

A Research Review on Buyer & Seller Negotiation in B2C E-Commerce

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Abstract--Negotiation is the incidental functionality of automated E-Commerce. There are several approaches deployed by various researchers in their automated E-Commerce model. In this research review paper we provide a review on various negotiation mechanisms which are deployed in various E-Commerce models.

Keywords

Negotiation, Agent, multi-agent, trust, Co-operation.

1. Introduction

1.1 Negotiation

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 a profitable state of business. Very limited numbers of researchers have implemented the trust, cognitive parameters and domain oriented negotiation model in the MAS based e-commerce. They have paid attention to the cognitive parameters 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 approach cannot be used for complete cognitive parameters based agent selection and classification for

negotiation in B2C e-commerce. The model will try to describe 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. In this review work we describe the application of cognitive parameters based agent selection for negotiation in the purchase domain in a cooperative system. In this negotiation domain, through the cooperative negotiation mechanism the set of seller agent fulfills the set of requirements of buyer agents.

2. B2C Negotiation Models used in various literature

2.1 Cognitive model

Mukun Cao et al, proposes a goal deliberated agent architecture equipped with a multi-strategy selection model for automated negotiation system, and experimentally evaluates its effects in the computer-computer negotiation. In this study there are three significant contributions which are: The first significant contribution is the goal deliberated agent architecture, Once the negotiation starts, this significant contribution can support the agent to autonomously select an

appropriate strategy to negotiate with the external environment without any human intervention. Unlike the multi-strategy selection mechanism proposed in [39] that is constructed upon subjective probability matrix, their architecture model excludes the human influents. Hence, their model accords with the main connotation of the agent theory, i.e., autonomy. Comparing with [40] which designed negotiating agent architecture only from the buyer's viewpoint in a one-buyer-many seller context, their approach goes beyond their spectrum as a more general and robust architecture model for both buyer and seller. Therefore their model has the ability to cope with a variety of negotiation situations in e-commerce, including one-to-one, one-to-many, and many-to-many. On the other hand, since implementing an autonomous agent architecture model is always a pending problem in the prior studies [1, 20] they utilize goal deliberation technology to integrate strategy selection mechanism into the agent architecture from a theoretical layer. Furthermore, they elaborate in detail the concrete implementation method for the architecture model from a software engineering perspective, so it is possible to realize a practical agent system with strategy selection capability.

In their work the second contribution in addition to contributing to the system architecture present a multi-strategy selection model complementing the research of negotiation strategy. There are two major approaches to designing the negotiation

strategy: the heuristic based approach and the machine learning approach [21].

(1) The heuristic-based approach abides by a fixed concession function to implement the concession process, e.g., [17,37, 23]. However, totally different from the previous studies, the multi-strategy choice model projected within their work that permits the agent to pick AN acceptable offer strategy in the time-dependent strategy area, so it will affect the dynamical negotiation state of affairs in keeping with the opponent's offer. The experimental results show that, comparing with the benchmark work their model leads to a higher negotiation success rate.

(2) The machine learning approach, on the other hand, mainly predicts the opponent's future negotiation behaviour relying on the availability of past negotiation history as a training set [26] or requiring a large number of rounds of offer exchanges in a negotiation episode [12] before the agent can build an effective learning model. The proposed strategy selection model in their work is not to predict but to imitate the opponent's negotiation behaviour so that it can better adapt to the opponent's ever changing offers, consequently improve the negotiation success rate. Moreover, the machine learning approach needs rather more historical data to complete the prediction process [14, 2]. In their model, however, only 3 rounds of past negotiation data are needed to create effective feedback against the current negotiation progress. More significantly, in terms of the theory and technology of automated negotiation, our multi-

strategy selection model actually creates a novel concession mode, which is the main method for the both sides to reach an agreement. The extant method normally utilized a preset concession mode, usually a monotonic or segmented [17] concession function, to realize the concession process. Beyond the prior studies, their strategy selection mechanism has no preset mode and the concession offer curve is completely generated dynamically, thereby increasing the flexibility and robustness of the negotiation system to a maximum extent. As such, their mechanism provides a new thought for the study of concession model in automated negotiation. On the a lot of sensible aspect, the third contribution is that, through huge experiments, valuable empirical information (including agent's initial settings for negotiation strategy, reservation value and deadline) for building and mistreatment the human-computer negotiation system has been acquired, therefore representing a step near a lot of realistic sensible e-commerce agent-based negotiations. From the study we find that, according to opponent's offer the ability to dynamically change and adjust the negotiation strategy is a required function for a negotiating agent. That can significantly help the practical design and implementation of the construction and application of a human-computer negotiation system.

2.2 Fact-Based E-Negotiation Model

Hasan and Al-Sakran implemented the Fact-Based E-negotiation model: initially, buyer and seller

assign the weight of each negotiation attribute and choose the concession strategy (anxious, careful, or greedy type [30]), and submit them to their negotiation agents. Both concession strategies and attribute weights of each side are unknown to the other side. The values of negotiation attributes are delivered to the relevant opponent agent. The objective of e-negotiation is to maximize utility function and the worst case should not make the utility function value lower than a predefined one. Otherwise the negotiation process should be terminated. In every negotiation round, the SA will estimate the buyer's intention and forecast his acceptance probability. The seller agent must calculate its own evaluation function, and then determine its actions and refresh its parameters for the next round. In each negotiation round, the negotiation agent (either buyer's or seller's) receives an opponent's offer and checks if it is within its expectation, then makes a decision whether to accept, reject or continue the negotiation. In case of continuing the process, one side changes its bid to show a motivation to compromise, and continues negotiation with the other side. The latter evaluates the proposal of the opponent, and decides whether to accept it or not. If the opponent rejects the proposal, he adjusts the attribute value, generates counter-proposal, and returns it to the bidder. The process continues until the attribute values reach a balance where both sides accept the proposal, or one or both side(s) reached their least acceptable limit, and therefore the negotiation is failed.

In their work a description of B2C e-commerce negotiation model is presented. The primary job of this model is to conduct negotiations on behalf of 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 system 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.

2.3 Opponent Model

Jihang Zhang et al, implement a major research challenge in this area is opponent modelling [33, 34, 35, 36]. 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 [37]. 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 multi-issue negotiation, 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 order. In order to propose such an order, agents need to know their opponent 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 order. In recent years, many different approaches have been proposed to help agents to predict their opponents' preferences. These include: genetic algorithm-based prediction [18], statistical analysis-based prediction [29, 28] and machine learning-based prediction. However, all these approaches have different limitations. For example, the approaches in [29, 28] require previous negotiation data to make the prediction and the approach in [41] may need a long training time before the prediction algorithm becomes effective.

In their work, they proposed a bilateral multi-issue negotiation in order to overcome the above prediction limitations and to improve the negotiation results. The goal of the proposed negotiation approach is to increase both agents' utilities, which can be employed by both of them. Bayesian theory is employed to predict the opponent's preference in their proposed negotiation. The major contributions of the proposed approach are that

- (1) The proposed preference prediction algorithm does not require any previous negotiation data about the opponent to initialise the prediction. The prediction procedure is an online procedure and only based on the analysis of opponent's counter-orders that are proposed in the on-going negotiation.
- (2) The proposed approach has integrated a counter-order proposition algorithm, which is capable of trading issues effectively based on the predicted preference of the opponent. Therefore,

both agents can increase their utilities from the mutual beneficial order.

2.4 Unknown Opponent model

Siqi Chen et al, implemented learning unknown opponents in complex negotiations [31]. This is achieved through the employed decomposition technique that performs trend analysis of the received utility curve and the Gaussian processes that permit accurate trend prediction and also provide a measure of confidence about the prediction another strength is the adaptive concession-making mechanism. On the basis of learnt opponent model and conservative aspiration level function, this mechanism suggests the desired utility at each step of the negotiation to concede towards opponents in a rational manner. Last but not the least, their work includes the extensive simulations that take a variety of performance criteria into account, using a standard and open competition infrastructure and state-of-the-art negotiating agents. The major weakness of the approach is the high computation load of the proposed approach, which results in its inability to deal with negotiation scenarios where a large number of proposal exchanges are needed in a short period.

Research contributions of the work include providing an agent-based negotiation approach that researchers in the community could employ to:

(1) Learn an opponent's strategy given no prior information regarding opponent privacy (e.g., strategy preference) is available.

(2) Make concession in the course of a negotiation in an adaptive manner in response to uncertainty of complex negotiators

(3) Propose new offers with high likelihood of being accepted by the other negotiation party. Also, their work presents a useful game-theoretic analysis based on the empirical results to investigate the robustness of the proposed negotiation approach. A practical contribution is in providing a good benchmark for measuring the efficiency of a newly proposed approach to complex negotiations.

OMAC opens several new research avenues, among which we consider the following as most promising. First, as preference learning is another helpful way to improve the efficiency of a negotiation, especially when the opponents are unknown, they plan to consider integrating some preference learning technique into the proposed approach for further boosting its performance. Second, another important negotiation form, which is also common in practice, is concurrent negotiation. However, this negotiation form is relatively poorly understood compared to sequential negotiation as considered in this review paper.

They suggest to explore whether and in how far principles and mechanisms underlying OMAC can be successfully used and adapted to concurrent

negotiation scenarios. Third, human negotiators are more flexible and less predictable than automated negotiators. Playing against human negotiators therefore pose particularly high demands on the adaptive and predictive abilities of an automated negotiator. As OMAC is strong in these abilities when playing against other computational agents, it appears to be a promising choice for human-machine negotiations. It would therefore be interesting to find out how well OMAC (equipped with an appropriate communication interface) performs when playing against different types of human negotiators. They believe that this can lead to valuable insights w.r.t. the design of automated negotiation strategies as well as the strategic behaviour of human negotiators. In the work they proposed preference learning techniques.

2.5 Negotiation Model

Amir Vahid 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 [22]. With the advances of cloud technology, operations such as discovery, scaling, monitoring and decommissioning are accomplished automatically. Therefore, negotiation between 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 [7]. Furthermore, they detect the effect of modifying parameters in cloud computing environment, to find the right configuration of time dependent tactic such as initial offer value and deadline on negotiation outputs that include ratio of deals made, and inequality index. They proposed negotiation strategy 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.

They proposed a time-dependent negotiation strategy capable of assessing the reliability of offers to fill the gap between decision-making and bargaining [9]. To select an appropriate configuration for different negotiation objectives (e.g. number of deals made), they investigated the consequences of modification of parameters such as deadline, initial offer and type of time-dependent tactic (polynomial or exponential). Although many of the works in the literature apply the same pattern of concession for all clients when negotiating in parallel, they argued that discriminating regarding the pattern of concession

helps cloud providers to accommodate more requests and thus increase their profit [16]. Their views were tested against correctly time-dependent views, and it represent that its dominance in generating more profit for providers. Furthermore, they show how providers could dynamically and based on market condition increase or decrease the COD to raise their revenue.

2.6 CPN (Colored Petri Nets) Model

Meriem Taibi et al, implemented that 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. For facilitate the contract negotiation in Multi Agent System, They developed The FIPA Contract Net Protocol was developed to facilitate contract negotiation in Multi- Agent Systems, therefore it is important to analyse the protocol to assure that it terminates correctly and satisfies other important properties. In this review paper they focus on agent interactions in e-commerce oriented automated negotiation based on FIPA Contract Net Protocol.

In the field of MAS analysis, several studies have been proposed for modelling these systems by Petri nets. In [6], a model was proposed for a promotional game of viral marketing on the Internet. Specially, authors used stochastic Petri nets for modelling a multi-agent wish list. As well, [19] used colored Petri nets (CPN) as a

formal method to model a containerized transport system, then simulate and solve the storage problem. [13] applied a multiagent model formalization using CPN, to study a hunting management system. Elfallah-Segrouchni, Haddad and Mazouzi in [3] also proposed to use the CPN formalism to model interaction protocols. Elfallah-Segrouchni, Haddad and Mazouzi described in [11] transcriptions of AUML diagrams into CPN models.

Elfallah-Segrouchni, Haddad and Mazouzi start modeling by defining main parameters characterizing their CPN model: the structural representation and tokens coloration. They present a model of the protocol in CPN Tools [5].

Structural representation in their modelling, they consider:

1. Places represent agents states (before and after sending or receiving operations).
2. Transitions model sending and receiving actions or some processing actions.
3. Tokens express the different agents and the various exchanged messages.
4. Incoming arcs labels specify data required for firing the associated transition.
5. Outgoing arcs labels specify data produced by a firing.
6. Italic symbols above places (i.e. AGT, MES, etc) indicate the color (or type) of tokens in these places.

Negotiations protocols are basis of automated negotiation which can carry out in an open system between agents come from different organizations

if they follow the specifications. In this paper, they have presented a colored PN model for negotiation protocol in MAS using FIPA Contract Net Protocol. The long-term goal is to allow analyze such systems, to ensure correctness and performances expected by users.

2.7 Bilateral Single-Issue negotiation Model

Fenghui Ren et al, proposed that in autonomous agent negotiation Bilateral agent negotiation is considered as a fundamental research issue. Generally, in every negotiation round a predefined negotiation decision function and utility function are used to generate an offer according to a negotiator's negotiation strategy, preference, and restrictions. But, when the negotiator's utility function is nonlinear then such a negotiation procedure may not work well, and therefore it is difficult to generate the unique offer. This is because if the negotiator's utility function is discrete, the negotiator may not find an offer to satisfy its expected utility exactly and 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. Therefore to solve these type of problem, they propose a novel negotiation model. Firstly, they introduced a 3D model to illustrate the relationships between an agent's utility function, negotiation decision function and offer generation function. Then they are proposed two negotiation mechanisms to handle two types of nonlinear utility functions which are given as follows respectively.

1. A multiple offer mechanism is introduced to handle non-monotonic utility functions
2. An approximating offer mechanism is introduced to handle discrete utility functions.

At last, they proposed a combined negotiation mechanism 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.

They demonstrate the negotiation procedure between two agents with nonlinear utility functions by employing the proposed negotiation model. It was shown that the proposed negotiation model can efficiently handle the negotiations when agents employ the nonlinear utility functions, and successfully help agents to reach the agreement.

They proposed a bilateral single-issue negotiation model 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. To handle non-monotonic utility functions they introduced a multiple offer mechanism, and to handle discrete utility functions they introduced an approximating offer mechanism. Finally, in more general situations to handle nonlinear utility functions these two mechanisms i.e multiple offer mechanism and approximating offer mechanism were combined. 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.

Conclusions

Domain oriented negotiation is the emergent functionality of automated B2C E-Commerce. There are several models deployed by various researchers in their automated B2C E-Commerce models for domain oriented negotiation strategies. In this research review paper we provide a review on various B2C negotiation models which are deployed in various domain oriented negotiations. This review paper analysed several electronic markets and their corresponding negotiation protocols from economic, game theoretic, and business perspectives. They discussed how competitive negotiation protocols, and online auctions in particular, are inappropriate for online retail markets.

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