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Lifecycle Model of a Negotiation Agent: A Survey of Automated Negotiation Techniques

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Abstract

Negotiation is a complex process. The decision making involved in several stages of negotiation makes its automation complex. In this paper we present a lifecycle model of a negotiation agent in which we identify the individual components that comprise automated negotiation and the interactions between those components. We present a survey of methods used in the automated negotiation literature fitting them to the components of our lifecycle model. While discussing the opponent modeling component, we present the taxonomy of opponent models. The lifecycle model is generic enough to accommodate most of the frameworks in the literature. To this end we fit the methods used in some of the automated negotiation frameworks in the literature to the lifecycle.

Keywords Automated negotiation · Lifecycle model · Multi-agent systems · Agent-based e-commerce

1 Introduction

Automated negotiation has gained importance in the recent years owing to the growth in e-commerce and cloud-based applications. In a multi-agent environment, a negotiating agent exhibits autonomy and hence does not require a human during

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negotiation. But the initial requirements need to be specified by a human before the actual negotiation begins. The complexity involved in decision-making during automated negotiation has sparked much research in this area. Automated negotiation may make use of artificial intelligence techniques (Gerding et al. 2000; Kraus 1997; Li et al. 2003), game theory (Gerding et al. 2000; Kraus 1997; Li et al. 2003; Jennings et al. 2001; Binmore and Vulkan 1999; Liang and Yuan 2008; Osborne and Rubinstein 1990; Rubinstein 1982; Chen et al. 2002; Chatterjee 1996) or evolutionary programming (Choi et al. 2001; de Jonge and Sierra 2016; Tu et al. 2000).

In our survey, we primarily focus on bilateral negotiations which are negotiations between exactly two participants. We refer to the participants as 'agents' as every participant is expected to exhibit autonomy in an automated negotiation setting. The agents send offers and receive counter-offers. An offer is a set of values for a set of attributes over which the agents negotiate. Offers or counter offers are generated by the agents based on their own set of 'preferences'. Preferences denote a preferred set of values of attributes that are being negotiated. Preferences are usually taken from the user. Sending an offer and receiving a counter-offer completes one round of negotiation. Multiple rounds of negotiation may take place and in every round, an agent has numerous possibilities to decide with respect to generation of counter-offer and agreement. The decision is influenced by user preferences, opponent's offers, negotiation strategy adopted by the agent, negotiation deadline, negotiation context, etc. Many rounds of negotiation take place until both the agents are satisfied with a particular offer. At this stage, they are said to have reached an 'agreement'. The challenges in automated negotiation include reaching an optimal agreement, avoiding non-agreement, shortening the duration of negotiation and learning the preferences of the other agent (opponent) through their offers. These challenges offer huge scope for research.

2 Related Work

In the literature there have been previous works in which negotiation process model is described phase-wise. A generic negotiation lifecycle is presented in (Robinson and Volkov 1998). The lifecycle is designed for human negotiations with support for automated negotiations whereas our work is specifically for automated agent-based negotiations. The negotiation lifecycle proposed by Robinson and Volkov (Robinson and Volkov 1998) is illustrated by instantiating it for labor contract negotiation from the perspective of a company owner.

A negotiation support system named INSPIRE (Kersten and Noronha 1999) was developed to enable users to negotiate through the world wide web cross-culturally. The INSPIRE process model includes three phases of negotiation, namely, preparation phase, negotiation phase and post-negotiation phase with each phase including a specific set of activities. The system provides support for human-to-human negotiations guiding them to reach Pareto-optimal agreements. Our model is for fully automated negotiation systems and we describe the theoretical model behind each activity in each phase. INSPIRE was later extended into "Aspire" system (Kersten and Lo 2003) by incorporating a negotiation agent named Atin.

Atin does opponent modeling and suggests possible strategies to the user. Aspire is also a negotiation support system and not a fully automated negotiation system.

Bosse and Jonker (2005) compare the dynamics of agent negotiation with human negotiation. For this purpose, the negotiation process is formalized by introducing states. The state of a negotiation process includes the state of each participating agent. To analyze the differences between human and computer negotiation, properties related to performance and properties related to steps of negotiation are investigated.

Similarly, Braun et al. (2006) presents a negotiation process model that provides structure to the negotiation process and splits negotiation into five phases. The model has provisions for revisit of some phases and skipping of some phases wherever necessary but does not elaborate on how and when the phases may be revisited. Our model is more comprehensive showing how the phases are repeated and includes the background theoretical model for each phase. An architecture named BOA architecture has been proposed by Baarslag et al. (2014) which separates negotiation strategy to three components, namely, bidding strategy, opponent model and acceptance strategy. GENIUS (Lin et al. 2012) negotiation platform has been designed according to this architecture in order to allow users to design components separately while developing agents. Several agents submitted to the automated negotiation agents competition (ANAC) (Klein et al. 2003) has been analyzed and fitted to the BOA architecture. Our model is more comprehensive with utility model treated as a separate component and includes pre-negotiation and post negotiation phases. Our work aims to fit all the work available in the negotiation literature to our model.

Several surveys have been published previously in the area of automated negotiation (Li et al. 2003; Jennings et al. 2001; Braun et al. 2006; Williams 2012). A survey of negotiation techniques based on game-theory and economics is presented by Kraus (2001). In that work, the author touches upon logical approaches to argumentation. In argumentation approaches, an agent tries to convince the opponent of an offer by placing logical arguments. Several frameworks related to argumentation have been proposed in the literature (Amgoud et al. 2007; Oren and Norman 2010; Schroeder 1999; Sierra et al. 1998). Surveys on argumentation based techniques have been presented by Maudet et al. (2006) and Dimopoulos and Moraitis (2014). To make the paper concise, we do not discuss further about argumentation-based approaches.

A comprehensive survey on opponent models is presented by Baarslag et al. (2015). The focus of the survey is mainly on the opponent models while, in our work, we survey techniques used in all phases of negotiation. The taxonomy of opponent models presented in Baarslag et al. (2015) classifies opponent models based on attributes that are predicted by the opponent model while our classification is based on the techniques used for opponent modeling.

Although there have been several research efforts towards negotiation lifecycle model and several surveys, we fit our survey around a comprehensive lifecycle model which includes both the processes and the theoretical background of the processes in automated negotiation.

3 The Lifecycle Model of a Negotiating Agent

The lifecycle model for negotiation (Fig. 1) offers 'separation of concerns' (SoC). Apart from giving an overview on the negotiation process as a whole, the model breaks up the process into separate components each of which may be viewed individually. Each component offers a huge potential for research as evidenced by the number of papers related to each component that have been published so far. The model also includes the theoretical aspect behind each component so that

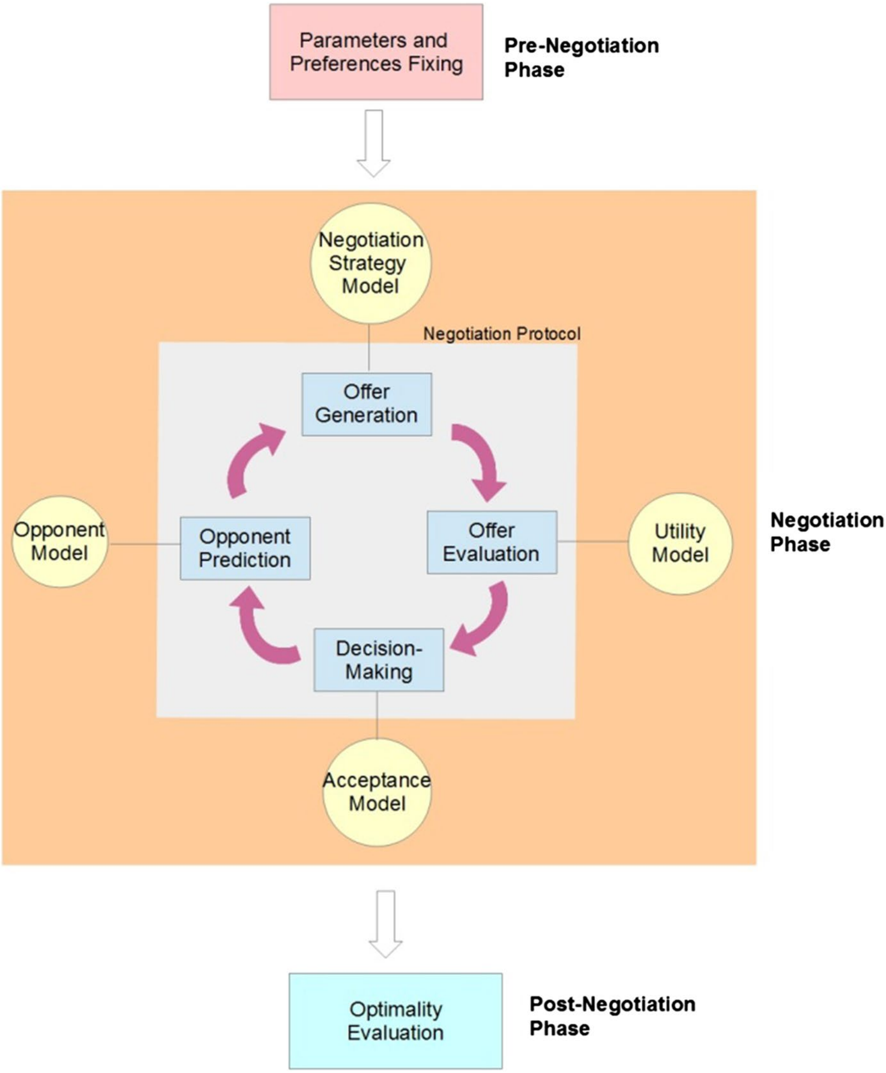

Fig. 1 Lifecycle of a negotiating agent

the scope for research in each component becomes clear. The lifecycle is generic enough to accommodate most of the existing negotiation frameworks into it.

The lifecycle of a negotiation agent is divided into three phases: pre-negotiation phase, negotiation phase and post-negotiation phase. Fixing attributes and preference elicitation are in the pre-negotiation phase. Offer generation, opponent modeling and offer evaluation are in the negotiation phase while assessing the optimality of offers is in the optional post-negotiation phase.

The primary roles of a negotiation agent are preference elicitation from user and negotiation with opponent. Preference elicitation may be done before the negotiation starts or incrementally during the negotiation. A cooperative agent strives for negotiation with less number of proposal exchanges and reaching optimal agreement. With individual preferences hidden from each other, agents model the opponent by predicting the opponent's preferences or its negotiation strategy through the proposals the opponent offers. Opponent modeling helps agents to generate offers more acceptable to the opponent and hence results in faster and optimal agreements. Opponent modeling is an optional component which is not required in negotiations with complete information about the opponent.

Generation of offers by an agent depends on the negotiation strategy that is followed by the agent. The strategy may be changed during negotiation based on opponent's strategy predicted through opponent modeling. The offers of an opponent or an agent's own offers are evaluated using a utility function. A utility function evaluates the satisfaction obtained for an offer. Utility values for an offer are usually placed between 0 and 1 with 0 representing worst offer and 1 representing best offer. Thus, an agent generates an offer, receives the counter offer from the opponent, evaluates the counter offer, models the opponent based on the counter offer and follows a certain negotiation strategy to generate more offers. All of these functions have been incorporated into the lifecycle model.

4 Pre-negotiation Phase

Pre-negotiation phase is preparatory phase in which the attributes to be negotiated and their preferences are finalized. Attributes to be negotiated depend on the domain of negotiation and they have to be finalized by the participants of the negotiation. Each participant also privately fixes its preferences of attributes. This includes parameter weights and negotiation range. Weight of a parameter indicates how much importance the negotiator attaches to a particular parameter. Negotiation range is the set of values between the preferred value and the reserved value. Preferred value is the best value and reserved value is the worst possible value of a parameter that can be taken by a negotiator. A negotiator never accepts an offer that lies beyond the reserved value. A deadline which denotes the maximum time limit up to which negotiation may be done may also be fixed during this phase. If negotiators do not reach an agreement until deadline, negotiation stops without an agreement.

Preference elicitation is an important research topic in the pre-negotiation phase. A model for incrementally eliciting preferences from user has been proposed by Baarslag and Gerding (2015). The method elicits preferences during negotiation optimally considering elicitation costs and the effect of learning gained from the additional information. Thus, only the most essential information is elicited saving the user from elicitation fatigue. A hybrid approach using case-based reasoning (CBR), artificial neural network and particle swarm optimization has been proposed by Fang and Xin (2008). It allows sharing of past experiences and retrieval of previous knowledge of negotiations and elicits user preference in a fast manner avoiding mistakes. A default-then-adjust method has been described by Luo et al. (2006) for obtaining user trade-off strategies and preferences. The system allows for acquiring trade-off related information through an interview and allows for adjustment of strategies and preferences by improving some attribute. A method for elicitation of user preferences based on KBANN (Knowledge-based Artificial Neural Network) is presented by Haddawy et al. (2003). The approach is demonstrated for preference elicitation under certainty and under uncertainty. The ANN built is a representation of approximate user preferences and it is trained using standard gamble questions. A model for finding an optimal point where more querying will not add useful information is proposed by Baarslag and Kaisers (2017). A survey of elicitation techniques is presented by Chen and Pu (2004). But the survey is not specific for negotiation settings.

Fixing the attributes is public activity done between all the participants in a negotiation. All participants may decide on a set of attributes or a dominant participant may fix the attributes while the others accept those attributes. The preferences are set by the participants individually and in agent-based negotiations, input to the agents. In some negotiation settings, partial preference information may be known to the opponent (Jonker et al. 2007; Fatima et al. 2002; Aydoğan and Yolum 2010). Once the attributes and preferences are set, negotiators are ready to begin the negotiation. Though preferences are almost never changed during the course of negotiation, dynamic preferences have also been considered in the literature (Ren et al. 2014; Ranaldo and Zimeo 2013).

5 Negotiation Protocols

The lifecycle of a negotiating agent during negotiation phase is governed by a negotiation protocol. Negotiation protocol sets rules specifying which action is done when (Rosenschein and Zlotkin 1994). In an automated negotiation, there are various protocols that define the overall course of negotiation based on which the agents can negotiate. They are one-shot negotiation, alternating-offers protocol, simultaneous-offer protocol and unrestricted-offers protocol. Apart from these there are protocols such as the contract-net protocol (Smith 1980) for distributed agents to communicate and protocols specifically for negotiation of complex contracts (Klein et al. 2003). Another protocol (Caillere et al. 2016) is for multi-lateral negotiation in contexts where agents have to make a joint decision.

In one-shot negotiation (Ragone et al. 2006a, b; Saha et al. 2005; Ji et al. 2014), an agent makes an offer and the opponent either accepts it or rejects it. It is the simplest form of negotiation. It is also the least flexible protocol. The agent which makes the offer has the control over what to offer. This protocol may be useful in contexts where the agent making the first offer has an obligation to end up with an agreement. In those cases, the agent would make the offer more acceptable to the opponent and hence facilitate fast agreement.

In alternating-offers protocol (Rubinstein 1982), the agents alternately make proposals. It starts with one agent making a proposal and the other agent accepts it, rejects it or makes a counter proposal. The process is repeated by both the agents until one of the agents accepts or rejects the other's proposal or until time-out. This protocol allocates equal chance to both the negotiators and each negotiator has the time to analyze a counter-offer generated by the opponent and also to generate a suitable offer to the opponent. This protocol is the most suitable for bilateral and also automated negotiations. Most of the present works in negotiations employ this protocol. In their work Zheng et al. (2015) use sequential offers protocol, a generalization of the alternating offers protocol in which offers are proposed in a pre-determined sequence. Alternating offers protocol for multi-lateral negotiation is presented by Aydoğan et al. (2017). Another variation of alternating offers protocol is presented by Baarslag et al. (2017) in which the authors propose proposal of partial offers in the context of permission management in IoT domain.

Contrary to this, in simultaneous-offer protocol (Endriss 2006; Pan et al. 2013), all the participants make a proposal at the same time. If one of the offers is accepted by all the participants, agreement is reached. Otherwise, all the participants together make their next proposals. Simultaneous-offer protocol is more suited to multi-agent negotiation with all agents negotiating simultaneously. Monotonic concession protocol which is a type of simultaneous offer protocol and the associated strategies for negotiation have been discussed in Rosenschein and Zlotkin (1994), Zeuthen (1930) and Harsanyi (1956). A sequential protocol, in which an agent makes an offer knowing the responses of the preceding agents, is considered in Freitsis (2000).

The unrestricted-offers protocol allows any agent to place any number of proposals at a time or in a sequence. Whenever a suitable offer is proposed by an opponent, an agent may accept that offer. In Lang and Fink (2015) two negotiation protocols—one based on simulated annealing and another based on genetic algorithms—are proposed and the requirements of a negotiation protocol are listed. The applicability of meta-heuristic techniques to negotiation protocols is still unexplored and offers scope for research.

6 Negotiation Phase

Negotiation phase is the phase in which actual negotiation takes place. As mentioned in the previous section, the negotiation phase is governed by a negotiation protocol which defines when and how many offers can be sent by a participant at a time. Negotiation phase includes offer generation, offer evaluation and opponent modeling. Each of these is repeated for several rounds of negotiation before an agreement or the deadline is reached.

6.1 Offer Generation: Negotiation Strategy Model

A negotiation agent has to generate the initial proposal to be sent to the opponent if it begins the negotiation. In every round of negotiation, unless the agent accepts an opponent's offer, it has to generate a counter proposal for each offer proposed by the opponent. Counter offer generation requires previous offer sent to the opponent and a negotiation strategy. An agent may follow a particular negotiation strategy defined by the negotiation strategy model.

Negotiation approaches can be classified into three major categories—namely Game theoretic approach, argumentation-based approach and heuristic approach (Jennings et al. 2001). Negotiation strategy model differs for each negotiation approach. When an agent generates an offer, it may choose a certain strategy depending on the opponent or for its own benefit. Lomuscio et al. (2003) defines an agent's negotiation strategy as the "specification of the sequence of actions the agent plans to make during the negotiation". One of the first negotiation strategies to be proposed was Zeuthen's strategy which is based on willingness to risk conflict. The degree of willingness to risk a conflict in a negotiation between agent a and agent b at a time t is given by

$$Risk(a,t) = \begin{cases} 1 & \mathit{if\ utility}_a(\delta(a,t)) = 0 \\ \frac{utility_a(\delta(a,t)) - utility_a(\delta(b,t))}{utility_a(\delta(a,t))} & \mathit{Otherwise} \end{cases} \tag{1}$$

where $\delta(i, t)$ represents an offer by agent i at time t and $utility_i(\delta)$ represents the utility to agent i for an offer δ. While Zeuthen's strategy does not guarantee the solution to be in Nash equilibrium, an extension to Zeuthen's strategy by Zlotkin and Rosenschein (1989) does while also maximizing individual utilities.

A negotiation may also be viewed as a combination of multiple negotiation tactics. Negotiation tactic defines the way an agent interacts with an opponent with respect to the offers that the agent generates. There are three families of tactics (Faratin et al. 1998), namely time-dependent tactics, resource-dependent tactics and behavior dependent tactics. Over the course of negotiation, an agent may apply a set of tactics based on the previous history of negotiations and based on the agent's design. Of the various tactics, time-dependent tactics are the most commonly used family of tactics in the literature (Pan et al. 2013; Cao et al. 2015; Sim et al. 2009; Fatima et al. 2005; Yu et al. 2013; Sánchez-Anguix et al. 2013). Dastjerdi and Buyya (2015) classify the negotiation tactics used in SLA negotiations in the literature based on the context, techniques used, issues and reservation values.

6.1.1 Combination and Selection of Strategies

In Cao et al. (2015) a model for multi-strategy selection has been proposed. Theoretical model and algorithm for multi-strategy selection based on opponent behavior have been developed. The method creates a new concession model which dynamically changes between conceder and boulware tactics without being monotonic or segmented. Zheng (2014) combines concession and trade-off approaches and proposes an algorithm which mixes concession and trade-off when the strategy of the opponent is unknown. A genetic algorithm-based method has been described in Matos et al. (1998) for adopting a combination of strategies during negotiation. Choi et al. (2001) propose a genetic algorithm-based method for selection of a concession-matching tactic. Similarly, Q-learning is used to make the agent learn and adapt to the negotiation environment by finding a weighted combination of tactics (Cardoso and Oliveira 2000). There are several works that select strategies based on meta-heuristics (Tu et al. 2000; Bi and Xiao 2012; Kolomvatsos and Hadjieftymiades 2014; Rubenstein-Montano and Malaga 2000).

6.2 Offer Evaluation: Utility Model

Once an agent generates and sends an offer to the opponent, it has to wait to receive the acceptance or a counter offer from the opponent. If acceptance is received, it leads to agreement. If a counter offer is received, the agent has to evaluate it to make a decision on whether to accept it or to generate a new counter proposal. For this evaluation, a utility model is used. Utility evaluates the satisfaction that an agent has in an offer received from an opponent.

Utility model is usually represented by utility functions. A utility function is a function that takes an issue value as an input and gives the satisfaction of an agent over that value as output. It represents the preference relation of an agent. In economics, there are several utility functions such as Cobb–Douglas utility function, Constant Elasticity of Substitution (CES) and quadratic utility functions that are commonly used. An intuitive utility function may represent linear increase or linear decrease of utilities as the values increase or decrease. For example, if a seller desires high cost for an item, his cost utility constantly increases as the selling cost increases. But there are contexts where utility increases or decreases up to a certain point and then reverses direction. For example, the more a medicine is taken the earlier it may cure a disease. But after a certain amount, if it is taken in larger quantities, the medicine may do more harm than treating the disease. This is an example where utility increases up to a certain threshold and then starts decreasing.

Utility functions may be treated as cardinal utilities or ordinal utilities. If the magnitude of utilities is treated as significant quantity, they are treated as cardinal utilities. In contrast, if the ranking order of utilities only matter, they are treated as ordinal utilities. For evaluation of an offer during negotiation, the actual utility values are taken into consideration and hence the utilities calculated are treated as cardinal. Utility functions may be linear, logarithmic, exponential, etc. and the appropriate function is chosen depending on the domain of negotiation. Linear utilities are assumed in most of the works in negotiation literature (e.g. Yu et al. 2013; Matos et al. 1998; Yan et al. 2007; Klein et al. 2003; Restificar and Haddawy 2004) but there are many works that consider non-linear utility functions (Bosse and Jonker 2005; Sánchez-Anguix et al. 2013; Klein et al. 2003; Ito et al. 2007; Lai et al. 2008).

An example of a set of non-linear utility functions for a single-issue (Bosse and Jonker 2005) is

$$U_A(x,t) = \begin{cases} x \times \delta^{t-1} & \textit{if } t \le n \\ 0 & \textit{otherwise} \end{cases} \tag{2}$$

$$U_A(y,t) = \begin{cases} y \times \delta^{t-1} & \textit{if } t \le n \\ 0 & \textit{otherwise} \end{cases} \tag{3}$$

where [x,y] is an offer proposed at time t where x and y denote agent a's share and agent b's share respectively. The possible set of offers is $\{[x,y] \mid 0 \le x \le 1$, and $x + y = 1\}$.

In Zheng (2014) general exponential function is used to model agent preferences. The utility function to represent lower-is-better parameter where x ($0 \le x \le 1$) is the value of a parameter is:

$$u_1(x) = \frac{e}{e-1} \times \left(e^{-x} - e^{-1}\right) \tag{4}$$

The function used to represent utility of higher-is-better attribute is:

$$u_2(x) = \frac{1}{e-1} \times (e^x - 1) \tag{5}$$

The von Neumann-Morgenstern utility functions (Keeney et al. 1993) include the effects of discounting and bargaining costs. Lai et al. (2008) considers three types of non-linear utility functions, namely, exponential and additive utility functions, exponential and dependent utility functions and constant elasticity of substitution utility functions. Zheng et al. (2013) uses hyperquadric function which is a more general form of Cobb–Douglas functions while Lai and Sycara (2009) uses CES utility function.

In the negotiation literature, single attribute utility functions are commonly used to evaluate utilities of individual issues and they are combined as a weighted sum to derive the total utility (Zheng 2014). The general assumption is that the issues are independent. For dependent issues, multi-attribute utility functions (MAUT) (Keeney et al. 1993) may be used (Barbuceanu and Lo 2000). More recently, a novel approach to offer evaluation is proposed by Zhan et al. (2018) without using utility functions. In their paper, the authors propose Atanassov intuitionistic fuzzy constraint-based method to handle human-friendly fuzzy offers.

6.3 Opponent Prediction: Opponent Model

Opponent preference prediction includes a variety of techniques used by an agent to predict the preferences of an opponent in a bilateral negotiation based on the history of counter-offers received from the opponent. In the lifecycle, opponent model is distinct in the sense that it is a model that can predict the other models. The opponent model of an agent may learn the utility model, acceptance model or negotiation strategy model of an opponent. All opponent models available in the current literature may be classified into statistical models, machine-learning models, heuristic models and models that use other techniques. Figure 2 shows the taxonomy of opponent models proposed so far in the literature.

6.3.1 Statistical Models

The most common statistical models are models that use Bayesian learning (Sim et al. 2009; Yu et al. 2013; Buffett and Spencer 2007; Hindriks and Tykhonov 2008; Zeng and Sycara 1998; Zhang et al. 2014, 2015; Narayanan and Jennings 2006). Bayesian models learn opponent preference profile from the offers received from the opponent. For each new offer, the information learnt is updated. Another common statistical model is regression analysis. Regression analysis is used for opponent modeling in Ren et al. (2014), Yu et al. (2013), Hou (2004), Brzostowski and Kowalczyk (2006) and Agrawal and Chari (2009). In Ren et al. (2014), the history of offers from the opponent are fitted to quadratic regression function. Then using regression analysis and assumption that higher concession is

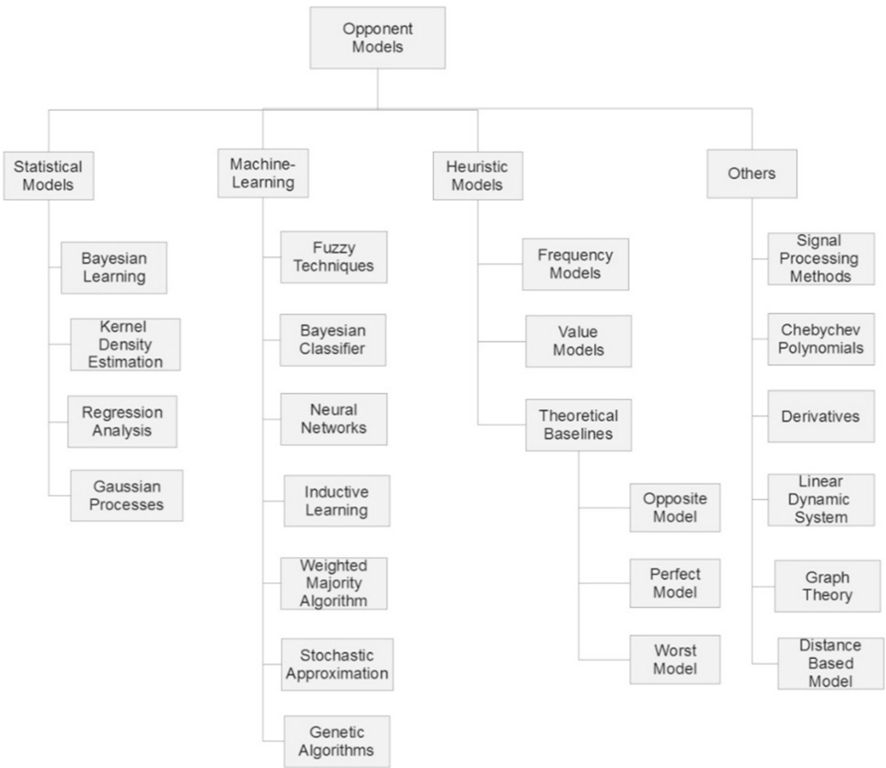

Fig. 2 Taxonomy of opponent models

given for issues with lesser weights and lesser concession for issues with higher weights, the future offers are predicted.

Coehoorn and Jennings (2004) apply kernel density estimation (KDE) for opponent preference prediction. The basis of this method is a kernel defined by $\int K(X)dx = 1$. The weight of an issue is predicted using difference between the last two offers received for that issue. Kernels are formed by centering a kernel at a believed issue weight proportionate to the difference between last two offers. The estimated weight of the issue is the expected value using the estimate as a probability density function. (Baarslag et al. 2015) predict the opponent's concession strategy using Gaussian process with Matern covariance function and a linear mean function. Williams et al. use Gaussian Process regression for their agent IamHaggler (Williams 2012, 2013) to predict the opponent's concession rate.

6.3.2 Machine Learning Models

There are several works in the literature that use fuzzy techniques for opponent preference prediction. One of the most prominent works is by Faratin et al. (2002) that uses fuzzy similarity to model the opponent preferences so as to generate offers that are more acceptable to the opponent. A method similar to the fuzzy similarity approach is also used in Cheng et al. (2005, 2006). In Richter et al. (2009) fuzzy Markov decision process is used to represent the behavior of an opponent to obtain negotiation strategies of the opponent. Lai et al. (2010) propose a method for opponent strategy modeling using a fuzzy clustering approach based on fuzzy c-means clustering. The opponent strategy is recognized by reducing or enlarging concession value in subsequent offers and observing the consequences in fuzzy probability constraints.

Bayesian classification is another machine learning technique that uses Bayesian theory to classify objects into a pre-defined set of classes. The probability that an object belongs to particular class among a set of classes is determined given observed evidence E. In Buffett and Spencer (2007), the classifier is first trained by classifying a set of offers to a preference relation class using k-means clustering. For each new offer received, the classifier updates probabilities of each class and correctly classifies new offer to the preference relation class.

Neural networks are used in Baarslag et al. (2013) and Masvoula (2013) for predicting opponent preferences. In Baarslag et al. (2013), the output layer of the neural network consists of the negotiation issues. The input layer is associated with the history of offers and counter-offers and current trial offer. The network is trained using Levenberg–Marquardt neural network training algorithm. The model predicts the opponent's counter-offer starting from the third offer. Papaioannou et al. (2009) presents a survey of neural networks in automated negotiations.

Aydoğan and Yolum (2012) propose an opponent prediction model that uses two inductive learning approaches, namely, Candidate Elimination algorithm (CEA) and ID3 and combines them into Revisable Candidate Elimination algorithm (RCEA). In this model, RCEA is used to learn consumer preferences. According to the learnt preferences, offers are generated.

Weighted majority algorithm (Baarslag and Gerding 2015) weights other prediction algorithms and builds a compound algorithm. Dynamic weighted majority algorithm (DWM) (Lai et al. 2008) is a variation of the weighted majority algorithm in which weighted experts can be dynamically created and removed in response to changes in performance. Noh et al. (2011) propose a modified DWM algorithm to predict issue weights and issue ranks of human in an agent-to-human negotiation setting based on the concession rates. Another machine learning technique used in opponent modeling is Stochastic approximation. It recursively updates the desired function with respect to the obtained empirical values until convergence (Choi et al. 2001).

Works in which genetic algorithms have been used for opponent modeling include (Masvoula 2013; Jazayeriy et al. 2011). Jazayeriy et al. (2011) describe method using genetic algorithms to learn the weight preferences of the opponent. The weights are first decoded into from crisp values into fuzzy values. The best-fitted chromosome (preference) for each fuzzy value will be selected as opponent's preference. Preferences will be mapped to the best value during each round of negotiation. (Masvoula 2013) proposes session-long learning agents that capture the current negotiation dynamics. Though the actual learning is done by a simple neural network, the neural network evolves with the use of genetic algorithm.

6.3.3 Heuristic Models

Heuristic models are based on certain general assumptions regarding how an opponent might generate offers. For example, a heuristic may be "an opponent generates preferred offers more often". Another heuristic may be "the opponent has exactly the opposite preference to the agent". Heuristic models include frequency models, value models and theoretical baselines. Frequency models (van Galen Last 2012; van Krimpen et al. 2013) predict the weights of issues from the variation of values offered for those issues. They predict an opponent's preference for a certain value of an issue from the frequency that the value is offered. The general assumption is, the more frequently a value is offered, the more preferred the value is for the agent. Value models assume that the issue weights are equal and work similar to frequency models by guessing preference of values from the frequency at which they are offered. Theoretical baselines are generally used for comparison of models. These include Perfect model, Worst model and Opposite model. Perfect model is a baseline model having exact knowledge of the preferences of the opponent. Worst model defines the estimated opponent utility as one minus actual utility. Opposite model defines opponent's utility as the opposite of the agent's utility calculated by subtracting the agent's utility from 1.

Apart from the above heuristic models, several other heuristics have been used in the literature. The opponent model proposed in (Jonker et al. 2007; Bosse et al. 2005; Jonker and Robu 2004) use a "guessing" heuristic in which preference order of an opponent is predicted. It is based on the heuristic that an opponent will be more willing to concede on less important preferences and vice versa. Carbonneau and Vahidov (2014) proposes a model for prediction of which issue an opponent may choose for concession based on the remaining concession potential for each issue. For this, a set of heuristics is applied. Some of the other heuristics are: assuming first offer is the best offer (Hindriks and Tykhonov 2008; van Galen Last 2012; van Krimpen et al. 2013) and liberal concessions for less important issues (Jonker et al. 2007; Coehoorn and Jennings 2004).

6.3.4 Other Models

There are several other opponent models proposed in the literature that cannot be grouped in any of the above sections. Chen and Weiss use wavelet analysis and cubic smoothing spline in their negotiation approach called OMAC (Chen and Weiss 2012, 2014) to predict opponent behavior. The timestamp and utility of each opponent offer are used to construct a time series to which discrete wavelet transformation is applied. The approximation component is then smoothed using cubic spline to predict future behavior of the opponent. Chebychev polynomials are used to approximate the probability function of acceptance in Saha et al. (2005). In repeated one-shot negotiations where the opponent either accepts or rejects, the probability function of acceptance is designed as a Chebychev polynomial and the coefficients of the polynomial is calculated with each acceptance or rejection by the opponent.

In Brzostowski and Kowalczyk (2006) the prediction of opponent behavior is constructed separately for time-dependent tactics and imitation tactics. The authors of Mok and Sundarraj (2005) use derivatives of Taylor's series approximation for modeling opponents that use time-dependent tactics. In Ozonat and Singhal (2010), the opponent's behavior is predicted with a Switching Linear Dynamical System (SDLS) which uses conditional Gaussian model instead of fixed Gaussian model used in LDS (Linear Dynamical System). The model also predicts the future trajectory of offers of the opponent based on which future offers to the opponent can be made by the agent.

The utility function of an opponent is modeled as a utility graph which is constructed as and when an agent receives more offers from the opponent (Robu et al. 2005). The agent first begins with a maximal item inter-dependency graph which represents all possible inter-dependencies between the issues. Then sub-utility graphs are updated based on whether an opponent considers two issues to be substitutable or not.

DOPPONENT model uses nearest neighbor method, a distance-based method to extract the preferences of an opponent. Distance between two bids is used to predict the utility function exploiting the linear relationship between estimated difference of utilities and real difference of utilities. Another work that deals with opponent modeling uses the wisdom of crowds (Chen et al. 2016) to learn the acceptable and non-acceptable offers of an opponent. The paper assumes a crowd of agents that might want to negotiate. For a cost these agents present labels related to whether an offer is acceptable or not to another agent. This collective knowledge could be used by the agents to generate acceptable offers for the opponent agent.

6.4 Offer Decision Making: Acceptance Model

A negotiation between two agents reaches an agreement when one of the agents decides to agree to an offer proposed by the other agent. Acceptance of an offer may be based on time or utility. Agents tend to agree to even lesser than expected utilities when negotiation deadline is nearer. This is because a negotiation without an agreement gives zero utility to both the parties. Moreover, time and cost spent on the negotiation and re-negotiation amounts to loss in most situations. Acceptance may also be based on the utility of an offer that the opponent offers. Many of the existing agents use a combination of time and utility-based acceptance models. When to accept an offer is determined by the acceptance model of an agent. The acceptance model of an agent is a function of time and utility of the agent and defines the condition on which an agent has to accept an offer by the opponent. Baarslag et al. (2013) define four generalized acceptance conditions and their combinations commonly used in the literature.

An agent A will accept an offer by agent B ($x^t_{B \rightarrow A}$) at time t if the utility of the offer calculated by agent A (U_A) is greater than the utility of the next offer of A to be sent to B at time t'. Some of the works in the negotiation literature that use this acceptance condition include (SáNchez-Anguix et al. 2013; Lai and Sycara 2009; Chen and Weiss 2012; Fatima et al. 2004; Krovi et al. 1999; Bahrammirzaee et al. 2013; Li et al. 2013).

The acceptance condition AC_{prev} denotes that agent A will accept an offer from agent B when the utility of the offer is greater than the utility of the previous offer sent by A to B (Yan et al. 2007; Ros and Sierra 2006).

The acceptance condition AC_{const} denotes that agent A will accept an offer from B if the utility of the offer is greater than a threshold α (Bi and Xiao 2012; Hao et al. 2014).

Unlike the above three acceptance conditions, AC_{time} is a time-based acceptance condition that accepts when a certain amount of time T passes.

In addition to the above four generalized conditions, a logical combination of these conditions may also be used. For example, an agent IamHaggler (Williams 2012) accepts when

$$AC_{const}(0.88) \vee AC_{next}(1.02, 0) \vee AC_{prev}(1.02, 0)$$

A combined acceptance condition may be defined by

$$AC_{combi}(T, \alpha) \overset{def}{\Leftrightarrow} AC_{next} \vee AC_{time}(T) \wedge (U_A\left(x^t_{B \rightarrow A}\right) \geq \alpha)$$

which denotes an offer from B to A can be accepted when AC_{next} holds or the deadline is almost reached and the current offer is better than a threshold α. α may be changed according to requirements to denote the maximum utility over a time window or average over a time window or any other value. The choice of α is domain-dependent.

7 Post-negotiation Phase

The negotiation phase may result in an agreement being reached or deadline being reached without agreement. The post-negotiation phase is an optional phase in which the optimality of the agreement may be assessed if agreement had been reached. Some of the metrics used to assess the optimality of an agreement are sum of utilities (Zhang et al. 2014; Ros and Sierra 2006), average utility, distance from Pareto frontier (SáNchez-Anguix et al. 2013; Lai et al. 2008; Jazayeriy et al. 2011; Gatti and Amigoni 2005), nearness to Nash point (SáNchez-Anguix et al. 2013), nearness to Kalai-Smorodinsky point and number of rounds of negotiation (SáNchez-Anguix et al. 2013). (Baarslag et al. 2013) details the measures to predict performance of opponent models.

Measures based on utilities are based on utilitarianism theory in which maximum total welfare is preferred. A negotiation that results in higher utilities for both the negotiators is better than a negotiation that results in high utility for one individual. Sum and product of utilities measure social welfare while difference of utilities measures the fairness of a solution. A good negotiation gives a solution with high total utility with minimal difference of utilities.

Nash solution (Nash Jr 1950) and Kalai-Smorodinsky solution (Kalai and Smorodinsky 1975) are axiomatic approaches [as against strategic approach of Rubinstein (1982)] which determine unique solution to a bargaining problem. These are based on game-theory and the problems are formulated based on utility values. Nash solution satisfies four axioms—(1) Pareto-efficiency (2) symmetry (solution should not distinguish between opponents) (3) invariance to equivalent payoff representation (a linear transformation of utility function should not alter the outcome of the bargaining process) (4) independence of irrelevant alternatives. In the Kalai–Smorodinsky solution, the fourth axiom is replaced by monotonicity. An egalitarian solution was proposed in Kalai (1977) which includes both independence of irrelevant alternatives and monotonicity axioms.

8 Mapping of Negotiation Frameworks to the Lifecycle Model

We now list some of the works in the literature and the mapping of lifecycle model to each work. This gives an overview of the various negotiation techniques used in different phases of the lifecycle. We identify and map the methods used in each work to the phases of lifecycle model. Table 1 presents a survey for which we identify the models used in negotiation and post-negotiation phases of the lifecycle.

Table 1 Models used in the negotiation and post-negotiation phases of lifecycle in several works

Work	Negotiation strategy model	Utility model	Opponent model	Acceptance model	Negotiation protocol	Optimality evaluation metric
Choi et al. (2001)	Genetic algorithm-based selection of strategy	Product function	Stochastic approximation	–	Alternating offers protocol	Number of rounds, payoff
Fatima et al. (2004)	Selection of time-dependent tactics	Von Neumann–Morgenstern utility functions	None	(i)	Alternating offers protocol	Pareto-optimality
Bahrammirzaee et al. (2013)	Adaptive (time-dependent and behavior dependent)	Linear scoring function	Heuristics	(ii)	Modification of alternating offers protocol and monotonic concession protocol	Multiple (joint utility, number of rounds)
Yu et al. (2013)	Adaptive concession strategy	Linear	Regression analysis and Bayesian learning	–	Alternating offers protocol	Number of rounds
Jonker et al. (2007)	Attribute planning concession strategy	Ease utility (calculate from input by user) and financial utility (linear continuous)	Guessing heuristic	–	Alternating offers protocol	Pareto optimality
Chen and Weiss (2012)	Adaptive concession	Linear	Standard wavelet decomposition and cubic smoothing spline	(i)	Alternating offers protocol	Utility values, ANAC scores
Dastjerdi and Buyya (2015)	Time-dependent strategy	Linear	None	(i)	Alternating offers protocol	Inequality index based on utilities
(de Jonge and Sierra 2016)	Genetic algorithms-based strategy	Non-linear utility functions	None	Variation of (i)	Alternating offers protocol	Individual utilities, social utilities

Table 1 (continued)

Work	Negotiation strategy model	Utility model	Opponent model	Acceptance model	Negotiation protocol	Optimality evaluation metric
Zhan and Luo (2016)	Not discussed	Fuzzy offer evaluation	Offer similarity	(iii)	Alternating offers protocol	Generates acceptable offers. Optimality not aimed
Abdelatey (2017)	Time-dependent strategies	Linear	None	(i)	Foundation for intelligent physical agents (FIPA) protocol	Individual utilities
Zheng et al. (2015)	Concession and offer generation using alternating projections	Non-linear (continuous and concave)	None	Closest to average (multi-issue)	Sequential-offer protocol	Nash bargaining solution

9 Summary

Automated negotiation is a challenging area of research which is comprised of many issues that offer immense scope for research. Vast amount of research has been done in this area. Our aim is to group papers in this area and fit them to the lifecycle model so that each aspect can be explored individually. Preference elicitation, utility model in negotiation and acceptance model are three such issues which have been less focused than others. Preference elicitation is applicable to many fields. But there is not much work related to preference elicitation in negotiation. Most works assume that preferences are read from the user before the beginning of negotiation. There is scope for research of negotiations that accommodate the changing preferences of a user. Though utility model is a well-established concept in economics, there are few research papers that study the applicability and performance of various utility functions in a negotiation setting. Similarly, the impact of acceptance conditions in a negotiation has not been explored. Opponent model has been vastly explored and many techniques have been applied for better opponent prediction. But there is still scope for research in applying meta-heuristic models to opponent modeling.

In this paper, we proposed a lifecycle model of a negotiation agent and presented a survey of negotiation techniques fitting them to the lifecycle model. The model splits the whole negotiation process into various components and presents the interactions between them. We also presented the taxonomy of opponent models classified based on techniques used for opponent modeling. The lifecycle model is generic and a negotiation agent may be designed based on the components of the model. It allows separation of concerns which in turn lets easier identification of issues.

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