

Reasoning about Goal Revelation in Human Negotiation

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Participants in negotiation often lack information about each others' goals, but are reluctant to reveal their own goals. Decision-theoretic reasoning using machine-learned models of negotiations can outperform humans in anticipating goal revelation.

This article describes the use of computer-based protocols for facilitating and modeling human negotiations in strategic settings where the parties lack information about each other's goals and incentives. Such settings are endemic in many negotiation contexts, from electronic commerce to

diplomatic relations.^{1,2} Often, this lack of information about the participants' underlying interests prevents the parties from reaching beneficial agreements, or from reaching agreements altogether. To date, evidence about the effect of information exchange on human negotiation is inconclusive: while it can lead to more equitable outcomes among the negotiation parties,³ it might also result in the exploitation of a vulnerable party.⁴

As an example, consider a hypothetical scenario in which friends in an online social network need to agree on a restaurant for dinner. All of them share the common goal of enjoying their activity, but they also have individual preferences that might conflict with each other. One of the friends might insist on eating at a place that's far away, so she might reveal that she's gluten

intolerant, and that her preferred restaurant is gluten free. However, revealing her interests might also have a cost: the rest of the group might suggest a gluten-free restaurant that's nearer, but that the person in question doesn't like.

A negotiation protocol can allow people to reveal their goals—and request others to do the same—at fixed points during a repeated negotiation process. The one we designed was inspired by interest-based negotiation protocols designed for computational agents that allow participants to exchange information about their underlying objectives.⁵

The Colored Trails Game

We evaluated our protocol empirically using Colored Trails (CT; www.eecs.harvard.edu/ai/ct/),

a free testbed that provides an analog to the ways in which goals, tasks, and resources interact in the real world. CT consists of a computer board game in which participants take turns proposing take-it-or-leave-it offers to each other under time constraints.

CT was developed for investigating the decision making that arises in task settings, where the key interactions are among goals, the tasks required to accomplish those goals, and the resources needed to perform the tasks. The empirical investigations described in this article used a particular configuration of CT played by two players on a 5 × 5 board of colored squares. Each player had a designated goal square and a piece on the board, initially located in one of the non-goal squares.

At a CT game's onset, players received a set of seven colored chips chosen from the same palette as the squares. To move a piece into an adjacent square, a player must turn in a chip of the same color as the square. Players have a full view of the board and each others' chips and positions, but they can only see their own goal location.

A CT game comprises three phases. In the communication phase, players alternate between one of two roles: proposer players can offer some subset of their chips to be exchanged with some subset of the chips of

responder players, and responder players can in turn accept or reject proposers' offers. If no offer is made or if each offer is declined, both players are left with their initial allocation of chips. The game controller prevents players from offering chips they don't have or from asking for chips the other player doesn't have. In the

exchange phase, the game controller enforces chip exchanges (if an agreement is reached). Finally, in the movement phase, the game controller automatically moves both players as close as possible to the goal square.

The scoring function for each player depends solely on individual performance: 100 points for reaching the goal, 10 points for each chip left in a player's possession, and 15 points deducted for any square in the shortest path between a player's final position and goal square (in case the goal isn't reached). We chose these parameters so that getting to the goal was by far the most important component, but if a player couldn't do that, he or she could get as close as possible. The score each player received if no offer was made was identical to the score each player received if the responder rejected the offer.

Figure 1 shows snapshots of the CT GUI for the interest-based negotiation protocol of one of the games used in our experiment. The main window panel in Figure 1a includes the board and

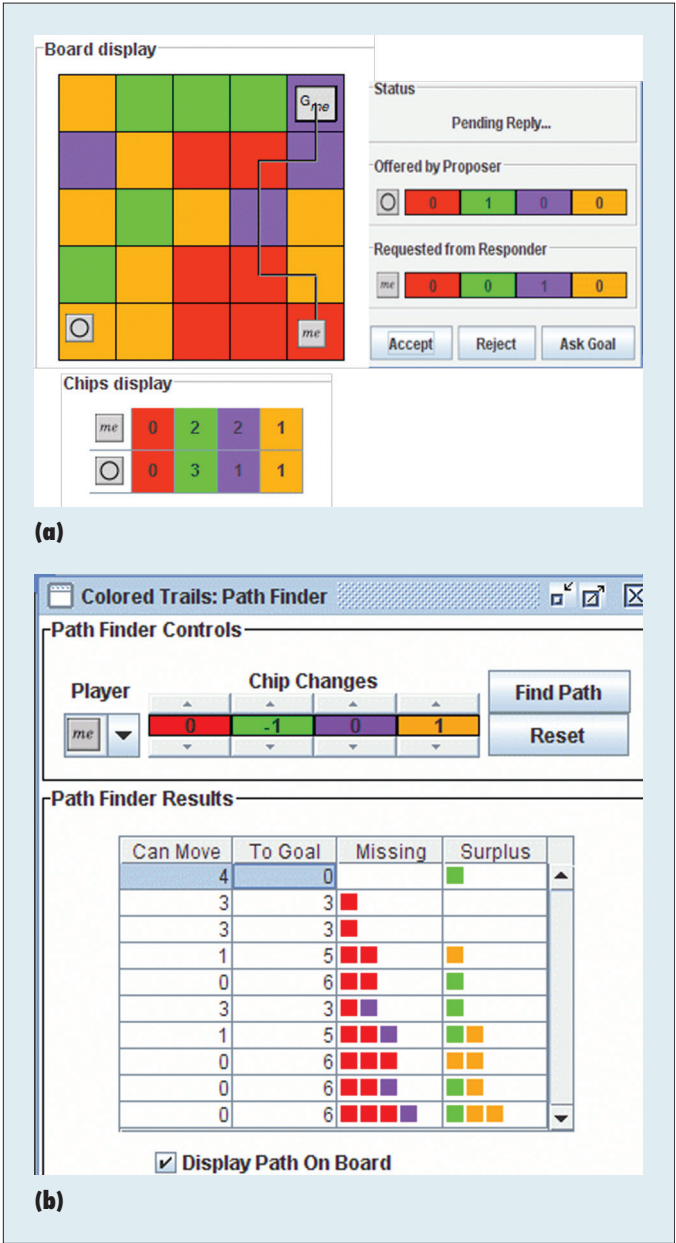


Figure 1. Snapshot of a Colored Trails (CT) game using an interest-based negotiation protocol. The (a) main and pending offer panels and (b) decision-support tool offer players a wide list of options.

using the path outlined on the board, but the O player lacks the chips to get to the goal (note that the O goal isn't shown here). The *me* player has received an offer: one purple chip in exchange for one green chip. The proposer uses the "propose exchange" panel to make the offer or to ask for the other player's goal. The "path finder" panel in Figure 1b provides decision-support tools for use during the game. Specifically, it displays a list of suggested paths to the goal, the missing chips required to fulfill a particular path, the surplus chips left over once a potential path has been fulfilled, and the best position the agent can reach relative to its scoring function. These paths are optimized for a given chip distribution and player, as queried by the player, such that they represent the best route given a player's objectives. Players can view this information for the chip set currently in their possession or for any hypothetical chip set.

Our study adapts and compares two negotiation protocols from the literature in CT. One is called position-based negotiation, wherein each negotiator's communication is limited to proposing exchanges based on their own statically-defined positions. The other, interest-based negotiation, allows negotiators an additional layer of communication to exchange information about the goals that motivate them to negotiate.¹⁰

In both the interest- and the position-based protocols we adapted for CT, neither player can see the other's goal at the game's onset, and players are randomly allocated as proposers or responders.

In the position-based protocol, once a responder receives an offer, it can accept it, in which case the offer is realized, both players automatically move toward the goal, and the game ends. If the responder rejects

the offer, the game controller reverses the players' roles, and the new proposer player (formerly the responder) can make an offer to the new responder player (formerly the proposer). Figure 2a shows a state-based representation of this protocol.

The interest-based protocol is an extension of the position-based protocol that allows players, in a controlled fashion, to ask about and reveal their goals. Once a responder receives an offer from the proposer, he has the option to ask the proposer for her goal, in addition to rejecting or accepting the offer. If the responder chooses not to ask for the goal, the game proceeds as in the position-based negotiation case. If the responder chooses to ask the proposer for her goal, the proposer now has the option to agree to reveal her goal or to make another offer to the responder, which is effectively a rejection of the revelation request. Responders can ask proposers for their goals numerous times, but once a goal is revealed, it can't be asked about or revealed again. Goal revelations are always truthful. It isn't possible to misreport a player's goal in this game. Figure 2b shows a state-based representation.

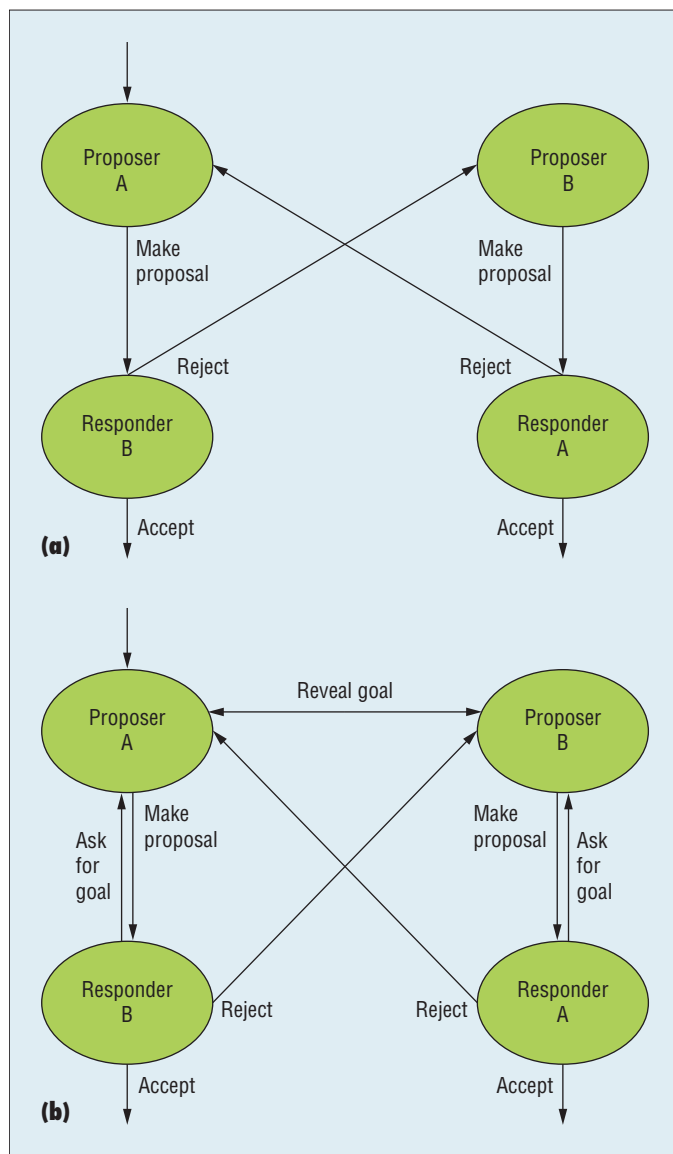


Figure 2. Two alternative protocols for repeated negotiation: (a) a position-based negotiation (PBN) protocol, with the goal revelation disallowed, and (b) an interest-based negotiation (IBN) protocol, with the goal revelation allowed.

Empirical Methodology

For the remainder of this article, we'll refer to the session involving the interest-based negotiation protocol as the *IBN condition* and the session

involving a position-based negotiation protocol as the *PBN condition*. Twenty-two subjects participated in the experiment, drawn from a pool of students and adults residing in the Boston area; 12 people participated in the IBN condition, and 10 in the PBN condition. Each person received an identical 30-minute tutorial on CT and played a series of games in succession.

Subjects' scores weren't revealed at any point during the experiment—we identified each subject with a serial number. The participants sat in front of a terminal for the entire length of the experiment and could not see or speak to any of the other participants (we obtained approval from Harvard's Institutional Review Board on the use of human subjects). No subject was paired up with any other subject more than once, and subjects weren't told about the identity of their counterparts. We paid participants in a manner consistent with their aggregate scores in all the games they played. Between games, players engaged in a neutral activity that didn't affect their payment (answering questions about their mood), designed to minimize the effects of past games on future performance.

We generated the games played from a distribution to meet the following criteria: at least one player could reach a goal, possibly independently, or by some exchange with the other player; and it wasn't possible for both players to reach their respective goals independently. This ensures that it's worthwhile for players to negotiate. For each game, we recorded the board and chip settings, as well as the actions of both players and their associated scores in the game.

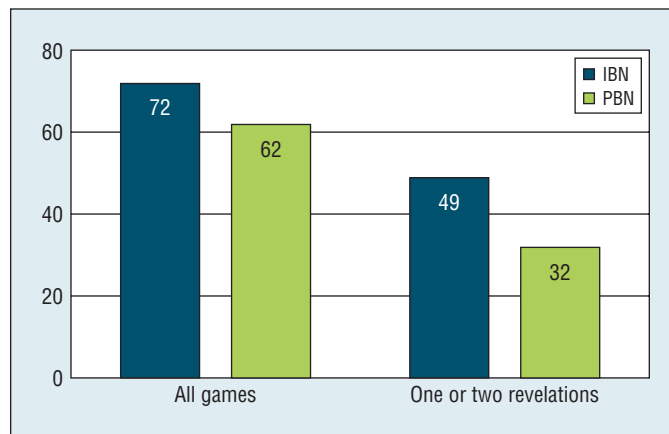


Figure 3. Average benefit in the IBN/PBN condition. The benefit to a player in a game is defined as the difference between the final score in the game and the no-negotiation alternative score.

Results

We analyzed 65 games played in both conditions. In 14 of them, players were codependent (both players needed each other to get to the goal), and in the other 51, one of the players needed the other player. Most IBN games didn't feature a single goal revelation. However, when they were solicited (76 percent of the offers), players revealed their goals more often than not. In 39 games, one goal was revealed—in 10 games, two goals were revealed, making for a total of 59 revelations. In all, at least one goal was revealed in 43 percent of the games.

Figure 3 shows the average benefit to participants in the IBN condition (left entry) and the PBN condition (right entry) when playing the same 65 games. The benefit to a player in a game is defined as the difference between the final score in the game and the no-negotiation alternative score, computed using the scoring function described earlier. If no agreement is reached, a player's benefit is zero. The results are measured with respect to the games in which one or two goals were revealed in the IBN condition (marked "goal revelations") and the total set of games played in both conditions (marked "all games").

As Figure 3 shows, for those games with at least one goal revelation, the

combined average benefit for players in the IBN condition (49 points) was significantly larger than the average benefit for players in the PBN condition (32 points, paired t -test $t(29) = 1.7$; $p = 0.04$). Not shown in the figure is the lack of a significant difference in the players' benefit in the two conditions for those games for which there was no revelation.

However, when considering all games (including those for which there was no revelation), the combined average benefit for players in the IBN condition (72 points) was significantly larger than the benefit for players in the PBN condition (62 points, paired test $t(64) = 1.60$; $p = 0.04$).

Next, we did a pair-wise comparison between the number of games that reached agreement in both conditions. Our analysis revealed that 16 of the games that resulted in agreement in the IBN condition failed to reach agreement in the PBN condition. In contrast, only seven of the games that succeeded in the PBN condition failed to reach agreement in the IBN condition, and this difference was statistically significant: $\chi^2(1; N = 65) = 3.92$; $p = 0.04$. We can thus conclude that goal revelation had a positive effect on the performance of players in the IBN condition, in that it led to higher scores and agreement ratios as compared to the corresponding games in the PBN condition.

The Effect of Players' Dependency Relationships

Table 1 shows the benefit to players as a function of their dependency relationships and the number of goal revelations. Across both conditions, the benefit for dependent players was

Table 1. Average benefit in IBN/PBN conditions for different player dependencies (significant difference in bold).

	Goal revelations		
	0	1, 2	All games
Independent player	19/0	-9/-15	15/-2
Dependent player	49/59	56/35	40/50

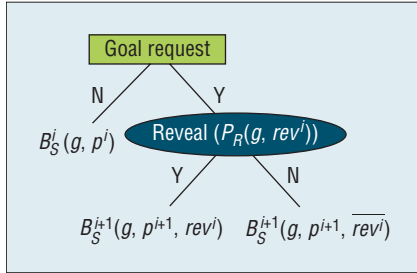


Figure 4. Decision tree for goal-revelation requests.

consistently higher than for independent players. When one or two revelations occurred, the dependent player in the IBN condition gained significantly more benefit than in the PBN condition (56 points versus 35 points, $SE = 2.3$; $t(26) = 2$; $p = 0.02$). (The difference in benefit between the independent player in the IBN and PBN condition (-9 versus -15) wasn't statistically significant.) The overall benefit to independent players in the IBN condition was significantly higher than in the PBN condition (15 versus -2 points, $SE = 2.3$; $t(48) = 2.3$; $p = 0.01$). This is primarily due to their significant gain of 19 points over their PBN scores in IBN games where no goals were revealed.

A Decision-Theoretic Paradigm for Goal Revelation Requests

To demonstrate the significance of our study for agent designers, we used a decision-theoretic approach to make goal-request decisions in the game. The model integrates standard machine-learning techniques for predicting and emulating people's goal-revelation behavior. We refer to participants who queried their partners about their goal as "goal solicitors" and to participants who subsequently revealed

their goal as "goal revealers." Let g denote a CT game, and let $NNA_S(g)$ denote the no-negotiation alternative score for the solicitor S . Let $PO_S^i(g, p^i)$ denote the score for the solicitor that's associated with a proposal p at round i in g . The benefit to the solicitor for this proposal is defined as $B_S^i(g, p^i) := PO_S^i(g, p^i) - NNA_S(g)$.

Consider a solicitor that's reasoning about whether to ask the other participant to reveal its goal after receiving some offer p^i at round i . The outcome of this decision depends on whether the other participant agrees to reveal its goal. Figure 4 shows this reasoning process as a decision tree from the viewpoint of the solicitor agent. The leaves of the tree represent the expected benefit to the solicitor from offers in round $i + 1$ in case the other participant revealed its goal in round i (denoted $B_S^{i+1}(g, p^{i+1}, rev^i)$) or didn't reveal its goal in round i (denoted $B_S^{i+1}(g, p^{i+1}, \overline{rev^i})$). If the solicitor decides not to ask the other participant to reveal its goal, it receives the benefit $B_S^i(g, p^i)$ that's associated with the offer p^i .

The expected benefit to the solicitor from asking the other participant to reveal its goal is defined as

$$\begin{aligned}
 EU_S(g, ask^i) &:= (P_R(g, rev^i) \cdot B_S^{i+1}(g, p^{i+1}, rev^i) \\
 &\quad + \overline{P_R(g, rev^i)} \cdot B_S^{i+1}(g, p^{i+1}, \overline{rev^i})) \\
 &\quad + P_R(g, rev^i) \cdot B_S^i(g, p^i) + \overline{P_R(g, rev^i)} \cdot B_S^i(g, p^i)
 \end{aligned} \tag{1}$$

The expected benefit to the solicitor for not asking to receive the goal is just the benefit of the offer it's given in round i :

$$EU_S(g, ask^i) := B_S^i(g, p^i, rev^i).$$

The optimal strategy for the solicitor is to make a goal revelation request at round i if $EU_S(g, ask^i) > EU_S(g, ask^i)$.

There are two challenges to using this decision tree to make a goal revelation request. First, the other player's revelation decision in round $i + 1$ isn't known to the solicitor at round i . We addressed this by employing a naive Bayes classifier to estimate the likelihood that the other participant will reveal its goal in game g at round i . This is represented by the probability $P_R(g, rev^i)$. For each game g , the features for this classifier represented the information that was available to the solicitor at round i . These features included $NNA_S(g)$ (the no-negotiation alternative score for the solicitor), $B_S(g, p^i)$ (the solicitor's benefit from the proposal at round i), and the round number i . The second challenge is that the proposals in round $i + 1$ aren't known to the solicitor at round i . We addressed this by estimating the benefit of these offers, analyzing data collected on the offers made during the games. We computed the expected performance of the solicitor agent from using the tree to decide whether to ask the other participant for its goal. We limited this evaluation to making goal requests after receiving the first offer in the game. The performance was measured as the expected benefit from offers made or received by the solicitor, given the solicitor's decision whether to request the other's goal. We used the naive Bayes classifier to estimate the probability $P_R(g, rev^i)$.

We compared the performance of the tree-using solicitor to that of people, by simulating human behavior in the game. To this end, we constructed naive Bayes classifiers for emulating people's goal-request and goal-revelation behavior. The features for the classifier for emulating people's goal-request behavior included the

no-negotiating alternative score for the solicitor NNA_S , and the benefit to the solicitor associated with the offer at round i , $B_S^i(g, p^i)$. The features for the classifier for emulating people's goal-revelation behavior represented information that was available to the other participant (the "potential revealer") at round i . These features included the no-negotiating alternative score for the potential revealer NNA_R , and the benefit to the potential revealer associated with the offer at round i , $B_R^i(p^i, rev^i)$.

We measured people's performance by computing the expected benefit from offers in the second round, using an Expectimax tree.⁶ This tree has an identical structure to the decision tree in Figure 4, but the probability of asking and revealing goals were computed using the emulation models described earlier.

We evaluated the decision tree by using it to make goal-revelation requests. For each of the games, we computed the expected utility to solicitors using the decision-theoretic paradigm described earlier. We compared this expected utility with that incurred by people, using the emulation model to compute the likelihood that people actually reveal their goals. A computer agent using the decision-theoretic paradigm would choose not to ask for goal revelation in a game if the likelihood of revelation was lower than 44 percent. We used 10-fold cross validation to learn the parameters for the classifiers; all the classifiers achieved precision and recall measures above 70 percent, significantly better than random guessing. The average benefit to goal solicitors using the decision-theoretic model to make decisions was -5.04 , which was significantly higher than the average benefit to people (-6.4 , t -test, $p = 0.03$). This shows that combining decision-theoretic modeling

with standard machine-learning techniques can form the basis of an agent design for making decisions with people in our setting of choice.

Our results establish the role of IBN protocols as mechanisms of cooperation in settings of incomplete information. It also demonstrates the efficacy of using decision-theoretic and standard machine-learning techniques to computationally model people's behavior in such settings. We found that, generally, dependent players are likely to reveal their goals when asked, and this information usually isn't abused by solicitors. Indeed, they choose to use this information as a tool for assisting the revealers. The resulting net gain to goal revealers also increases the social benefit of both participants. Solicitors generally dislike asking for others' goals and choose to do so mainly in cases where there are few other avenues open for beneficial exchanges.

There are few empirical studies of human negotiation strategies in repeated interactions, so our study is significant. Ariel Rubinstein⁷ provided a theoretical model for prescribing negotiating strategies that are optimal under certain conditions. Other work in psychological literature about strategic interaction has focused on specific domains (seller-buyer disputes⁸ or completely abstract settings such as the prisoner's dilemma). Jeffrey Loewenstein and Jeanne Brett⁹ conducted a study that studied how goal framing prior to the negotiation procedure affects strategy revision. But none of these works compared the effects of goal revelation directly within repeated negotiation. Work in automated negotiation in AI has proposed algorithms for argumentative strategies that support or

attack the different positions of parties in a negotiation.^{10,11} This work directly extends these studies by showing that argumentative-type protocols are advantageous to people.

But ultimately, our study is significant for the study of computer-mediated negotiation in two ways. First, it shows that computer systems can facilitate people's goal revelation decisions in negotiation, let them reach more beneficial agreements, and improve their overall performance. Second, it demonstrates the efficacy of using computational approaches to model people's goal-revelation behavior when negotiating under incomplete information. ■

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