POMDP based Negotiation Modeling

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Abstract. As the world gets increasingly connected, business and political negotiations need to happen not just between people of similar cultural background but also across people of different cultures. An agent-based computational model of negotiation would help in understanding and improving the inter-cultural negotiation process. A major challenge in the development of such autonomous agents lies in developing the reasoning model of the agent. In this paper, we discuss the issues and challenges of developing a POMDP-based agent model for inter-cultural negotiation. POMDPs are promising for the following reasons: (a) POMDPs provide a decentralized way of solving the problem which is an inherent characteristic of the negotiation domain. (b) POMDPs provide a natural way to capture the sequential nature of the bargaining process i.e. they capture the process rather than just focusing on the outcome. (c) POMDPs can express the various important factors that affect negotiation such as culture.

1 Introduction

Negotiation is an interactive process by which multiple parties with limited common knowledge try to arrive at an agreement over a set of issues with possibly conflicting preferences over the issues. The topic of negotiation has received wide attention across various fields such as political science [8], economics [17], behavioral sciences [21], computational sciences [14] etc. For example, political scientists are interested in analyzing and predicting the negotiation processes between various countries and cultures while computer scientists are more interested in building computational models that can be embodied in automated agents. Most work in computational modeling to-date has focused on the outcome of a negotiation. In this paper, we propose a computational modeling approach for a general purpose negotiation problem with special emphasis on capturing the process of negotiation. While the approach presented is general, we pay special attention to the cultural aspects of the problem and show that our approach has a natural way of capturing such factors. Numerous studies (see [10] and references therein) have established that culture plays a crucial role in the way a negotiation progresses and our aim is to be able to evaluate these effects in a formal framework.

Game-theoretic techniques are an important class of computational techniques that have been used to study negotiation (see Section 5 for a discussion of other techniques). Most game-theoretic models in strategic interactions among self-interested agents (negotiation is an instance of this) aim to find solutions in terms of equilibrium point concepts (e.g., Nash equilibria). However, it may be computationally intractable to find such an equilibrium point. Moreover, it has been noted that, in a negotiation scenario, people may not follow the strategy corresponding to the game-theoretic equilibria [7]. Thus, traditional game-theoretic techniques are not suitable for modeling the evolution of the negotiation process. To capture the evolution of the negotiation process, we model the negotiating agents as a dynamical system that evolves in time. In particular, we model the negotiation problem in a decision-theoretic framework as a Partially Observable Markov Decision Process (POMDP) [12]. The advantages of the POMDP-based modeling approach are as follows: (a) Our approach is decentralized, i.e., each agent solves her own POMDP model while maintaining a belief about the other agents. This is in contrast to most game theoretic approaches where the payoffs of all the agents are assumed to be common knowledge. (b) In contrast to most computational models that are concerned only with the outcome, POMDPs provide a natural way to capture the sequential nature of the process while incorporating the new observed data such as the other agent's actions; additionally POMDPs provide ways to refine an agent's belief about other agents. (c) POMDPs can incorporate the effect of cultural factors in a natural way, e.g., given the action of the opponents and their cultural background, it uses the knowledge in interpreting the actions of the opponent, or in deciding the best action to take (please see the discussion in the next paragraph). The purpose of this paper is to illustrate with a simple negotiation example the construction of the POMDP model for negotiation. We also point out the various challenges in the development of a POMDP model (see Section 3).

Figure 1 illustrates a common way of representing how cognitive schemata [26] change during negotiations. The figure shows how schema's filter and interpret incoming stimuli and guide outgoing reactions for a simple two-party (say, A and B) interaction, e.g., for resolving a conflict. Party A's schema enters in two places. First, it is the lens through which party B's behavior will be interpreted and second it is the filter through which A's actual intentions will give rise to concrete behaviors visible to the other party. In this way, schema's become relevant whenever an individual is taking information from the outside world or offering behavior to the outside world. A's culture and history of interaction with B (or members of B's culture) will influence party A's schema. Important components of a schema are goals (what is appropriate to try to achieve), norms (what is appropriate behavior to go about getting what you want), and beliefs and attributions about the character of the other person . A's schema includes "who B is", which influences A's interpretation of B's behavior "what B is doing". This drives A's intentions or strategies for subsequent moves (e.g., should A be cooperative or not). A's intentions will then drive A's behavior, as filtered again through A's schema, which, includes norms for appropriate behavior. Since this is a symmetric situation, B's schema filters A's behavior and influences how B interprets that behavior, which influences how B intends to respond.

We now provide a brief intuition on how the cognitive schema presented in Figure 1 naturally fits into a POMDP model. To illustrate this, we provide here an informal description of the POMDP model while a more formal description is provided in Section 3. Figure 2 (taken from [12]) shows the working of a POMDP. The world of the POMDP

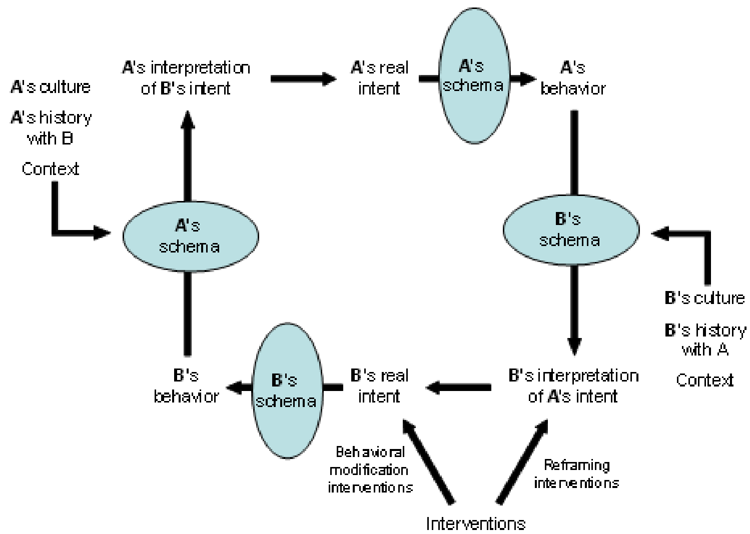

Fig. 1. Cognitive schema in dynamic collaboration and negotiation.

is composed of states. Initially, an agent believes that it is in a particular state or has a probability distribution over states, called the belief state. The agent takes an action and gets an observation of the new state she reaches. Given that the new state may not be directly inferred from the observation, the state estimator (labeled SE) derives the new belief state based on the last action, the current observation and the previous belief state. Once the new belief state is calculated, the agent takes a new action and the process continues till an end state is reached. The block labeled π represents the POMDP policy. The policy of the POMDP maps a belief state to an action. Informally, the policy is a table which can be computed beforehand that maps a belief state (and hence an observation) to the optimal action. We now model the POMDP from the perspective of party A for the cognitive schema presented in Figure 1. The context consisting of A's culture and A's history with B directly maps to the initial belief of a POMDP model, i.e., the context specifies the probability distribution over the states at the start. A's interpretation of B's intent and the various possible interventions map to the observation in a POMDP, while A's schema and real intent becomes part of the state space. A's behavior gets captured in the action set of the POMDP. The perceived model of B is also represented in the state space of A's POMDP. Similar mapping can be done for agent B. This direct mapping between a general purpose cognitive schema for negotiation and a POMDP model, reinforces our belief that modeling the negotiation problem as a POMDP may be a good approach to follow.

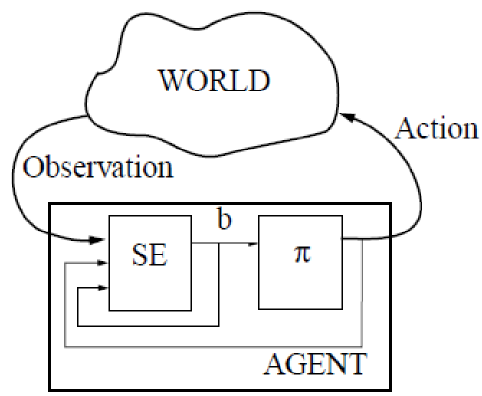

Fig. 2. Working of a POMDP

2 A general purpose negotiation setup

We now introduce the general purpose negotiation setup that we consider in this paper. In Section 3.1, we will present a simple example to illustrate the POMDP based model discussed below. Consider $i \in \{1, 2, .., n\}$ self-interested agents negotiating a set of issues $j \in \{1, 2, .., m\}$. The set of issues being negotiated can be of different kinds, some involving simple price bargaining while others involve more complex dialogue based negotiations. Given that each agent is inherently different, they have different expectations on what a fair solution is, what a fair way to negotiate would be etc. The differences between each agent can be captured through the notion of types. We assume that each agent has a type $T \in \{t_1, t_2, .., t_n\}$ based on which she acts. For purposes of this paper, we assume that an agent knows its type T while it has a probability distribution over the opponent types $T' \in \{t'_1, t'_2, .., t'_n\}$. The type of an agent is derived as a function of numerous individual factors. One such factor can be the agent's personality which can be classified as either *Selfish* or *Altruist*. While this is a coarse representation, a finer representation can involve mixtures in various proportions of these two personalities. Therefore, if a personality value of 0 represents Selfish agent and 1 represents an Altruist, 0.5 will represent an *Equality* opponent, namely a player who is interested in obtaining value both for herself and the other player. Other possible factors that can be included in the agent's type include the agent's motivation and the history of negotiations of the agent. The type space of an agent can then be obtained as a cartesian product over the set of all the factors.

We also assume that the agents know the cultures of all the other agents at the start of the game. As described in [5], various cultural factors such as individualism and collectivism, egalitarianism versus hierarchy, direct versus indirect communication and other factors play a significant role in forming the initial model of the opponent especially in the absence of any other significant individual-tailored information. Therefore, culture may be modeled as skewing the prior probability over the opponent types and hence helps in building a realistic initial belief that an agent has about the other party. It can happen that over the course of negotiation an agent realizes that the initial belief it held about the other agent may not be true and hence refines the model as the negotiation progresses. We now describe how the POMDP framework captures the general negotiation process just presented.

3 The Partially Observable Markov Decision Process Framework

In Section 1 we provided an informal description of the POMDP model. Formally, a POMDP can be represented as the tuple $\{S, A, T, \Omega, O, R\}$, where S is a finite set of states; A is a finite set of actions; $T(s, a, s')$ provides the probability of transitioning from state s to s' when taking action a; Ω is a finite set of observations; $O(s', a, o)$ is the probability of observing o after taking an action a and reaching state s' and $R(s, a)$ represents the reward function. A belief state b, is a probability distribution over the set of states S. A value function over a belief state is defined as: $V(b) = max_{a \in A} R(b, a) + \beta \sum_{b' in B} T(b, a, b') V(b')$. Once the negotiation problem is cast into the POMDP framework, many algorithms both heuristic and exact exist in the literature to find the approximate/optimal POMDP policies [12], [20]. A policy here refers to the mapping between a belief state (and hence the observation at that time-step) to an action. Effectively, the agent solves the POMDP and obtains a policy table. The agent can then use this table to decide on the appropriate action to take at each time-step based on the observation the agent obtains at that time-step and the state the agent is in.

The main challenge in casting a negotiation as a POMDP lies in defining the tuple $\{S, A, T, \Omega, O, R\}$ for an instance of the problem. The state space S can be defined using the knowledge of the problem domain and the various factors affecting negotiation that has been identified in the behavioral sciences literature [21]. The action space A and the space of observations Ω can also be formed using domain knowledge as well as knowledge about the strategies used by people in a negotiation (that has been identified in the behavioral sciences domain). From the point of view of modeling, the main hurdle lies in coming up with the appropriate parameters for the state transition function, T, observation function O, and the reward function R. One way to overcome this is to conduct negotiation experiments using test-subjects and design the experiments in such a way so as to extract the parameters using machine learning techniques.

The solution of the POMDP model above will be a policy that prescribes the action an agent should take given the state of the world she believes that she is in. In general, finding an optimal policy, i.e., a policy that optimizes the expected value of R may not be computationally tractable. However, for purposes of this work, we may not need to solve the complete POMDP. Instead we assume that our agent has an initial belief of the model of the other negotiating agents based on cultural and other appropriate factors. If such an assumption can be made, which is true in our domain since the culture of the negotiating parties is assumed to be known, the POMDP becomes easier to solve, by converting to a belief MDP. Here, the belief MDP refers to a MDP where the set of states were derived by calculating all the possible belief states of the POMDP.

Another generic concern about modeling using a POMDP is that the POMDP policy is deterministic, i.e., for a given belief state, the action taken by the agent is unique. Thus, it is theoretically possible for an opponent to learn the negotiating agent's policy and exploit it. However, in the negotiation domain, it is an open problem whether it is practically possible for the opponent to exploit a POMDP playing agent. Moreover, efficient algorithms that do a controlled policy randomization for countering such deception tactics have been developed for belief MDPs and we plan to utilize them in our work (see [19] for details).

We now summarize the steps for finding the optimal POMDP policy before getting into the modeling details. Informally, given an initial belief, solving a POMDP involves the following steps:

- Convert the POMDP to a belief MDP by enumerating all the possible belief states and applying the other relevant transformations [12].
- The newly obtained (belief) MDP can be solved efficiently using the standard Value or Policy iteration algorithms [3] to obtain the policy table.
- The agent can then use this policy table to map the newly obtained observation to a relevant action in real-time.

3.1 Simplified negotiation problem in a POMDP framework

We now present a simple negotiation example to illustrate various aspects of the POMDP model. We consider a transactional negotiation scenario where two agents are negotiating over the price of a single item. Agent 1 is assumed to be the seller and agent 2 the buyer. We assume that the best price for the buyer is 0 while it is 10 for the seller. Note that this scale captures a general set of scenarios since any other scale can be normalized and shifted to fit in this. The corresponding worst case scenario is 10 for buyer and 0 for the seller. We assume that a single factor namely the personality determines the type of all the agents. As defined earlier we model personality via a value between 0 to 1, where 0 corresponds to Selfish type and 1 corresponds to Altruist. Any other intermediate value represents a mixture between these two personality types. We assume that both the agents know each other's culture. In the following subsection, we present the seller's POMDP for this simple example.

3.2 World States: S

S is the set of world states. For the negotiation problem, we model the state of the POMDP as the following vector: $< MyType, OpponentType, CurrentNegotiationState >$. In our simplified example, $MyType$ (corresponding to seller) is a single number ranging between 0 to 1 based on my personality. For explanation purposes we focus on a particular state in which the agent is of Equality type. Assigning a value to $MyType$ becomes harder as additional factors get added such as motivation, history of negotiation etc. The second component in our POMDP model is the $OpponentType$ (corresponding to buyer) which is again modeled as a single number since we consider a single factor. Note that there can be infinite values that this single number can take since personality is a continuous variable. For simplicity of state representation, we discretized the personality factor to lie in the set (of 11 values) $\{0, 0.1, 0.2, .., 0.9, 1\}$. If a new factor gets added, the set of new types can be obtained as a cartesian product of the old types and the set of values for the new factor. The third component of our state is the $CurrentNegotiationState$. We represent this using the following vector: $< MyPrice, OpponentPrice >$. $MyPrice$ is the current price that I want to sell the item for while the $OpponentPrice$ refers to the price the buyer wants the item for. For simplicity of representation, we discretized both $MyPrice$ and $OpponentPrice$ to lie in the set $\{0, 1, .., 9, 10\}$. The price scale can be enlarged or shrunk based on the domain. The set of states can then be obtained as a cartesian product of the set of values of each component of the state vector. Therefore, the total number of possible states for this representation is $1 * 11 * < 11 * 11 >$ = 1331.

3.3 Action set: A

The simplest way to construct the action set A for our simplified problem is to model the fact that each agent can negotiate for any of the 11 possible values at any time instance. However, this makes the POMDP harder to solve. We therefore make the following simplifying assumptions without necessarily bringing in any restrictions. In particular, we assume that if an agent quotes a price x, she will either remain at x or increase/decrease the current price by an integer z. Setting z to 2, we obtain that an agent can either remain at the same price or increase or decrease the price by a maximum of 2 units. The new action set corresponding to this would then be the set $\{Same, Concede1, Concede2, Retaliate1, Retaliate2, End\}$. Here, $Same$ would mean that the agent remains at the same price, $Concede1$ would mean add 1 to current price for buyer or subtract 1 for the seller while $Retaliate1$ would mean subtract 1 from the current price for the buyer while add 1 for the seller. End would mean that the agent agrees to the current price and the deal is closed. The action set gets complicated once we consider the fact that agents can have dialogues instead of a set of numbers.

3.4 Transition Function: T

A transition represents the probability with which an action a taken from a state s leads to a state s'. Transitions in our domain are stochastic. This is because when an agent takes an action say $Concede1$, it cannot be sure what the opponent's action would be and hence the state it reaches (which includes the opponent's current negotiation price). Figure 3 provides a pictorial description of our transition function. The leftmost state represents the state under consideration. In this state, $Mytype$ is 0.5 and the ground truth of the opponent's type is also 0.5. The current negotiation price for myself (the seller) is 10 while that of the buyer is 0. If the seller takes an action $Concede1$, i.e., seller proposes a new price of 9, the buyer can respond by remaining at 0 or moving to 1 or 2. Given the ground truth that the buyer is of $Equality$ type, our transition function would capture this fact by assigning a low transition probability (0.1 here) to state that has the buyer's current negotiation price remaining at 0 while assigning a higher probability (0.4 here) to states that have the buyer's current negotiation price as either 1 or 2. Note that we also allow for a small transition probability (0.1 here) where the ground truth about the buyer can change, i.e., she can no longer be $Equality$ type. This is to account for the fact that the buyer's behavior need not be fixed and can be a function of time and the seller's price. While we do not consider in this paper, similar argument can hold for the seller and can be easily represented in the POMDP at the cost of increased state space.

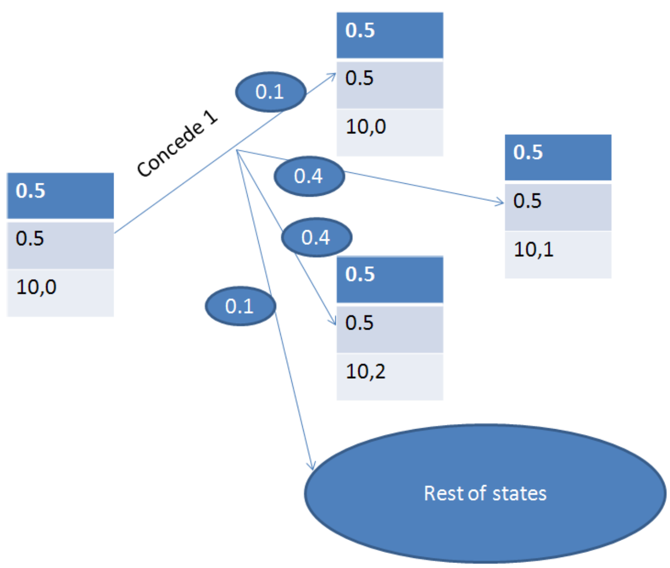

Fig. 3. A simple negotiation example encoded as a POMDP

3.5 Observations: Ω

The set of observations that an agent (seller here) observes are the actual prices quoted by the opponent. Therefore, there are 11 possible observations in the domain corresponding to the 11 possible prices the buyer can quote.

3.6 Observation function: O

Assuming that there is no noise in the observations i.e. if an agent quotes price p, the other agent actually sees that the quotation is p, the observation function is deterministic. This is because we model the quoted price as part of the state. Therefore, for each $P(o/s', a)$ = $P(ObservingPrice(x)/StateWithBuyerPrice(x), a)$ = 1 and 0 otherwise.

3.7 Reward function: R

There can be multiple ways to model the reward function. One potential way we consider here is: The reward is calculated as a function of the agent's type, its current negotiation price and the action it takes. For example, when a selfish agent at current price 0 takes action $Concede1$, she gets a small positive reward as opposed to a high negative reward incurred when the current price is 4.

4 Effect of culture on modeling the agents using POMDP

POMDP's are a standard framework to represent domains in which agents have partial observations of their surroundings. One example can be a robot which uses its sensors to determine its location while trying to reach a target [24]. In our negotiation domain, each agent has its own type. A negotiating agent can only observe the actions of its opponent but the true type of the opponent remains hidden. The POMDP framework allows representation of this partial knowledge and accounts for this uncertainty while calculating the optimal negotiation strategy. An important factor that determines the type of the opponent is her culture. The rest of this section focuses on how cultural factors affect the POMDP modeling.

4.1 Including culture in modeling initial beliefs

In the modeling of a negotiating agent as a POMDP, the agent knows information such as her type and the offers made by both parties but does not know exactly the type of the opponents. Therefore, the agent maintains a probability distribution over the opponent types as a possible model of the opponent. At the start of the negotiation, the agent would not have observed any opponent actions. In the absence of any information, one possible initial model of the opponent would then be to maintain a uniform distribution over all the types. This means that the agent has an initial belief which is a uniform distribution over all the states with negotiation value 0 for buyer and 10 for seller. However, this is not the case when we take culture into consideration. If the agent is negotiating with an agent from the same (her own) culture, we would expect the agent to model the opponent more accurately which strongly skews the initial belief. When the negotiation includes agents from different cultures, the agent's initial beliefs are usually a stereotype of the opponent's culture [26].

4.2 Effect of Culture on agents' observations

Culture has a dramatic effect on the observations made by the negotiating agent throughout the negotiation process. A negotiating agent, after taking an action, gets the opponents action as the observation. In our simplified example, the negotiating agent observes the price quoted by the opponent. The interpretation of this observation refines the agent's model of the opponent. For example, if the agent modeled her opponent as an altruist initially, it can later refine the opponent model as the negotiation progresses to account for observations that make the opponent seem selfish. While this refining process can correct initial bias, culture may play a significant role here. For example, many studies on culture in negotiation have reported that different cultures express the same intentions differently (referred to as interventions in the cognitive schema). Therefore, when an agent makes an offer or utters a dialogue that is her own mind is expressing altruism, this observation can be interpreted wrongly by the opponent and the opponent's belief can be updated incorrectly.

4.3 Culture in States, Transitions and Rewards

We now show how cultural factors could affect the other components of the POMDP tuple namely states, transitions and rewards. For example if a self interested agent negotiates with an agent from a culture in which there is a high probability of altruism, there would be a low transition probability to states that would have resulted from a negotiation between two self interested agents. Thus culture affects both the states being reached and the design of the transition function. The reward function which defines the payoff an agent can expect from performing an action a in state s, could be strongly affected by culture. Agents from different cultures are expected to have different goals and hence different rewards for the same actions. For example, in Middle Eastern culture there is a high value for respect and hence high rewards associated with actions that show respect even though the action may not be beneficial monetarily.

5 Related work

There is a vast body of research for identifying the relevant psychological factors and building a theory of negotiation [21, 28]. We will briefly discuss here the literature that consider cultural effects in negotiation (for a more in-depth discussion see [10]). The effect of the cultural background of the negotiators on the negotiation process and the negotiation outcome has been studied both theoretically and experimentally in the behavioral sciences literature (see [10, 25, 6]). Cultural values and norms affect the importance people ascribe to different issues and their interpretation of the opponents behavior. Brett [5] identifies and discusses the effect of three cultural values in cross-cultural negotiation: (a) individualism versus collectivism (b) egalitarianism versus hierarchy, and (c) high versus low context communication. There is a cultural stereotype between the East and the West based on these values. A typical Western individual is presumed to be individualistic, egalitarian and uses low context communication whereas a typical Eastern individual is collectivist, hierarchical, and uses high-context communication. However, this is a very gross characterization and cultural differences within neighboring regions also affect negotiation ([16] discusses this in the context of East Asian cultures). Although the knowledge of the opponents culture may be helpful in negotiation, there has been studies showing that negotiations can break down when negotiators adjust to their opponents culture and try to overcompensate [1]. Another important cultural factor in negotiation is cultural *sacred values* of the negotiators. People have high emotional attachment to the sacred values [2] and any act during the negotiation process perceived to violate them may result in a breakdown of the process.

There has also been some effort into building computational models of negotiation and building software agents for negotiation (see [4, 15] and references therein). However, there is relatively little work on including the effect of culture in the computational models of negotiation (except [11]). The computational models for negotiation use a variety of techniques from game theory [18, 7], probabilistic decision theory [27], bayesian learning [29], and other heuristic approaches [9]. It has been noted that the way people act in a negotiation (or in general strategic interaction) scenario do not correspond to the game-theoretic equilibria [7, 13]. The decision theory-based approaches encode the agents preferences in a utility function and choose the decision with highest expected utility. Moreover, most game-theoretic and decision-theoretic models are mainly interested in the outcome of the negotiation-game instead of the process of the negotiation. We are crucially interested in both outcome and process in modeling cultural effects in negotiation. That being said, game-theoretic techniques may still be useful in analyzing the different outcomes in negotiation due to cultural differences and this is an open research problem.

To model the effect of culture in the negotiation process, we need our model to be expressive enough to model the interactive process between the agents. The agents should also be able to maintain and update knowledge about their opponents. Therefore, in this paper, we use a POMDP for modeling the negotiation process. POMDPs have been used before in modeling human social interaction where knowledge of the opponents need to maintained [22]. More recently, POMDPs have been used in a game-theoretic setting for modeling a finite repeated game between two agents [23].

6 Conclusions and Future Work

In this paper, we first showed the mapping of a general cognitive schema for negotiation to a POMDP model. We then described the POMDP setup for a general negotiation problem and discussed the challenges in modeling a negotiation problem using POMDPs. We presented a simple example of a single-issue transactional negotiation to illustrate the POMDP formulation. While many competing techniques to model a negotiation problem exist, the POMDP based modeling has the following advantages: (a) POMDPs provide a decentralized way of solving the problem which is an inherent characteristic of the negotiation domain. (b) POMDPs provide a natural way to capture the sequential nature of the bargaining process i.e. they capture the process rather than just focusing on the outcome. (c) POMDPs can express the various important factors that affect the negotiation such as culture. We also discussed how cultural factors can be accounted for and how they affect the POMDP modeling.

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