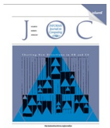

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Multi-Issue Automated Negotiations Using Agents

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Software agents can perform effectively as negotiators in automated negotiation settings. We present a model for software agents that can automate negotiations by implementing a multi-issue learning heuristic that allows agents to learn from the bidding behavior of opponents. The performance of agents is evaluated using an experimental study involving human subjects. The results indicate that software agents can act as effective surrogates of human negotiators under some circumstances.

Key words: bargaining; decision making; software; heuristic
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1. Introduction

Advances in artificial intelligence, software engineering, and networking have contributed to development of software agents. A potentially useful application of software agents is in automated negotiations. Successful negotiations require partners to search through a multidimensional space for an agreeable point. The dimensions of this space are negotiation issues like price, delivery terms, interest-free credit period, etc. This search can be slow and cognitively demanding on negotiators. Humans, due to limited information-processing capabilities (Simon 1957) and biases (Kahneman 1992, Kristensen and Garling 2000, Tversky and Kahnemann 1974), seldom perform effectively during negotiations. Tversky and Kahnemann found that human decision making was prone to errors and biases as humans often used heuristics like framing and anchoring to reduce complex decision tasks to simpler operations. Raiffa (1982) also observed that human negotiators often failed to reach agreements when in fact a mutually beneficial agreement was possible. Given that humans often resort to heuristics for decision making, which can lead to suboptimal outcomes, an opportunity exists for deploying agents using sophisticated heuristics to negotiate on behalf of humans to minimize the effects of biases and other cognitive limitations.

Agent-based negotiations can be useful in many scenarios. Consider, for example, emerging electronic markets for perishable goods and services such as electricity, flight seats, and flowers where there is a limited time window to complete negotiations. In these markets, transient market opportunities require that buyers and sellers reach an agreement quickly (Kambil and Heck 1998). Agents can also be useful in traditional exchanges like commodities exchanges where they could negotiate with more players than human traders could, leading to more favorable outcomes (Chicago Board of Trade 1998). In e-procurement systems, agents could negotiate with multiple suppliers to fulfill orders.

Software agents can automate negotiations, since they are intelligent, proactive, mobile, and autonomous. Software agents can mimic human preferences and can learn and adapt to the environment. By making objective decisions, agents can reduce the impact of subjective biases that are common in human behavior and can help humans achieve superior negotiation outcomes. Using this as the basis, we present a *multi-issue learning heuristic* (MILH) to automate multi-issue bilateral negotiations. MILH has been implemented in mobile Java agents using the Aglets toolkit (Lange and Oshima 1998).

Negotiations have been modeled and studied from various perspectives such as game theory, dynamic programming, and artificial intelligence. Game-theoretic models use Nash equilibria and the Shapley value to identify equilibrium negotiation outcomes, but make restrictive assumptions (Kraus and Wilkenfeld 1993), and focus more on the negotiation outcomes rather than on the process itself. An alternate approach views the agent's optimal decision-making process as a stochastic control problem that could be solved using dynamic programming (Deveaux et al. 2001). Artificial-intelligence approaches model or provide solutions to facets of negotiations like learning the opponent's behavior and the environment, providing efficient search strategies for locating the point of agreement, and automating the process. Examples include case-based reasoning, genetic algorithms, and Bayesian learning.

Case-based approaches like PERSUADER (Sycara 1990) match recorded instances of negotiations to the current situation, so they are not effective for situations not matching cases in the repository. Genetic algorithms play one negotiation strategy against another, using the outcome to produce improved strategies (Oliver 1996), but too many generations of negotiations are required to produce a good strategy. Heuristics search the negotiation space for an agreeable point. Bayesian approaches learn about the opponent from observed behavior using Bayesian probability updates (Zeng and Sycara 1998), but prior probabilities are difficult to estimate.

Research prototypes for negotiations support are called negotiation support systems (NSSs). Examples include *Negotiation Assistant* (Rangaswamy and Shell 1997) and *Inspire* (Kersten and Noronha 1999). These systems assist a negotiator by eliciting preferences, generating utility functions, making offer recommendations, and analyzing an opponent's offer. NSSs do not conduct the actual negotiations as they do not provide heuristics.

The Kasbah agent system, a notable automated negotiation system (Chavez and Maes 1996), uses a simple negotiation heuristic based on predefined price decay or increment functions. This heuristic does not facilitate learning or adaptation. Therefore sophisticated opponents can gain an upper hand while negotiating. Negotiation performance can be improved by using information on opponent reservation values, where reservation value (RV) for an issue is the least acceptable bid for that issue, and the duration for which the opponent is willing to negotiate. These two pieces of information can be learned by agents from opponent's behavior. Bazaar agents (Zeng and Sycara 1998) learn and form beliefs about opponent RVs from observing behavior and using Bayesian updates.

Families of polynomial and exponential functions model concession behaviors during negotiations, such as Boulware, conceder, and imitative (Faratin et al. 1998). Boulware behavior entails maintaining close to the initial offer almost until the end, and then yielding to the RV. In contrast, conceder behavior entails conceding very early close to the RV, and imitative behavior imitates the opponent. Agents in Faratin et al. (1998) do not learn and, unlike Kasbah agents, do not support fully automated negotiations, as humans have to intervene to provide weights that are used in combining various behaviors to create a complex negotiation strategy.

An approach using prioritized fuzzy constraints has been used for bilateral multi-issue negotiations in a semi-competitive environment where negotiating agents cooperate on a limited basis by exchanging constraints to reach an agreement (Luo et al. 2003). This approach is not suitable for competitive negotiations. Multi-issue negotiations under time constraints have been addressed by Fatima et al. (2004), where trade-offs between issues are ignored and probabilities of various opponent strategies and RVs must be known. An approach that uses historical data related to previous encounters with an opponent is presented in Paurobally et al. (2003) for negotiations of mobile services.

The approaches described above either do not address the multi-issue nature of negotiations or do not exploit trade-offs among issues. In multi-issue negotiations, if opponent priorities for issues are not the same as one's own, then integrative solutions (i.e., expanding the pie) are possible (Raiffa 1982). Multiple issues have been considered jointly during negotiations to incorporate trade-offs by Fatima et al. (2006), but this approach requires various probabilities for the Bayes update rule. No practical and sophisticated agents exist to support real-world automated negotiations involving multiple issues. We present agents based on a new multi-issue heuristic that learns opponent RVs and the number of offer/counter offer cycles that the opponent is likely to support, by observing the opponent's bidding behavior. MILH does not have the drawbacks of a Bayesian approach because no prior probabilities are estimated, and uses embedded utility functions of humans to generate offers in a multidimensional space covering multiple negotiation issues. Our goal is to realize superior negotiation outcomes for the human user who uses the MILH agent. This advances NSS by presenting systems that can be fully automated, while having the potential to be as effective as humans in competitive negotiations.

Section 2 presents MILH. Section 3 presents an overview of the experimental study, and results. Section 4 concludes this paper. The Online Supplement to this paper on the journal's website describes the curve-fitting learning procedure used by MILH, hybrid agents used in experiments, and details of the experimental study and data analysis.

2. Multi-Issue Learning Heuristic (MILH)

Our problem context is bilateral multi-issue competitive negotiations where each negotiator strives to maximize her individual gains. Both negotiators know the negotiation issues and range of values (issue domain). The priorities of issues can be different for the negotiators, so integrative agreements are possible. Each negotiator has private information such as her own RV, the approximate number of iterations (offer/counter cycles) to have during negotiations, issue priorities, and a utility function to maximize.

There are two types of issues: *Increasing utility issues*, such as price for a seller, which increase the utility of a negotiator (i.e., seller) with an increase in the issue value; and *decreasing utility issues*, such as price for a buyer, which decrease the utility of a negotiator with an increase in the issue value. For increasing utility issues, RVs are the lowest values acceptable; for decreasing utility issues, RVs are the highest acceptable values.

Either negotiator can make the first offer. An offer consists of acceptable values for all the issues from their respective issue domains. When a negotiator makes an offer, her opponent can accept the offer and reach an agreement, make a counter offer, or terminate negotiations.

2.1. Assumptions Specific to MILH

Three assumptions underlie MILH. Let $u_i(\mathbf{x})$ denote the utility function of negotiator (agent or player) i, ($i = 1$ for self and $i = 2$ for opponent) where $\mathbf{x} = (x_1, \ldots, x_n)$ is a vector of n issues. If $\mathbf{x}$ were accepted by an opponent, then $u_i(\mathbf{x})$ would be the utility value realized by i at agreement. First MILH assumes that $\partial u_1(\mathbf{x})/\partial x_k$ and $\partial u_2(\mathbf{x})/\partial x_k$ have opposite signs, i.e., negotiators conflict over all issues. If I_i is a set of increasing utility issues for negotiator i, and D_i is a set of decreasing utility issues (see Table 1 for formal definitions), then $I_1 = D_2$ and $D_1 = I_2$. This is a reasonable assumption given that in competitive negotiations, a gain for one is a loss for the other; the degree of gain or loss may be different to the negotiators due to differences in their issue priorities. The second assumption is that negotiators are maximizers of their expected utility, so their utility functions drive their behavior (Mumpower 1991). The third assumption is that negotiators yield close to their RVs for one or more issues before terminating negotiations. This assumption does not require the negotiators to follow any specific bidding behavior such as monotonicity of bids, but merely specifies the end state of negotiations before a negotiator quits.

2.2. MILH High-Level Overview

MILH agents demonstrate complex behavior ranging from accommodative to imitative to nonaccommodative. MILH uses two major steps iteratively. In the first step, opponent RVs are estimated along with the number of iterations that the opponent is likely to have before quitting negotiation (details are in Section 2.3). In the second step, MILH uses the estimate of opponent RVs and the estimate of the number of iterations in making an offer (see Section 2.4 for details). MILH strives to reach agreement at the estimated last iteration of the opponent, where MILH presumes that the opponent is close to her RVs for one or more issues. If reaching an agreement at the estimated opponent RVs is not possible, then in the ending phase, MILH makes concessions to reach an agreement provided her own RV constraints are met. Concessions on issues in the beginning and middle of negotiations are made in inverse proportion to the loss of one's own utility (details are in Section 2.4). To discourage gaming by the opponent, MILH follows an imitative behavior if the opponent does not make concessions, and if no progress is made during negotiations, MILH terminates negotiations.

Table 1 Notation

Symbol	Description
$x_{i,j,k}$	Value of issue k in the offer made by negotiator i at iteration j, where $i = 1$ for self and $i = 2$ for the opponent.
$\mathbf{x}_{i,j}$	$= (x_{i,j,k})_{k=1,\ldots,n}$ is a vector of n issue values in an offer made by negotiator i at iteration j.
$r_{i,k}$	RV of negotiator i for issue k.
$\mathbf{r}_i$	$= (r_{i,k})_{k=1,\ldots,n}$ is a vector of actual RVs of negotiator i for n issues.
$\hat{r}_{i,j}$	$= (\hat{r}_{i,j,k})_{k=1,\ldots,n}$ is a vector of estimated RVs of negotiator i at iteration j for n issues.
I_i	$= \{k \mid k \in \{1, \ldots, n\} \wedge \partial u_i(x)/\partial x_k \geq 0\}$, is the index set of increasing utility issues for negotiator i. For these issues, utility value is nondecreasing with an increase in the issue value.
D_i	$= \{k \mid k \in \{1, \ldots, n\} \wedge \partial u_i(x)/\partial x_k < 0\}$, is the index set of decreasing utility issues for negotiator i. For these issues, utility value is nonincreasing with an increase in the issue value.
τ_j	Expected total number of iterations in negotiations estimated at iteration j.
min_range_k	Lower bound of issue k domain.
max_range_k	Upper bound of issue k domain.
t_min_range	Minimum number of iterations possible.
t_max_range	Maximum number of iterations possible.

2.3. Learning by MILH Agents

MILH agents estimate the opponent's RVs by constantly learning from the opponent's bidding behavior. A negotiation spans multiple iterations. At iteration 1, in the user-driven mode, an initial estimate of the opponent's RV as well as the estimated total number of iterations in negotiations is provided by the user, while in the automated mode, the initial estimates are generated from a continuous uniform probability distribution over some range, by the MILH agent itself. MILH then refines these initial estimates of the opponent's RVs using offer points available until the current iteration.

To estimate RVs and the total number of iterations, MILH uses the following model of opponent concession behavior based on exponential function (1) (Faratin et al. 1998):

$$x_{2,j,k} = \begin{cases} mn_k + \alpha_k(mx_k - mn_k) & \text{when } k \in D_2 \\ mn_k + (1-\alpha_k)(mx_k - mn_k) & \text{when } k \in I_2 \end{cases}$$
$$\alpha_k = e^{(1-\min(j,\, t_{\max_k})/t_{\max_k})^{\beta_k} \ln(\zeta_k)}, \tag{1}$$

where mn_k is the minimum value of issue k that the opponent may use, mx_k is the maximum value of issue k that the opponent may use, β_k is the degree of concavity/convexity of the opponent's concession curve for issue k, ζ_k, denotes the fraction of $mx_k - mn_k$ added to mn_k in modeling the starting bid of the opponent, $0 < \zeta_k < 1$, and $t_{\max_k}$ is the number of iterations before an opponent concedes to her RV for issue k. Given mn_k, mx_k, β_k, ζ_k, and $t_{\max_k}$, the model determines the offer by the opponent for issue k at the jth iteration. Although other concession models could be used, the model above captures a wide range of bidding behaviors: $\beta_k < 1$ represents Boulware behavior while $\beta_k > 1$ represents conceder behavior.

Given opponent offer points $x_{2,1,k}, \ldots, x_{2,j,k}$, available at iteration j for any issue k, MILH forms parameter estimates $\widehat{mn}_{j,k}$, $\widehat{mx}_{j,k}$, $\hat{\beta}_{j,k}$, and $\hat{\zeta}_{j,k}$ for mn_k, mx_k, β_k, and ζ_k respectively at the jth iteration, by fitting (1) over the j offer points of the opponent, while fixing $\hat{t}_{\max_{j,k}}$, which is an estimate of $t_{\max_k}$ at the jth iteration. The estimates $\widehat{mn}_{j,k}$ and $\widehat{mx}_{j,k}$ are used for estimating opponent RVs $\hat{r}_{2,j,k}$ as follows: $\hat{r}_{2,j,k} = \widehat{mn}_{j,k}$ when $k \in I_2$; $\hat{r}_{2,j,k} = \widehat{mx}_{j,k}$ when $k \in D_2$. $\hat{t}_{\max_{j,k}}$ is also determined by fitting (1), but keeping $\widehat{mn}_{j,k}$ or $\widehat{mx}_{j,k}$ fixed, as seen below. Because estimates are imprecise when the number of opponent offer points is low, the curve-fitting procedure is used beginning with iteration 3.

Opponent RVs and $\hat{t}_{\max_{j,k}}$ are determined as follows.

1. At iteration $j = 1$ there are two cases: In the user-driven mode, get $\hat{r}_{2,1}$ and τ_1 from the human user; in the automated mode, set $\hat{r}_{2,1,k} = min\_range_k + \pi(max\_range_k - min\_range_k)$ where π is a continuously uniformly distributed random number between l and u such that $0 < l < \pi < u < 1$; $\tau_1 =$ uniformly distributed discrete random number in the range t_min_range to t_max_range.

2. For any issue k, form the estimate $\hat{t}_{\max_{j,k}}$ as follows. For $j \leq 3$, set $\hat{t}_{\max_{j,k}} = \tau_1$. Else for $j > 3$, if $k \in I_2$, fix $\widehat{mn}_{j,k} = \hat{r}_{2,j-1,k}$ and if $k \in D_2$ fix $\widehat{mx}_{j,k} = \hat{r}_{2,j-1,k}$ and then via the curve-fitting procedure (see Appendix A in the Online Supplement) form the un-weighted estimate $\hat{t}^c_{\max_{j,k}}$ of $t_{\max_k}$; Compute $\hat{t}_{\max_{j,k}} = (j/\max(\tau_{j-1}, j))\hat{t}^c_{\max_{j,k}} + (1 - j/\max(\tau_{j-1}, j))\tau_1$

3. Compute $\tau_j = \max_{k=1,\ldots,n}(\hat{t}_{\max_{j,k}})$.

4. For any issue k, use $\hat{t}_{\max_{j,k}}$ computed in Step 2 and by curve fitting to (1), set $\hat{r}^c_{2,j,k} = \widehat{mx}_{j,k}$ if $k \in D_2$ and $\hat{r}^c_{2,j,k} = \widehat{mn}_{j,k}$ if $k \in I_2$. Compute $\hat{r}_{2,j,k} = (j/\max(\tau_j, j))\hat{r}^c_{2,j,k} + (1 - j/\max(\tau_j, j))\hat{r}_{2,1,k}$. Set $\hat{r}_{2,j,k} = \min(\hat{r}_{2,j,k}, x_{2,j,k})$ when $k \in I_2$; $\hat{r}_{2,j,k} = \max(\hat{r}_{2,j,k}, x_{2,j,k})$ when $k \in D_2$.

In iteration 1, in the user-driven mode, the user of the MILH agent provides the initial starting estimates $\hat{r}_{2,1,k}$ and τ_1, while in the automated mode the heuristic itself sets the values of the two parameters. The estimation procedure is initiated only when three offer points are available from the opponent. More weight is attached to the initial estimates $\hat{r}_{2,1,k}$ and τ_1 in the beginning, and as the heuristic learns when more offer points are available, higher weight is given to the curve-fitting estimates.

To prevent the curve-fitting procedure from overestimating $\hat{t}_{\max_{j,k}}$ when opponent values for issue k do not change over multiple iterations, only the first m offer points for issue k are used in curve fitting. Let $x_{2,1,k,\ldots,}x_{2,m,k,\ldots}x_{2,p,k}$ be the sequence of offer points for issue k made by the opponent over p iterations and if there exists an index value m such that $1 < m < p$, and $x_{2,m,k} \neq x_{2,m-1,k}$ and $x_{2,m,k} = x_{2,m+1,k} = \cdots = x_{2,p,k}$, then only $x_{2,1,k,\ldots,}x_{2,m,k}$ are used for issue k.

To identify m, the following steps are used:

Let $\theta_{j,k}$ be the normalized slope between offer points at iterations j and $j-1$ for the kth issue value:

$$\theta_{j,k} = \frac{|x_{2,j,k} - x_{2,j-1,k}|}{x_{2,j-1,k}}, \quad j > 1. \tag{2}$$

Given some threshold level $v > 0$, then if there exists some iteration $j > 1$ such that $\theta_{j,k} > v$, index m is such that $j < m < p$, $\theta_{m,k} \neq 0$ and $\theta_{m+1,k} = \theta_{m+2,k} = \cdots = \theta_{p,k} = 0$.

The opponent (i.e., $i = 2$) can exhibit nonmonotonic behavior by making offers such that $x_{2,j+1,k} \geq x_{2,j,k}$ for $k \in I_2$ or $x_{2,j+1,k} \leq x_{2,j,k}$ for $k \in D_2$. The estimation heuristic takes care of the noise due to nonmonotonic behavior during curve fitting, by setting $x_{2,j+1,k} = x_{2,j,k}$.

2.4. Automated Bidding

MILH computes automatic bids by observing the behavior of opponents. Let $\mathbf{d}_{i,j}$ denote a n dimensional direction vector of the move by negotiator i at iteration j, $\mathbf{d}_{i,j} = (d_{i,j,k})_{k=1,\ldots,n}$, and $t_{i,j}$ denote a scalar representing the step size of the move. If MILH (index $i = 1$, i.e., self) makes an offer $\mathbf{x}_{1,j-1}$ at iteration $j-1$, then at iteration j, MILH computes an offer $\mathbf{x}_{1,j}$ given by (3):

$$\mathbf{x}_{1,j} = \mathbf{x}_{1,j-1} + t_{1,j}\mathbf{d}_{1,j}. \tag{3}$$

As per (3), $i = 1$'s offer at iteration j is computed by calculating the move i makes from the previous point $\mathbf{x}_{1,j-1}$ in a multi-dimensional space (where the dimensions correspond to the various negotiation issues), in the direction given by $\mathbf{d}_{1,j}$ with step size $t_{1,j}$. $\mathbf{d}_{1,j}$ is computed using (4):

$$\mathbf{d}_{1,j} = \left[-C\Big/\frac{\partial u_1(\mathbf{x})}{\partial x_1}, \ldots, -C\Big/\frac{\partial u_1(\mathbf{x})}{\partial x_n}\right]\Big/\mathbf{x} = \mathbf{x}_{1,j-1},$$

$$\text{where } C = \max\left[\left|\frac{\partial u_1(\mathbf{x})}{\partial x_1}\right|, \ldots, \left|\frac{\partial u_1(\mathbf{x})}{\partial x_n}\right|\right]\Big/\mathbf{x} = \mathbf{x}_{1,j-1}. \quad (4)$$

$\mathbf{d}_{1,j}$ is a descent direction that leads to minimal utility loss from the current point $\mathbf{x}_{1,j-1}$ on the utility surface of negotiator $i=1$. The magnitude of the kth component of the direction vector is inversely proportional to the loss of utility for every unit concession of issue k. Thus MILH yields on issues in inverse proportion to the loss in utility due to concessions. For a linear utility function, $\mathbf{d}_{1,j}$ is a constant vector.

The step size $t_{1,j}$ of a move made by MILH during iteration j is determined using (5):

$$u_1(x)|_{x=x_{1,j-1}+t_{1,j}\mathbf{d}_{1,j}} - u_1(x)|_{x=x_{1,j-1}} = \frac{du_1}{dt}\bigg|_{t=j-1}\Delta j. \quad (5)$$

The basis for (5) is that MILH (i.e, $i=1$) makes an offer given by $\mathbf{x}_{1,j-1} + t_{1,j}\mathbf{d}_{1,j}$ such that the loss in utility relative to the previous offer $x_{1,j-1}$ is equal to $du_1/dt|_{t=j-1}$ given that $\Delta j = 1$. The concession rate du_1/dt is determined by taking the derivative of a function that represents utility as a function of iterations. MILH does not specify any particular concession rate to use.

Although MILH computes an offer based on the step size computed in (5), the actual step size used is determined by the opponent's behavior. If the opponent does not make any concessions, MILH does not make any unilateral concessions and triggers an imitative behavior. Given an opponent's current offer, the change metric σ for triggering imitative behavior is computed. This metric can be based on two possible schemes. In (6), σ denotes the maximum change in the magnitude across all issues of the opponent's current offer at iteration j with respect to her previous offer as a proportion of the previous offer:

$$\sigma = \begin{cases} \max k \in \{1,\ldots,n\} |(x_{2,j,k} - x_{2,j-1,k})/x_{2,j-1,k}| \\ \qquad \text{for } j>1 \\ 1 \qquad \text{for } j=1. \end{cases} \quad (6)$$

Alternately, σ can be computed based on average change:

$$\sigma = \begin{cases} \left(\sum_{k\in D_2}(x_{2,j,k} - x_{2,j-1,k})/x_{2,j-1,k} \right. \\ \qquad \left. + \sum_{k\in I_2}(x_{2,j-1,k} - x_{2,j,k})/x_{2,j-1,k}\right)\Big/|I_2\cup D_2| \\ \qquad \text{for } j>1 \\ 1 \qquad \text{for } j=1. \end{cases} \quad (7)$$

It can be seen from (6) and (7) that if the opponent's current offer does not change from her previous offer at any iteration $j>1$, then $\sigma = 0$. Only when $\sigma > a$, where a is a threshold, then MILH presents an offer that changes with respect to the previous offer by $t_{1,j}\mathbf{d}_{1,j}$. Otherwise, the magnitude of the change with respect to the previous offer for any issue k, is $\min(|t_{1,j}d_{1,j,k}|, \sigma x_{1,j-1,k})$.

There are other constraints that determine an offer. First, the MILH offer should meet the MILH agent's RV constraints. Second, the offer should not yield more than what the opponent has offered. Third, the offer should not yield more than the estimated opponent RV. Fourth, the offer should yield an amount at least equal to the previous offer (i.e., monotonic behavior on the part of MILH). Thus the offer by MILH is given by (8):

$$x_{l,j,k} = \begin{cases} \min(\max(round(x_{1,j-1,k} - \min(|t_{1,j}d_{1,j,k}|, \\ \quad \delta\sigma x_{1,j-1,k})), r_{1,k}, \hat{r}_{2,j,k}, x_{2,j,k}), x_{1,j-1,k}) \\ \quad \text{for } k \in I_1 \\ \max(\min(round(x_{1,j-1,k} + \min(|t_{1,j}d_{1,j,k}|, \\ \quad \delta\sigma x_{1,j-1,k})), r_{1,k}, \hat{r}_{2,j,k}, x_{2,j,k}), x_{1,j-1,k}) \\ \quad \text{for } k \in D_1. \end{cases} \quad (8)$$

In (8), $round(x)$ rounds x to the nearest value in the domain of x, $\delta = 1$ when $\sigma \le a$, else $\delta = \infty$ when $\sigma > a$.

Additional parameters defined for MILH are as follows: Δ_k *is* a parameter used in updating an offer and is between 0 and 1 for issue k, ε_k is a tolerance value close to zero for checking if issue k values in two offers are equal, f is between 0.5 and 1 where $f\tau_j$ denotes the number of iterations beyond which MILH demonstrates an accommodative behavior in resolving deadlocks, and $e_{1,k}$ is a small difference between the starting bid and max_range_k (or min_range_k) for issue k based on issue type.

The steps of MILH are summarized next.

Steps for $j=1$:

1. Get initial estimate of the opponent RVs $\hat{r}_{2,1}$, own RVs $\mathbf{r}_1$, and duration estimate τ_1 either from user (user-driven mode) or estimate these values using Step 1 in Section 2.3 (automated mode);

2. Get initial offer $\mathbf{x}_{1,1}$ from user (in user driven mode) or in automated mode, set $x_{1,1,k} = max\_range_k - e_{1,k}$ (when $k \in I_1$) or $x_{1,1,k} = min\_range_k + e_{2,k}$ (when $k \in D_1$).

3. Get offer $\mathbf{x}_{2,1}$ from opponent.

Repeat Steps 4–14 for $j \ge 1$

4. If $(|x_{1,j,k} - x_{2,j,k}| \le \varepsilon_k \;\; k = 1,\ldots,n)$ agreement reached. Stop negotiations.

5. Set $j = j+1$

6. If $j<3$ then set $\tau_j = \tau_1$ and $\hat{r}_{2,j} = \hat{r}_{2,1}$

7. If $j \ge 3$ then estimate τ_j and $\hat{r}_{2,j}$ using the steps in Section 2.3.

8. Compute $\mathbf{d}_{1,j}$ from (4), $t_{1,j}$ from (5), and σ from either (6) or (7).

9. If $(\sigma > a)$ then set $\delta = \infty$, else $\delta = 1$. Compute $\mathbf{x}_{1,j}$ from (8).

10. If $(|x_{1,j,k} - x_{2,j,k}| \leq \varepsilon_k,\ k = 1, \ldots, n)$ then agreement reached, stop negotiations.

11. If $j \geq \tau_j$, then if $((\forall k \in I_1,\ x_{2,j,k} \geq r_{1,k}) \wedge (\forall k \in D_1,\ x_{2,j,k} \leq r_{1,k}))$ set $x_{1,j,k} = \min(\max(r_{1,k}, x_{2,j,k}, \hat{r}_{2,j,k}(1 - \Delta_k)), x_{1,j-1,k})\ \ \forall k \in I_1$, and set $x_{1,j,k} = \max(\min(r_{1,k}, x_{2,j,k}, \hat{r}_{2,j,k}(1 + \Delta_k)), x_{1,j-1,k})\ \ \forall k \in D_1$; else if $(\sigma < a)$ stop negotiations.

12. If $((\mathbf{x}_{1,j} = \mathbf{x}_{1,j-1}) \vee (\mathbf{x}_{2,j} = \mathbf{x}_{2,j-1})) \wedge (j \geq f\tau_j)$ then if $(x_{2,j,k} \geq r_{1,k},\ \ \forall k \in I_1) \wedge (x_{2,j,k} \leq r_{1,k},\ \ \forall k \in D_1) \wedge (|(x_{2,j,k} - \hat{r}_{2,j,k})/\hat{r}_{2,j,k}| \leq \Delta_k,\ \ \forall k \in I_1 \cup D_1)$, update $\mathbf{x}_{1,j}$ by setting $\mathbf{x}_{1,j} = \mathbf{x}_{2,j}$, make offer and reach agreement, stop negotiations.

13. If $(\mathbf{x}_{1,j} = \mathbf{x}_{1,j-1} = \mathbf{x}_{1,j-2}) \wedge (j \geq f\tau_j) \wedge (x_{2,j,k} \geq r_{1,k},\ \ \forall k \in I_1) \wedge (x_{2,j,k} \leq r_{1,k},\ \ \forall k \in D_1)$ then update $\mathbf{x}_{1,j}$ by setting $\mathbf{x}_{1,j} = \mathbf{x}_{2,j}$, make offer and reach agreement, stop negotiations. Else if $(\mathbf{x}_{1,j} = \mathbf{x}_{1,j-1} = \mathbf{x}_{1,j-2}) \wedge (j \geq f\tau_j) \wedge \neg((x_{2,j,k} \geq r_{1,k},\ \ \forall k \in I_1) \wedge (x_{2,j,k} \leq r_{1,k},\ \ \forall k \in D_1))$ no agreement reached, stop negotiations.

14. Make offer $\mathbf{x}_{1,j}$.

As seen from this summary of steps, the computed offer $\mathbf{x}_{1,j}$ in Step 9 is subject to further modifications in Steps 11–13 before it is presented to the opponent. In Step 11, if the current iteration is at least equal to τ_j and MILH agent's RV constraints are met by an opponent offer, then MILH computes an offer that is $1 - \Delta_k$ and $1 + \Delta_k$ times the estimated RV of the opponent for $k \in I_1$ and $k \in D_1$ respectively, and subject to the min and max constraints in Step 11. Thus as iteration τ_j is reached, MILH is willing to concede beyond the estimated RV of the opponent, subject to some constraints. If a deadlock is reached in Step 12, the number of iterations is at least $f\tau_j$, MILH agent's RV constraints are satisfied, and the opponent's current offer is within the $\Delta_k \hat{r}_{2,j}$ bound of the estimated RV of the opponent ($\hat{r}_{2,j}$), then MILH accepts the opponent's current offer. If MILH agent's offer value computed does not change over the last three iterations, the number of iterations is at least $f\tau_j$, and MILH agent's RV constraints are satisfied, then MILH reaches an agreement at the current offer of the opponent in Step 13.

MILH terminates negotiations without reaching an agreement under two conditions. First (in Step 11), when the current iteration is at least τ_j, the opponent's current offer does not meet MILH agent's RV constraints, and the change in the opponent's current offer with respect to her previous offer is less than the minimum required threshold. Second (in Step 13), when MILH agent's offer does not change for the last three iterations, the number of iterations elapsed are at least $f\tau_j$, and the opponent's current offer does not meet MILH agent's RV constraints.

3. Experiment Overview and Results

An experimental study involving human subjects was used to test the effectiveness of MILH. Five issues (A, B, C, D, E) were used in experimental negotiations based in the context of employer-employee negotiations. A 2×2 factorial design similar to Bazerman and Neale (1982) was used for the experimental study in Figure 1, by manipulating the employee role and employer role. In Cell 1, a subject performing the role of an employee negotiated with hybrid agents that performed the role of employers. Hybrid agents were nonlearning agents whose bids were obtained by combining the bids generated from four exponential functions and four polynomial functions (Faratin et al. 1998) so that complex concession behavior that was not easy to predict could be obtained (see Appendix B in the Online Supplement).

In Cell 3, subjects playing the role of employees negotiated with MILH agents who acted as employers. In Cell 0, MILH employee agents negotiated with hybrid employer agents, while MILH employee agents negotiated with MILH employer agents in Cell 2. A total of ten subjects were equally divided between Cell 1 and Cell 3. Each subject was required to conduct ten rounds of actual negotiations after two training rounds, leading to ten observations per subject per cell.

Ten different hybrid agents were created at random and all the employee negotiators (humans and MILH agents) negotiated with the same ten hybrid agents to facilitate performance comparisons. However, no subject or agent negotiated against the same employer twice. MILH agents acting as employees as well as employers operated in the automated mode as opposed to the user driven mode. As a result of these manipulations, a total of fifty observations were obtained per cell.

To motivate subjects, a two-stage binary-lottery preference-induction procedure (Rietz 1993) was used, based on induced value theory (Smith 1976) that assumed that subjects could be induced to display the desired preference structure. Details of the two-stage procedure and the utility function used can be found in Appendix C in the Online Supplement.

The performance of MILH agents relative to human subjects was estimated by comparing the mean

Employer	Hybrid	Cell 0	Cell 1
	MILH	Cell 2	Cell 3
		MILH	Human
		Employee (subjects)	

Figure 1 **Experiment Setup**

Table 2 Summary Statistics for Negotiator Utilities in Successful Negotiations

Opponent (employer-type)	(Employee-type) MILH	Human
Hybrid	Cell 0 ($N = 50$) *Subject*: 0.81 (0.06)* *Opponent*: 0.37 (0.08)	Cell 1 ($N = 43$) *Subject*: 0.82 (0.05) *Opponent*: 0.36 (0.09)
MILH	Cell 2 ($N = 46$) *Subject*: 0.63 (0.13) *Opponent*: 0.60 (0.13)	Cell 3 ($N = 40$) *Subject*: 0.61 (0.14) *Opponent*: 0.63 (0.15)

*Mean utility (standard deviation).

utilities attained by subjects (employees) and their opponents (employers) for negotiations that led to an agreement. The number of successful negotiations for each pair of employer-employee combination is shown as N in Table 2, where each cell had a maximum of 50 observations. The greatest success in completing negotiations occurred when MILH as employees negotiated with hybrid employer agents (Cell 0), where all negotiations led to agreements. At the other extreme, human subjects as employees negotiating with MILH employer agents (Cell 3) only had 40 completed negotiations leading to a success rate of 80%. Table 2 presents summary statistics of utilities attained by negotiators in successful negotiations.

As seen from the table, employees obtained higher utilities against hybrid employers than against MILH employers. Table 2 also shows that MILH agents and humans achieved comparable utilities. Detailed data analysis in Appendix D of the Online Supplement confirms that MILH agents were evenly matched with human subjects in negotiation performance. MILH agents as employees, however, had a higher agreement rate than human subjects as they successfully completed 96 out of 100 negotiation rounds (Table 2), compared to 83 successes by human subjects. This represented a 15% improvement over human subjects, without compromising utilities. Readers are referred to Appendix C and Appendix D in the Online Supplement for further details on the experiment and data analysis.

4. Conclusions

MILH to our knowledge is the first learning heuristic to fully automate multi-issue negotiations without estimating a multitude of probabilities as done in Bayesian approaches. MILH also considers trade-offs between issues.

Experimental results indicate that MILH agents performed significantly better than hybrid agents and that MILH agents attained utility values that were comparable to those attained by humans, but completed more negotiations successfully than humans.

An important factor that determines the effectiveness of MILH is the accuracy of MILH estimates of opponent RVs. We plan to explore machine-learning techniques for improving this estimation. We will also explore whether an average-change-based metric for countering gaming given by (7) performs better than the maximum-change based metric given by (6).

We could not consider all possible negotiation scenarios involving the experimental factors due to limitations in recruiting subjects. The selection of subjects also affected the generalizability of results. Although the sampling frame as described in the Online Supplement was graduate students with negotiation experience or coursework, subjects were selected from a convenience sample.

For experimental control we used the same general form for the utility function with the same coefficient of risk aversion for all subjects. Reality exhibits a wide variety of risk preferences, including risk-seeking behaviors. Although MILH does not anticipate any specific form for an opponent's utility function, the experimental results have been verified only in one specific experimentally induced risk-preference behavior. Further experiments are needed to verify the external validity of results for the general population and diverse negotiation contexts.

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