Automated Negotiations*

Can Automated Agents Proficiently Negotiate with Humans?

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1. INTRODUCTION

Negotiation is a process in which interested parties confer with the aim of reaching an agreement. The ability to negotiate successfully is critical for any social interaction. In particular, automated negotiators should be able to proficiently interact and collaborate with people. Negotiation surrounds our every day life even without noticing or paying careful attention to it. We often find ourselves in situations, whether simple or complex, which require negotiations. They can either be bilateral or multilateral negotiations. They can also be simple and ordinary, like haggling over a price in the market or deciding on a meeting time. Nonetheless, they can also have colossal effects on the lives of millions, such as negotiations involving inter-country disputes and nuclear disarmament [14]. No matter what the domain, negotiation is not an easy task. Even what might be perceived as a "simple" case of a single-issue bilateral bargaining over a price in the market can demonstrate the difficulties that arise during the negotiation process. In fact, it may demonstrate the complexity of the negotiation process and the modeling of the environment. In this case there are two sides, each with her own preferences, that might, or might not, be known to the other party. In addition, some of these preferences might conflict and thus reaching an agreement would require a certain degree of cooperation or concession.

Keeping all this in mind, the negotiation domain is an attractive environment for automated agents, resulting in many benefits. Automated agents can be used with humans in the loop or without them. On the one hand, they can alleviate some of the efforts required of people during negotiations and also assist people that are less qualified in the negotiation process. On the other hand there may be situations in which automated negotiators can even replace human negotiators. Another possibility is for people embarking on important negotiation tasks to use these agents as a training tool, prior to actually performing the task. Thus, success in developing an automated agent with negotiation capabilities has great advantages and implications. The design of automated agents that proficiently negotiate is a challenging task, as there are different environments and constraints that should be considered.

The negotiation environment defines the specific settings of the negotiation. Based on these settings, different considerations should then be taken into account. We describe the possible settings in the following subsection.

In this paper we focus on the question of whether an automated agent can proficiently negotiate with human negotiators. To this end we define a proficient automated negotiator as one that can achieve the best possible agreement for itself. This, of course, also depends on the preferences of the other party and thus adds complexity to the design of such an agent.

1.1 The Negotiation Environment

When designing an automated agent, the designer needs to take into account the environment in which the agent will operate. The environment determines several parameters which dictate the number of negotiators taking part in the negotiation, the time frame of the negotiation and the issues on which the negotiation is being conducted. The number of parties participating in the negotiation process can be two (bilateral negotiations) or more (multilateral negotiations). For example, in a market there can be one seller but many buyers, all involved in negotiating over a certain item. On the other hand, if the item is common, there may also be many sellers taking part in the negotiation process.

The negotiation environment also consists of a set of objectives and issues to be resolved. Various types of issues can be involved, including discrete enumerated value sets, integer-value sets, and real-value sets. A negotiation consists of multi-attribute issues if the parties have to negotiate an agreement which involves several attributes for each issue. Negotiations that involves multi-attribute issues allow making complex decisions while taking into account multiple factors [18]. The negotiation environment can consist of non-cooperative negotiators or cooperative negotiators. Generally speaking, cooperative agents try to maximize their combined joint utilities (e.g., see [40]) while non-cooperative agents try to maximize their own utilities regardless of the

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other sides' utilities.

Finally, the negotiation protocol defines the formal interaction between the negotiators: whether the negotiation is done only once (one-shot) or repeatedly, and how the exchange of offers between the agents is conducted. A common exchange of offers model is the alternating offers model [32]. In addition, the protocol states whether agreements are enforceable or not, and whether the negotiation has a finite or infinite horizon. The negotiation is said to have a finite horizon if the length of every possible history of the negotiation is finite. In this respect, time costs may also be assigned and they may increase or decrease the utility of the negotiator.

Figure 1 depicts the different variations in the settings, along with the location of each system that is described in Section 3. For example, point D in the cube represents bilateral negotiations with multi-attribute issues and repeated interactions, while point B represents multi-lateral negotiations with a single attribute for negotiation and a one-shot encounter.

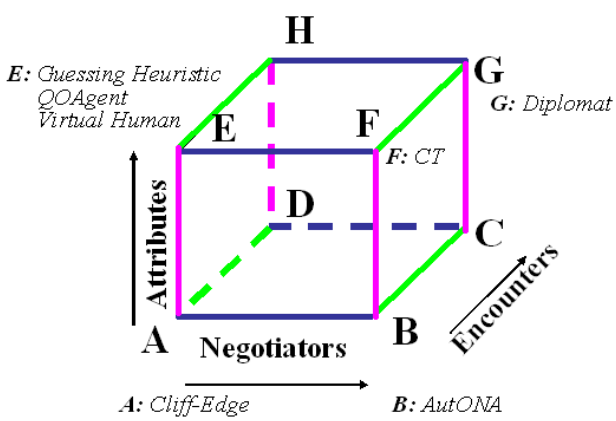

Figure 1: Variations of the negotiation settings.

The negotiation domain encompasses the negotiation objectives and issues and assigns different values to each. Thus, an agent may be tailored to a given domain (e.g., the *Diplomat* agent [22] described below is tailored to a specific domain of the Diplomacy game) or domain independent (e.g., the *QOAgent* [24] described below).

1.2 The Information Model

The information model dictates what is known to each agent. It can be a model of complete information, in which each agent has complete knowledge of both the state of the world and the preferences of other agents; or it can be a model of incomplete information, in which agents may have only partial knowledge of either the states of the world or the preferences of other agents (e.g., bargaining games with asymmetric information), or they may be ignorant of the preferences of the opponents and the states of the world [33]. The incomplete information can be modeled in different ways with respect to the uncertainty regarding the preferences of the other party. One approach to modeling the information is to assume that there is a set of different agent types and the other party can be any one of these types.

1.3 Human-Agent Negotiations

The issue of automated negotiation is too broad to cover in a short review paper. To this end, we have decided to concentrate on adversarial *bilateral bargaining* in which the automated agent is matched with people. The challenges in this area could motivate readers to pursue this field (note that this sets the focus and leaves most auction settings outside the scope of this article, even though automated agents that bid in auctions competing with humans have been proposed and evaluated in the literature (e.g., Grossklags and Schmidt [11])).

1.3.1 Automated Negotiator Agents

The problem of developing an automated agent for negotiations is not new for researchers in the fields of Multi-Agent Systems and Game Theory (e.g., Kraus [20] and Muthoo [26]). However, designing an automated agent that can successfully negotiate with a human counterpart is quite different from negotiating with another automated agent. Although an automated agent that played in the Diplomacy game with other human players was introduced by Kraus and Lehmann [22] some twenty years ago, the difficulties of designing proficient automated negotiators have not been resolved. In essence, in most research, assumptions are made that do not necessarily apply in genuine negotiations with humans, such as assuming complete information or the rationality of the opponent negotiator. In this sense, both parties are assumed to be rational in their behavior (e.g., the decisions made by the agents are described as rational and the agents are considered to be expected utility maximizing agents that cannot deviate from their prescribed behavior). Yet, when dealing with human counterparts, one must take into consideration the fact that humans do not necessarily maximize expected utility or behave rationally. In particular, results from social sciences suggest that people do not follow equilibrium strategies [6, 25]. Moreover, when playing with humans, the theoretical equilibrium strategy is not necessarily the optimal strategy [38]. In this respect, equilibrium based automated agents that play with people must incorporate heuristics to allow for "unknown" deviations in the behavior of the other party. Moreover, when people are the ones that design agents, they do not always design them to follow equilibrium strategies [12]. Nonetheless, some assumptions are made, i.e. mainly that the other party will not necessarily maximize its expected utility, however, if given two offers it will prefer the one with the highest utility value.

Lastly, it has been shown that whether the opponent is oblivious or has full knowledge that its counterpart is a computer agent can change the overall result. For example, Grossklags and Schmidt [11] showed that efficient market prices were achieved when human subjects knew that computer agents existed in a double auction market environment. Sanfey et al. [34] matched humans with other humans and with computer agents in the Ultimatum Game and showed that people rejected unfair offers made by humans at significantly higher rates than those made when matched with a computer agent.

1.3.2 Automated Agents Negotiating with People

Researchers have tried to take some of these issues into consideration when designing agents that are capable of proficiently negotiating with people. For example, dealing only with the bounded rationality of the opponent, several researchers have suggested new notions of equilibria (e.g., the *trembling hand equilibrium* described in Rasmusen ([30], p. 139)). Approximately ten years ago, Kasbah, a seminal negotiation model between agents designed by humans, was presented in the virtual marketplace by Chavez and Maes [5]. Here, the agent's behavior was fully controlled by human players. The main idea was to help users in the negotiation process between buyers and sellers by using automated negotiators. Chavez and Maes's main innovation was, not so much the sophisticated design of the automated negotiators, but rather the creation of a multi-agent negotiation environment. Kraus *et al.* [21] describe an automated agent that negotiates proficiently with humans. Although they also deal with negotiation with humans, there is complete information in their settings. Other researchers have suggested to shift from quantitative decision theory to qualitative decision theory [36]. In using such a model it is not necessary to assume that the opponent will follow the equilibrium strategy or try to be a utility maximizer. Another approach was to develop heuristics for negotiations motivated by the behavior of people in negotiations [22]. However, the fundamental question of whether it is possible to build automated agents for negotiations with humans in open environments has not been fully addressed by these researchers.

Another direction currently under pursuit is the development of virtual humans to train people in interpersonal skills (e.g., Kenny *et al.* [19]). Achieving this requires implementing cognitive and emotional modeling, natural language processing, speech recognition and knowledge representation. This in addition to constructing and implementing the appropriate logic for the task at hand (e.g., negotiation), is in order to make the virtual human into a good trainer. An example of their research prototype, in which trainees conduct real-time negotiations with a virtual human doctor and a village elder to move a clinic to another part of the town out of harms way is given in Figure 2.

Figure 2: Example of virtual humans' negotiations.

Commercial companies and schools have also displayed interest in automated negotiation technologies. Many courses and seminars are offered for the public and for institutions. These courses often guarantee that upon completion you will "know many strategies on which to base the negotiation", "Discover the negotiation secrets and techniques", "Learn common rival's tactics and how to neutralize them" and "Be able to apply an efficient negotiation strategy" (e.g., [1, 27]). Yet, in many of these courses, the agents are restricted to one domain and cannot be generalized. Some of the automated agents cannot be adapted to the user and are restricted to a single attribute negotiation with no time constraints.

Nonetheless, human factors and results of laboratory and field experiments reviewed in esteemed publications (e.g., [9, 29]) provide guidelines for the design of automated negotiators. Yet, it is still a great challenge to incorporate these guidelines in the inherent design of an agent to allow it to proficiently negotiate with people.

2. THE MAIN CHALLENGES

The main difficulty, though, in the development of automated negotiators is that in order to negotiate proficiently with a human counterpart, they have to be able to work in settings with both opponents with bounded rationality and incomplete information. The difficulty can also stem from the fact the humans are also influenced by behavioral aspects and by social preferences that hold between players (such as inequity-aversion [2] and reciprocity [4]). Thus, it is difficult to predict individual choices.

Tackling the issues of bounded rationality and incomplete information is a complex task. To achieve this, an automated agent is required to have two inter-dependent mechanisms. The first is a decision making component which works via modeling human factors. This mechanism is in charge of generating offers and deciding whether to accept or reject offers made by the opponent. The challenge behind this mechanism does not lie in the computational complexity of making good decisions, but rather in reasoning about the psychological and social factors that characterize human behavior. The second component is learning, which allows the agent to infer the opponent's preferences and strategies, based on his actions.

Another inherent problem in the design of the automated agent is the ability to generalize its behavior. While humans can negotiate in different settings and domains, when designing an automated agent a decision should be made whether the agent should be a general purpose negotiator, that is, will be able to successfully negotiate in many settings and be domain-independent (e.g., Lin *et al.* [24]), or the agent will only be suitable for one specific domain (e.g., Ficici and Pfeffer [8], Kraus and Lehmann [22]). Perhaps the advantage of the agent's specificity is the ability to construct better strategies that could allow it to achieve better agreements, as compared to a more general purpose negotiator. This is due to the fact that the specificity allows the designer to debug the agent's strategy more carefully and against more test cases. By doing so, the designer can fine-tune the agent's strategy and allow for a more proficient automated negotiator. Agents that are domain independent, on the other hand, are harder to test against all possible cases and states.

The issue of trust also plays an important role in negotiations, especially when the other side's behavior is unpredictable. Successful negotiations depend on the trust established between all parties, which can depend on cheap-talk during negotiations (that is, unverifiable information with regard to the other party's private information [7]) and the introduction of unenforceable agreements. Based on the actions and information each party can update its reputation (for better or for worse) with regard to the other party and thus build trust between the sides. Some of the systems that we review below do allow cheap-talk and unenforceable agreements. Building trust can also depend on past and future interactions with the other party (e.g., one-shot interaction or repeated interactions). In this article, though, due to limited space we do not cover the issue of trust in detail. Readers can for example refer to [31] for a comprehensive review on the topic of trust.

Another important issue is how automated agents can be evaluated and compared. Such an evaluation is important in order to select the most appropriate agent for the task at hand. Yet, no single criteria is defined. The answer to the questions of "what constitutes a good negotiator agent?" is multifaceted. For example, is a good agent an agent that:

- achieves a maximal payoff when matched with human negotiators? But will it also generate these payoffs when matched with other automated agents, which might be more accessible than human negotiators, and which also exist in open environments?
- generates a maximal combined payoff for both negotiators, that is, the agent is more concerned with maximizing the combined utilities than its own reward?
- allows most negotiations to end with an agreement, rather than one of the sides opting-out or terminating the negotiations with a status-quo outcome?
- is domain dependent and its technique is suitable only for that domain or one that is domain independent and can be adapted to several domains? This might be an important factor if an agent is required to adapt to dynamic settings, for example.
- behave in such a manner that would leave its counterpart speculating whether it is an automated negotiator or a human one?

In this article we do not define what or whether there is a best answer. We also do not claim that a best answer indeed exists. Yet, researchers should take these and other measures into consideration when designing their agents. Perhaps, certain criteria and benchmarks are in order to allow an adequate comparison between automated agents.

In the rest of this article we will review automated agents that incorporate the two mechanisms of decision making via modeling human factors and learning the opponent's model. By doing so they try to tackle the aforementioned challenges in bilateral negotiations. While many automated negotiators' designs have been suggested in the literature, we only review those that have actually been evaluated and tested with human counterparts. This is mainly due to the fact that in order to test the proficiency of an automated negotiator whose purpose is to negotiate with human negotiators, one must match it with humans. It is not suffice to test it with other automated agents, even if they were supposed to have been designed by humans as bounded rational agents, due to many of the reasons previously mentioned.

3. TACKLING THE CHALLENGES

In this section we describe several automated agents that try to tackle the challenges and proficiently negotiate in open environments. All of the described agents were evaluated with human counterparts. It is worth noting that most of the agents described below use structured (or semi-structured) language and do not implement any natural language processing methods (with one exception of the Virtual Human agent). In addition, the agents vary with respect to their characteristics. For example, some are domain-dependent, while others are domain-independent and are more general in nature; some use the history of past interactions to model the opponent, while others only have access to current interaction data. Figure 3 depicts a general architecture for an automated agent design. We begin by describing the oldest agent of all of them, i.e. the *Diplomat* agent.

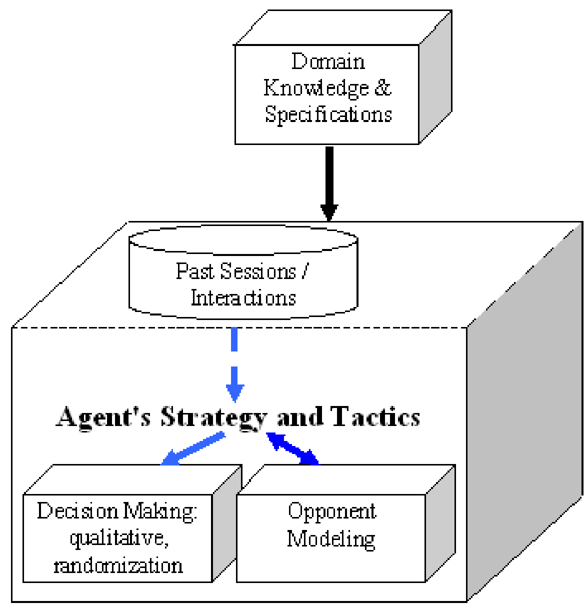

Figure 3: Architecture of a general agent's design.

3.1 The *Diplomat* Agent

Over twenty years ago Kraus and Lehmann developed an agent called *Diplomat* [22], that played the Diplomacy game (see Figure 4) with the goal to win. The game involves negotiations in multi-issue settings with incomplete information concerning the other agents' goals, and misleading information can be exchanged between the different agents. The negotiation protocol extends the model of alternating offers and allows simultaneous negotiations between the parties, as well as multiple interactions with the opponent agents during each time period. The issue of trust also plays an important role, as commitments might be breached. In addition, as each game consists of several sessions, it can be viewed as repeated negotiation settings.

The main innovation of the *Diplomat* agent is, most prob-

Figure 4: The Diplomacy game.

ably, the fact that it consists of five different modules that work together to achieve a common goal. Different personality traits are implemented in the different modules. These personality traits affect the behavior of the agent and can be changed during each run, which allows *Diplomat* to change its 'personality' from one game to another and to act nondeterministically. In addition, the agent has a limited learning capability which allows it to try to estimate the personality traits of its rivals (e.g., their risk attitude). Based on this, *Diplomat* assesses whether or not the other players will keep their promises. In addition, *Diplomat* incorporates randomization in its decision making component. This randomization, influenced by *Diplomat*'s personality traits, determines whether some agreements will be breached or fulfilled.

The results reported by Kraus and Lehmann show that *Diplomat* played well in the games in which it participated, and most human players were not able to guess which of the players was played by the automated agent. Nonetheless, the main disadvantage of *Diplomat* is that it is a domain-dependent agent - i.e. suitable only for the Diplomacy game. Since the game is quite complex and time consuming not many experiments were carried out with human players to validate the results and reach a level of significance. Yet, at the time *Diplomat* did open a new and exciting line of research, some of which we review below.

We continue with a more recent agent which is also constrained to a specific domain and involves single-issue negotiations. However, it also takes into account the history of past interactions to model the opponents.

3.2 The *AutONA Agent*

Byde *et al.* [3] developed *AutONA*, which is an automated negotiation agent. Their problem domain involves multiple negotiations between buyers and sellers over the price and quantity of a given product. The negotiation protocol follows the alternating offers model. Each offer is directed at only one player on the other side of the market, and is private information between each pair of buyers and sellers. In each round, a player can make a new offer, accept an offer, or terminate negotiations. In addition, a time cost is used to provide incentives for timely negotiations. While the model can be viewed as one-shot negotiations, for each experiment, *AutONA* was provided with data from previous experiments.

In order to model the opponent, *AutONA* attaches a belief function to each player, which tries to estimate the probability of a price for a given seller and a given quantity. This belief function is updated based on observed prices in prior negotiations. Several tactics and heuristics are implemented to form the strategy of the negotiator during the negotiation process (e.g., for selecting the opponents with which it will negotiate and for determining the first offer it will suggest to the opponent). Byde *et al.* also allowed cheap-talk during negotiations, that is, the proposition of offers with no commitments. The results obtained from the experiments with human negotiators revealed that the negotiators did not detect which negotiator was the software agent. In addition, Byde *et al.* found that *AutONA* is not sufficiently aggressive during negotiations and thus many remained incomplete. Their experiments showed that at first *AutONA* performed worse than the human players. Thus, a modified version, which fine-tuned several configuration parameters of the *AutONA* agent, improved the results which were more in line with those of human negotiators, yet not better. They conclude that different environments would most likely require changing the configurations of the *AutONA* agent.

After reviewing the *AutONA* agent, we proceed with agents that are applicable to a larger family of domains. The next agent is applicable to the Cliff-Edge family of domains. A Cliff-Edge environment is characterized by a conflict between the desire to maximize profits while preventing the entire deal from falling through. An example of such a domain is the Ultimatum Game. The ultimatum game is an experimental economics game in which two players have to decide how to divide a sum of money between them. The first player can propose a division while the second player can either accept the proposal or reject it. Only if the second player accepts the offer the money is split between the two. The game is played only once.

3.3 The *Cliff-Edge Agent*

Katz and Kraus [16] proposed an innovative model for human learning and decision making. Their agent competes repeatedly in one-shot interactions, each time against a different human opponent (e.g., sealed-bid first-price auctions, ultimatum game). Katz and Kraus utilized a reinforcement learning algorithm, which integrates virtual learning with reinforcement learning. That is, offers higher than an accepted offer are treated as successful (virtual) offers, notwithstanding that they were not actually proposed. Similarly, offers lower than a rejected offer are treated as having been (virtually) unsuccessfully proposed. A threshold is also employed to allow for some deviations from this strict categorization. The results of previous interactions are stored in a database, which is used for later interactions. The decision making mechanism of Katz and Kraus's Ultimatum Game agent follows a heuristic based on the qualitative theory of Learning Direction [35]. Simply speaking, if an offer is rejected at a given interaction, then at the next interaction the proposer will offer the opponent a higher offer. In contrast, if an offer is accepted, then during the following interaction the offer will be decreased. Katz and Kraus show that their algorithm performs better than other automated agents. When compared to human behavior, there is an advantage to their automated agent over the human's average payoff.

Later, Katz and Kraus [17] improved the learning of their agent by allowing gender sensitive learning. In this case, the information obtained from previous negotiations is stored in three databases, one is general and the other two are each associated with a specific gender. During the interaction, the agent's algorithm tries to determine when to use each database. Katz and Kraus show that their gender-sensitive agent yields higher payoffs than the generic approach, which lacks gender sensitivity.

However, Katz and Kraus's agent was tested in a single-issue domain with repeated interactions that are used to improve the learning and decision making mechanism. It is not clear whether their approach would be applicable to negotiation domains in which several rounds are made with the same opponent and multi-issue offers are made. In addition, the success of their gender sensitive approach depends on the existence of different behavioral patterns of different gender groups.

The agents described next are tailored to a rich environment of multi-issue negotiations. Similar to the agent proposed by Katz *et al.* the history of past interactions is used to fine-tune agents' behavior and modeling.

3.4 The *Colored-Trails Agents*

Ficici and Pfeffer [8] were concerned with understanding human reasoning, and using this understanding to build their automated agents. They did so by means of collecting negotiation data and then constructing a proficient automated agent. Both Byde *et al.* 's *AutONA* agent [3] and the Colored-Trail agent collect historical data and use it to model the opponent. Byde *et al.* used the data to update the belief regarding the price for each player, while Ficici and Pfeffer used it to construct different models of how humans reason in the game.

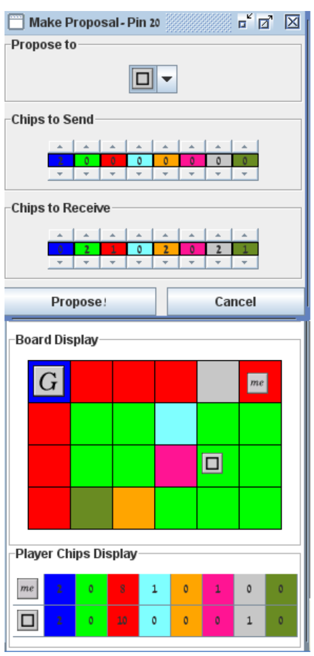

Figure 5: The Colored-Trail game screenshot.

The negotiation was conducted in the Colored Trails game environment [12], which is a game played on a nxm board of colored squares. Players are issued colored chips and are required to move from their initial square to a designated goal square. To move to an adjacent square, a player must turn in a chip of the same color as the square. Players must negotiate with each other to obtain chips needed to reach the goal square (see Figure 5). Their learning mechanism involved constructing different possible models for the players and using gradient descent to learn the appropriate model. Ficici and Pfeffer trained their agents with results obtained from human-human simulations and then incorporated their models in their automated agents, which were later matched against human players. They show that this method allows them to generate more successful agents in terms of the expected number of accepted offers and the expected total benefit for the agent. They also show that their agent contributes to the social good by providing high utility scores for the other players. Ficici and Pfeffer were also able to show that their agent performs similarly to human players.

In order for the *Colored-Trails Agent* to model the opponent, prior knowledge regarding the behavior of humans is needed. The learning mechanism requires sufficient human data for training and is currently limited to one domain only.

Gal *et al.* [10] also discuss automated agent design in the domain of the Colored Trails. They present a machine-learning approach for modeling human behavior in a two-player negotiation, where one player proposes a trade to the other, who can accept or reject it. Their model tries to predict the reaction of the opponent to the different offers, and using this prediction it determines the best strategy for the agent. The domain on which Gal *et al.* tested their agent can also be viewed as a Cliff-Edge environment, more complex than the Ultimatum Game, upon which Katz and Kraus evaluated their agent [16].

Gal *et al.* show that the proposed model successfully learns the social preferences of the opponent and achieves better results than the Nash equilibrium, Nash bargaining computer agents, and human players.

We continue now with agents that are domain-independent and propose an agent with more generality than the aforementioned agents.

3.5 The *Guessing Heuristic Agent*

Jonker *et al.* [15] deal with bilateral multi-issue and multi-attribute negotiations which involve incomplete information. The negotiation follows the alternating offer protocol and is conducted once with each opponent. Jonker *et al.* designed a generic agent that uses a "guessing heuristic" in the buyer-seller domain[1]. This heuristic tries to predict the opponent's preferences based on its offers' history. This is under the assumption that the opponent's utility has a linear function structure. Jonker *et al.* assert that this heuristic allows their agent to improve the outcome of the negotiations. Regarding the offer generation mechanism, they use a concession mechanism to obtain the next offer. In their experiments, the automated agent acts as a proxy for the human user. The user is involved only in the beginning when he inputs the preference parameters. Then the agent generates the offers and the counter-offers. When comparing negotiations involving only automated agents with negotiations involving only humans, the agents usually outperformed the humans (in the buyer's role). Yet, in an additional experiment they matched humans versus agent negotiators. In this experiment, humans only played the role of the buyer. When comparing the human vs. agent negotiations to that of only

[1] Although Jonker *et al.* discuss and present results on one domain only, they state that their model is generic and has also been applied in other domains.

automated agents, the humans attained somewhat better results than the agents (in the buyer's role), based on the average utilities. The authors believe this should be accounted to the fact that humans forced the automated negotiators to make more concessions then they themselves did.

The next agent we discuss also deals with bilateral multi-issue negotiations that involve incomplete information. Nonetheless the negotiation protocol is richer than that of the *Guessing Heuristic Agent*.

3.6 The *QOAgent*

The *QOAgent* [24] is a domain independent agent that can negotiate with people in environments of finite horizon bilateral negotiations with incomplete information. The negotiations consider a finite set of multi-attribute issues and time-constraints. Costs are assigned to each negotiator, such that during the negotiation process, the negotiator might gain or lose utility over time. If no agreement is reached by a given deadline a status quo outcome is enforced. A negotiator can also opt-out of the negotiation if it decides that the negotiation is not proceeding in a favorable manner. Similar to the negotiation protocol in the *Diplomat* agent's domain, the negotiation protocol in the *QOAgent*'s domain extends the model of alternating offers such that each agent can perform up to $M > 0$ interactions with the opponent agent during each time period. In addition, queries and promises are allowed which adds unenforceable agreements to the environment. With respect to incomplete information, each negotiator keeps his preferences private, though the preferences might be inferred from the actions of each side (e.g., offers made or responses to offers proposed). Incomplete information is expressed as uncertainty regarding the utility preferences of the opponent, and it is assumed that there is a finite set of different negotiator types. These types are associated with different additive utility functions (e.g., one type might have a long term orientation regarding the final agreement, while the other type might have a more constrained orientation). Lastly, the negotiation is conducted once with each opponent.

As for incomplete information, the *QOAgent* tackles the problem by applying a simple Bayesian update mechanism, which, after each action tries to infer which utility best suits the opponent (whether when receiving an offer or when receiving a response to an offer). For the decision making process, the approach used by the *QOAgent* is more of a qualitative approach [36]. While the *QOAgent*'s model applies utility functions, it is based on a non-classical decision making method, rather than focusing on maximizing the expected utility. The *QOAgent* uses the maximin function and the qualitative valuation of offers. Using these methods the *QOAgent* generates offers and decides whether to accept or reject proposals it has received.

Lin *et al.* [24] tested the *QOAgent* in several distinct domains and their results show that the *QOAgent* reaches more agreements and plays more effectively than its human counterparts, when the effectiveness is measured by the score of the individual utility. They also show that the sum of utilities is higher in negotiations when the *QOAgent* is involved, as compared to human-human negotiations. Thus, they assert, that it is indeed possible to build an automated agent that can negotiate successfully with humans. However, it is also important to state that their agent has certain limitations. They assume that there is a finite set of different agent types and thus their agent cannot generate a dynamic model (and perhaps a more accurate one) of the opponent. In addition, they have not shown whether their agent can also maintain high scores when matched with other automated agents, which is an important characteristic of open environment negotiations. Moreover, the *QOAgent* does not scale well when numerous offers are proposed, which can cause its performance to deteriorate.

Finally, we conclude with a description of a more complex type of agent that incorporates many features, far beyond the negotiation strategy itself.

3.7 The *Virtual Human Agent*

Kenny *et al.* [19] describe work on virtual humans that are used for interpersonal training for skills, such as: negotiation, leadership, interviewing and cultural training. To achieve this they require a large amount of research in many fields (such as: knowledge representation, cognitive and emotional modeling, natural language processing, etc.). Their intelligent agent is based on the Soar Cognitive Architecture, which is a symbolic reasoning system used to make decisions.

Traum *et al.* discuss the negotiation strategies of the virtual human agent in more detail [37]. In their paper they describe a set of strategies implemented by the agent (e.g., when to act aggressively if it seems that the current outcome will incur a negative utility, or when to find the appropriate issue on which to currently negotiate). The strategy chosen each time is influenced by several factors: the control the agent has over the negotiations, the estimated utility of an outcome and the estimated best utility of an outcome, the trust the agent bestows the opponent and the commitment of all agents to the given issues. The virtual agent also tries to model the opponent by reasoning about its mental state.

Traum *et al.* tested their agents in several negotiation scenarios. One of these scenarios is a simulation for soldiers that practice and conduct bilateral engagements with virtual humans, and in situations in which culture plays an important role. In this case, the different actions can be selected from a menu which includes appropriate questions based on the history of the simulation thus far. The second domain requires trainees to communicate with an embodied virtual human doctor to negotiate and convince him to move a clinic, located in a middle of a war zone, out of harm's way (see Figure 2). Their prototypes are continuously tested with cadets and civilians. Traum *et al.* are more concerned with the system as a whole and thus they do not provide insights with respect to the proficiency of their automated negotiator. Regarding the environment, they state that the subjects enjoy using the system for negotiations and that it also allows them to learn from their mistakes.

Traum *et al.* also report some of the existing limitations of their system. Currently, the virtual agent cannot consider arbitrary offers made by a human negotiator. In addition, more strategies are required to better cover the environment's rich settings. They also state that the negotiation problem can be addressed more in depth (following other researchers who have focused mainly on the negotiation field), rather than in breadth (as presently conducted in their system).

After having reviewed all the agents we conclude with a brief discussion on the characteristics and the design of future agents.

Agent	Main contribution
Diplomat	Changing the agent's personality heuristics Non deterministic behavior / randomization
AutONA	Tactics and heuristics Incorporating data from past interactions Concession mechanism
Cliff-Edge	Virtual learning Incorporating data from past interactions Gender-sensitive approach Non deterministic behavior / randomization (implicitly)
Colored-Trails	Incorporating data from past interactions Machine learning
Guessing Heuristic	Generic agent / domain independent Concession mechanism
QOAgent	Generic agent / domain independent Qualitative decision making Non deterministic behavior / randomization
Virtual Human	Tactics and heuristics Cognitive architecture

Table 1: Main contributions of each agent.

3.8 The Rule of Thumb for Designing Automated Agents

We should probably begin with the conclusion. Despite the title of this section, there may not be a good rule of thumb for designing automated negotiators with human negotiators. Table 1 summarizes the main contributions made by each of the reviewed agents. If we look into the design of all the aforementioned agents, we cannot find one specific feature that connects them or can account for their good negotiation skills. Nonetheless, we can note several features that have been used in several agents. Agent designers might take these features into consideration when designing their automated agent, while also taking into account the settings and the environment in which their agent will operate.

The first feature is *randomization*, which was used in *Diplomat*, *QOAgent* and also (though not explicitly) in the *Cliff-Edge* agents. The randomization factor allows these agents to be more resilient (or robust) to adversaries that try to manipulate them to gain better results on their part. In addition, it allows them to be more flexible, rather than strict, in accepting agreements and ending negotiations.

The second feature can be viewed as a *concession strategy*. Both the *AutONA* agent and the *Guessing Heuristic* agent implemented this strategy, which influenced the offer generation mechanism of their agent. A concession strategy might also have a psychological effect on the opponent which would make it more comfortable for the opponent to accept agreements or to make concessions on his own as well.

The last feature which was common in several agents is the use of a *database*. The database can be built based on previous interactions with the same human opponent or it can be built for all opponents. The agent consults the database to better model the opponent, to learn about possible behaviors and actions and to adjust its behavior to the specific opponent. A database of the history can also be used to obtain information about the behavior of the opponents, if such information is not known, or cannot be characterized, in advance.

Lastly, though not exactly a feature, but worth mentioning, is that none of the agents we reviewed implemented *equilibrium strategies*. This is an interesting observation and most likely is due to the fact that these strategies have been shown to behave poorly when implemented in automated negotiators matched with human negotiators, mainly due to the complex environment and the bounded rationality of people. In some cases (e.g., [21]) experiments have shown that when the automated agent follows its equilibrium strategy the human negotiators who negotiate with it become frustrated, mainly since the automated agent repeatedly proposes the same offer, and the negotiation often ends with no agreement. This has been shown in cases in which the complexity of finding the equilibrium is low and the players have full information.

4. CONCLUSIONS

In this article we presented the challenges and current state-of-the-art automated solutions for proficient negotiations with humans. Nonetheless we do not claim that all existing solutions have been summarized in this article. We briefly state the importance of automated negotiators and propose suggestions for future work in this field.

4.1 The Importance of Automated Negotiators

The importance of designing an automated negotiator that can negotiate efficiently with humans cannot be understated and we have shown that indeed it is possible to design such negotiators. By pursuing non-classical methods of decision making and a learning mechanism for modeling the opponent it could be possible to achieve greater flexibility and effective outcomes. As we have shown, this can also be accomplished without constraining the model to the domain.

Many of the automated negotiation agents are not intended to replace humans in negotiations, but rather as an efficient decision support tool or as a training tool for negotiations with people. Thus, such agents can be used to support training in real life negotiations, such as: e-commerce and electronic negotiations (e-negotiations), and they can also be used as the main tool in conventional lectures or online courses, aimed at turning the trainee into a better negotiator.

To this date, it seems that research in AI has neglected the issue of proficiently negotiating with people, at the expense of designing automated agents aimed to negotiate with rational agents or other automated agents (e.g., [39]). Others have focused on improving different heuristics and strategies and the analysis of game theory aspects (e.g., [20, 26]). Nonetheless it is noteworthy that these are important aspects in which the AI community has certainly made an impact. Unfortunately, not much progress has been made with regard to automated negotiators with people, leaving many unfaced challenges.

4.2 Suggestions for Future Research

The work is far from being complete and the challenges are still exciting. To entice the reader, we list a few of these challenges below.

The first challenge is to enrich the negotiation language. Many researchers restrict themselves to the basic model of alternating offers whereby the language consists of offers and counter-offers alone. Rich and realistic negotiations, however, consist of other types of actions (e.g., threats, comments, promises and queries), as well as simultaneous actions (that is, each agent can perform up to $M > 0$ interactions with the other party each time period). It is essential that these actions and behaviors are modeled in the automated negotiators to allow better negotiations with human negotiators.

Another challenge, also discussed in the introduction, is the need for a general all-purpose automated negotiator. With the vast amount of applications and domains, automated agents cannot be restricted to one single domain and must be adaptable to different settings. The tradeoff between the performance of a general purpose automated negotiator and a domain-dependent negotiator should be considered and methods for improving the efficacy of a general purpose negotiator should be sought. Achieving this will also contribute to the feasibility of comparing between different automated agents when matched with people. Preliminary work on this facet is already under pursuit by Hindriks *et al.* [13] and Oshrat *et al.* [28], however, we believe the aspect of generality should be addressed more by researchers. In this respect, metrics should be designed to allow a comparison between agents. To achieve this some of the questions of "what constitutes a good negotiator agent?" as described in Section 2 should be answered as well.

In addition, argumentation, though, dealt with in the past, still poses a challenge for researchers in this field. For example, about ten years ago Kraus *et al.* [23] presented argumentation as an iterative process emerging from exchanges among agents to persuade each other and bring about a change in intentions. In their work they developed a formal logic that forms a basis for the development of a formal axiomatization system for argumentation. In particular, Kraus *et al.* identified argumentation categories in human negotiations and demonstrated how the logic can be used to specify argument formulations and evaluations. Finally, they developed an agent which was implemented, based on the logical model. However, this agent was not matched with human negotiators. Moreover, there are several open research questions associated with how to integrate the argumentation model into automated negotiators. Since the argumentation module is based on logic and thus is time consuming, a more efficient approach should be used. In addition, the current model is built on a very complex model of the opponent and therefore should be incorporated in the automated negotiator's model of the opponent. In order to facilitate the design, a mapping between the logical model and the utility based model is required.

To conclude, in recent years the field of automated negotiators that can proficiently negotiate with human players has received much needed focus and the results are encouraging. We present several of these automated negotiators and show that it is indeed possible to design such proficient agents. Nonetheless, there are still challenges which pose interesting research questions that need to be pursued and exciting work is still very much in progress.

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