ease these burdens and make e-commerce attractive to a greater number of people. These agents will assist their principals in the various stages involved in the buying process as identified by Guttman, Moukas, and Maes (1998) including need identification, product brokering, merchant brokering, negotiation, purchase and delivery, and service and evaluation. These can be implemented using agent techniques.

An outstanding benefit of utilizing intelligent agents in the e-marketplace is in the propagation of trust information. In the traditional marketplace, trust information flows very slowly from person to person by word-of-mouth and people relied on this mechanism to select reputable business partners (Bolton et al., 2004). Dishonest sellers exploit this system easily and cheat in transactions here and there multiple times before their bad reputation spreads around the marketplace. Conversely, in the e-marketplace with intelligent agents equipped with efficient trust estimation model, fraud is drastically
reduced, since dishonest acts in transactions quickly spread through the multi-agent community.

**Problem Statement**

The electronic marketplace of today teems with millions of participants, and a myriad of goods and services offered by different vendors with varying degrees of quality and prices. In addition, there is the presence of dishonest and fraudulent participants, prowling on unsuspecting trading partners to cheat in transactions, thereby increasing their profit to the detriment of their victims. This makes the selection of high-quality goods and services, as well as honest trading partners, a daunting task.

In order to make good deals, participants in the electronic marketplace need to employ the use of intelligent agents and delegate them to search for goods and services, select potential trading partners, and sometimes make decisions on transactions. These agents require the ability to reliably evaluate trading partners and pick only trustworthy ones if they will make good deals and limit loss for their principals. Trust thus plays a very important role in the selection of business partners in the e-marketplace employing the use of intelligent agents. However, prevalent trust mechanisms available in the e-marketplaces of today employ a simple technique of averaging aggregated user ratings resulting in participants incurring severe losses from doing business with dishonest partners. Furthermore, such a technique is not characteristic of multi-agent strategies. There is therefore a need for a new trust estimation model that will take into account all the necessary characteristics of the system to address these lapses.
Purpose of Study

This work aims at developing a configurable granular trust scheme that buyer agents can use to evaluate seller agents before selecting trading partners in order to substantially limit or even eliminate loss in the Electronic Marketplace. Buyer agents are the focus of this work because buyers tend to be at the receiving end of fraud in the electronic marketplace because of the simple fact that buyers usually pay for goods and services without the privilege of inspecting the physical goods or trying out services until the seller delivers.

Justification

It was expected at the turn of the millennium, that over one-quarter of all businesses will be “on-line” by 2003 and e-commerce in its broadest sense will continue to grow at an average rate of 33% per year (The Boston Consulting Group, 2000; Pratt, 2002, both as cited in Innovation & Information Consultants, 2004). Recent studies, however, reveal a slower growth rate. For example, comScore, Inc., in its third quarter 2010 U.S. retail e-commerce sales estimates, showed that online retail spending went up only 9% versus the previous year (comScore, 2010a). In spite of this slower growth, e-commerce continues to become, by the day, a major part of global economy, with retail e-commerce netting a spending volume of $13.55 billion in the first 29 days of the November–December 2010 holiday season in the United States market. Spending on Cyber Monday alone reached $1.028 billion, representing the heaviest online spending day in history and the first to surpass the billion-dollar threshold (comScore, 2010b).

The growth rate and the volume of spending attributed to e-commerce make it imperative to safeguard this important component of the economy. This work helps to
improve effectiveness, reduce or eliminate loss on the part of buyers, and improve the overall trading experience of participants by accurately modeling the trustworthiness of sellers so that buyers can confidently chose honest sellers while avoiding the dishonest ones. This is a desirable contribution, which will help to increase and sustain the growth of e-commerce, as potential adopters will no longer be scared away because of the inherent presence of fraudulent participants in the electronic marketplaces.

Methodology

The study approach employed in this work included a review of extant and relevant literature on trust as it applies to intelligent agents in e-commerce. This set the foundation for the underlying assumptions, concepts, and theories necessary for the model design. In addition, it involved the assessment and evaluation of various strategies from previous related works. Relevant strategies were adapted, improved upon, and combined with original ideas to yield the CONGRATS model—a configurable granular trust scheme proposed in this work. Finally, it culminated in a simulation of the interactions among buyer and seller agents in order to test the proposed trust model and verify its performance.

Thesis Organization

This thesis is comprised of four chapters. This first chapter contains the introduction to the work. It contains the general concept of electronic commerce and discusses multi-agent technology in the light of e-commerce. In addition, it contains the problem statement, the purpose of the study, the motivation for undertaking the study, and the methodology adopted.
Chapter 2 discusses the concept of trust in multi-agent systems. It goes further to explore the various approaches to trust modeling and estimation in multi-agent systems as contained in extant literature.

Chapter 3 contains a summary of previous related research, the system model, the design, the implementation and simulation, and computational results are contained therein.

The conclusion of the work and a highlight of possible areas for future work are contained in chapter 4. Following this last chapter are the reference list and appendices containing source codes of implementation.
CHAPTER 2

TRUST AND ITS MODELING

Introduction

Trust is a very important concept in the everyday life of humans. Its importance is seen in the most diverse situations—from friendship to marriage, from buying a used book to buying a used car, from election of local officials to international cooperation. The importance of trust makes it draw more and more attention from researchers in diverse research fields, more so when most human activities involve interaction and cooperation with others. Generalizing, Hardin (2001) opines that if everyone with whom we interact is trustworthy, we tend to trust everybody; and if the society were full of people who lack trustworthiness, we would not trust anyone. Trust is a useful tool for simplifying the world and for coping with risks in it and uncertainty (Falcone & Castelfranchi, 2004).

Trust is a complex concept and as such lends itself to definitional diversity. Although this diversity of definition can lead to confusion, McKnight and Chervany (1996) argue that it points out the fact that trust is appropriately difficult to define narrowly. They found out that in defining trust, researchers have used various related words. Of the eight most common words, “belief” ranks highest at 24% followed by “expectancy” at 20%. In line with the foregoing, Windley (2005) defines trust as a firm belief in the veracity, good faith, and honesty of another party, with respect to a
transaction that involves some risk. Dasgupta (1988) defines trust in the sense of correct expectations about the actions of other people that have a bearing on one’s own choice of action when such action must happen first before one can monitor the actions of those others. Concerning intelligent agents as found in e-marketplaces, Gambetta (1988) sees trust as a particular level of the subjective probability with which an agent assesses that another agent or group of agents will perform a particular action, both before it can monitor such action and in a context in which it affects its own action. Lee and See (2004) introduced another interesting perspective of trust by defining it as the attitude that an agent will help achieve an individual’s goals in a situation characterized by uncertainty and vulnerability.

Grimsley, Meehan, Green, and Staord (2003) identified two types of trust that affect human interactions to be vertical trust and horizontal trust. Vertical trust captures the trust relationships that exist between individuals and institutions. For example, when an individual needs a mechanic to repair his car, he may consider the Better Business Bureau’s rating of the mechanic. On Amazon.com, a buyer tends to have peace of mind buying from a seller when the item carries a “Fulfilled by Amazon” seal. Here, trust is not on the individual providing the service but on the institution backing him. Horizontal trust represents the trust that results from direct encounter with entities or inferred from observations and opinions of others. For example, when someone wants to buy an item on eBay, he checks the seller’s feedback score and decides to trust the seller if it is appreciably high.

These notions of trust are complementary and often used in concert during everyday decision-making. When an individual wishes to make a dinner reservation, she
may consider awards and certifications given to potential restaurants by local or national organizations (vertical trust), as well as the experiences of her friends (horizontal trust). Since the digital world is just a logical extension of human society, researchers have naturally developed both horizontal and vertical trust models for use in distributed systems such as the e-marketplace. Trust is dynamic in nature in that it changes with experience, with the modification of the different sources it is based on, with the emotional state of the trusting party, with the modification of the environment in which the trusted is supposed to perform, and so on (Falcone & Castelfranchi, 2004).

**Trust and Reputation**

Trust is synthesized from various elements, the most prominent being reputation. The relationship between trust and reputation is such that the two are quite often confused with each other. Reputation is an opinion or view of one about an entity, formed and updated along time through direct interactions or through information provided by others about their experiences with that entity in the past (Sabater & Sierra, 2001). Thus reputation is a by-product of previous actions, be they those of others or ours. Each of such interactions leaves an impression that cumulates over time and is perceived as an entity’s reputation. Mui, Halberstadt, and Mohtashemi (2002) aptly capture this view in their definition of reputation as perception that an agent creates through past action about its intentions and norms. Thus, the reputation of an entity serves as a basis for others to guess what to expect in future interactions—in other words how much trust to place on that entity.

The various sources that yield the information from which an entity’s reputation derives, including direct encounter, direct observation, and others’ report, correspond to
specific subsets of reputation typology as presented by Mui et al.—encounter-driven, observed, and propagated reputation. The first two are more reliable. The third may suffer from information falsification and/or withholding.

Putting things in perspective, one can say that reputation and trust are highly correlated concepts, and reputation is one important element that affects the building of trust with others. Although reputation is a contextual quantity (Mui et al., 2002), an entity’s reputation can be a good predictor of how much trust others are willing to put in it. There is no doubt, then, why many researchers include reputation in trust estimation and modeling in multi-agent systems.

**Traditional Trust Estimation in Practical E-marketplaces**

Bolton et al. (2004) noted in their work that many online markets rely on electronic feedback systems to promote trust between participants in transactions. The prevalent method of implementation of this electronic feedback system is rating. Partners rate each other at the end of a transaction indicating how satisfied or dissatisfied they were with the online transaction and in some cases leave some feedback comments. Potential trading partners use these ratings when making a decision on whether to enter into a deal or not. Amazon.com and eBay.com are good examples of e-marketplaces where the feedback rating system is used. Both allow buyers and sellers alike to leave feedback rating, but feedback ratings by sellers on Amazon.com do not get as much attention as on eBay where the reputation of the buyer is as important as that of the seller.

According to Amazon.com (2011), seller feedback is an important element in buyer purchasing decisions. In addition, feedback rating is also a key metric used by Amazon.com to measure seller performance, and high feedback rating is a critical factor
for success on Amazon.com. Amazon.com uses the 1-to-5-star rating system. Buyers rate sellers after a transaction from 1 star (awful) to 5 stars (excellent), broken down into positive feedback = 5 or 4 stars; neutral feedback = 3 stars; and negative Feedback = 2 or 1 stars. In addition, buyers may answer some optional questions about specific aspects of the transaction with the provision for some short comment summarizing their experience. Figure 1 is a screenshot of the buyer feedback on Amazon.com.

![Buyer feedback on Amazon.com](https://www.amazon.com/gp/feedback/leave-customer-feedback.html/ref=fb_by_lfb)

Figure 1: Buyer feedback on Amazon.com.

Accompanying the nickname of a seller on a listed item at Amazon.com is a summary of the seller’s feedback. This includes a star-scale representation of the
The seller’s profile contains more details about the feedback rating including positive, neutral, and negative ratings accumulated over 30 days, 90 days, 365 days, and lifetime. Other tabs in the member profile page give further details about the seller, such as shipping rates and return policy. Figure 2 is a screenshot of the profile of a member seller with Amazon.com.

Figure 2: Seller profile on Amazon.com.
After each transaction via eBay, the buyer and the seller can rate each other by leaving ratings and short feedback comments about the transaction. Rating from buyers can be negative, neutral, or positive feedback but sellers can leave buyers positive feedback or choose not to leave feedback. Through these ratings over time, eBay members develop a feedback profile or reputation. Members receive +1 point for each positive rating, 0 point for each neutral rating, and -1 point for each negative rating (eBay, 2011).

Multiple transactions between trading partners are taken into consideration while calculating the feedback score. For transactions happening in the same week defined as Monday through Sunday, Pacific Time, the seller's feedback score is adjusted based on the total number of positives and negatives left by the buyer. It is assigned -1 if the seller receives more negatives than positives from the same buyer, +1 if the seller receives more positives than negatives from the same buyer, and 0 if the seller receives the same number of negatives and positives from the same buyer. For transactions happening in different weeks, each rating is imputed to the seller (eBay, 2011).

The feedback score is one of the most important pieces of a Feedback Profile. It is the number in parentheses next to a member's user ID and is also located at the top of the feedback profile. It is the arithmetic sum of all the feedback ratings received. When a member’s feedback score is more than 10, a yellow star appears beside the member I.D. and different colored stars are associated with different ranges of the feedback scores. As the feedback score increases, the star will change color, all the way to a silver shooting star for a score above 1,000,000. The cumulative scores for positive, neutral, and negative are listed on a member’s profile for the past month, past 6 months, and past 12
months, as are recent ratings. All the feedback ratings, feedback comments, and the raters’ profiles and the number of mutually withdrawn feedback are visible to the public.

Figure 3 is a snapshot of the profile of a member seller with eBay.

On eBay, in addition to leaving a general rating of positive, neutral, or negative for a transaction, buyers can anonymously rate specific aspects of the transaction with detailed seller ratings. These aspects include accuracy of description of items, communication, shipping time, and shipping and handling charges. The arithmetic average of each of these aspects over the past 12 months is displayed on the seller’s feedback profile. This is similar to the concept used on Amazon.com.

Figure 3: Seller profile on eBay.com.
Drawbacks of the Traditional Trust Systems

The traditional trust estimation models are based on intuitions, which lack theoretical or empirical supports (You, 2007). For example, the ratings are stored centrally and the reputation value computed as the sum of those ratings over a short period of 6 months. Thus, reputation in these models is a global single value representing a user’s overall trustworthiness within the past 6 months. This is too simple for applications in multi-agent systems.

They are also easy to manipulate by fraudulent users. A user may cheat in a few interactions after obtaining a high reputation value, but still retains a positive reputation. In addition, they only consider the trustworthiness of an agent as one dimension (Huyhn, Jennings, & Shadbolt, 2006a). Furthermore, reputation values in these systems contain very little information. Anyone needing deeper understanding of these systems needs to look for textual comments for more information. They are therefore not well suited for agents who rely on the power of numbers in order to make decisions autonomously.
CHAPTER 3

MODEL DESIGN

Previous Related Works

Researchers over the years have employed different strategies to estimate and model trust in multi-agent systems. Some works (Griffiths, 2005; Tran, 2010) have relied on direct encounter between agents as the only singular factor in trust estimation; others (Sabater & Sierra, 2001; Huynh et al., 2006a; Huynh, Jennings & Shadbolt, 2006b) have incorporated witness reports into the design of trust estimation models. Whereas some studies (Teacy, Patel, Jennings, & Luck, 2005; Vogiatzis, MacGillivray, & Chli, 2010) have employed the use of probabilistic techniques, others have used statistical methods (Matt, Morge, & Toni, 2010) and social networks analysis (Hang, Wang, & Singh, 2009; Walter, Battiston, & Schweizer, 2009) in trust estimation.

FIRE Model

Huynh et al. (2006a) designed an integrated trust and reputation model, FIRE, which uses four sources of trust information to evaluate the trustworthiness of the seller agents. These four sources include direct experience, witness information, role-based rules, and third-party references provided by the evaluated agents. Direct experience yields Interaction Trust (IT), witness information yields Witness Reputation (WR), role-based rules give rise to Role-based Trust (RT), and third-party references provide
Certified Reputation (CR). Apart from RT, each of the trust components is derived from a rating system with values in the range $[-1, +1]$.

FIRE integrates all four sources of information and computes the overall trust value as the normalized weighted sum of the components, each with a corresponding user-defined coefficient and deduced reliability. Certified Reputation, in particular, enhances FIRE since the evaluating agent need not source for this information itself. Its addition reduces the possibility of failure to evaluate the trustworthiness of the target agent due to a lack of information. Huynh et al. (2006a) believe that integrating these various sources will enhance the precision of the trust model.

**MDT Model**

Proposed by Griffiths (2005), the multi-dimensional trust (MDT) presents agents with the ability to model the trustworthiness of others along several dimensions. It takes a multi-dimensional approach by decomposing trust to represent various beliefs according to different dimensions of an interaction. MDT is built on the premise that every interaction between agents is made up of expectations which can fail, succeed with lower than expected quality, or succeed at a higher than expected cost. These expectations are dimensions of trust. Each trust dimension encompasses the beliefs of the agent corresponding to competence, disposition, dependence, and fulfillment.

Dimensions are weighted based on the current preferences of the agents and combined with other factors when delegating a task, to enable agents to select appropriate cooperative partners. The MDT model also gives agents a finer grained model of other agents. The drawback to this model is that it relies on only direct experience of the
evaluating agent and as Wang and Wu (2011) noted, it does not allow any sharing of trust information.

Motivation

Although, many trust models and systems have been proposed in the literature, a universally agreed trust model is yet to be seen (Wang & Wu, 2011). This is because some are either too complex to be practicable or just not suitable for applications in the e-marketplace. Furthermore, those in use (like on Amazon.com and eBay) do not offer the needed level of protection as fraudsters can easily manipulate them. There is a need for a trust estimation model that intelligent agents in the e-marketplace will use to reliably evaluate trading partners and pick only trustworthy ones to make good deals in order to limit loss for their principals.

CONGRATS

This work proposes a “CONfigurable GRAnular Trust Scheme” (from here simply referred to as CONGRATS) that buyer agents can use to effectively select seller agents in a multi-agent e-marketplace, in order to substantially limit or even eliminate loss in the e-marketplace. Configurability and granularity are the outstanding strengths of this model. Configurability allows the model to achieve better performance under diverse sets of conditions. It also empowers the model to be adapted to other application domains. Granularity allows trust to be decomposed into many dimensions and correctly modeled to take into consideration specific and unique characteristics of the domain of application. The various notations and symbols used in the proposed CONGRATS model are presented in Table 1.
Table 1

**Notations and Symbols Used in the Proposed Model.**

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
<th>Possible Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>$a, b$</td>
<td>Agent identifiers</td>
<td></td>
</tr>
<tr>
<td>$d$</td>
<td>Agent’s dispositional value</td>
<td>$[0, 1]$</td>
</tr>
<tr>
<td>$N_e^r$</td>
<td>Maximum number of ratings per expectation dimension to store</td>
<td>$[\geq 1]$</td>
</tr>
<tr>
<td>$dT_{a,b,n}^e$</td>
<td>Dispositional trust of the evaluating agent $a$ on the evaluated agent $b$</td>
<td>$[0, 1]$</td>
</tr>
<tr>
<td>$dT_{a,initial}^e$</td>
<td>Initial dispositional trust assigned by agent $a$’s principal</td>
<td>$[0, 1]$</td>
</tr>
<tr>
<td>$updatedDT_{a,b,n}^e$</td>
<td>Periodically updated dispositional trust of the evaluating agent $a$ on the evaluated agent $b$</td>
<td>$[0, 1]$</td>
</tr>
<tr>
<td>$Pr_{en}$</td>
<td>An agent’s personal expectation rating in a dimension</td>
<td>$[0, 100]$</td>
</tr>
<tr>
<td>$Rr_{el}$</td>
<td>Instance of a referee’s expectation rating in a dimension</td>
<td>$[0, 100]$</td>
</tr>
<tr>
<td>$Wr_{el}$</td>
<td>Instance of a witness’s expectation rating in a dimension</td>
<td>$[0, 100]$</td>
</tr>
<tr>
<td>$r_{max}$</td>
<td>Maximum allowed rating value</td>
<td>100</td>
</tr>
<tr>
<td>$w_{rti}$</td>
<td>Weighting factor assigned to referee trust information</td>
<td>$[0, 1]$</td>
</tr>
<tr>
<td>$w_{wti}$</td>
<td>Weighting factor assigned to witness trust information</td>
<td>$[0, 1]$</td>
</tr>
<tr>
<td>$pR^e_b$</td>
<td>Public reputation of agent $b$ in an expectation dimension</td>
<td>$[0, 1]$</td>
</tr>
<tr>
<td>$w_{dTR}$</td>
<td>Weighting factor assigned to dispositional trust</td>
<td>$[0, 1]$</td>
</tr>
<tr>
<td>$w_{pR}$</td>
<td>Weighting factor assigned to public reputation</td>
<td>$[0, 1]$</td>
</tr>
<tr>
<td>$T^e_b$</td>
<td>Trust on agent $b$ in a particular expectation dimension</td>
<td>$[0, 1]$</td>
</tr>
<tr>
<td>$w^e_j$</td>
<td>Weighting factor assigned to an expectation dimension</td>
<td>$[0, 1]$</td>
</tr>
<tr>
<td>$PV(b)$</td>
<td>Performance value of agent $b$</td>
<td></td>
</tr>
</tbody>
</table>
The proposed trust model draws inspiration from a typical human problem-solving process. Consider an employer who needs to fill an open position. First, there is an advertisement about the opening and then there are many applications received. Some of the applicants may be current or previous employees with whom the employer has had prior interactions. Yet some others may be fresh applicants with whom the employer has not had any prior interactions. The employer goes on to gather information about the applicants through many sources: employee files for the in-house applicants, applicant-nominated referees, and public agencies such as credit bureaus and law enforcement agencies. Specific traits that affect employability either positively or negatively are investigated through the sources of information, and the employer aggregates the weights of the various components of the information gathered from the different sources to decide on which of the applicants to trust with the new job.

The sources of trust information utilized to estimate the trust value in the proposed model include the ratings of direct transactions between the evaluating agent and the evaluated one, referee agents’ ratings of the evaluated agent about their direct transactions, and witness agents’ ratings of the evaluated agent about their direct transactions. From the standpoint of the evaluating agent, the two sources of information for this model are direct experience and reported experience. These two are the most commonly used information sources for trust and reputation computation (Huynh et al., 2006a; Sabater & Sierra, 2001; Zacharia & Maes, 2000). In addition, the various impact traits solicited through the different information sources represent different dimensions of trust (Griffiths, 2005) worth considering if agents must make loss-limiting choices in an e-marketplace.
Although a buyer agent can estimate a seller agent’s trust level using gathered trust information, You (2007) notes that an actual purchase may ensue only if the trust of the evaluated agent is desirable. This is intuitive and follows from a real-world fact that the trust between two business partners may not necessarily lead to a business transaction. Suffice it to say though that for the proposed model to be effective, agents in the e-marketplace need enter into transactions when trust level is favorable in order to generate review and feedback data. Thus, the evaluating agent’s evaluation (rating) of the transaction (if it does ensue) helps to enhance the accuracy of the trust estimation.

There exists no consensus among researchers as to what factors or parameters a trust model should incorporate. As seen in extant literature, researchers have taken the liberty to model trust the way they deem fit and as such decide on what parameters to incorporate in their design. This work, however, has examined existing works, borrowed relevant concepts from them, and combined them with novel original ideas to arrive at a practicable trust model that is robust and can be implemented in a real-life e-marketplace. The trust information gathering of CONGRATS builds on the existing feedback mechanisms of Amazon.com and eBay while the MDT (Griffiths, 2005) and FIRE (Huynh et al., 2006a) models have inspired the proposed trust estimation scheme.

Assumptions

In order to reduce complexity and make the model practicable, this work makes the following assumptions:

1. Agents can, and will properly evaluate and rate transactions.
2. Agents will make their rating data available whether as referees or witnesses.
3. Agents will be honest in exchanging information with one another.
Sources of Trust Information

According to Beatty, Reay, Dick, and Miller (2011), the principal focal point of trust in the marketplace is clearly the other party in an interpersonal buyer-seller relationship. This work will thus focus on gathering trust information from the participants in the e-marketplace in contrast to relying on a central market information system as seen in the SPORAS model (Zacharia & Maes, 2000), the feedback system of Amazon.com and eBay.

The level of knowledge of an agent about its environment and its partners may vary greatly during its life cycle due to the characteristic nature of the e-marketplace where agents can join and leave at will or even stay dormant for a long period. In addition, some of the various information sources may be unavailable or inadequate for trust estimation at some points. It is beneficial then to have multiple sources of trust information, configurable to suit the domain of application of this model. This work will rely on three sources of trust information: personal experience, referee report, or witness report.

Personal experience comes from the evaluating agent’s previous interactions with the target agent, yielding personal trust information ($pti$). Referees nominated by the target agent will report about their previous experiences interacting with the target agent yielding referee trust information ($rti$). Finally, other agents known to the evaluating agent will report about their previous interactions with the target agent yielding witness trust information ($wiki$).

Since referee and witness reports depend on third parties, they are susceptible to falsification and withholding. Referee and witness agents may provide false ratings or
withhold negative information to gain unwarranted trust for their seller partners. In order to focus on the philosophy of the proposed model while ensuring that it is actually effective, this work will not seek to address the problems of information falsification and withholding. I invoke the previous assumptions that agents are honest in exchanging information and are willing to share information with one another.

Rating

In CONGRATS, evaluating agents deduce trust from information about the evaluated agent’s behavior using ratings. A rating is the evaluation about an agent’s performance given by its partner in an interaction between them. Consider as an example where agent $a$ purchases an item from agent $b$ and there are expectations from agent $a$ that need to be met by agent $b$. At the end of the interaction, agent $a$ can evaluate the transaction in terms of those expectations (examples can include fulfillment, quality, time-to-ship, fairness of cost, safety of financial card information, possible refunds in the case of a returned item, etc.). From its evaluation, agent $a$ may give ratings about agent $b$’s service in each of those expectations for that particular interaction.

Ratings are tuples in the following form: $r = (b, \{v_{exp_i} \mid i = 1, 2, ..., n\})$, where $b$ is the evaluated agent and $v_{exp_i}$ is the rating value for the expectation $i$, and $n$ is the number of expectation dimensions. The value of $v$ is in a continuum $[0, max]$, where $max$ is the maximum rating allowed in the system, and left open to accommodate different rating scales making the rating system configurable. For example using the percentage system of grading we will have $v \in [0, 100]$ and on the simple 10-point scale we will have $v \in [0, 10]$. This is better than the MDT where interaction expectation
outcome is 0 or 1 since it allows agents to quantify the degree to which expectations are met in an interaction.

Each time an agent gives a rating, it is either stored in the agent’s local rating memory or discarded. The stored ratings will be retrieved when needed for sharing with other agents either as a referee or as a witness. Due to memory resource constraints, an agent may not be able to store all of its ratings. An agent will store a maximum number of ratings corresponding to the product of the number of ratings per expectation dimension $N^e_F$, and the cardinality of the expectation dimension built into the system over all the agents with which it has had a completed interaction. $N^e_F$ is a configurable option, determined at creation, by the agent’s principal.

Determining what rating to store or discard is the responsibility of each evaluating agent. Every rating is used in calculating the personal trust level of the rated agent before being stored or discarded. Figure 4 is a pseudo-function for determining what ratings to store.

```plaintext
function store_or_discard_rating(r_new)
begin:
    normalized_new = r_new * conversion_factor
    deviation_new = abs(dispositional_trust – normalized_new)
    candidate_rating_dev = max(deviation_old1, deviation_old2, … deviation_old$N^e_F$)
    if (deviation_new > candidate_rating_dev) then
        discard (r_new)
    else
        remove(candidate_rating) and store (r_new)
    end if
end do
```

Figure 4: A pseudo-function for determining what ratings to store.
After filling the allotted memory, every subsequent rating is converted to the scale of the dispositional trust on the rated agent in the relevant expectation dimension and then the deviation from the dispositional trust is computed. If the deviation is higher than the exiting previous highest deviation, the rating is discarded, or else it is stored in memory and the rating with the highest deviation is removed from memory.

When queried for a reference or witness, the agent shares only the rating whose adjusted value has the least deviation from its dispositional trust on the rated agent. Figure 5 is a pseudo-function for determining what ratings to share.

```plaintext
function rating_to_share(ratings_collection[]) begin:
    for each (expectation_dimension) do
        normalized_rating = rating * conversion_factor
        deviation = abs(dispositional_trust – normalized_rating)
    end do
    candidate_rating_dev = max(deviation1, deviation2, … deviationN_f)
    share(ratings_collection[candidate_rating])
end
```

Figure 5: A pseudo-function for determining what ratings to share.

Agent Disposition

In order to allow for configurability, every evaluating agent is made to have a disposition (pessimistic or optimistic) and is assigned a dispositional value, d∈[0,1]. Pessimists take on low values (implying high, perceived risk) while optimists, on the other hand, take on high values (implying low, perceived risk). Assigning this value is the responsibility of the principal on whose behalf the agent works to assign this value at creation and to adjust it accordingly depending on the desired performance of the agent.
An agent's disposition determines how generous it will be in assigning rating values to expectations in an interaction. Pessimists assign rating values less generously, while optimists assign rating values more generously.

Modeling Trust Granules

In every interaction, there are expectations; and the belief in the ability of a partner to meet such motivates participation. These expectations represent different dimensions of trust. Modeling trust along these dimensions gives agents a finer-grained model of others. This is the approach taken in this work and is in line with the work of Griffiths (2005). Like the multiplicity of sources for trust information, this multi-dimensional approach to trust modeling lends itself to configurability in various application domains. In the employment scenario, an employer needs to ensure that the applicant entrusted with a job has the ability to do the job (trust in competence) and will do the job satisfactorily (trust in reliability) among other expectations.

Agents can thus model trust along any number of dimensions according to their domain of application, motivations, and preferences. In the e-marketplace, for example, the buyer may have expectations along the dimensions of price, quality, fulfillment of transaction, processing time, financial information confidentiality, returns and refunds, etc. Every dimension in an interaction has a corresponding trust on a particular expectation defined to be a real number in the interval between 0 and 1. This is the likelihood that the agent will meet the expectation with values approaching 0 representing least likely and those approaching 1 representing most likely. The weight assigned to each of these expectations depends on the evaluating agent’s preferences. The
corresponding trust dimensions are periodically updated and an evaluating agent is able to consider all dimensions in future selection decisions.

For every expectation in an interaction between an evaluating agent $a$ and an evaluated agent $b$, the evaluating agent synthesizes an expectation trust, $T^e_b \in [0, 1]$ from two components. First there is $dT^e_{a,b,n} \in [0, 1]$ arising from a personalized, dispositional trust of the evaluating agent $a$ on the evaluated agent $b$. Then there is the public reputation $pR^e_b \in [0, 1]$ of the evaluated agent along the particular dimension. Before the evaluating agent $a$ gets to have any completed interaction experience with the evaluated agent $b$, $dT^e_{a,b,n}$ assumes an assigned trust value of the same scale, $dT^e_{a,initial}$, determined by agent $a$’s principal. At the end of a completed interaction, it is updated so that future trust computations depend on the previous value. This follows from the relation below:

$$dT^e_{a,b,n} = \begin{cases} dT^e_{a,initial}, & n = 1 \\ updated DT^e_{a,b,(n-1)}, & n > 1 \end{cases} \quad (1)$$

The dispositional trust is updated after the first completed interaction using the evaluating agent’s current rating in the various expectation dimensions and subsequently at predetermined intervals, using a cumulative moving average function to reduce overhead of memory lookup as number of interactions increase. The relation for achieving this is as follows:

$$updated DT^e_{a,b,n} = \frac{(n-1) \cdot r_{max} \cdot dT^e_{a,b,(n-1)} + pR_{en}}{n \cdot r_{max}} \quad (2)$$

The evaluated agent’s public reputation on a particular expectation dimension is computed from gathered trust information thus:
\[ pR_b^e = \left( \frac{\sum_{i=1}^{m} Rr_{e_i}}{m \cdot r_{max}} \cdot w_{rti} \right) + \left( \frac{\sum_{i=1}^{n} Wr_{e_i}}{n \cdot r_{max}} \cdot w_{wti} \right) \]  \hspace{1cm} \text{------------------------ (3)}

Here, \( Rr_{e_i} \) is an instance of a referee rating while \( Wr_{e_i} \) is an instance of a witness rating of the agent \( b \) in a particular dimension expectation. \( m \) and \( n \) each is the cardinality of the referee ratings and witness ratings respectively. \( r_{max} \) is as defined in (1), and \( w_{rti} \) and \( w_{wti} \) are the weights assigned to the two sources of reported trust with the condition that \( w_{rti} + w_{wti} = 1 \). These configurable weightings allow the evaluating agent to decide on how much importance to place on a particular source of trust information.

Finally, an evaluating agent \( a \) assigns to the evaluated agent \( b \) an expectation trust for each dimension thus:

\[ T_b^e = \left( dT_{a,b,n}^e \cdot w_{dT} \right) + \left( pR_b^e \cdot w_{pR} \right) \]  \hspace{1cm} \text{------------------------ (4)}

Here \( dT_{a,b,n}^e \) is as defined in (1) while \( pR_b^e \) is as defined in (3). \( w_{dT} \) and \( w_{pR} \) are the weights assigned by the evaluating agent to personal dispositional trust and communal reputation respectively with the condition that \( w_{dT} + w_{pR} = 1 \).

**Putting It All Together**

So far, trust has been modeled along the dimensions of the various interaction expectations using trust information from multiple sources. These grains of trust from different expectation dimensions will be combined to arrive at values that can be compared and which will eventually contribute to decision making on trading partner selection. The trust values so far derived represent views of an individual evaluating agent on the various expectation dimensions to be satisfied by the evaluated agent in an interaction. These are not directly comparable across agents since each evaluating agent has its own desires and expectations.
An agent when deciding on whom to interact with must consider the various dimensions of trust. The agent’s preferences as configured by its principal will determine the emphasis given to each of these dimensions. For example, a buyer agent in the e-marketplace may prefer to emphasize the quality of merchandise over the price whereas another may emphasize return policy over fulfillment time; yet another may be concerned primarily with getting the cheapest deal. All the expectation dimensions and their associated trust values combine to yield a single value used to determine which potential partner is the best choice according to an agent’s preferences.

This work uses the weighted sum model (WSM) (explained in Figure 6) for combining trust expectation dimensions to obtain a single performance value for each agent and comparing that against the performance values of other agents.

Given a set of alternatives \( \{A_1, A_2, A_3, ..., A_m\} \) and a set of decision criteria \( \{C_1, C_2, C_3, ..., C_n\} \), and suppose that \( w_j \) denotes the relative weight of importance of the criterion \( C_j \) and \( a_{ij} \) is the performance value of alternative \( A_i \) when it is evaluated in terms of criterion \( C_j \). Then, the total importance of alternative \( A_i \), denoted as \( A_i^{WSM} \), is defined as follows:

\[
A_i^{WSM} = \sum_{j=1}^{n} w_j a_{ij}, \quad i = 1, 2, 3, ..., m.
\]

Figure 6: The weighted sum model.

WSM is a simple multi-criteria decision analysis method for evaluating a number of alternatives in terms of a number of decision criteria applicable when all the data are expressed in exactly the same unit. This is the case in CONGRATS. Using this simple technique will ensure that CONGRATS is practically applicable with minimal overhead.

Every evaluating agent is configured with assigned relative weighting for each interaction expectation dimension in the system according to its desired performance
preferences. The values of the weightings $w_f^e$ defined by the evaluating agent’s preferences must be such that:

$$\sum_{j=1}^{n} w_j^e = 1$$  \hfill (5)

Individual weightings can take any value in the interval $[0 : 1]$ provided they all sum up to 1 as stipulated by (5). Thus, agents can select based on a single dimension by giving it a weighting of 1. This configurability is a major strength of CONGRATS, since the trust information maintained by the agent is the same, regardless of its current expectation weightings. For each evaluated agent $b$, a performance value is calculated as:

$$PV(b) = \sum_{j=1}^{n} w_j^e T_{bij}^e, \ i = 1, 2, 3, ..., m.$$  \hfill (6)

At this point, the evaluating agent has enough information to compare the evaluated agents. If the buyer agent is maximization oriented, the best alternative is the one that yields the maximum total performance value (Triantaphyllou, 2000). However, depending on the agent’s preferences, which include its personalized selection strategy, one of the evaluated agents may be chosen for an actual purchase interaction.
CHAPTER 4

SIMULATION AND RESULTS

Methodology

Trust builds up very slowly in a real e-marketplace. It would require a considerable length of time if real data were to be gathered and used to show the workability of the proposed model in this study. This difficulty in collecting empirical data was overcome by adopting an alternative to real system implementation. The approach employed was the simulation of a mini e-marketplace that allowed interactions among the buyer and seller intelligent agents. This generated the data used to evaluate and validate the proposed model. Randomization was used to mimic situations that could have been the case in a real-life e-marketplace. This method ensured that the uncertainty that exists in real-life situations manifests in the e-marketplace.

The choice of simulation method for this research is circumspect; it yielded the needed data at a minimal cost. In addition, the implementation shares in common with existing e-marketplace systems, users’ goal-orientedness and their use of historical feedback and ratings as a basis for judgment when choosing a trading partner. The traditional feedback and ratings of existing e-marketplace systems such as Amazon.com and eBay thus provide a base for the proposed model.
Design

The simulation system is a stand-alone Java application. It uses arrays to store sets of attributes that determine how seller agents and buyer agents behave in an interaction. Seller agents are grouped into tiers depending on their average dispositional value (ADV). This is the weighted average of their dispositional values along the various trust dimensions. Agents whose ADV falls within the disposition band [0.91, 1.0] are in tier one (T1) and those whose ADV falls within the disposition band [0.76, 0.90] are in tier two (T2). Seller agents whose ADV falls within the disposition band [0.51, 0.75] are in tier three (T3), whereas those whose ADV falls within the disposition band [0.26, 0.50] are in tier four (T4). Seller agents whose ADV falls within the disposition band [0.0, 0.25] are in tier five (T5). These tiers form the basis for analyzing the performance of the seller agents, not individually but as groups. T1 sellers are the most trustworthy, whereas T5 sellers are the least trustworthy.

In addition, the proposed model depends on the feedback history and ratings as stored and provided by the buyer agents. However, there is a concern whether trust should be updated after every transaction, evaluation, and rating or whether updating of trust values should be done at intervals to lessen the burden on the entire system. If updating of trust values happens every time a transaction is completed and a rating is done, the system will be spending the available computing resources on trust updating instead of handling other matters of importance. On the other hand, allowing trust updating to occur at intervals will border on the reliability of the system. This work adopted the former approach largely because of the limited number of buyer and seller
agents in the e-marketplace. Trust updating thus occurs every time a transaction comes to a successful completion and feedback ratings are available.

**Experiment Setup**

The simulation involved 10 seller agents and 21 buyer agents. There were two agents for each of the five tiers of trust, whereas there are seven buyer agents for the three separate models evaluated. Two trust dimensions representing product value/quality and time-to-process/shipping time were of concern in the simulation. There were 10 experiments in all, and each of these was comprised of 100 iterations. The average of the generated data was used as a more reliable measure for performance evaluation. Table 2 shows the experiment parameters and their values.

Table 2

*Experiment Parameters and Values*

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of trust expectations</td>
<td>2</td>
</tr>
<tr>
<td>Maximum rating allowed</td>
<td>100</td>
</tr>
<tr>
<td>Number of buyers</td>
<td>21</td>
</tr>
<tr>
<td>Number of sellers</td>
<td>10</td>
</tr>
<tr>
<td>Number of experiments</td>
<td>10</td>
</tr>
<tr>
<td>Number of iterations per experiment</td>
<td>100</td>
</tr>
</tbody>
</table>
Performance Evaluation

The evaluation focused on whether the proposed model helps buyers to select sellers that are more trustworthy and, in so doing, obtain significantly higher utility values than with the competing models. This involved the analysis of the averaged data from the multiple experiments leading to various deductions, which support the superiority of the proposed model over competing ones. These authenticate the robustness of the proposed trust model. The trust estimation models used in validating the proposed model are FIRE (Huynh et al., 2006a) and MDT (Griffiths, 2005). Results and trends are shown next.

Results

As shown in Figure 7, sellers in the trust tier T1 (the most trustworthy sellers) made far more sales than the rest of the sellers in trust tiers T2 – T5. Initially, there is no significant difference in the performance of the sellers, but as more iterations occur and buyers are able to correctly establish the trust levels of the sellers, the more trustworthy sellers got chosen more frequently, resulting in increased number of transactions.

Figure 8 shows the performance of the various groups of sellers corresponding to the trust tiers built into the system. In the first few iterations, the trustworthiness of the sellers tended not to affect the outcome of interactions. A significant change is observed at about the fifth iteration. T1 and T2 sellers significantly increased their sales, whereas the less trustworthy sellers (T3, T4, and T5) saw a significant drop in their sales. At about the 70th iteration, the system stabilizes and T1 sellers from this point forward accounted for about 45% of the total sales as contrasted to less than 10% of the total sales by T5 sellers. Figure 9 corroborates the foregoing deductions.
Figure 7: Seller group performance using transaction count over iterations.

Figure 8: Seller group performance using percentage sales.
Figure 9: Trust tier performance trend.
Figure 10 shows the performance of the various models under comparison using buyer group cumulative utility value. At the beginning, three models perform at about the same level. This trend changes shortly afterwards, and the proposed model overtakes and leads the others for the rest of the iterations. At the 100^{th} iteration, the cumulative utility value for the proposed model stands at 612.35 as contrasted to 518.96 and 421.28 for the FIRE and MDT models, respectively. Figures 11 and 12 show the average group utility value earned per iteration and the average utility value earned per transaction, respectively, for each model. These charts also show the better performance of the proposed model over the others.

Figure 10: Model performance using buyer group cumulative utility value.
Figure 11: Average group utility value earned per iteration.

Figure 12: Average value earned per transaction.
Figure 13 represents the performance gain of the proposed model over the two competing models. The proposed model (CONGRATS) trails the FIRE model, but leads the MDT model at the onset. As more interactions occur in subsequent iterations and the trust levels of the sellers are better estimated, the proposed model increases significantly in performance over the other models. At about the 60th iteration, the performance gain peaks at about 15% over FIRE and a little more than 30% over MDT.

Figure 13: Performance gain of the proposed model over compared models.
CHAPTER 5

CONCLUSION AND FUTURE WORK

In this study, I have proposed a trust estimation scheme that buyer agents can use to effectively select trusted sellers, thereby limiting or even eliminating loss in the e-marketplace of today. In the simulated mini e-marketplace, CONGRATS significantly increased the overall performance of intelligent buyer agents. More transactions occurred between buyers and the most trustworthy sellers. In a real e-marketplace, CONGRATS inarguably will reduce loss to an infinitesimal level and consequently boost buyer confidence. In addition, this success can be replicated in domains other than e-commerce.

I have demonstrated that CONGRATS has an edge over select trust estimations models like FIRE and MDT. Compared to FIRE and MDT, CONGRATS had a performance gain of 15% and 30%, respectively, as well as an average earning of 0.89 (out of 1.0) per transaction in contrast to 0.70 and 0.62 per transaction, respectively. Cumulative utility gain among buyer groups stood at 612.35 as contrasted to 518.96 and 421.28 for the FIRE and MDT models, respectively.

Buyer agents selected the most trusted (T1) sellers 45% of the time for interaction, whereas T2 sellers were selected 20% of the time. This leaves only 35% of the transactions to the three least trusted seller groups—T3, T4, and T5. This distribution
will ensure that monopoly does not arise; ensuring that trusted agents do not wield more power than necessary in the e-marketplace. Without this mechanism, trusted sellers may start cheating after they have gained much trust in the agent community.

This study considered one commodity market with every seller dealing on the same item. It will be interesting to investigate how CONGRATS will behave in a multiple commodity market with a mix of sellers dealing on only one type of commodity and sellers dealing in multiple commodities. In addition, it assumed that buyer agents are honest and always give feedback. Future research will investigate the effects of fraudulent feedback, be it a withheld rating or falsified rating on the performance of CONGRATS. Furthermore, this study assumed that agent dispositions remain unchanged so that seller agents remain in their trust band and will always offer services reflecting such. Future work will explore scalability issues by extending the simulation so that intelligent agents can join and leave freely at runtime and seller agents migrate from one trust band to another.
APPENDIX

SOURCE CODES
package congrats;

import java.util.*;

/**
 * @author Ogbonnaya Akpa ID#: 138244
 * @course CPTR699 Master's Thesis
 * @title CONGRATS Simulator
 */

public class Main {

    /* Variable Declarations here... */
    static final int numberOfIterations = 1;
    static final int dim = 2; /* number of expectation dimensions */
    static final int numB = 21; /* number of buyers*/
    static final int numS = 10; /* number of sellers*/
    static final int numR = 3; /* number of referees */
    static final int numW = 3; /* number of witnesses */
    static final double maxRating = 100.0;

    //BUYER-SPECIFIC VARIABLES
    /* [buyerId][sellerId]buyerArray = new double [numB][numBA][exp1R, exp2R, ...] */
    static double[][][]{ buyerRatings = new double[numB][numS][dim];
    /* [buyerId][sellerId][exp1dT, exp2dT, ..., expNdT] */
    static double[][][]{ buyerDispTrust = new double[numB][numS][dim];
    /* [buyerId][count of interactions with sellers] */
    static int[][][] buyerInteractionLog = new int[numB][numS][1];

    //SELLER-SPECIFIC VARIABLES
    /* [sellerId][ref1, ref2, ..., refN] */
    static int[][] sellerReferees = new int[numS][numR];

    //MEASURES VARIABLES
    /* [count of interactions with buyers] */
    static int [] sellerInteractionLog = {0,0,0,0,0,0,0,0,0,0};
    static int []{ sellerBuyerLog = new int[numS][numB];
    /* [cumulative utility for group] */
    static double[] buyerGroupUtility = {0.0, 0.0, 0.0};
    static int[] sellerGroupCount = {0, 0, 0, 0, 0};
    static int[] sellerTierBreakdown = {0, 0, 0, 0};

//REUSABLE VARIABLES
static int norts = 0; //number of ratings to store
static int ref1 = -1, ref2 = -1, ref3 = -1; // seller supplied referees
static int wit1 = -1, wit2 = -1, wit3 = -1; // buyer solicited witnesses
static int buyerGroup = -1; //buyer group identifier
static int sellerGroup = -1; //seller group identifier
static int numberOfInt = 0; //number of interactions
static double disposition = -1.0; //buyer disposition
static double Wexp1 = -1.0; //weighting for expectation dimension 1
static double Wexp2 = -1.0; //weighting for expectation dimension 2
static double Wdt = -1.0; //weighting for dispositional trust
static double Wpr = -1.0; //weighting for personal rating
static double Wrti = -1.0; //weighting for referee rating information
static double Wtti = -1.0; //weighting for witness rating information
static double sumRefExp1Ratings = 0.0;
static double sumRefExp2Ratings = 0.0;
static double sumWitExp1Ratings = 0.0;
static double sumWitExp2Ratings = 0.0;
static double sellerExp1DispTrust = 0.0;
static double sellerExp2DispTrust = 0.0;
static double sellerExp1RefReputation = 0.0;
static double sellerExp2RefReputation = 0.0;
static double sellerExp1WitReputation = 0.0;
static double sellerExp2WitReputation = 0.0;
static double sellerExp1PubReputation = 0.0;
static double sellerExp2PubReputation = 0.0;
static double sellerExp1Trust = 0.0;
static double sellerExp2Trust = 0.0;
static double[] sellerPerfValue = {0.0, 0.0, 0.0, 0.0, 0.0, 0.0};

//BUYER CONFIGURATION DATA
/* [buyerId][att1, att2, ..., attN] */

static double [][] buyerArray = {
  //Group A – CONGRATS
  {0.75, 0.5, 0.5, 0.5, 0.5, 0.5, 0.5, 0.5, 1.0},
  {0.60, 0.5, 0.5, 0.5, 0.5, 0.5, 0.5, 0.5, 1.0},
  {0.90, 0.5, 0.5, 0.5, 0.5, 0.5, 0.5, 0.5, 1.0},
  {0.80, 0.5, 0.5, 0.5, 0.5, 0.5, 0.5, 0.5, 1.0},
  {0.99, 0.5, 0.5, 0.5, 0.5, 0.5, 0.5, 0.5, 1.0},
  {0.50, 0.5, 0.5, 0.5, 0.5, 0.5, 0.5, 0.5, 1.0},
  {0.49, 0.5, 0.5, 0.5, 0.5, 0.5, 0.5, 0.5, 1.0},
  //Group B – MDT
  {0.75, 0.0, 0.0, 1.0, 0.0, 0.5, 0.5, 2.0},
  {0.60, 0.0, 0.0, 1.0, 0.0, 0.5, 0.5, 2.0},
  {0.90, 0.0, 0.0, 1.0, 0.0, 0.5, 0.5, 2.0}
};
//Group C - FIRE
{0.75, 0.5, 0.5, 0.5, 0.5, 1.0, 0.0, 3.0},
{0.60, 0.5, 0.5, 0.5, 0.5, 1.0, 0.0, 3.0},
{0.90, 0.5, 0.5, 0.5, 0.5, 1.0, 0.0, 3.0},
{0.80, 0.5, 0.5, 0.5, 0.5, 1.0, 0.0, 3.0},
{0.99, 0.5, 0.5, 0.5, 0.5, 1.0, 0.0, 3.0},
{0.50, 0.5, 0.5, 0.5, 0.5, 1.0, 0.0, 3.0},
{0.49, 0.5, 0.5, 0.5, 0.5, 1.0, 0.0, 3.0}
};

//SELLER CONFIGURATION DATA
/* [sellerId][att1, att2, ..., attN] */
static double [][] sellerArray = {
    {0.73, 0.79, 2.0}, //T2
    {0.70, 0.70, 3.0}, //T3
    {0.30, 0.30, 4.0}, //T4
    {0.10, 0.10, 5.0}, //T5
    {0.60, 0.68, 3.0}, //T3
    {0.50, 0.50, 4.0}, //T4
    {0.77, 0.81, 2.0}, //T2
    {0.20, 0.20, 5.0}, //T5
    {1.00, 1.00, 1.0}, //T1
    {0.90, 0.92, 1.0}, //T1
};

static void simMarket() {
    //INITIALIZE SOME LOCAL VARIABLES
    //referees and witnesses
    int refs = 0, wits = 0;
    //Arrays for randomizing buyers and sellers
    int [] selectSellers = {0,1,2,3,4,5,6,7,8,9};
    int [] selectBuyers = {0,1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20};

    //sellerReferees array
    for(int i = 0; i < numS; i++){
        for (int j = 0; j < numR; j++){
            sellerReferees[i][j] = -1;
        }
    }
}

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/buyerInteractionLog arrays
for(int i = 0; i < numB; i++){
    for(int j = 0; j < numS; j++){
        for(int k = 0; k < 1; k++){
            buyerInteractionLog[i][j][k] = 0;
        }
    }
}

//SIMULATE MINI E-MARKET THE SPECIFIED NUMBER OF TIMES
int seller = 0;
int buyer = 0, chosen = -1;

//Shuffle sellers so that no order is strictly followed
shuffle(selectSellers);

//FOR EVERY BUYER DO ...
while (buyer < numB) {
    //Initialize current variables
    disposition = buyerArray[buyer][0]; //buyer disposition
    Wrti = buyerArray[buyer][1]; //weighting for referee rating information
    Wwti = buyerArray[buyer][2]; //weighting for witness rating information
    Wdt = buyerArray[buyer][3]; //weighting for dispositional trust
    Wpr = buyerArray[buyer][4]; //weighting for public trust
    Wexp1 = buyerArray[buyer][5]; //weighting for expectation dimension 1
    Wexp2 = buyerArray[buyer][6]; //weighting for expectation dimension 2
    buyerGroup = (int) buyerArray[buyer][7]; //buyer group

    //Randomize the number of sellers to participate in this round
    Random randGen = new Random();
    int numSelect = randGen.nextInt(selectSellers.length);

    //Use a boolean to track first interaction with a seller
    boolean first = true;

    //Scrutinize every seller in shuffled array and chose one
    for (int sellerLoop = 0; sellerLoop < numSelect; sellerLoop++) {
        //Assign seller from shuffled array
        seller = selectSellers[sellerLoop];

        //Use personal experience if previous interactions
        numberOfInt = buyerInteractionLog[buyer][seller][0];
        if (numberOfInt > 0) {
            first = false;
        }
sellerExp1DispTrust = buyerDispTrust[buyer][seller][0];
sellerExp2DispTrust = buyerDispTrust[buyer][seller][1];
}
else {
    sellerExp1DispTrust = 1.0;//disposition;//1.0;
sellerExp2DispTrust = 1.0;//disposition;//1.0;
}

//@Use referee ratings
//@Initialize referee ratings field
sumRefExp1Ratings = 0.0;
sumRefExp2Ratings = 0.0;
ref1 = sellerReferees[seller][0];
ref2 = sellerReferees[seller][1];
ref3 = sellerReferees[seller][2];

if(ref1 >= 0 || ref2 >= 0 || ref3 >= 0){//Check for availability of referees
    if(ref1 >= 0){
        sumRefExp1Ratings = sumRefExp1Ratings +
        buyerRatings[ref1][seller][0];
        sumRefExp2Ratings = sumRefExp2Ratings +
        buyerRatings[ref1][seller][1];
        refs = 1;
    }
    if(ref2 >= 0){
        sumRefExp1Ratings = sumRefExp1Ratings +
        buyerRatings[ref2][seller][0];
        sumRefExp2Ratings = sumRefExp2Ratings +
        buyerRatings[ref2][seller][1];
        refs = 2;
    }
    if(ref3 >= 0){
        sumRefExp1Ratings = sumRefExp1Ratings +
        buyerRatings[ref3][seller][0];
        sumRefExp2Ratings = sumRefExp2Ratings +
        buyerRatings[ref3][seller][1];
        refs = 3;
    }
    sellerExp1RefReputation = sumRefExp1Ratings / (refs * maxRating);
sellerExp2RefReputation = sumRefExp2Ratings / (refs * maxRating);
}

//@Use witness ratings
//@Initialize witness ratings field
sumWitExp1Ratings = 0;
sumWitExp2Ratings = 0;
shuffle(selectBuyers);
wit1 = selectBuyers[1];
wit2 = selectBuyers[2];
wit3 = selectBuyers[3];

if(wit1 >= 0 || wit2 >= 0 || wit3 >= 0)//Check for availability of witnesses
  if(wit1 >= 0){
    sumWitExp1Ratings = sumWitExp1Ratings +
    buyerRatings[wit1][seller][0];
    sumWitExp2Ratings = sumWitExp2Ratings +
    buyerRatings[wit1][seller][1];
    wits = 1;
  }
  if(wit2 >= 0){
    sumWitExp1Ratings = sumWitExp1Ratings +
    buyerRatings[wit2][seller][0];
    sumWitExp2Ratings = sumWitExp2Ratings +
    buyerRatings[wit2][seller][1];
    wits = 2;
  }
  if(wit3 >= 0){
    sumWitExp1Ratings = sumWitExp1Ratings +
    buyerRatings[wit3][seller][0];
    sumWitExp2Ratings = sumWitExp2Ratings +
    buyerRatings[wit3][seller][1];
    wits = 3;
  }
  sellerExp1WitReputation = sumWitExp1Ratings / (wits * maxRating);
sellerExp2WitReputation = sumWitExp2Ratings / (wits * maxRating);
}

/* Calculate seller's public reputation for expectation dimensions */
sellerExp1PubReputation = (sellerExp1RefReputation * Wrti) +
(sellerExp1WitReputation * Wwti);
sellerExp2PubReputation = (sellerExp2RefReputation * Wrti) +
(sellerExp2WitReputation * Wwti);

//compute trust for each expectation ---------------------------------------
sellerExp1Trust = (sellerExp1DispTrust * Wdt) +
(sellerExp1PubReputation * Wpr);
sellerExp2Trust = (sellerExp2DispTrust * Wdt) +
(sellerExp2PubReputation * Wpr);

//compute performance value for each seller -------------------------------
sellerPerfValue[seller] = (sellerExp1Trust * Wexp1) +
(sellerExp2Trust * Wexp2);
// Make seller selection
chosen = randGen.nextInt(numS);
for (int sellerLoop = 0; sellerLoop < numS; sellerLoop++) {
    if (sellerPerfValue[chosen] < sellerPerfValue[sellerLoop]) {
        chosen = sellerLoop;
    }
}
sellerGroup = (int) sellerArray[chosen][2];

// Make updates and generate report data
if (chosen >= 0) {
    // Increase interaction counts
    sellerInteractionLog[chosen]++;
    buyerInteractionLog[buyer][chosen][0]++;
}

// Set seller referees
if (sellerReferees[chosen][0] < 0) {
    sellerReferees[chosen][0] = buyer;
} else if (sellerReferees[chosen][0] > 0 && sellerReferees[chosen][1] < 0) {
    sellerReferees[chosen][1] = buyer;
} else if (sellerReferees[chosen][0] > 0 && sellerReferees[chosen][1] > 0 &&
    sellerReferees[chosen][2] < 0) {
    sellerReferees[chosen][2] = buyer;
}

// Cummulate Buyer group utility gain
if (buyerGroup == 1) {
    buyerGroupUtility[0] = buyerGroupUtility[0] + sellerArray[chosen][0];
    if (sellerGroup == 1) {
        sellerTierBreakdown[0]++;
    } else if (sellerGroup == 2) {
        sellerTierBreakdown[1]++;
    } else if (sellerGroup == 3) {
        sellerTierBreakdown[2]++;
    } else if (sellerGroup == 4) {
        sellerTierBreakdown[3]++;
    }
}
else if(sellerGroup == 5){
    sellerTierBreakdown[4]++;
}
} else if(buyerGroup == 2){
} else if(buyerGroup == 3){
}
}

//Cummulate Seller group count
if(sellerGroup == 1){
    sellerGroupCount[0]++;
} else if(sellerGroup == 2){
    sellerGroupCount[1]++;
} else if(sellerGroup == 3){
    sellerGroupCount[2]++;
} else if(sellerGroup == 4){
    sellerGroupCount[3]++;
} else if(sellerGroup == 5){
    sellerGroupCount[4]++;
}
}

//Rate transaction -------------------------------------------------------------------
//Rating = seller value * buyerDisposition * maxRating
buyerRatings[buyer][chosen][0] = sellerArray[chosen][0] * buyerArray[buyer][0] * maxRating;
buyerRatings[buyer][chosen][1] = sellerArray[chosen][1] * buyerArray[buyer][0] * maxRating;

//Update trust and other values ------------------------------------------------------
if(first){
    buyerDispTrust[buyer][chosen][0] = buyerRatings[buyer][chosen][0] / maxRating;
    buyerDispTrust[buyer][chosen][1] = buyerRatings[buyer][chosen][1] / maxRating;
} else{
buyerDispTrust[buyer][chosen][0] = (((numberOfInt) * maxRating * buyerDispTrust[buyer][chosen][0])
+ buyerRatings[buyer][chosen][0])
/ ((numberOfInt + 1) * maxRating);

buyerDispTrust[buyer][chosen][1] = (((numberOfInt) * maxRating * buyerDispTrust[buyer][chosen][1])
+ buyerRatings[buyer][chosen][1])
/ ((numberOfInt + 1) * maxRating);

} //Loop to next buyer
buyer++;

doGarbageCollection();

//HELPER METHODS GO HERE ...

/* This method generates the data used for CONGRATS Model Evaluation */
static void generateReport() {
  for (int j = 0; j < sellerGroupCount.length; j++){
    System.out.print(sellerGroupCount[j] + "," + "\t");
  }
  System.out.format(" %6.2f %s \t", buyerGroupUtility[0], ",");
  System.out.format(" %6.2f %s \t", buyerGroupUtility[1], ",");
  System.out.format(" %6.2f %s \t", buyerGroupUtility[2], ",");
}

static void generateTierBreakdown(){
  for (int i = 0; i < sellerTierBreakdown.length; i++){
    System.out.print(sellerTierBreakdown[i] + "\t");
  }
  System.out.format(" %6.2f \t", buyerGroupUtility[0]);
}

//This method shuffles an array.
static void shuffle(int [] array){
  Random rand = new Random();
  int num1 = 0, num2 = 0, temp = 0;
  for(int i = 0; i < array.length*5; i++){
    num1 = rand.nextInt(array.length);
    num2 = rand.nextInt(numS);
    temp = array[num1];
    array[num1] = array[num2];
    array[num2] = temp;
  }
}
static void doGarbageCollection() {
    Runtime r = Runtime.getRuntime();
    r.gc();
}

/**
 * Execution starts here
 * @param args - there are no runtime arguments
 */
public static void main(String[] args) {
    System.out.println("RUN\tT1\tT2\tT3\tT4\tT5 \t CONGRATS \t MDT \t FIRE");
    for(int i = 0; i < 100; i++){
        System.out.println("n" + (i + 1) + ",");
        simMarket();
        generateReport();
        //generateTierBreakdown();
    }
    System.out.println("\n\n\n");
}
REFERENCE LIST
REFERENCE LIST


