The Value of Information in Automated Negotiation: A Decision Model for Eliciting User Preferences

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ABSTRACT

Consider an agent that can autonomously negotiate and coordinate with others in our stead, to reach outcomes and agreements in our interest. Such automated negotiation agents are already common practice in areas such as high frequency trading, and are now finding applications in domains closer to home, which involve not only mere financial optimizations but balanced trade-offs between multiple issues, such as cost and convenience. As a simple example, a smart thermostat controlling a heat pump could provide demand response to the electricity grid if the inconvenience is offset by the grid relieve incentives. In such situations, the agent represents a user with individual and a priori unknown preferences, which are costly to elicit due to the user bother this incurs. Therefore, the agent needs to strike a balance between increasing the user model accuracy and the inconvenience caused by interacting with the user. To do so, we require a tractable metric for the *value of information* in an ensuing negotiation, which until now has not been available. In this paper, we propose a decision model that finds the point of diminishing returns for improving the model of user preferences with costly queries. We present a reasoning framework to derive this metric, and show a myopically optimal and tractable stopping criterion for querying the user before a fixed number of negotiation rounds. Our method provides an extensible basis for interactive negotiation agents to evaluate which questions are worth posing given the marginal utility expected to arise from more accurate beliefs.

Keywords

Negotiation agent; Automated negotiation; Value of information; Preference elicitation; User preferences; Uncertain preferences; Optimal query

1. INTRODUCTION

Negotiation agents, with their ability to ensure mutual coordination on multiple objectives between many different actors, are on the rise in a number of applications, such as cloud computing [1, 44], pervasive computing [40], and smart grids [29, 41]. In such settings, the agent can help represent users in complex negotiations in an automated manner [30]. As autonomous negotiation on behalf of users advances into every-day life, negotiation agents are increasingly required to be sensitive to the users' individual needs and requirements. A typical example of this occurs in the smart grid domain, where agent-based electronic energy systems can help local communities share their energy by negotiating autonomously between local home owners. Such agents need to carefully consider and query the preferences of each individual user to allocate resources in a fair and personalized manner.

An important obstacle for personalized, computerized negotiators is that in many real-life settings, eliciting the necessary preference information from the user is a costly endeavor, as multiple interactions with the system can result in user inconvenience and bother. Furthermore, the multi-objective nature of negotiation, where many win-win package-deal agreements can be made [26], makes it impossible to elicit the space of negotiation outcomes in its entirety. However, the vast majority of current state of the art negotiation agents (e.g. [16, 21, 23, 25, 46]) cannot assist with a more interactive approach based on uncertainty, as they consider their user model to be given and fully specified.

To support a more user-centric approach, automated negotiators are required to not only strike deals with limited available user information, but also to interactively extract more accurate user preference information to ensure the right decisions are made during the negotiation process. This requires striking the right balance between increasing the user model accuracy and the inconvenience caused by repeated interaction with the user.

We address one of the major challenges for finding the point of diminished returns for improving the user model, namely that currently, we have no good metrics for the *value of information* in a negotiation; that is, we have no way to weigh the value of information gained by additional elicitation of user preferences against the marginal benefit towards the negotiation outcome. A key impediment to this is that the exchange of offers is a complex interactive process that evolves over time and depends on the information state about both the user and the opponent. Methods such as recommender systems developed for these kind of interactions are not sufficient for the challenges posed by highly autonomous negotiation systems, which, rather than providing recommendations or support to the user, need to act and perform autonomously in competitive environments with minimal online feedback. Typical information-based methods such as maximizing entropy of the utility informa-

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tion are not well-tailored to negotiation either: since only a specific set of agreements are likely to occur in a negotiation (e.g. Pareto-efficient outcomes), the value of preference information can vary wildly among the many possible outcomes. In other words, we need performance-based measures which consider the complete value chain from preference information to agreement utility.

The state of the art thus requires extension with at least three key novel aspects to facilitate an elicitation-driven negotiation approach based on the value of information: (1) a decision model that can capture and reason about uncertain utility information about the user (as well as the opponent) and can query the user for more preference information; (2) a tractable measure of the estimated expected utility of a negotiation; i.e., a simulation of an entire negotiation exchange; (3) a stopping criterion that can weigh the estimated post-query value of information against the elicitation costs. These three problems are naturally intertwined, as any computational model for assessing the value of information requires knowledge about the negotiation strategy to be followed, which in turn depends on an estimate of the likely negotiation outcomes.

We present a generic and efficient look-ahead negotiation strategy that addresses these challenges by computing the expected value of improving preference information for the entire negotiation process. This provides the foundation for a robust and myopically optimal querying strategy that can select a query that ensures the highest expected negotiation payoff. We incorporate our model in an existing negotiation simulation platform, and we show through experimental evaluation that our model outperforms benchmark strategies and is robust with regard to violating some of its assumptions. At the same time, since the value of information calculation involves maximizing utility under uncertainty, our approach yields an optimal negotiation strategy policy under uncertain utility information. Our approach is also generic, in the sense that it is compatible with general preference modeling and strategy modeling components that are readily available in the negotiation literature (e.g. [6, 7, 8, 16, 24, 27, 43, 47]).

We anticipate applications of our methods in systems (energy management systems being one example) that can negotiate on behalf of a user and that have the ability to query a user to specify their preferences when needed. Our approach fits in a broader vision of an interactive negotiation agent that has knowledge about what questions can be asked at what costs, and can decide, using our method, which question is worth posing given the utility expected to arise from it.

2. PROBLEM SETTING

Let $\Omega = \{\omega_1, \ldots, \omega_n\}$ denote the space of all possible outcomes of the negotiation. An agent conducts a negotiation on behalf of a user, and every $\omega \in \Omega$ represents a possible agreement of a multi-issue negotiation (i.e. a contract that specifies the value of a number of negotiable issues), of which the utility for the user is initially not completely known.

The agent interacts with the user and the opponent (or a representative of a pool of opponents) by exchanging offers (see Figure 1). The agent can make a decision to follow a certain bidding strategy, or to reduce uncertainty about the user's utility by posing a query. We use the term 'query' for concreteness, but it could take the form of any interaction method that results in information from the user (e.g. clicking a button, providing text input, or requesting access to meta-information such as location). We are interested in the general question of estimating beforehand how much benefit an agent stands to obtain from posing a query to the user.

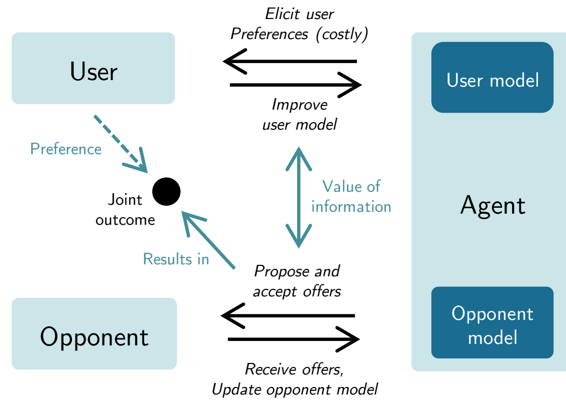

Figure 1: The interactions between the user, the agent, and the opponent. The value of information is the marginal increase in utility that the agent expects to obtain by eliciting additional information from the user.

The agent negotiates with an opponent according to a mutually agreed-upon negotiation protocol that governs the rules of the exchange of offers. Any agreement must be reached before a fixed number of offers proposed by the agent (called negotiation rounds or *deadline*) D, operating as a force on the parties to concede [12]. When an agreement is not reached before that time, the players end up in a disagreement outcome with zero utility.

The value of information in a negotiation ultimately represents the added value for the possible agreements resulting from it. As a result, the agent will need to look ahead when contemplating an offer by considering the possible outcomes of the negotiation; i.e., the agent must account for any sequence of rejected offers and possible follow-up offers up until the look-up horizon induced by the deadline. Because negotiation takes place by a process of concession-making over time [42], previous offers and updated information about the user and the opponent can influence the entire negotiation thread. As a result, the decision scenario is not simply to pick the best offer at one particular stage, but the agent needs to consider the expected value of a series of planned offers; i.e., a policy π has the form $\pi = (x_1, \ldots, x_m)$ without duplicates, with $x_i \in \Omega$ and $m \leq D$. The challenge here is that only a limited number of offers can be generated, combined with stochastic effects of the agent's policy caused by the uncertainty about the opponent's preferences.

In order to accurately fulfill its representational role, the agent keeps track of the user's preferences through its user model. Following [14], rather than aiming at a completely specified utility function, the agent dynamically maintains a probability distribution representing its beliefs about the user's utility function. We consider stochastic utility distributions $u_\omega \in [0, 1]$ for every outcome $\omega \in \Omega$ (thus having finite expected value $\mathbb{E}u_\omega$), with a belief $p = P(U)$ given by the joint probability density function $P(U)$, where $U = (u_{\omega_1}, \ldots, u_{\omega_n}) \in V = [0, 1]^n$, and with cumulative distribution function $F(v_1, \ldots, v_n) = P(u_{\omega_1} \leq v_1, \ldots, u_{\omega_n} \leq v_n)$, representing the agent's beliefs about the user's utilities.

In addition, the agent incrementally improves an opponent model through its interactions with the opponent (see Figure 2). The set of acceptable offers is unbeknown to the agent, and therefore, the agent models a set of independent probabilities α_ω that denotes the chance of the opponent accepting an offer $\omega \in \Omega$. The priors for α_ω can be constructed from earlier interactions or a database of similar encounters, while updated values can be inferred from preference and strategy modeling components during the negotiation (e.g., using techniques described in related work [16, 27, 43]).

The agent's task is to decide on a bidding policy that maximizes the user's utility over the outcomes, given its available approximation of the user's preferences. As the agent's information about the user may be limited, a consequent aim is to elicit more preference information when that leads to better decisions. For example, the agent could ask the user to rate a certain outcome in Ω, or to compare two of them. For that purpose, the agent has elicitation actions in the form of performing queries $q \in Q$ that influence p. As in prior work [9], each query q has a discrete, constant response space R_q of possible answers and a response model in the form of a response probability $P(r \mid p, q)$ and updated conditional preference model $p_r = P(U \mid r)$ for every $r \in R_q$, which we shall denote by $p \mid r$ for the sake of readability.

Every query q also has an associated cost $c(q)$, which the agent needs to balance against its marginal benefit in negotiation performance.

The following example illustrates our model and will be revisited to clarify solution concepts in later sections.

Example 1. *Suppose Alice participates in a smart energy collective through an energy management system (i.e. an agent) that negotiates energy deals with community members on her behalf. Through the recommendations of local optimization techniques (e.g. a peak shaving algorithm or battery ramping system), the agent has determined that there are two mutually exclusive energy proposals, x and y, to be considered to send out to a neighbor.*

The first deal, x, is to offer part of the battery capacity right now, which has an expected probability α_x to be accepted by the neighbor. This can be regarded as a safe, yet suboptimal option, with a known utility u_x, where we assume $u_x < \frac{3}{4}$. The second deal, y, is an offer to volunteer an amount of energy 15 minutes later, with acceptance probability α_y. This would likely be a better deal, but there is more uncertainty involved as well (for instance because of uncertainty about the weather conditions and the resulting throughput of the solar panels, or uncertainty about Alice's energy usage). The utility u_y is unknown to the agent, who assumes that all values between $\frac{1}{2}$ and 1 are equally likely (i.e., a uniform prior on the subinterval, and hence, $\mathbb{E}u_y > u_x$). Assuming that $D > 1$ and considering that $\Omega = \{x, y\}$ consists of merely two offers, there are exactly two possible policies depending on which offer is sent out first: $\pi_1 = (x, y)$ and $\pi_2 = (y, x)$.

Suppose that to reduce uncertainty about Alice's value of y, the query set Q contains one available query q that splits the possible range of u_y in half: "Is $u_y > \frac{3}{4}$?", which can be posed at cost $c(q)$ and has two possible responses $R_q = \{yes, no\}$, both with equal prior probability.

The question is: under what circumstances should the agent pose q to Alice?

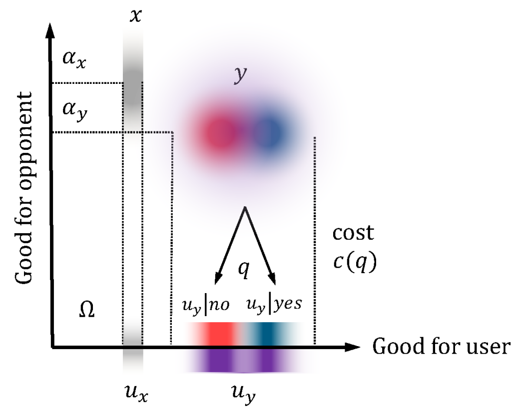

Figure 2: While the user utility u_x of $x \in \Omega$ is certain, there is high uncertainty about utility u_y of $y \in \Omega$ (prior to posing queries, in purple). Posing the query q can split this uncertainty, at cost $c(q)$, in high utility ($u_y \mid yes$, in blue), or low utility ($u_y \mid no$, in red).

3. THE VALUE OF ELICITING NEW INFORMATION

To determine whether additional information from the user warrants the ensuing querying cost, the agent should balance the value of the current negotiation state with potential benefit of performing an elicitation step. This means the agent faces a decision, as we make more explicit below, between obtaining either an immediate expected reward under uncertainty, or the expected value of information of an elicitation action.

3.1 Expected Utility with Uncertain Preferences

The ability to reduce uncertainty about both the user and the opponent influences the course of the negotiation in different ways. When pursuing a bidding policy, uncertainty about the opponent induces a range of possible agreements; therefore, the agent must select a policy that maximizes utility taking into account the expected opponent responses. If, in addition, there exists uncertainty about the user's utility, the agent also needs to consider all possible user instantiations that correspond to the agent's belief state. This thus involves yet another expectation (regarding preferences) over the expectation regarding opponent replies.

To make this precise, as before, let the beliefs about the utility distributions u_ω be given by probability distribution function p for every $\omega \in \Omega$, and let policy $\pi = (x_1, \ldots, x_D)$ articulate the sequence of bids the agent plans to offer to the opponent, where α_{x_k} denotes the chance that the opponent accepts x_k. It is convenient to view Ω as all possible outcome states induced by π, where $P(\text{agreement } \omega \mid \pi)$ denotes the probability of reaching an agreement state ω when the agent follows policy π. This probability can be computed in a straightforward way: if ω does not occur in π it is zero; otherwise $\omega = x_k$ for some $k \in \{1, \ldots, D\}$, and the chance of reaching agreement x_k is then equal to the probability that $x_1, \ldots, x_{k-1}$ get rejected, while x_k gets accepted, which equals $\alpha_{x_k} \prod_{j=1}^{k-1}(1 - \alpha_{x_j})$.

Note that for *known* utility functions U, we could easily specify the agent's expected utility (EU), namely:

$$EU(\pi, U) = \sum_{\omega \in \Omega} P(\text{agreement } \omega \mid \pi) \cdot u_\omega.$$

The optimal policy π^* that maximizes expected utility would then be

$$\pi^* = \arg\max_\pi EU(\pi, U).$$

Following Boutilier's notion of *expected* expected utility [10], we can now state the expected expected utility (EEU) of a policy π under uncertain preferences p:

$$\begin{aligned} EEU(\pi, p) &= \int EU(\pi, u) p(u) \mathrm{d}V \\ &= \sum_{\omega \in \Omega} \int P(\text{agreement } \omega \mid \pi) \cdot u_\omega p(u) \mathrm{d}V \\ &= \sum_{\omega \in \Omega} P(\text{agreement } \omega \mid \pi) \mathbb{E}_p[u_\omega]. \end{aligned} \tag{1}$$

It is the agent's goal to maximize EEU, be it in the current state, or after a query. Hence we adopt a myopically optimal elicitation view here, although our model could easily be extended to include a horizon of multiple queries (see also our discussion). The full value of information that takes into consideration all possible responses to every future query is in general intractable [14]. We do, however, test our agent in a non-myopic setting in our experiments (Section 4) and demonstrate the robustness of our approach in such a setting.

For the bidding strategy on the other hand, looking ahead is essential (and tractable, given the time horizon induced by the deadline) for establishing a utility estimate of the outcome. Hence, the agent requires a non-myopic method to look ahead, given a set of beliefs about the user's preferences, to decide which 'top-ranking' bids to send out, and to assess the expected expected utility of the selected policy.

Example 2 (cont'd)**.** *To evaluate which π maximizes EEU, we can compute Alice's expected expected utility of the two policies π_1 and π_2 prior to posing any queries:*

$$\begin{aligned} EEU(\pi_1, p) &= \sum_{\omega \in \Omega} P(\textit{agreement } \omega \mid \pi) \mathbb{E}_p[u_\omega] \\ &= \alpha_x u_x + (1 - a_x) \alpha_y \mathbb{E} u_y, \end{aligned}$$

while likewise,

$$EEU(\pi_2, p) = (1 - \alpha_y) \alpha_x u_x + \alpha_y \mathbb{E} u_y.$$

Interestingly, we can show that the values of α_x and α_y have no bearing on the relative ranking of π_1 and π_2; it is easy to prove that π_2 dominates π_1 from the fact alone that $\mathbb{E} u_y > u_x$, and hence

$$\max_\pi EEU(\pi, p) = (1 - \alpha_y) \alpha_x u_x + \alpha_y \mathbb{E} u_y.$$

3.2 The Value of Information in Negotiation

We now turn to computing the marginal value of posing queries to the user, given the agent's goal to maximize EEU. The (myopic) *expected value of information* ($EVOI$) [9] of a query q, given belief state p, can be computed by considering the difference between the expectation (with respect to responses $r \in R_q$) of the expected utility of being in state $p \mid r$ and the expected utility of immediately making a decision in state p:

$$EVOI(q, p) = \mathbb{E}_r \left[\max_\pi EEU(\pi, p \mid r) \right] - \max_\pi EEU(\pi, p). \tag{2}$$

Thus, the agent's should pose a query if and only if the expected value of information outweighs the costs, and if such a query exists, to select one that maximizes the difference. In other words, the agent's aim is to find:

$$q^* = \arg\max_q \left[EVOI(q, p) - c(q) \right]. \tag{3}$$

It follows from (2) and (3) that selecting the most informational query involves computing an optimal EEU policy $\sum_{q \in Q} |R_q| + 1$ times. In principle, this would require, for each query, to check all D-sized subsets of Ω to determine the optimal sequence of bids with respect to $p \mid q$, for which exhaustive search would be infeasible even for small-sized Ω. However, it turns out that the additional structure of our problem formulation enables us to tractably obtain an optimal policy π^*, using results from simultaneous search theory [13], as we present below.

3.3 Optimal Querying

In simultaneous search problems, a decision maker is tasked with a simultaneous choice among a number of ranked stochastic options, in order to establish an optimal portfolio in terms of expected reward [13]. We will use a solution concept from simultaneous search called local marginal improvement (i.e. greedy search) to pinpoint the best query to optimize EEU. For any set of bids $X \subseteq \Omega$, define $\mathrm{sort}(X)$ as its corresponding sequence consisting of elements $x \in X$ sorted by descending utility in terms of $\mathbb{E} u_x$. That is, $\mathrm{sort}(X) = (x_1, \ldots, x_{|X|})$, such that $\forall_i (x_i \in X \wedge \mathbb{E} u_{x_i} \geq \mathbb{E} u_{x_{i+1}})$.

We are now ready to specify our elicitation algorithm that computes the point of diminishing returns for queries available to the agent.

Querying Algorithm. *Compute policy π_p^* for the current state p by iteratively selecting, in a greedy manner, the D bids that maximize expected negotiation payoff EEU. In the same way, compute, for every query, the policy $\pi_{p|r}^*$ for every possible response state r. Select the query that maximizes the posterior EEU substracted with the cost, but only if it represents a marginal improvement over adhering to π_p^*. (See Algorithm 1.)*

The policy search defined by Algorithm 1 is greedy in the sense that once $\pi^*(p)$ has selected a set of bids $\{x_1, \ldots, x_{k-1}\}$ for a belief state p, it iteratively chooses the best *addition* x_k with respect to the bidding policy in the making:

$$x_k \mapsto EEU(\mathrm{sort}(\{x_1, \ldots, x_k\}), p).$$

For instance, for $D = 1$, Algorithm 1 simply selects the offer with the highest expected myopic payoff:

$$x_1 = \arg\max_{\omega \in \Omega} EEU(\omega) = \arg\max_{\omega \in \Omega} \alpha_\omega \mathbb{E} u_{x_\omega}.$$

For subsequent bids, the bidding sequence specified by $\pi^*(p)$ depends on the expected utility order of every selected bid. For example, the agent might include risky, more tentative offers in an initial subsequence of the policy and make expected utility compromises over time (i.e. as the agent nears the deadline). The algorithm then weighs up each querying

Algorithm 1: Querying Algorithm

Input: The current negotiation state, with belief state p and candidate queries Q.
Output: A query in Q, or no operation.

1 **begin**
  `// And let` q^* `be the argmax`
2   $m \longleftarrow \max_{q \in Q} \sum_{r \in R_q} P(r \mid q) EEU(\pi^*(p \mid r), p \mid r) - c(q)$
  if $m > EEU(\pi^*(p), p)$ **then**
3   **return** q^*
4 **Function** $\pi^*(p)$
5   **for** $k \in \{1, \ldots, D\}$ **do**
6     $x_k \longleftarrow \underset{\omega \in \Omega \setminus \{x_1, \ldots, x_{k-1}\}}{\arg\max} EEU(\texttt{sort}(\{x_1, \ldots, x_{k-1}, \omega\}), p)$
  `// Sort result in decreasing order`
7   $\pi^* \longleftarrow \texttt{sort}(\{x_1, \ldots, x_D\})$ **return** π^*

cost against the highest expected utility increase resulting from adhering to π^*.

We can now prove our main result, using techniques from simultaneous search theory [13], that this greedy strategy is in fact optimal:

Proposition 3.1. *Algorithm 1 selects the myopically optimal query*

$$q^* = \arg\max_q \left[EVOI(q, p) - c(q) \right],$$

whenever $EVOI(q^*, p) > c(q^*)$.

Proof. Note that $EEU(\pi^*(p), p)$ does not depend on q; therefore, by expanding $EVOI(q, p)$ using equation (2), we obtain $q^* = \arg\max_q EVOI(q, p) - c(q)$, provided that we can show that $EEU(\pi^*(p), p) = \max_\pi EEU(\pi, p)$ for every state p. To do so, note that by using equation (1), we have:

$$\max_\pi EEU(\pi, p) = \max_\pi \sum_{\omega \in \Omega} P(\text{agreement } \omega \mid \pi) \mathbb{E}_p[u_\omega]$$
$$= \max_{(x_1, \ldots, x_D) \in \Omega^D} \sum_{i=1}^{D} \alpha_{x_i} \mathbb{E}_p \left[u_{x_i} \right] \prod_{j=1}^{i-1} (1 - \alpha_{x_j}).$$

Define $g(S) = EEU(\text{sort}(S), p)$ for any $S \subseteq \Omega$. Using the linearity of EEU over $\mathbb{E}_p[u_{x_i}]$, it is easy to show that $EEU((x_1, \ldots, x_m), p) \leq g(\{x_1, \ldots, x_m\})$ for any $m \in \mathbb{N}$ and $x_1, \ldots, x_m \in \Omega$. Furthermore, it is easy to prove that g is monotonic; i.e., $g(A) \leq g(B)$ for any $A \subseteq B \subseteq \Omega$. This means the maximum of EEU must occur on a sorted sequence of size D:

$$\max_\pi EEU(\pi, p) = \max_{S \subseteq \Omega, |S| = D} g(S).$$

Now define $c(k) = 0$ for $k \leq D$ and $c(k) = \infty$ for $k > D$. Using the monotonicity of g again, we obtain:

$$\max_\pi EEU(\pi, p) = \max_{S \subseteq \Omega} \left[g(S) - c(|S|) \right].$$

Since g is downward recursive and c is a convex increasing function defined in terms of $|S|$, it follows from [13] that it is optimal to follow a greedy approach in terms of steepest ascent for marginal improvement; i.e., to incrementally include ω such that $g(S \cup \{\omega\}) - c(|S| + 1) - (g(S) - c(|S|))$ is maximized, and to stop once the marginal improvement becomes negative. By definition of c, this is equivalent to repeatedly adding ω such that $g(S \cup \{\omega\}) - g(S)$ is maximized when $|S \cup \{\omega\}| \leq D$, and to stop once $|S \cup \{\omega\}| > D$. This follows the definition of function $\pi^*(p)$ in line 3 exactly, and hence, $\pi^*(p)$ maximizes $\pi \mapsto EEU(\pi, p)$.

Lastly, due to the comparison in line 2, a query q^* is returned if and only if

$$\mathbb{E}_r \left[EEU(\pi^*(p \mid r), p \mid r) \right] - c(q^*) > EEU(\pi^*(p), p),$$

where the expectation $\mathbb{E}_r$ is taken over R_{q^*}. Using equation (2) again, this is equivalent with $EVOI(q^*, p) > c(q^*)$. □

Our querying algorithm can easily be embedded into a negotiation strategy as follows. Let the querying algorithm locate an optimal query q^*, condition state p on the user's response r^*, and repeat this process with state $p \mid r^*$ until, at some point, a state p' is reached where it becomes more favorable to follow $\pi^*(p')$.

Note that the querying algorithm is only optimal with respect to the agent's beliefs about the user and the opponent. This information is of course prone to change at later stages of the negotiation; therefore, a new optimal solution can be calculated at the outset of every deliberation period. Fortunately, the complexity of the querying algorithm greatly improves over an exhaustive search over all sequences in Ω for every query in Q:

Proposition 3.2. *The complexity of the Querying Algorithm is* $O(|Q| \cdot n)$*, where* $n = |\Omega|$.

Proof. The submodule $\pi^*(p)$ of Algorithm 1 sorts the set $\{x_1, \ldots, x_{k-1}, \omega\}$ D times before it is passed on to compute the expected utility. However, the sorted version of $\{x_1, \ldots, x_{k-1}\}$ can be re-used in the next iteration, so interleaving ω can be achieved in $O(\log k)$. Therefore, computing $\pi^*(p)$ involves testing $\sum_{k=1}^{D} (n - k + 1) \log k = O(n)$ outcomes. Since π^* is evaluated for every query and every response state on line 2, the resulting overall complexity is $O(|Q| \cdot n)$. □

Observe that with a constant number of queries, the complexity of the Querying Algorithm is simply $O(n)$. However, it may often be reasonable to have the query set depend on n. For instance, to enable a user to specify the relative order of certain outcomes, Q could contain all queries of the form $\{u_{\omega_i} <_? u_{\omega_j} \mid \omega_i, \omega_j \in \Omega, \omega_i \neq \omega_j\}$, leading to overall $O(n^3)$ complexity. The complexity of the algorithm further depends on how the posterior update $p \mid r$ is carried out. For example, one way to represent a discrete belief space about the user's preferences (which we will elaborate on in our experimental setup in Section 4), is by maintaining an $n \times m$ matrix that holds the probabilities p_{ij} of bid ω_i having utility u_j for a given set $\{u_1, \ldots, u_m\}$ of possible utilities. In the worst case, updating the matrix involves visiting each entry, leading to $O(|Q| \cdot m \cdot n)$ complexity.

Example 3 (cont'd)**.** *To establish when the agent should pose the query q to Alice, let us see what happens when q is asked:*

- *If Alice responds positively to the query $u_y > \frac{3}{4}$ (with probability $P(yes \mid u_y) = \frac{1}{2}$), then $\mathbb{E}[u_y \mid yes] = \frac{7}{8} > u_x$, thus π_2 is still clearly the best policy and so:*

$$\max_{\pi} EEU(\pi, p \mid yes) = \frac{7}{8}\alpha_y + u_x\alpha_x(1-\alpha_y).$$

- *Otherwise, a negative response implies $u_y \leq \frac{3}{4}$ (anticipated with probability $P(no \mid u_y) = \frac{1}{2}$), and then the best policy depends on the relative order of $\mathbb{E}[u_y \mid no] = \frac{5}{8}$ and u_x. Recall that we assumed u_x to be known and in the range $[0, \frac{3}{4}]$. We know that y remains more attractive than x for any $u_x \in [0, \frac{5}{8}]$: in that case, nothing changes about the agent's action and the value of information automatically degenerates to zero. However, when $u_x \in [\frac{5}{8}, \frac{3}{4}]$, π_1 prescribes the optimal policy, and so:*

$$\max_{\pi} EEU(\pi, p \mid no) = u_x\alpha_x + \frac{5}{8}\alpha_y(1-\alpha_x).$$

Hence, by taking the expectation over the two possible answers $r \in R_q$ (i.e. simply averaging the two equations above), we obtain the expected value of being in a response state:

$$\mathbb{E}\max_{\pi} EEU(\pi, p \mid r) = u_x\alpha_x + \frac{3}{4}\alpha_y - (\frac{1}{2}u_x + \frac{5}{16})\alpha_x\alpha_y.$$

Finally, we can compute the expected value of information of q by subtracting the expected utility before the response:

$$EVOI(q, p) = \left(\frac{1}{2}u_x - \frac{5}{16}\right)\alpha_x\alpha_y.$$

Note how this is positive for the range of $u_x \in [\frac{5}{8}, \frac{3}{4}]$ and that the value of information increases with the likelihood of the offers being accepted; i.e., the value of a query scales with the size of the negotiation pie.

Now, the decision of the agent is simple: the query should be asked if and only if $c(q) < EVOI(q, p)$.

Our model thus provides a tractable and myopically optimal querying strategy for the context of uncertain user utilities when there is the option to pose one query. In practice, however, a negotiation process involves an ongoing encounter, with possibly multiple interactions with the user. In principle, a myopic querying approach might fail to identify the optimal query with respect to the utility of the final agreement state because it neglects the value of future queries. Hence, in a typical negotiation situation, an agent may wish to incrementally update the user model to incorporate new information at every stage. In the following section we investigate the robustness of our approach for such a setting.

4. EXPERIMENTS

The following experiments demonstrate the applicability of our model in two ways. First, they show our model can be implemented in practice, using an existing negotiation platform, where it is able to negotiate on competitive benchmark negotiation scenarios. Second, its performance exhibits the model's resilience to violating some of the assumptions made in the theoretical analysis.

4.1 Setup

To analyze the performance of our querying strategy, we tested it across a number of established negotiation scenarios from the literature against a set of baseline and benchmark querying strategies. We employed the negotiation platform Genius [33], which is an environment that contains a repository of existing negotiation scenarios that can be used to evaluate generic automated negotiators' strategies.

We selected three small, undiscounted negotiation scenarios that featured in the Automated Negotiating Agent Competition of 2012 [3] and which display a spread of domain characteristics, namely: *Laptop* (a high number of win-win outcomes), *Flight Booking* (integrative, with both good and bad outcomes), and *Fifty-fifty* (fully distributive). These scenarios are modeled after real-life negotiation scenarios and define the (actual) normalized utilities between 0 and 1 for both the user and the opponent. Our negotiation setup complements the original utility tuples from literature with three additional model choices: the opponent strategy, utility uncertainty and the set of queries.

The agent exchanges bids with the opponent using the alternating offers protocol [38] with a deadline of $D = 10$ rounds. The opponent makes no offers, but has a fixed set of offers A that it will accept. We make use of a simple identity mapping between opponent utilities and acceptance probabilities, so that more preferred offers by the opponent are more likely to be accepted. Note that the set A is not known to the agent, as it only has access to the acceptance probability. Since the opponent acts stochastically, we repeat every negotiation in each scenarios 10 times to increase statistical significance.

Second, the negotiation agent maintains a belief with uncertainty over the actual utilities of each outcome. The user's utility is thus defined by the negotiation scenario but is not known by the agent. Instead, the user acts as an oracle to the agent by answering truthfully to each query, thereby reducing the uncertainty of the user model. In order to remain close to the original specification of the domains, we specify the agent's belief as a discrete probability distribution over all utility values observed in the domain. Note that this choice is just for the clarity of exposition, and our model is compatible with other specifications thereof. Such a discrete belief system can be represented by a matrix over all outcomes and values, and is in our experiments initialized with the most uninformed prior; i.e., all utilities are considered equally likely for all outcomes. Extensions to other priors that feature variation in uncertainty is trivial in our model (e.g. a confusion matrix, sampling a random number of alternative candidate utilities for each outcome).

Finally, to enable the agent to reduce uncertainty about the user, the agent has at its disposal queries of the form $q_{\omega,c}$ ="Is $u_\omega > c$?". These are boolean queries with $R_{q_{\omega,c}} = \{yes, no\}$. We define the set of queries to cover the whole outcome space and to include a regular spread of utility cutoff points: $Q = \{q_{\omega,c} \mid \omega \in \Omega, c \in \{0.1, 0.2, \ldots, 0.9\}\}$. Every query has identical cost $c(q_{\omega,c})$, but we vary this cost as a parameter in our experiments.

4.2 Benchmarks

We compare our approach (called *Optimal Query Agent*, or *OQA*) with three other querying strategies, which all use the same underlying bidding strategy. Every querying strategy is tested on the same set of scenarios, using the same priors

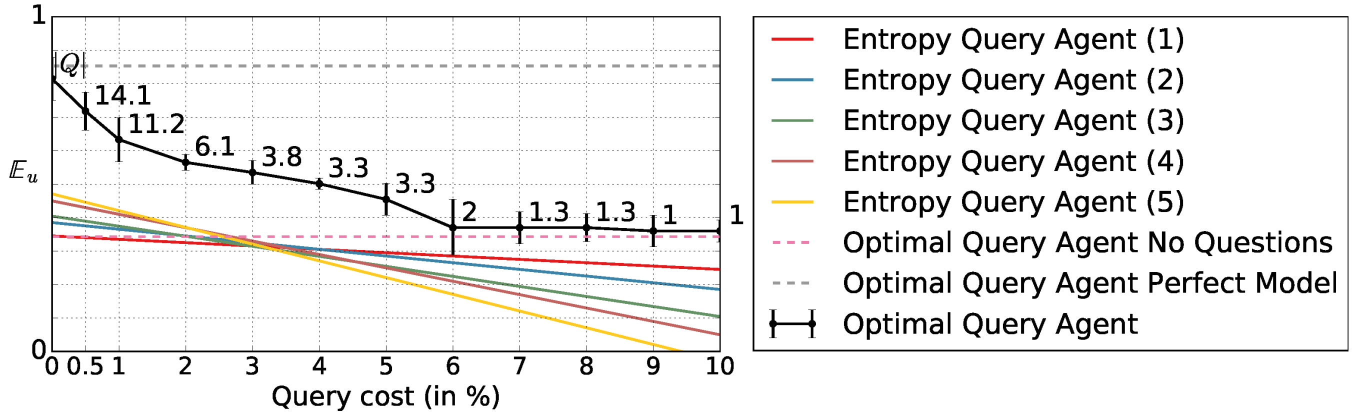

Figure 3: The average performance of each querying strategy as a function of the querying cost (as a percentage of the maximum attainable utility). The numbers above the *Optimal Query Agent* graph indicate the average number of queries posed to the user given the corresponding query cost (out of $|Q| = 258$).

for the user and opponent model. Furthermore, all strategies employ $\pi^*(p)$ as defined in Algorithm 1 to determine the bids to send out; their only difference is the fashion in which they query the user. Hence, differences in performance can be attributed exclusively to the effectiveness of each querying strategy.

We include two baseline querying strategies: *No Questions* and *Perfect Model*. The former does not perform any queries and thus relies solely on prior utility information; the latter acts as a theoretical upper bound. It possesses, by momentarily inspecting the user's real utilities, perfect knowledge (i.e., its user model representation is identical to the identity matrix), and hence it does not require additional information from the user.

Our benchmark strategy *Entropy Query Agent* comprises a family of strategies: informally, for given k, the *Entropy Query Agent* incrementally selects those queries from Q that maximize entropy in the user model by dividing the posterior in half. That is, in each state p, it selects the query $\arg\min_{q \in Q} \left| P(yes \mid p, q) - \frac{1}{2} \right|$. The user response is used to update p, followed by another query selected by the same principle, until a total of k queries have been posed. Note that, in contrast to our approach, this measure thus emphasizes increasing the accuracy of the user model, rather than taking into account the effect of information on the eventual outcome.

4.3 Results

The results of our experiments are shown in Figure 3, where the average obtained utility of each querying strategy is depicted for varying query costs. It can be seen that the *OQA* outperforms the benchmarks across all costs. The mean performance of *OQA* is significantly higher than the mean accuracy of each incarnation of the *Entropy Query Agent* for every cost (majority of p-values < 0.001). Additionally, we performed a one-sample t-test to compare the *OQA* against the *No Questions* agent and found its mean performance significantly higher at the 5% significance level for all query cost below 6%. Additionally, we performed the non-parametric Wilcoxon-Mann-Whitney test, which does not assume any distribution of the measurements, which yields identical results to the t-tests in terms of statistical significance.

Figure 3 illustrates that for low cost, the *OQA* will perform a large number of queries and thereby obtain an almost perfect user model. Note that the *OQA* does not quite reach the level of the *Perfect Model*, even for zero querying cost, due the limited resolution of the query set Q. Increasing the number of cut-off points would easily alleviate this, albeit at the cost of increased computation time. As costs increase, the expected utility declines until the lower bound of the *No Questions* strategy is reached: here, query costs are prohibitively high, and relying on prior information becomes optimal.

5. RELATED WORK

Negotiation under incomplete information has been studied in many different forms, although few have focused on incomplete utility about the user. This has been noted by Luo, Jennings and Shadbolt [35], who observe serious shortcomings of existing research with regard to what knowledge a user needs to impart to the agent to ensure proper corresponding negotiation behavior and how to effectively acquire this knowledge from the user.

The lack of work around incomplete user preferences is in part because of a prevalent focus of negotiation literature on uncertainty about the opponent [8]. For example, Lai, Sycara and Li [31] discuss a general model for uncertainty in negotiation with respect to incomplete information focused on the opponent, while the agent has a given preference order and corresponding utility function. In follow-up research [32], the model is shown to be applicable when an agent's preference is not explicitly characterized, although it is not stochastic in nature. For instance, it is assumed that, given a number of offers, an agent can judge the utility level of the offers and find the best one. In [26], an agent architecture is presented for multi-attribute negotiation under incomplete preference information, but this pertains to the opponent alone. Similarly, previous work on bargaining under incomplete information [15] assumes bargainers are uncertain about the adversary's payoff. Incomplete information about the other agent's goals and subsequent plans has also been studied [48], while assuming crisp utilities for the agent itself.

Another source of uncertainty can be the negotiation environment, which can include factors such as the deadline and reservation value; e.g., Fatima et al. [22] focuses on this kind of incomplete information. Similarly, in [37], a heuristic model is presented for negotiations in incomplete information settings, referring to uncertainty induced by the choice of multiple potential service providers.

Some other work on preference uncertainty in negotiation has moved away from multi-attribute utility-based models. For instance, an agent may represent its preferences using constraints (e.g. [36, 34]) or orderings of alternatives (e.g. [19]), which may aid it in learning about the opponent and in its elicitation process. An important representational framework for non-utility based negotiation are CP-nets [11]. Using CP-nets, the qualitative preference orderings of each party can be expressed in a compact and efficient way (see for example [2]) to learn the opponent's preferences in negotiation.

Fuzzy set theory is another approach to addresses the vague boundaries of utilities specifications in negotiation. In [17], a fuzzy representation is used for rules that express the actions to be taken by the agent, but the agent's preferences are represented by crisp, additive utility functions. The fuzzy constraint based model by Luo et al. [36] is also relevant here, as it is concerned with how requirements are expressed by the user; for example, a user may specify constraints such as "rental period > 6 (months)". This method is used by agents as a communication device to locate a joint outcome and is not concerned with elicitation or cost.

One of the few papers that considers elicitation and negotiation in tandem is [4]. However, this work only considers obtaining the utility of a single offer, which upon querying becomes fully known. The negotiation can only take place with known utilities and does not support stochastic utility information.

Perhaps most related to our work is the default-then-adjust acquisition technique from [35] which explores how knowledge about the user's trade-offs can be acquired. Similar to our work, it is also concerned with finding the appropriate type of information to elicit from the user, but mainly with an aim goal to obtain more accurate beliefs about the user's trade-offs using constraints, as opposed to costly querying to increase the overall expected negotiation performance.

A important feature of our model is the optimality of greedy search in decreasing utility. This has also been explored in sponsored search, where ads can be placed in ranked slots [18]. A result by Kempe and Mahdian [28] (which does not incorporate costs) yields a simple optimal greedy placement of ads according to similar criteria to ours. In [5], simultaneous search is used for formulating a negotiation strategy, but this work does not consider stochastic utility values or elicitation roles for either party.

Our underlying decision model is inspired by [9], although we consider general queries as opposed to gamble questions and focus on decision scenarios where computing the optimal action is in principle intractable. We do not use a POMPDP formulation of [9] here, since we adopt a myopically optimal elicitation view that is sufficient for our situation. As a result, our model can guarantee convergence and tractability due to the increased underlying structure of the problem.

6. CONCLUSION AND DISCUSSION

In this paper, we consider a negotiating agent that represents a user with only limited user preference information available. In order to weigh up the elicitation cost against expected gains in agreement utility, we define a new measure that computes the value of information of queries for a negotiation. Based on this, we derive an effectively computable strategy for finding the most informational query to pose to the user and we prove that it is myopically optimal. Our experiments demonstrate that our method significantly outperforms other benchmark strategies and our results show graceful degradation of our approach even when the assumptions with respect to which optimality has been proven do not fully hold.

Given that finding the optimal repeated querying strategy for elicitation is intractable [14], a myopic querying strategy such as presented here provides a sensible trade-off between computational complexity and performance. Nevertheless, if needed, a fixed, multi-query look-ahead is easily incorporated in our model, at the cost of computational load, by considering the cartesian product set Q^k of sending out k queries. The preferred approach will generally depend on the negotiation domain: myopic look-ahead may be preferable especially when the information state (including the opponent model) is volatile, for example when the exchanges of bids with the opponent are only occasionally interspersed with a querying action towards the user.

In our experiments, we considered idealized elicitation actions based on queries which extract the user's utility range of certain outcomes. When more information is provided about the particular form of the utility function, we may also elicit information about its underlying structure; for example, for linear utility functions, user preferences could be effectively obtained through information about the issue weights. The research field of user-involved preference elicitation could offer valuable insights in this regard (see [39] for an overview) and offers a range of alternative methods for adapting the user model, such as example critiquing and trade-off analysis.

A general feature of our approach is that each query can be accompanied with arbitrary bother costs. For future work, it would be interesting to establish a user bother cost function for negotiation interactions specifically, in combination with measures for when the user model is satisfactorily accurate [20]. Our approach is also compatible with general acceptance probability models such as proposed by Saha et al. [43]. An alternative way to construct the agent's acceptance probability model is to combine existing opponent utility models with models of the opponent's target utility. For instance, the preference model by Williams et al. [45] which is based on Gaussian processes could serve as a probabilistic opponent utility model, and could be integrated with a regression model such as developed by Chen et al. [16]).

In view of the compatibility of our approach, we daresay to provide an essential stepping stone towards our vision of representational negotiation agents that actively query the user only when needed, and thereby prepare the future in automation with true agency.

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