Automated Win-Win Negotiation in B2C E-Commerce: A Research Review

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Abstract

Win-Win negotiation is the emergent ethical functionality of automated E-Commerce win-win negotiation can be achieved through co-operative negotiation mechanism. There are several approach deployed by various researcher in there co-operative negotiation based automated E-Commerce. In this research review paper we provide a review on various co-operative negotiation mechanisms which are deployed in various E-Commerce models.

Keywords : *Negotiation, Agent, multi-agent trust, Data mining, Co-operation.*

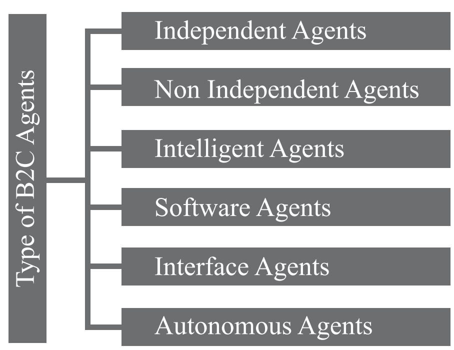
Introduction

Negotiation is one of the established processes for an interaction between a buyer and a seller to reach at an agreement stage where both of them are at profitable state of business. Various classical as well as modern intelligent computing methods such as knowledge based systems (KBS), case based reasoning (CBR), artificial neural nets (ANN) and genetic algorithm (GA) have been deployed to implement the various steps in a negotiation process. Multi agent systems (MAS) have also been used to represent the buyers and sellers as agents and the broker as a coordinator agent. In this model the job of the coordinator agent is to take the required items of the buyer agent and to find out the proper seller agent(s) who can supply the items to satisfy the constraints on the requirement of the buyer agent as well as on the seller agents in supply of the items. The buyer agent constraints are related with price, quality, quantity, brand, payment mode etc. The seller agent constraints are related with the price and quality (Jennings 2003). Very limited numbers of researchers have implemented the trust and other cognitive parameters in the negotiation process. We have paid attention to the cognitive parameter such as preference, desire, intention, commitment, capability, trust etc. as cognitive parameters for the selection of buyer and seller agents. Many different approaches for the selection of buyer agent have been reported in the literature. These approaches differ in procedures, technologies and methods. Each approaches cannot be used for complete cognitive parameters based agent selection and classification for negotiation in B2C e-commerce. The model will try to describe in this work basically provides interaction between buyer agents and seller agents through broker agent and customer orientation based selection of potential buyer agent for valuable seller agent for negotiation in e-commerce. We will describe the application of cognitive parameters based agent selection for negotiation in the purchase domain in a cooperative system. In this domain the buyer agent has a set of requirements and set of seller agent fulfill the buyer agent's requirements through cooperative negotiation mechanism. We will further describe customer orientation based Multi-agent system in negotiation process. The customer orientation is of three type domains: profit centric, customer understanding, and customer relationship for selecting the most profitable buyer agent for potential seller agent. Further we have made a study to determine the rules, importance of the cognitive and business parameters such as preference, commitment, intention, desire, price, payment mode, quantity and quality and address mode etc.,. For classification and categorization of profitable buyer agents and potential seller agents using data mining (DM) techniques like ANN, C&RT and feature selection method. Finally we will try to develop trust building strategies using data mining method integrated multi-agent system for cooperative and competitive e-market with the help of logical combination of predictive results of features selection, and computational results.

Types of B2C Agent are involve in various negotiation

Agents are people who represent the interests of the principal decision makers. They act on the principal's behalf with varying degrees of authority. They are employed in negotiations specifically because of their expertise, specialized knowledge, and experience.

Figure 1: Types of B2C Agents



Independent Agents

Independent agents must be compensated for their services. Many of these independent agents earn their income through commissions .The more an agent sells, then the more they earn in commission. It is not uncommon for an independent agent to inflate the sale to increase their commission. Independent agents are also interested in the enhancement of their professional reputation. Obviously these agents desire, to not only attract more clients, they want to get the best clients. Some examples would include a real estate agent, or a broker who negotiates the buying and selling of goods and services on behalf of another party.

Non Independent Agents

This type of agent works directly for a company or organization. An example 'would be a company's purchasing department whose staffs negotiates the lease or acquisition of supplies or equipment. Another example would be a union representative acting on behalf of a union. The agent's know-how is clearly the most constructive reason why they are employed by decision makers to best represent their interests. The other side of the coin reveals that agents may have other self-serving interests of their own. These contrary interests might be in conflict with the aims of the people who engage their services. Let's unravel this tangle. So that we are aware of potential contrary interests that agents might bring to the table.

Intelligent Agents

In this type of agent we attempt to achieve one-to-many negotiation by conducting a number of coordinated simultaneous one-to-one negotiations. The previous version (Kowalczyk, et. al., 2000) was directed at facilitating one-to-one multi-attribute negotiation. In our current prototype, a number of agents, all working on behalf of one party, negotiate individually with other parties. Each agent conducts a direct negotiation with a prospective seller or buyer. After each negotiation cycle, these agents report back to a coordinating agent which evaluates how well each agent has done and issues new instructions accordingly. Each individual agent conducts its reasoning by using constraint-based techniques for evaluating and generating offers. The intelligent agents autonomously negotiate multi-attribute terms of transactions in an e-commerce environment tested with the personal computer trading problem.

Software Agents

A software agent is a piece of software that functions as an agent for a user or another program, working autonomously and continuously in a particular environment (Michael Wooldridge J.). It is inhibited by other processes and agents, but is also able to learn from its experience in functioning in an environment over a long period of time.

Software agents offer various benefits to end users by automating repetitive tasks. The basic concepts related to software agents are:

1. They are invoked for a task.
2. They reside in "wait" status on hosts.
3. They do not require user interaction.
4. They run status on hosts upon starting conditions.
5. They invoke other tasks including communication.

There are a number of different software agents, Including:

Buyer Agents

These agents revolve around retrieving network information related to good and services.

Monitoring and Surveillance Agents

These agents observe and report on equipment.

Data-Mining Agents

These agents find trends and patterns in many different sources and allow users to sort through the data to find the information they are seeking.

Interface Agents

An interface agent to be a program that can also affect the objects in direct manipulation interface, but without explicit instruction from the user (Michael Wooldridge J.). The interface agent reads input that the user presents to the interface, and it can make changes to the objects the user sees on the screen, though not necessarily one-to-one with user actions. The agent may observe many user inputs, over a long period of time, before deciding to take a single action, or a single user input may launch a series of actions on the part of the agent, again, possibly over an extended period of time. An interface agent could be considered to be a "robot" whose sensors and effectors are the input and output capabilities of the interface and for that reason are sometimes also referred to as "softbots". Sometimes the interface agent is actually represented anthropomorphically as a face on the screen, such as in the Apple film Knowledge

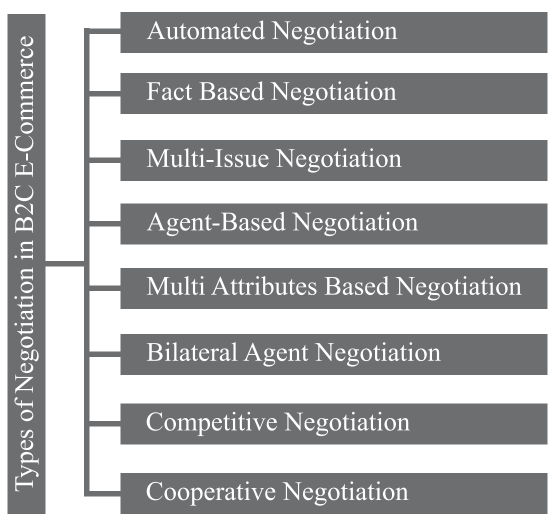
Navigator. The best-known examples of interface agents are intelligent tutoring systems and context-sensitive help systems is a good example. In such systems, the user may operate the interface with complete disregard for the agent, but, if called upon, the agent may also display suggestions, or perform direct-manipulation actions on objects in the displayed interface, based on input implicitly collected from the user. Other kinds of interface agents may critique the user's behaviour, or augment the user's direct-manipulation actions with extra computed information that the user may find helpful.

Autonomous Agents

An autonomous agent is an agent program that operates in parallel with the user. Autonomy says that the agent is, conceptually at least, always running . The agent may discover a condition that might interest the user and independently decide to notify him or her. The agent may remain active based on previous input long after the user has issued other commands or has even turned the computer off. An assistant may not be of much practical help if he or she needs very explicit instruction all the time and constant supervision while carrying out actions. Assistants can be time-savers when they are allowed to act independently and concurrently. Allowing an interface agent to run off-line and in parallel with the user directing attention to other activities enables the user to truly delegate tasks to the agent.

Types of Negotiation in B2c E-Commerce

Figure 2: Types of Negotiation in B2C E-Commerce



Automated Negotiation

Bosse T. stated that automated negotiation plays an important role in dynamic trading in e-commerce. Its research largely focuses on negotiation protocol and strategy design. There is a paucity of further scientific investigation and a pressing need on the implementation of multi-strategy selection, which is crucially useful in human–computer negotiation to achieve better online negotiation outcomes. The lack of such studies has decelerated the process of applying automated negotiation to real world problems With the rapid growth of global emarkets, there has been a significant interest in designing Automated Negotiation System (ANS) (Ketter W., et al., 2012) that can serve as surrogates for human business decision-makers, where software agents are designed to autonomously act on behalf of the real-world parties (Yang, et. al., 2013). According to Bosse T. automated negotiation is becoming crucially important and pervasive and agents promise exciting opportunities to turn conventional transactions into an automated, cost-efficient manner, the study of ANS has piqued increasing interest in the scholarly fields of e-commerce and artificial intelligence (Luo et al., 2102). While the e-commerce and AI literatures mirror that the ANS can be used in computer–computer and human–computer negotiations, extant studies on ANS primarily focus on the former, leaving the latter comparatively unexplored (Lin et. al., 2010). In fact, human involvement in decision-making is still required in most of present online negotiations, and with the ever mushrooming growth of e-commerce and e-markets, there is an increasing potential for the use of software agents to more effectively and efficiently negotiate with human negotiators. The human–computer negotiation plays a paramount role in the e-commerce oriented applications, especially in the B2C context where software agents act as business provider (Bosse et. al., 2005). Compared with the traditional online sales mode where customers view the basic product or service information on the website and often need to negotiate with human salespeople through a “contact us” link, a human–computer ANS can help business organizations to reduce the labour cost for negotiation and greatly increase the transaction efficiency to the optimum extent. Prior work have been conducted to design various human–computer (Lin et. al., 2010) negotiating agent which demonstrate that a software agent can proficiently negotiate with and even outperform people. Owing to the randomness of the human's behaviour, the human–computer negotiation context is assumedly more complicated. The human–computer negotiation system accordingly needs much smarter software agents to negotiate with the human negotiators effectively. In automated negotiation, people entrust the software agent to negotiate automatically online, and normally expect that the agent can try different strategies to obtain a better negotiation outcome. In such cases, the ability to quickly and autonomously select an appropriate strategy among the candidates according to negotiation situation changes is a very important perspective for evaluating the designed agent's intelligence level.

Fact-Based Negotiation

Braun P., et al proposed a model for intelligent agent in negotiation between buyer and seller in B2C Commerce using big data analytics. The developed model is used to conduct negotiations on behalf of prospective buyers and sellers using analytics to improve negotiations to meet the practical requirements. The objective of this model is to explore the opportunities of using big data and business analytics for negotiation, where big data analytics can be used to create new opportunities for bidding. Using big data analytics sellers may learn to predict the buyers' negotiation strategy and therefore adopt optimal tactics to pursue results that are to their best interests. An experimental design is used to collect intelligent data that can be used in conducting the negotiation process. Such approach will improve quality of negotiation decisions for both parties. Negotiation is one of the major components of many e-commerce activities, such as auctions, scheduling, contracting, and so on, and is one area that can greatly benefit from intelligent automation. They consider negotiations as a form of interaction between parties with conflicting goals who wish to cooperate in order to reach an agreement that will benefit all negotiating parties, a process that can be both complicated and time-consuming.

E-commerce negotiation is a decision-making process that seeks to find an electronic agreement, which will satisfy the requirements of two or more parties in presence of limited information and conflicting preferences (Braun et. al., 2006). In e-commerce negotiations buyers and sellers search for possible solutions until agreement is reached or negotiations fail. Both buyers and sellers can conduct their own utility assessment for every solution. The goal of negotiation is to seek a solution that optimizes utility value for both of them. Due to recent technological advances mentioned above all organizations involved in B2C commerce are forced to improve existing and develop new services to retain old customers and attract new one. Customers negotiate for better deals, and e-commerce business organizations are negotiating in order to keep their customers, to build lasting relationships, and to increase customer satisfaction Negotiation is one of such services. In a view of increased role of negotiations in B2C commerce it is appropriate to give this particular topic the attention it deserves. Negotiation can significantly benefit from big data analytics. Using analytics will allow businesses to shorten negotiation time and effort associated with it on one side. On the other side, it will help customers lacking knowledge of negotiation procedures and negotiation skills.

The success of e-negotiation in B2C commerce depends on volume of provided data and information, and how they are used to optimize the negotiation operations. The size of data is big enough to extract huge volumes of valuable knowledge that may determine firm's success or failure (Rajpurohit, 2013). Using big data analytics a seller may learn to predict the buyer's negotiation strategy and develop and adopt optimal tactics to achieve results that are to his best interests. The ability to manage and transform data into useful information and utilize it as a strategic differentiator is a key contributor to the success of B2C negotiation. The B2C negotiation process must be designed to take advantage of large volumes of consumer data that have become available in recent years due to the Internet, social networking, mobile telephony applications, RFID and sensor applications, and new technologies that create and capture data, size of which is growing exponentially. Collected data are mainly unstructured and contain valuable customer's opinion and behavioural information. Big data analytics can be defined as integrated Technology, technology, practices, methodologies, and applications that analyse critical business data to help an organization better understand its business and make real time decisions. In this work a description of B2C e-commerce negotiation model is presented. The primary job of this model is to conduct negotiations on behalf prospective buyers and sellers representatives. It employs multiple software agents that represent specific functional of the system and applies big data analytics. Based on analytics results, agents are able to improve their behaviours over time and take proactive and reactive negotiation actions. From that analytics knowledge, they may get better with selecting and achieving goals and taking correct actions.

The model provides the customizable user interface. Information filled in by the buyer will be stored in the buyer's profile and used for generation of the original offer. Negotiations are conducted by multiple negotiator agents with several organizations in parallel to speed up the negotiation process; the best counter-offer is selected by the agent server and presented to the buyer.

Multi-Issue Negotiation

Baarslag T., et al implemented multi-issue negotiation, with information available about the agents' preferences, a negotiation may result in a mutually beneficial agreement. In a competitive negotiation environment, however, self-interested agents may not be willing to reveal their preferences, and this can increase the difficulty of negotiating a mutually beneficial agreement. In order to solve this problem, this work proposes a Bayesian-based approach which can help an agent to predict its opponent's preference in bilateral multi-issue negotiation. The proposed model employs Bayesian theory to analyse the opponent's historical offers and to approximately predict the opponent's preference over negotiation issues. A counter-offer proposition algorithm is also integrated into the prediction approach to help agents to propose mutually beneficial offers based on the prediction results. Experimental results indicate good performance of the proposed approach in terms of utility gain and negotiation efficiency. In multi-agent systems, agents usually need to cooperate with each other in order to achieve certain goals in a shared environment. However, the agents may have conflicts about how to cooperate with each other to achieve these goals and this involves negotiation. Agent negotiation is a form of decision making where agents jointly explore possible solutions in order to reach an agreement (Baarslag, et. al., 2013). In recent decades, agent negotiation technology has been widely developed to solve issues in different areas, such as business transactions in e-commerce (Huang, et. al., 2010) and service management in cloud computing. With the support of agent negotiation technology, many operations which originally required human intervention can be conducted automatically and intelligently by autonomous agents, and this means that very large amounts amount of time and money can be saved. Currently, one major research challenge in this area is opponent modelling. More precisely, during a negotiation, agents usually need to use a number of negotiation parameters (i.e. deadline, preference, reservation utility and concession strategy) to make wise decisions so that a win-win agreement can be reached. Some cooperative negotiation strategies have assumed that these negotiation parameters are public information. In a competitive environment (non-cooperate negotiation), however, self-interested agents usually keep their negotiation parameters secret in order to avoid being exploited by their opponents. Without the knowledge of opponents' negotiation parameters, agents may have difficulty in adjusting their negotiation strategies properly to a reach win-win agreement. In order to overcome this difficulty, prediction approaches has been integrated into agents' negotiation strategies in recent years to estimate opponents' negotiation parameters.

In this work, one of the most important negotiation parameters is the negotiation preferences on negotiation issues, because the preferences can play a critical role in terms of agents utility gains and the success rate of a negotiation. Precisely speaking, in multi-issue negotiation, an agent's preference indicates the agent's weighting over different negotiation issues. A high weighted issue can help agents to generate more utility comparing with a low weighted issue. During a multi-issue negotiation, an offer that an agent proposed should not only maximise its own utility, but also try to minimise the damage on its opponent's utility, so that the opponent agent will be more willing to accept the offer. In order to propose such an offer, agents need to know their opponents' preferences on negotiation issues. According to the opponent's preference, an agent can trade of negotiation issues. In other words, while an agent makes some concession on its opponent highly weighted issues, it also tries to gain some payoff from the low weighted issues, so that both agents can benefit from the offer. In recent years, many different approaches have been proposed to help agents to predict their opponents' preferences. These include (Chen, et. al., 2015): genetic algorithm-based prediction, statistical analysis-based prediction and machine learning-based prediction (Ros, et.

al., 2006). However, all these approaches have different limitations. For example (Pan, et. al., 2013), the approaches in require previous negotiation data to make the prediction and the approach in may need a long training time before the prediction algorithm becomes effective. The motivation for this approach was to produce mutually beneficial offers for agents through preference prediction and issue trade-off. Specifically, a set of hypothesises about the opponent's preference is initialised before negotiation starts, and then Bayesian theory is used to analyse the counter-offer proposed by the opponent in each negotiation round and the most suitable hypothesis is chosen to help the agent to generate offers. The proposed negotiation approach was tested in different scenarios, and the experimental results have proved that their negotiation approach can help agents to reduce the time needed to reach an agreement. Agents who applied their negotiation approach could get more utilities when the negotiation ended.

Agent-Based Negotiation

Jennings, et al. implemented Agent-based negotiation is about computational autonomous agents that attempt to arrive at joint agreements in competitive consumer-provider or buyer–seller scenarios on behalf of humans (Jennings et al., 2001). As one of the most fundamental and powerful mechanisms for solving conflicts between parties of different interests, recent years have witnessed a rapidly growing interest in automated negotiation, mainly due to its broad application range in fields as diverse as electronic commerce and electronic markets, supply chain management, task and service allocation, and combinatorial optimization. As a result, agent-based negotiation brings together research topics of artificial intelligence, machine learning, game theory, economics, and social psychology (Chen, Hao, Weiss, Tuyls, & Leung, 2014).

Dependent on the assumptions made about the negotiating agents' knowledge and the constraints under which the agents negotiate, negotiation scenarios show different levels of complexity. The following assumptions, which are reasonable in view of real-world applications and which underly their work, induce high complexity and raise particular demands on the abilities of the negotiators. First, the agents have no usable prior information about their opponents – neither about their preferences (e.g., their preferences over issues or their issue value ordering) nor about their negotiation strategies. Then, the negotiation is constrained by the amount of time being elapsed, the participants therefore do not know at any time during negotiation how many negotiation rounds there are left and they have to take into account at each time point (i) the remaining chances for offer exchange and (ii) the fact that the profit achievable through an agreement decreases over time ("negotiation with deadline and discount"). (iii) each agent has a private reservation value below which an offered contract is not accepted. Thereby they adopt the common view that an agent obtains the reservation value even if no agreement is reached in the end. This implies that breaking-off a negotiation session would be potentially beneficial especially when the time-discounting effect is substantial and the other side is being very tough. Together these assumptions make negotiations complicated (yet realistic), where efficiently reaching agreements are particularly challenging. They refer to such type of negotiations as complex negotiations afterwards.

Multi Attributes Based Negotiation

Dastjerdi, et al proposed Cloud service level agreement negotiation is a process of joint decision-making between cloud clients and providers to resolve their conflicting objectives. With the advances of cloud technology, operations such as discovery, scaling, monitoring and decommissioning are accomplished automatically. Therefore, negotiation between cloud clients and providers can be a bottleneck if it is carried out manually. Their objective is to propose a state-of-the-art solution to automate the negotiation process for cloud environments and specifically infrastructure as a service category. The proposed negotiation strategy is based on a time-dependent tactic. For cloud providers, the strategy uniquely considers utilization of resources when generating new offers and automatically adjusts the tactic's parameters to concede more on the price of less utilized resources. In addition, while the previous negotiation strategies in literature trust offered quality of service values regardless of their dependability, their proposed strategy is capable of assessing reliability of offers received from cloud providers. Furthermore, to find the right configuration of the time-dependent tactic in cloud computing environments, they investigate the effect of modifying parameters such as initial offer value and deadline on negotiation outputs that include ratio of deals made, and inequality index. The proposed negotiation strategy is tested with different workloads and in diverse market conditions to show how the time-dependent tactic's settings can dynamically adapt to help cloud providers increase their profits.

In the Service Level Agreement Negotiation (SLAN) phase, discovered providers and the user negotiate on the quality of services. Finally, an SLA contract will be achieved if two parties reach an agreement on a set of quality of service (QoS) values. Then, the acquired service will be continuously monitored in the monitoring phase. If the monitoring service detects that predefined thresholds are reached, services are scaled dynamically in the scaling phase. Finally, in the decommissioning phase, last minute operations are carried out before the service is terminated (Redl C., et. al., 2012). With the advances of cloud technology, operations such as discovery, scaling, monitoring and decommissioning are accomplished automatically (Joshi K., et. al., 2014). Therefore, negotiations between cloud services clients and providers can be a bottleneck if they are carried out manually. Hence, the objective of this work is to propose a solution that automates the negotiation process in cloud computing (specifically infrastructure as a service) environments.

Cloud SLAN is a process of joint decision-making between cloud users and providers to resolve their conflicting objectives. Cloud services have cost, availability, and other non-functional properties on one hand and generate profits on the other hand. In cloud environments, both clients and providers have cost– benefit models for negotiation and decision-making. Therefore, SLA negotiation automation requires mapping of the knowledge and objectives of policy makers to lower level decision-making techniques. The first step towards the automation is finding, capturing, and modelling goals and objectives of parties involved in the negotiation. The second step is finding a proper strategy to use the goals in the low-level negotiation process.

Automated SLAN has attracted a great deal of interest in the context of Service Oriented Architecture (SOA), grid computing and recently cloud computing. Studies in these contexts mainly focused on offering negotiation strategies that maximize the user's utility values and the number of signed contracts. However, they have not considered infrastructure management issues in the bargaining strategy. It means that cloud providers are willing to concede on the price of resources which are less utilized, and that has to be reflected in the negotiation tactics. In addition, previous works have not considered reliability in the negotiation process. These researches assume that service requestors would trust whatever QoS criteria values providers offer in the process of negotiation. Nevertheless, providers may offer a QoS value during the negotiation that was not fully achieved according to the monitored QoS data.

E-commerce systems are important systems widely used by internauts. To automate most of commerce time-consuming stages of the buying process, software agent technologies proved to be efficient when employed in different e-commerce transaction stages. The FIPA Contract Net Protocol was developed to facilitate contract negotiation in Multi-Agent Systems, it is therefore important to analyse the protocol to ensure that it terminates correctly and satisfies other important properties. In this work they focus on agent interactions in e-commerce oriented automated negotiation based on FIPA Contract Net Protocol.

An e-commerce MAS is a MAS that connects multiple sellers and buyers agents on a single electronic marketplace called E-marketplace, where many interactions take place (Lawley et. al., 2006). Agents involved are cognitive agents, able to communicate intentionally. Contract Net creates a means for contracting as well as subcontracting tasks (or jobs), in this sense Initiators are managers and Participants are contractors. An Initiator could be an agent willing to buy some good or wanting to sell the right to supply some good. Participants, in each case, would be agents wanting to sell the good or willing to buy the right to supply the good. The Interaction Protocol is composed of a sequence of four main steps, the agents must go through the following loop of steps to negotiate each contract.

1. The Initiator announces a "call for proposal" (CFP).
2. Participant Agents who receive the announcement can answer by either a Proposal, a reject or a not understood response, indicating they did not understand the announcement.
3. Initiator receives and evaluates proposals; sends a Contract to participant agents whose proposals are accepted refuse to other agents.
4. At the end of interaction, the participant sends to the buyer agent, an Inform message to confirm the action achieving, or a failure message in a failure case.

Bilateral Agent Negotiation

Bilateral agent negotiation is considered as a fundamental research issue in autonomous agent negotiation, and was studied well by researchers (Fran, 1998). Generally, a predefined negotiation decision function and utility function are used to generate an offer in each negotiation round according to a negotiator's negotiation strategy, preference, and restrictions. However, such a negotiation procedure may not work well when the negotiator's utility function is nonlinear, and the unique offer is difficult to be generated. That is because if the negotiator's utility function is non-monotonic, the negotiator may find several offers that come with the same utility at the same time; and if the negotiator's utility function is discrete, the negotiator may not find an offer to satisfy its expected utility exactly. In order to solve such a problem, they propose a novel negotiation model in this work. Firstly, a 3D model is introduced to illustrate the relationships between an agent's utility function, negotiation decision function and offer generation function. Then two negotiation mechanisms are proposed to handle two types of nonlinear utility functions respectively, i.e. a multiple offer mechanism is introduced to handle non-monotonic utility functions, and an approximating offer mechanism is introduced to handle discrete utility functions. Lastly, a combined negotiation mechanism is proposed to handle nonlinear utility functions in general situations by considering both the non-monotonic and discrete. The experimental results demonstrate the effectiveness and efficiency of the proposed negotiation model.

In this work, a bilateral single-issue negotiation model was proposed to handle nonlinear utility functions. A 3D model was proposed to illustrate the relationships between an agent's utility function, negotiation decision function, and time constraint. A multiple offer mechanism was introduced to handle non-monotonic utility functions, and an approximating offer mechanism was introduced to handle discrete utility functions. Finally, these two mechanisms were combined to handle nonlinear utility functions in more general situations. The procedure of how an agent generated its counter offers by employing the proposed 3D model and negotiation mechanisms was also introduced. The experimental results indicated that the proposed negotiation model and mechanisms can efficiently handle nonlinear utility agents, and successfully lead the negotiation to an agreement.

To date, a variety of automated negotiation agents have been created. While each of these agents has been shown to be effective in negotiating with people in specific environments, they lack natural language processing support required to enable real-world types of interactions. In this work they present NegoChat, the first negotiation agent that successfully addresses this limitation. NegoChat contains several significant research contributions. First, they found that simply modifying existing agents to include an NLP module is insufficient to create these agents. Instead, the agents' strategies must be modified to address partial agreements and issue-by-issue interactions. Second, they present NegoChat's negotiation algorithm. This algorithm is based on bounded rationality, and specifically Aspiration Adaptation Theory (AAT). As per AAT, issues are addressed based on people's typical urgency, or order of importance. If an agreement cannot be reached based on the value the human partner demands, the agent retreats, or downwardly lowers the value of previously agreed upon issues so that a "good enough" agreement can be reached on all issues. This incremental approach is fundamentally different from all other negotiation agents, including the state-of-the-art KBAgent. Finally, we present a rigorous evaluation of NegoChat, showing its effectiveness. NegoChat, an agent that contains the following three key contributions: First, NegoChat successfully incrementally builds agreements with people, something current automated negotiators do not do. Second, NegoChat integrates natural language into its agent, allowing people to practice his or her negotiation skills from anywhere, without installing any complicated software. Third, Negochat performs better than the current stateof-the art agent, achieving better agreements in less time. Users are also happier with NegoChat and think the agent is fairer.

Competitive Negotiation

Frank R.H., et al proposed that negotiation is a form of decision-making where two or more parties jointly search a space of possible solutions with the goal of reaching a consensus. Economics and Game Theory describe such an interaction in terms of protocols and strategies. The protocols of a negotiation comprise the rules (i.e., legitimate actions) of the game. An example of a simple negotiation protocol is the non-discriminatory English auction where (in one form) the only legal action is to (publicly) bid higher than the current highest bid by at least the minimum bid amount before the auction closes.

Competitive negotiations can be described as the decision-making process of resolving a conflict involving two or more parties over a single mutually exclusive goal. The Economics literature describes this more specifically as the effects on market price of a limited resource given its supply and demand among self-interested parties (Frank et. al., 1996). The Game Theory literature describes this situation as a zero-sum game where as the value along a single dimension shifts in either direction, one side is better off and the other is worse off .The benefit of dynamically negotiating a price for a product instead of fixing it is that it relieves the seller from needing to determine the value of the good a priori. Rather, this burden is pushed into the marketplace itself. A resulting benefit of this is that limited resources are allocated fairly – i.e., to those buyers who value them most. As such, competitive negotiation mechanisms are common in a variety of markets including stock markets (e.g., NYSE and NASDAQ), fine art auction houses (e.g., Sotheby's and Christie's), flower auctions (e.g., Aalsmeer, Holland), and various ad hoc haggling (e.g., automobile dealerships and commission-based electronics stores). More recently, software agents have been taught competitive negotiation skills (e.g., auctioneering and auction bidding skills) to help automate consumer-to-consumer, business-to-business, and retail shopping over the Internet (Guttman R., et. al.).

Cooperative Negotiation

Lewicki R., et al implemented the degree of cooperation among negotiators falls within a continuum. After all, even in competitive negotiations, all parties need to cooperate sufficiently to engage in negotiation as well as agree on the semantics of the negotiation protocols. However, one clear distinction that can be made between competitive and cooperative negotiations concerns the number of dimensions that can be negotiated across. For example, all of the competitive negotiation protocols discussed in the previous section allow for negotiation only within the price dimension. The cooperative negotiation protocols that we discuss in this section, on the other hand, allow agents (and humans) to negotiate over multiple dimensions.

Therefore, cooperative negotiations can be described as the decision-making process of resolving a conflict involving two or more parties over multiple interdependent, but non-mutually exclusive goals (Lewicki et. al., 1997). The study of how to analyze multi-objective decisions comes from economics research and is called multi-attribute utility theory (MAUT) (Keeney et. al., 1976). The game theory literature describes cooperative negotiation as a nonzero-sum game where as the values along multiple dimensions shift in different directions, it is possible for all parties to be better off.

In essence, cooperative negotiation is a win-win type of negotiation. This is in stark contrast to competitive negotiation which is a win-lose type of negotiation. Desired retail merchant-customer relationships and interactions can be described in terms of cooperative negotiation the cooperative process of resolving multiple interdependent, but non-mutually exclusive goals. A merchant's primary goals are long term profitability through selling as many products as possible to as many customers as possible for as much money as possible with as low transaction costs as possible. A customer's primary goals are to have their personal needs satisfied through the purchase of well-suited products from appropriate merchants for as little money and hassle (i.e., transaction costs) as possible. A cooperative negotiation through the space of merchant offerings can help maximize both of these sets of goals.

From a merchant's perspective, cooperative negotiation is about tailoring its offerings to each customer's individual needs resulting in greater customer satisfaction. From a customer's perspective, cooperative negotiation is about conversing with retailers to help compare their offerings across their full range of value resulting in mutually rewarding and hassle-free shopping experiences.

Conclusion

This review work provides an exhaustive review on automated negotiation based E-Commerce. The review work basically based upon co-operative and competitive negotiation paradigm in B2C E-Commerce. Most of the co-operative negotiation models provide win-win situation where as competitive negotiation lack this win-win situation.

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