



**UNIVERSITI PUTRA MALAYSIA**

**MACHINE LEARNING APPROACH FOR OPTIMIZING NEGOTIATION  
AGENTS**

**NG SOK CHOO**

**FSKTM 2007 12**



**MACHINE LEARNING APPROACH FOR OPTIMIZING NEGOTIATION  
AGENTS**

**By**

**NG SOK CHOO**

**Thesis Submitted to the School of Graduate Studies, Universiti Putra Malaysia,  
in Fulfilment of the Requirements for the Degree of Master of Science**

**April 2007**



## **DEDICATION**

**To my Parents,  
To my Brothers and Sisters.**

**Choo**



Abstract of thesis presented to the Senate of Universiti Putra Malaysia in fulfilment of the requirements for the degree of Master of Science

**MACHINE LEARNING APPROACH FOR OPTIMIZING NEGOTIATION AGENTS**

By

**NG SOK CHOO**

**April 2007**

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**Faculty : Computer Science and Information Technology**

The increasing popularity of Internet and World Wide Web (WWW) fuels the rise of electronic commerce (E-Commerce). Negotiation plays an important role in e-commerce as business deals are often made through some kind of negotiations. Negotiation is the process of resolving conflicts among parties having different criteria so that they can reach an agreement in which all their constraints are satisfied.

Automating negotiation can save human's time and effort to solve these combinatorial problems. Intelligent Trading Agency (ITA) is an automated agent-based one-to-many negotiation framework which is incorporated by several one-to-one negotiations. ITA uses constraint satisfaction approach to evaluate and generate offers during the negotiation. This one-to-many negotiation model in e-commerce retail has advantages in terms of customizability, scalability, reusability and robustness. Since negotiation agents practice predefined negotiation strategies, decisions of the agents to select the best course of action do not take the dynamics of



negotiation into consideration. The lack of knowledge capturing between agents during the negotiation causes the inefficiency of negotiation while the final outcomes obtained are probably sub-optimal. The objective of this research is to implement machine learning approach that allows agents to reuse their negotiation experience to improve the final outcomes of one-to-many negotiation. The preliminary research on automated negotiation agents utilizes case-based reasoning, Bayesian learning and evolutionary approach to learn the negotiation. The genetic-based and Bayesian learning model of multi-attribute one-to-many negotiation, namely GA Improved-ITA and Bayes Improved-ITA are proposed. In these models, agents learn the negotiation by capturing their opponent's preferences and constraints. The two models are tested in randomly generated negotiation problems to observe their performance in negotiation learning. The *learnability* of GA Improved-ITA enables the agents to identify their opponent's preferable negotiation issues. Bayes Improved-ITA agents model their opponent's utility structure by employing Bayesian belief updating process. Results from the experimental work indicate that it is promising to employ machine learning approach in negotiation problems. GA Improved-ITA and Bayes Improved-ITA have achieved better performance in terms of negotiation payoff, negotiation cost and justification of negotiation decision in comparison with ITA. The joint utility of GA Improved-ITA and Bayes Improved-ITA is 137.5% and 125% higher than the joint utility of ITA while the negotiation cost of GA Improved-ITA is 28.6% lower than ITA. The negotiation successful rate of GA Improved-ITA and Bayes Improved-ITA is 10.2% and 37.12% higher than ITA. By having knowledge of opponent's preferences and constraints, negotiation agents can obtain more optimal outcomes. As a conclusion, the adaptive nature of agents will increase the fitness of autonomous agents in the

dynamic electronic market rather than practicing the sophisticated negotiation strategies. As future work, the GA and Bayes Improved-ITA can be integrated with grid concept to allocate and acquire resource among cross-platform agents during negotiation.



Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk ijazah Master Sains

**PENDEKATAN PEMBELAJARAN SECARA MESIN UNTUK  
MENGOPTIMUMKAN EJEN-EJEN PERUNDINGAN**

Oleh

**NG SOK CHOO**

**April 2007**

**Pengerusi : Profesor Madya Md. Nasir Sulaiman, PhD**

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Penambahan dalam pengumumgunaan “Internet” dan “World Wide Web” telah membawa perkembangan kepada perdagangan elektronik (Dagang E). Perundingan memainkan peranan penting dalam perdagangan elektronik kerana setiap urusan niaga akan terjadi daripada perundingan. Perundingan merupakan proses penyelesaian konflik di antara pihak yang berbeza ciri-ciri dengan mencapai satu persetujuan di mana segala rintangan akan dipenuhi.

Perundingan automatik boleh menjimatkan masa dan usaha manusia untuk menyelesaikan masalah pergabungan. Agensi Perniagaan Pintar (APP) adalah kerangkaan perundingan satu kepada banyak automatik berdasarkan ejen yang disertakan oleh beberapa satu kepada satu perundingan. Model perundingan satu kepada banyak ini mempunyai kelebihan dari segi kebolehgunaan, kebolehukuran, pengulangan dan pengukuhan. Oleh kerana perunding menggunakan strategi yang terancang, keputusan untuk memilih yang terbaik tidak mempertimbangkan dinamik perundingan. Kekurangan pengalaman dalam penguasaan ejen-ejen



sepanjang perundingan akan mengakibatkan ketidakcepan di samping keputusan yang kurang baik. Objektif penyelidikan ini ialah melancarkan pendekatan pembelajaran secara mesin yang membolehkan agen menggunakan pengalaman perundingan yang lepas untuk memajukan keputusan perundingan satu kepada banyak. Penyelidikan lepas tentang ejen perunding automatik mempergunakan taakulan berdasarkan kes, pembelajaran Bayesian dan pendekatan bersifat evolusi untuk belajar perundingan. Pempelbagaian gelagat dalam perundingan satu kepada banyak, yang dikenali sebagai GA Improved-ITA dan Bayes Improved-ITA yang berdasarkan generik dan model pembelajaran Bayesian telah dicadangkan. Dalam model ini, agen akan mempelajari perundingan dengan menguasai kegemaran dan rintangan parti penentang. Kedua-dua model ini diuji dalam masalah perundingan yang dihasilkan secara sembarangan untuk memerhatikan pertunjukan mereka dalam pembelajaran perundingan. Kebolehbelaian GA Improved-ITA membolehkan ejen-ejen untuk mengenalpastikan isu-isu kegemaran penentang. Ejen-ejen Bayes Improved-ITA membentuk struktur utiliti penentang dengan menggunakan proses pengemaskinian kepercayaan Bayesian. Kerja ujikaji telah menunjukkan bahawa pendekatan pembelajaran secara mesin boleh mendatangkan keputusan dalam perundingan. GA Improved-ITA dan Bayes Improved-ITA telah mencapai pertunjukan yang lebih baik dari segi pelunasan hutang perundingan, kos perundingan dan justifikasi keputusan perundingan dibandingkan dengan ITA. Kegunaan bersama bagi GA Improved-ITA dan Bayes Improved-ITA adalah 137.5% dan 125% lebih tinggi daripada kegunaan bersama bagi ITA manakala kos perundingan bagi GA Improved-ITA adalah 28.6% lebih rendah daripada ITA Kadar berjaya perundingan bagi GA Improved-ITA dan Bayes Improved-ITA adalah 10.2% dan 37.12% lebih tinggi daripada ITA. Dengan pengetahuan kegemaran dan



rintangan penentang, agen perunding boleh mencapai keputusan yang lebih memuaskan. Kesimpulan ialah penyesuaian agen-agen akan meningkatkan kepintaran ejen-ejen berdikari dalam pasaran elektronik yang dinamik daripada menggunakan strategi perundingan yang rumit. Sebagai kerja depan, GA dan Bayes Improved-ITA boleh digabungkan dengan konsep kisi-kisi untuk membagikan and memperoleh sumber di antara ejen yang berada dalam pelantaran seberangan semasa perundingan.

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Ng Sok Choo

May 2007



I certify that an Examination Committee has met on \_\_\_\_\_ to conduct the final examination of **Ng Sok Choo** on her Master of Science thesis entitled "Machine learning approach for optimizing negotiation agents" in accordance with Universiti Pertanian Malaysia (Higher Degree) Act 1980 and Universiti Pertanian Malaysia (Higher Degree) Regulations 1981. The Committee recommends that the candidate be awarded the relevant degree. Members of the Examination Committee are as follows:

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## **DECLARATION**

I hereby declare that the thesis is based on my original work except for quotations and citations, which have been duly acknowledged. I also declare that it has not been previously or concurrently submitted for any other degree at Universiti Putra Malaysia or other institutions.

---

**NG SOK CHOO**

Date: 30 May 2007



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## LIST OF ABBREVIATIONS AND NOTATIONS

<b>E-Commerce</b>	Electronic Commerce
<b>GAs</b>	Genetic Algorithms
<b>ITA</b>	Intelligence Trading Agency
<b>GBML</b>	Genetic Based Machine Learning
<b>LCS</b>	Learning Classifier System
<b>NSS</b>	Negotiation Support System
<b>GDSS</b>	Group Decision Support System
<b>NSA</b>	Negotiation Support System
<b>BATNA</b>	Best Alternative To the Negotiated Agreement
<b>AC</b>	Arc Consistency
<b>SJT</b>	Social Judgment Theory
<b>GBMLE</b>	Genetic-Based Machine Learning Environment
<b>BALE</b>	Bayesian Learning Environment
<b><math>R_i</math></b>	Ratio Value of Consecutive Offers



# CHAPTER 1

## INTRODUCTION

### 1.1 Background

The emergence of Internet and WWW revolutionizes the conduct of business and commerce. The Internet links thousands of organizations worldwide into a single network and creates a vast global electronic market place. Through computers and networks, buyers and sellers can complete purchase and sale transactions digitally regardless of their location. Besides, transactions such as establishing price, paying bills and ordering goods can be accomplished through the network with lower cost. According to Laudon and Laudon (2002), e-commerce is the process of buying and selling goods and services electronically, involving transactions using the Internet, networks and other digital technologies.

In terms of the nature of the participants in the transaction, e-commerce can be categorized as business-to-consumer e-commerce, business-to-business e-commerce and consumer-to-consumer e-commerce. Each category of the e-commerce involves buying and selling. Several descriptive theories and models attempt to capture buying behavior for e-commerce. For examples, there are Nissen's Commerce Model (Nissen, 1997), Felman's E-Commerce Value Chain (Feldman, 1999) and Maes and Media Lab's Consumer Buying Behavior (CBB) model for e-commerce (Moukas *et al.*, 2000). Although they are named differently, these models share a similarity on the fundamental stages of the buying process. CBB research has



defined buying process into six stages. They are need identification, product brokering, merchant brokering, negotiation, purchase and delivery as well as product service and evaluation. These stages represent an approximation and simplification of complex behaviors. They often overlap and migration from one stage to another can be nonlinear and iterative.

Among the six stages of the buying behavior, negotiation is a key component of e-commerce (Sandholm, 1999). Business deals are often made through negotiation. Negotiation is a process in which two or more parties with different criteria, constraints, and preferences, jointly reach an agreement on the terms of a transaction (Rahwan *et al.*, 2001). Generally, a negotiation involves one or more potential business partners; each of which has different business goals. These potential business partners exchange their goals in the form of offers and counter offers to see if they can agree to mutually acceptable terms of a transaction. The terms can be a definition of the good or service being traded, price and delivery date. A negotiation typically goes through a number of iterations. Nevertheless, there are impediments to apply human-based negotiation. First, the parties involved have to gather in a particular place at a fixed time to carry out the negotiation. The second concern is the time constraint. Negotiation is time consuming as it attempts to settle down various terms in a transaction for all parties while they may have opposite goals. If some parties do not concede, the negotiation may take forever to reach consensus.

Autonomous agents are intelligent software programs (Greenwald *et al.*, 2003). Based on the definition proposed by Wooldridge (1999), an agent is defined as “*a software system or system component that is situated in an environment, which it*

*can perceive and that is capable of autonomous actions in this environment in order to meet its design objectives*". The autonomous, social ability, reactivity and pro-activeness nature of software agents make them suitable to substitute human's role in negotiation. Software agents support and provide automation including the decision making to the negotiation stage in online trading. In the literature, many negotiation software agents have been proposed and implemented by researchers such as Kasbah (Maes & Chavez, 1996), Case-Based Negotiation agents (Zhang & Wong, 2001) and CSIRO's ITA (Kowalczyk & Bui, 2001). Nevertheless, these negotiation agents support one-to-one negotiation. To support fully autonomous multi-attribute one-to-many negotiation, ITA practices bilateral one-to-many negotiation by means of conducting a number of coordinated simultaneous one-to-one multi-attribute negotiations. This model of one-to-many negotiation opens up more alternatives to a party in a negotiation as one party can concurrently negotiate with several parties and finally deal with the one that can provide the best offer.

In ITA one-to-many negotiation, a number of agents, all working on behalf of one parties, negotiate individually with other parties. After a negotiation cycle, these agents report back to a coordinating agent that evaluate how well each agent has done and issue new instructions accordingly. The negotiation agents are free to exchange offers and counter offers as well as exercises different negotiation strategies. When new strategies become available, they can be added to the system at any point of time. The adaptability of these negotiation agents to the ever changing electronic marketplace environment leaves an important issue to the aptitude of intelligent agents in automated negotiations.

Artificial intelligence (AI) is the discipline that aims to understand the nature of human intelligence through the construction of computer programs that imitate intelligent behavior (Prasad, 2003). According to Hedberg (1996), intelligent agents are autonomous software entities that can navigate heterogeneous computing environments and can either be alone or working with other agents to achieve some goals. They serve as a new candidate for providing interoperability in a volatile and dynamic environment where interactions among ad hoc market players are difficult to plan. Thus, intelligent agents require on board intelligence to achieve their task, such as planning, reasoning and learning algorithms. As electronic marketplace environment keeps on changing over time, the ability of agents to learn the opponent agent's sophisticated preferences will produce more optimal negotiation outcomes.

## **1.2 Problem Statement**

Many current automated negotiation systems support one-to-one negotiation (Rahwan *et al.*, 2001). ITA is a framework for one-to-many negotiation by means of conducting a number of concurrent coordinated one-to-one negotiations implemented by Kowalczyk and Bui (2001). In ITA, a buyer can initialize a number of sub-negotiating agents or sub-buyers, negotiating with several seller agents simultaneously. Each of the seller agents practices its own negotiation strategy while they are negotiating with the sub-negotiating agents. This approach has many advantages over existing one-to-one negotiation systems proposed by Wong *et al.* (2000), Kowalczyk and Bui (2001) and Su *et al.* (2000) in terms of customizability, scalability, reusability and robustness. Nonetheless, this approach is deficient in several respects to optimize a negotiation.

The negotiation strategies of agents in ITA are static. Many negotiation agents such as Kasbah (Maes & Chavez, 1996), Tete-a-Tete (Guttman & Maes, 1998) and ITA (Rahwan *et al.*, 2001) were equipped with pre-programmed negotiation strategies. Since the strategies are programmed prior to the start of a negotiation, decision of negotiation agents to select the best course of action do not take the dynamics of negotiation into consideration. For example, a buyer or seller may change his decision during a negotiation due to the environmental factors or individual basis. If there is an adaptive agent such as Case-Based negotiation agents (Zhang & Wong, 2001), fuzzy e-negotiation agents system (Kowalczyk & Bui, 2000), Bayesian learning agents (Zeng & Sycara, 1998), genetic algorithm negotiation agents (Krovi *et al.*, 1999) and market driven negotiation agents (Kwang & Chung, 2003) to keep pace with the ever changing environment, the probability of obtaining successful negotiation will be higher than those agents without the learning ability.

Negotiation is a complicated process. It is about resolving conflicts of all the parties involved where they may have contrast goal. Thus, both buyer and seller encounter the problem of converging to the common area of interest on pricing and other terms of transaction during a negotiation. Many negotiations may breakdown because the parties fail to resolve their differences (Bazerman & Neale, 1992). In ITA, both parties in negotiation are represented by self-interested agents. The self-interested behavior makes these agents to only take their own preferences and constraints into consideration when they are making decisions. The lack of knowledge capturing between ITA agents during the one-to-many negotiation causes more time is spent for searching for feasible solutions that are satisfactory to all parties while the final outcomes obtained are probably sub-optimal (Li, 2002). However, in a negotiation,



it is ideal to achieve Pareto-optimal (Goicoechea *et al.*, 1982; Vincke, 1992) in which neither of the negotiators can improve the outcomes without loss to the other side at the end of a negotiation.

Moreover, the negotiation outcomes, including the time spent, profits and agent's decisions in ITA one-to-many negotiation, ride on the negotiation strategies being used. It should be noted that each individual seller agent in ITA is bound with a negotiation strategy. When conducting a concurrent negotiation with sub-negotiating agents, the seller agent with sophisticated strategy is probably running away with better outcomes at the end of the negotiation. However, the negotiation strategies will be obsolete after a period of time and new strategies are required to replace them. The need for manually updating the negotiation strategies over a time period is at controversy to the *autonomy* respect of intelligent agents discussed in Maes (1995), Wooldridge and Jennings (1995) and Nwana (1996).

This research is to improve the deficiencies of negotiation agents in ITA in order to optimize the negotiation final outcomes. These negotiation agents are adopted with the learning ability to learn the negotiation. Bayesian learning (Bayes, 1958) and Genetic algorithms (GAs) (Goldberg, 1989) are utilized respectively as the learning methods for the negotiation agents. The first method is based on Bazaar's learning agents and an extension of the negotiation learning model proposed by Zeng and Sycara (1998). The second method combines constraint satisfaction approach, proposed by Rahwan *et al.* (2001) in ITA agent framework to improve the negotiation outcomes.