An Effective Conversation Tactic for Creating Value over Repeated Negotiations

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ABSTRACT
Automated negotiation research focuses on getting the most value from a single negotiation, yet real-world settings often involve repeated serial negotiations between the same parties. Repeated negotiations are interesting because they allow the discovery of mutually beneficial solutions that don't exist within the confines of a single negotiation. This paper introduces the notion of Pareto efficiency *over time* to formalize this notion of value-creation through repeated interactions. We review literature from human negotiation research and identify a dialog strategy, *favors and ledgers*, that facilitates this process. As part of a longer-term effort to build intelligent virtual humans that can train human negotiators, we create a conversational agent that instantiates this strategy, and assess its effectiveness with human users, using the established Colored Trails negotiation testbed. In an empirical study involving a series of repeated negotiations, we show that humans are more likely to discover Pareto optimal solutions over time when matched with our favor-seeking agent. Further, an agent that asks for favors during early negotiations, regardless of whether these favors are ever repaid, leads participants to discover more joint value in later negotiations, even under the traditional definition of Pareto optimality within a single negotiation. Further, agents that match their words with deeds (repay their favors) create the most value for themselves. We discuss the implications of these findings for agents that engage in long-term interactions with human users.

Categories and Subject Descriptors
I.2.11 [**Artificial Intelligence**]: Human-agent Interaction – *virtual humans*

General Terms
Design, Experimentation, Human Factors.

Keywords
Human-agent interaction, Competitions among agents and humans, Teamwork in human-agent mixed networks

1. INTRODUCTION
Negotiation has become an important research topic in artificial intelligence, both in distributed problem solving (where fully autonomous agents must negotiate with each other) and human-machine interaction (where virtual agents must negotiate with human users). The central challenge in negotiation (which has to be solved by either humans or computers) is that it involves an apparent conflict between collective and individual self-interest: individuals typically want to maximize their own self-interest but must be cooperative enough to get the other side to agree. This often results in a tug-of-war where parties fight over how to distribute a fixed set of resources. However, the fact that preferences are sometimes asymmetric creates the opportunity to find win-win solutions that "grow the pie." A classic example of this is the fable of the two sisters that fought over an orange only to finally understand that one wanted the peel and the other wanted the juice. Thus, success for both human and machine negotiators requires an ability to discover solutions that, like the sisters and their orange, simultaneously satisfy both parties' interests.

Research on automated negotiation agents has focused on a specific notion of value-creation known as Pareto efficiency. A negotiated solution is Pareto efficient if it is impossible to improve one party's prospects without making the other's worse. To make this precise requires some representational assumptions, and we adopt a common formalism known as the bilateral multi-issue bargaining task [16]. Thus, the fable of the orange can be viewed a bilateral exchange (between the two sisters) involving two issues (the juice and the peel). In such negotiations, each party receives some (partial) utility for obtaining each issue and these utilities are often unknown to the other party (in the fable, each sister believes the other wants the same thing, whereas they have asymmetric preferences). Achieving Pareto efficiency requires a number of inferences. An algorithm must infer what the other party wants, integrate this with its own preferences, and search for a solution along the frontier of efficient solutions.[1] This is complicated by the highly restrictive way such algorithms typically communicate: e.g., solely by the exchange of offers [2]. Humans, and now virtual humans, can use richer forms of signaling such as spoken dialog [32], [33] and nonverbal communication [13], but little research exists to guide the effective use of these richer channels.

This paper explores an alternative form of value-creation, called Pareto efficiency *over time,* which becomes possible when parties are able to communicate more freely, such as through natural language. Prior negotiation research has focused on getting the most value from a single negotiation, yet real-world settings often involve repeated serial negotiations between the same parties. Repeated negotiations are interesting because they allow the discovery of mutually beneficial solutions that don't exist within the confines of a single negotiation. An example of this would be if each sister required the whole orange (maybe they needed to throw it at their husbands occasionally). If they were able to trade the orange back and forth each week, they could both satisfy their needs in a way that wouldn't be possible in a single negotiation. Pareto efficiency over time is rarely considered in the

Appears in: *Proceedings of the 14th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2015), Bordini, Elkind, Weiss, Yolum (eds.), May, 4–8, 2015, Istanbul, Turkey.*

computational literature [1], although it is an important tactic taught to human negotiators. In this paper, we describe and evaluate a dialog strategy that allows automated agents to establish a value-creating relationship with human users across time.

Business students are taught a variety of methods for creating Pareto efficiency over time. One common approach is known as *favors and ledgers* [28]. The intuition is to request a locally-unfair outcome now—a "favor"—in exchange for returning the favor in the future. Negotiators (informally) maintain a "ledger" to tally who owes what. This approach can be transformed into a formal mechanism. For example, a credit card exchange allows the transfer of goods now for a promise to pay later. Here, motivated by our interest in virtual humans, we investigate social mechanisms for enhancing joint-value, specifically signaling: for example, if an agent simply asked for a favor through natural language (i.e., signaled the intent to follow a favors and ledgers strategy), would this facilitate more efficient solutions across time?

In this paper, we demonstrate the potential benefits of "favor language" within a modest extension of the Colored Trails framework, a multi-player computer game frequently used to study negotiation between people and agents [21]. Colored Trails is able to generate a series of multi-issue bargaining tasks in which our agent can act. We make several contributions. First, we show that agents can use favor language to enhance joint rewards and Pareto efficiency *over time*. Second, we show that people discover more efficient solutions when agents use favor language, *even if agents fail to deliver on their promises.* Favor language seems to make people more focused on tradeoffs in the negotiation, allowing them to grow the pie. When agents fulfill their promised favors, this "created value" is shared with agents fairly, but when agents fail to deliver on their promises, people punish agents by withholding this value (a *cost of betrayal)*. We discuss the potential value of these techniques for agents who aim to engage in repeated interactions with other social actors.

2. BACKGROUND

2.1 Negotiation Games

Negotiation, both embodied and disembodied, is an important research topic across multiple scientific domains. Multi-issue bargaining, in particular, serves as *de facto* standard for research into social cognition, distributive problem solving and interpersonal skill-development. In artificial intelligence, this task serves a standard challenge problem for advancing automated models of social decision-making [2] and has practical importance across a variety of domains such as energy conservation [30]. In emotion research, bargaining tasks are used to examine how signaled or induced emotion shapes joint outcomes [34]. In conflict-resolution research it is used to study various social processes involved in resolving disputes [7]. In social neuroscience, it is used to examine specific brain regions associated with social cognition [4]. In game theory, it is used to advance rational models of multi-party decision-making [24]. Finally, in educational settings, bargaining games are used to teach a wide range of interpersonal skills including negotiation, conflict-resolution, teamwork, emotional intelligence and inter-cultural fluency (e.g., see the leadership exercises at the Northwestern Dispute Resolution Research Center). Educational contexts specifically may have other pedagogical goals outside of simply optimizing the negotiation strategy, for which adequate relationship models between partners are essential [35]. By developing methods to enhance the efficiency of negotiation outcomes, we expect this research will have broad impact.

In this context, repeated negotiations, and the formal and informal relationships therein, are important but often overlooked. The dynamics of relationships between negotiating partners play a critical role in the final outcome of many multi-issue tasks; indeed the relationship between truthfulness and trust—as well as eventual outcome—has been well established in the business and negotiation literature. However, designing agents that respond robustly to such "relational factors" is not often seen as critical, especially in many of the applications where virtual negotiators excel, such as online marketplaces.

2.2 Pareto Efficiency over time

The multi-issue bargaining task makes several simplifying assumptions that allow algorithms (and human participants) to efficiently reason about task-tradeoffs while retaining the core elements of real-world negotiations. Offers are typically formalized as an allocation (or level) on each of a number of distinct issues. For example, we might represent the orange from our earlier example as having two issues (juice and peel), each with three levels (give all to side A, split 50/50, or give all to side B). Each party assigns some utility to a deal (often formalized as a linear combination of weights associated with each issue allocation). Often this utility function is unknown to the other party and must be discovered either by communication or through the exchange of offers. Often there are incentives to misrepresent hidden information (e.g., lying about preferences or making and breaking promises), so that trust becomes a significant facilitator or obstacle to efficient solutions.

Within a given negotiation, division of resources between competing sides can be represented graphically by the set of points representing the utility that each participant receives from a given distribution. Each point that does not generate strictly less utility for both parties is considered to be Pareto optimal (lying on the Pareto frontier). Formally, given a set S of points representing the joint utility of a deal, the set of Pareto optimal points P is defined as:

$$P = \{p\} \mid \forall\ p \in S, \nexists\ q \in S, (p_x < q_x \vee p_y < q_y)$$

Thus, points falling below the curve generated by these points are considered sub-optimal (or "inefficient"), as it could be improved for one player without harming the other.

Unfortunately, when repeated negotiations are allowed to occur, simply combining Pareto optimal solutions in each individual negotiation can be arbitrarily inefficient over time. This is clearest when the Pareto frontier is convex (Figure 1). In this case, the "fair solution" (an even split, illustrated as deal "A" in Fig. 1), while efficient for that game, will lead to a solution for the combined game that is well below the Pareto optimal one. Conversely, choices B1 and B2 are efficient but unlikely to occur as they would be seen unfair, but combine to form a Pareto efficient solution *over time.* Formally, we can define this in the two-game solution as:

$$P_2 = \{p_1 + p_2\} \mid \forall\ p_1, \in S_1, \forall\ p_2 \in S_2, \nexists\ q_1 \in S_1, \nexists\ q_2 \in S_2$$

$$(p_{1x} + p_{2x} < q_{1x} + q_{2x} \vee p_{1y} + p_{2y} < q_{1y} + q_{2y})$$

Repeated negotiations over time allow the notion of "efficiency" to change. Favors and ledgers is one approach of social interaction that allows parties to discover and achieve such efficient solutions, by recognizing the implications of the change.

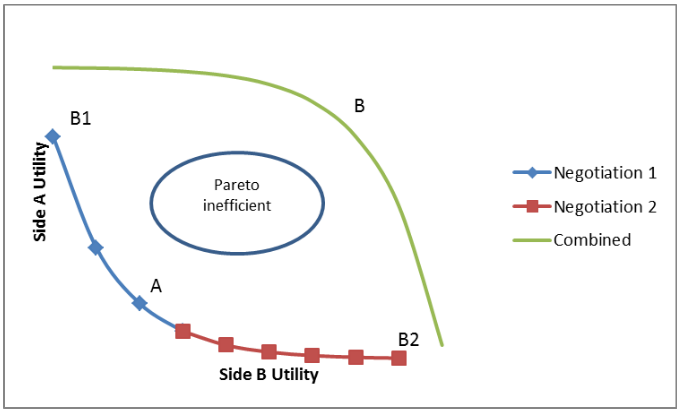

Figure 1: The space of negotiation options in a simple, two-game repeated interaction

Returning to the example of the sisters and the orange, if one sister realizes that she will get more oranges in the future, she might ask for a favor of the orange now, with the promise of returning the favor in some future negotiation. This technique of "banking" joint value can be very effective in negotiations, and help establish mutually beneficial relationships between negotiation partners [28]. Even in situations where payoffs are uncertain (one sister isn't sure her sister likes the peel), exchanging favors is still a viable strategy. Malicious manipulation of favor returns, in which one party claims to incur a favor by accepting a poor deal when in fact it was a good deal for them, is also possible.

2.3 Ultimatums and BATNA

Negotiations typically involve some give and take between parties but ultimately a point is reached where parties must decide to "take it or leave it." In the real-world, parties often have the option to walk away from a negotiation without a deal. For example, when negotiating the price of a new car, a smart negotiator already knows what price they could obtain at another car dealer. This allows them to abandon negotiations if they fail to improve upon this alternative. The concept of BATNA (Best Alternative To a Negotiated Agreement) is used to capture this notion. Many negotiation games provide each player a BATNA to represent the value they receive from walking away. In general, each player's BATNA may be unknown to the other party and not necessarily equal (if one player has a larger BATNA, this gives them more power in the negotiation).

The concept of BATNA helps link negotiation research with the rich literature on ultimatum games. Ultimatum games involve two parties—a proposer and a responder—who decide on a split some pie of resources (usually a sum of money). The proposer offers a split, which the responder may then choose to accept or reject. Acceptance results in the resources being split across the proposed lines, while a rejection results in both parties receiving a BATNA (which is zero in the classical formalization but can be any percentage of the total pie). Thus, the multi-issue bargaining task can be viewed as straightforward extension of the ultimatum game: allowing multiple pies (issues) and allowing responders to counter-propose back-and-forth some number of times. Alternatively, an ultimatum game is a special case of multi-issue bargaining with a single issue and only one round of propose-respond. Game theorists go so far as to argue the addition of multiple rounds adds no generality as "talk is cheap" and, ultimately, all negotiations collapse to an ultimatum.

We build on these concepts in the experiments below. We formalize negotiations as multi-issue bargaining, allowing multiple issues but, for simplicity and to reduce the cognitive burden on participants, we only consider a single round of propose-respond. Thus, each negotiation can be viewed as a multi-issue ultimatum game.

In our domain, we utilize repeated ultimatum games as the units of negotiations as this decision allows us to directly measure the amount of joint value discovered by the proposer. This history of ultimatum games can be to establish concepts like trust and favors as in games with multiple rounds of propose-respond. But, maintaining an accurate ledger is more critical, as each negotiation is self-contained, and all proposals are final. By measuring the amount of joint value generated both over time and within a single negotiation, it is possible to analyze both Pareto efficiency and Pareto efficiency over time in the same domain.

2.4 Human-Agent Interaction

Our immediate motivation behind this work is to inform the design of virtual humans for teaching negotiation skills, by validating the effectiveness of human negotiation tactics in a virtual context. Virtual humans have shown promise for teaching a variety of interpersonal skills [3]. An important aspect of such teaching is deliberate practice, usually with human role-players. Virtual humans can augment this training by serving as role-playing partners that are infinitely patient, always consistent with pedagogical principles, and able to explain their behavior in terms of course lessons. Some research has already explored the potential of virtual humans for negotiation training [6],[9], and this study aims to build upon this body of research and extend its applicability to situations where negotiations repeat over time.

Most automated approaches to negotiation have focused on agent-agent interaction and make strong limits on the type of information that can be exchanged between parties. More recently, there is growing interest in algorithms that can negotiate with people, either to resolve [22] or mediate conflicts [8], or to teach negotiation skills [12]. These agents incorporate more complex forms of signaling, such as emotional reactions to offers [13] or natural-language dialog [32] and sometimes involve sophisticated virtual embodiment [12]. Although some research has sought to provide a foundation for using these richer communication channels (e.g., [14] provides a framework for emotional signaling), most of this research has focused on short-term interactions and single negotiations. The present work investigates the use of natural-language dialog to facilitate Pareto efficiency across multiple negotiations.

Our agent operates in a negotiation domain characterized as multi-issue, and participates in a string of repeated negotiations with a human participant. The key aspect of repeated, multi-issue negotiations that we explore is that there may be optimal solutions that can only be discovered by contemplating several negotiations at once as the unit of analysis—a concept that has been considered when deliberating decision processes [23]. However, the question of what may encourage these superior instances of "integrative potential" to be discovered by one or both negotiators is not fully understood. The subjective opinion of value gained by each negotiator can have an effect on objective value discovered later [16], but we are interested further in *intentional* methods by which an agent might also increase this joint value. To that end, we manipulate both signaling future positions through negotiation actions as well as through language to show an effect on integrative potential discovered in future negotiations. We are interested in observing both the propensity to discover Pareto efficient solutions over time as well as Pareto efficient solutions occurring within a single negotiation.

The notion of signaling intention facilitates the favors and ledgers technique, in which one party may accept an unfavorable agreement in the current negotiation with the expectation that it will receive a similar treatment from its partner in a subsequent negotiation [28]. If favors are issued during negotiations that have little utility for the offering agent and are received during negotiations that have more utility, integrative potential can be achieved by both parties. However, such practices rely on trust, and violating the expectations established by prior signaling could be considered a betrayal. There is often a notable *cost of betrayal* associated with this behavior, though it stands to reason that this cost may or may not outweigh the short-term benefits that can be reaped from malicious or selfish action [25],[26].

3. GAME DESIGN

The use of virtual agents to elicit and analyze particular behaviors of humans in human-agent negotiation contexts has been well established [15]. While previous efforts can be framed as signaling behavior using emotional displays from fully realized virtual humans, our efforts signal intention using both behavior and language selection. To realize the multi-issue, multiple-negotiation domain that we explore, we used the Colored Trails testing framework. Colored Trails is a negotiation testbed for analyzing the strategies of participants, and has been used in several types of games, including revelation games [20],[29]. Our design involved a version of the interface that was deployable via the web and customized to allow our agent to engage in multi-issue bargaining games.

In Colored Trails, players both start with a set amount of different-colored "chips". By expending a chip, a player can move one space on the board of a similar color, with the intent to move toward a goal location. In our version, the closer a player gets to the goal, the more points they receive. The set of spaces that can be reached with the current set of chips is highlighted green on the board at certain stages of the game, which limits incidence of players choosing suboptimal routes (Figure 2).

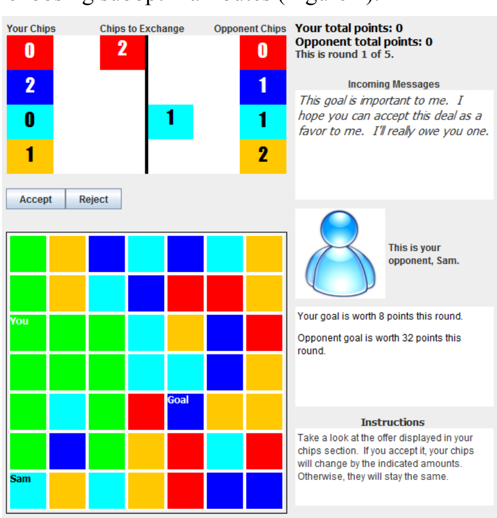

Figure 2: Web-deployment of Colored Trails framework

For an agent to be successful, it should endeavor to allow parties to discover as much integrative potential as possible. By maximizing this joint value, there is a greater amount that can be distributed. For pedagogical or teaching agents, this may be the end goal, as instructing human negotiators to discover such value may be sufficient. In competitive or optimizing contexts however, this strategy is also beneficial so long as it then results in some additional portion of the larger value being assigned to the agent by the other party. What is not clear is what the driving force behind this joint value may be.

We hypothesized that cueing participants to look for joint value across games by signaling a willingness to engage in favors through simple chat messages might be sufficient to generate discovery of joint value.[2] While we are primarily interested in showing that this can be an effective strategy for finding previously unattainable Pareto efficiency over time, cueing participants with behavior or action may yield greater ability to discover joint value even within a single negotiation. However, it is possible that while this may result in a greater joint value, it would also result in a greater share of that value being allocated to the player, with no benefit to the agent. Furthermore, a complex interaction may exist between signaling through action and signaling through language; a mismatch may be considered a betrayal from the human player's point of view and result in a much smaller share being allocated to the agent than would otherwise be attainable. The effects of culture, especially that of collectivist cultures, are known to affect negotiation results and may have a complex interaction with cueing favor exchange. To simplify our system, our design is such that it is optimized for U.S. participants, and subjects were chosen accordingly.

To effectively measure these issues, a multi-issue game consisting of five negotiations was designed in the Colored Trails framework. The first four negotiations are comprised of multi-issue ultimatum games where the agent acts as the proposer. These negotiations are set up to create two separate instances of integrative potential over time (Table 1). The player, acting as the responder, has the option to accept the offer, or to reject it and receive their BATNA. Since the BATNA of the player is known, the agent is capable of providing two broad classes of offers. "Poor" offers would result in a value for the player that is less than his/her BATNA, while "Good" offers would result in a value for the payer that is more than his/her BATNA. In a single negotiation, accepting offers less than one's BATNA is an irrational decision. However, if a participant wants to signal acceptance of a favor, it may be helpful to accept an offer below one's BATNA in order to hopefully signal reciprocal behavior in the future.

Broadly speaking, the agent could choose to offer either a poor or a good offer, and could also choose to frame it as a demand for a favor or not. After some combination of poor or good offers in the first four rounds, the player was given a chance to respond in the final round by crafting an offer. By measuring both the total value discovered in the final round as well as the balance of allocation between the player and the agent in that round, we were able to directly measure the integrative potential discovered, and measure the benefit of cooperation/cost of betrayal.

Table 1: Pareto optimality over time for a favor-seeking agent

Round 1	Favor opportunity	Integrative potential possible
Round 2	Return-favor opportunity	
Round 3	Favor opportunity	Integrative potential possible
Round 4	Return-favor opportunity	
Round 5	User-proposed offer	Joint value discovered?

The first four negotiations serve to establish a ledger. Depending on condition (favors returned vs. favors never returned), the ledger may be even or uneven. The favor language regulates how salient this ledger is made. In the final negotiation, with the user as the proposer, we see if establishing this relationship allows the user and agent to discover more efficient solutions within a single negotiation. This result would parallel more of the traditional, single-game unit of analysis that has been performed in prior literature. This motivates our 2 (favors returned vs. favors never returned)[3] by 2 (favor language vs. generic language) design (Table 2).

Table 2: Agent types in experimental conditions

	Favors returned	Favors never returned
Favor framing	Favor-seeking	Betraying
No favor framing	Cooperative	Competitive

4. EXPERIMENTAL DESIGN

Two hundred and sixty-nine participants were recruited using Amazon's Mechanical Turk service to participate in our study, with 151 males and 118 females. Participants were asked to affirm that they met our minimum requirements (over age 18, not color-blind, native language of English, U.S. resident), and all those that did were accepted. We screened out all responses that came from IP addresses outside the US. The requirements were chosen to maximize understanding of the natural language used as well as minimize effects stemming from cultural differences.

In this study, all participants interacted with a virtual agent. They were told that the system they would use had a computerized agent using artificial intelligence to conduct the negotiation. The agent was represented simply with a non-moving chat avatar, a gender-neutral name, and a box that represented messages sent by the agent. This simplified design was chosen to allow the natural language selected to be the driving force behind any effects, rather than the known effects of emotional expression in more lifelike virtual agents.

Participants were identified by an anonymous unique ID assigned by Mechanical Turk. Participants first took part in a pre-game survey that contained a short video tutorial explaining the basis of the Colored Trails game. They then participated in five negotiations within the game. The first four negotiations involved them acting as the responder in a multi-issue ultimatum game, and the final round involved them acting as the proposer. The participants were not informed about the nature of ultimatum games or anything about the behavior of the agent, but were simply told that they would play for five negotiations, and that in some negotiations they would have to respond and in others they would have to craft an offer themselves. Participants were paid a flat, market rate for their participation on Mechanical Turk. They were also informed that they would earn "lottery tickets" based on the number of points they accrued in the game. These tickets were used to enter them in a drawing for several $10 gift cards, which was awarded after the conclusion of the study.

In the design of the agent, we manipulated both its ability to signal intention using messages in the chat window as well as its ability to signal intention by varying the quality in offers. Thus, the experiment was comprised of a 2 (offer language framing) by 2 (offer quality) design. The design and the reference names of the agents are shown above in Table 2.

The favor-seeking agent always asked for a favor in the first and third rounds. If that favor was granted by the player, then the agent always reciprocated the favor explicitly through text "Hey, thanks for doing me that favor before. Let me help you out in return." and implicitly through a beneficial offer in rounds 2 and 4. If the favor was not granted by the player, the agent still made a beneficial offer in rounds 2 and 4, but used more generic language such as "I think you'll find this offer to be satisfactory." Please refer to Table 3 for a comprehensive description of all language used by the agent.

Table 3: Language used by the agent[4]

Round	Generic Language	Favor Language
1	"I think this deal is acceptable."	"This goal is important to me. I hope you can accept this deal as a favor to me. I'll really owe you one."
2	"I think you'll find this offer to be satisfactory."	"Hey, thanks for doing me that favor before. Let me help you out in return."[5]
3	"I think this arrangement is fair."	"This goal is important to me. I hope you can accept this deal as a favor to me. I'll really owe you one."
4	"I think this deal will interest you."	"Hey, thanks for doing me that favor before. Let me help you out in return."[5]
5	"Ok, I am ready to receive your offer!"	"Ok, I am ready to receive your offer!"

The betraying agent acted identically to the favor-seeking agent in rounds 1 and 3, but always gave poor offers and always used generic language in rounds 2 and 4.

The cooperative agent always used generic language in all rounds, but gave beneficial offers in rounds 2 and 4.

Finally, the competitive agent always used generic language and always gave poor offers.

Although the betraying agent misrepresents its intent to return favors, none of our agents lie about the actual return of favors. The betraying agent does not claim to return favors when it does not, nor does the favor-seeking agent claim that it failed to return a favor when it has done so. Such a manipulation would in essence decompose condition into a further four cells, and is not covered by this study.

Table 4: Payoffs Per Round

Round	Favor-seeking or cooperative (player : agent)	Betraying or competitive (p : a)	BATNA (p : a)
1	1 : 32	1 : 32	2 : 8
2	32 : 1	4 : 8	8 : 2
3	1 : 32	1 : 32	2 : 8
4	32 : 1	4 : 8	8 : 2

Each round of the game offered differing payouts to each side of the negotiation, and each party was capable of scoring a fraction of the points even if no agreement was reached. However, agreements could be used to maximize points across pairs of rounds. For example, not reaching agreement on rounds 1 or 2 would result in the payout:

Agent: 8 points, 2 points = 10 points

Player: 2 points, 8 points = 10 points

whereas one possible agreement might yield the payout:

Agent: 32 points, 1 point = 33 points

Player: 1 point, 32 points = 33 points

The latter example lies on the Pareto Optimality frontier for the pair of games, whereas the former does not. However, if each game is considered individually, the (8,2) solution does lie on the Pareto frontier for that individual game. Thus, only by choosing the far less fair solutions at the extreme of any individual negotiation's Pareto frontier can the combined Pareto frontier over time be reached. The payoffs available in each condition and the respective BATNAs are detailed in Table 4.

In the final round, participants were allowed to make an offer to the agent. All agent types accepted any offer proposed, and the total points that were received by the agent and the player represented a measure of the integrative potential in that negotiation.

After concluding the game, participants were asked to complete a post-game survey where several additional measures were collected, and manipulation/attention checks were performed [27]. Those participants that failed any of the four check questions were excluded. These exclusions left 167 participants, 100 male and 67 female, with 38, 40, 48, and 41 in the favor-seeking, betraying, cooperative, and competitive conditions, respectively. Out of the 269 participants recruited, 167 were retained, for a 38% drop-out rate (which is comparable to other Mechanical Turk studies).

5. EVALUATION AND RESULTS

Our primary goal is to show that the Pareto efficient solution over time is reached more often by those players that engage in favor exchange than by those that do not. From this, we can also explore the potential cost of betrayal as well as any effect favor language may have on discovering Pareto solutions even in the single-game case. As such, we first examine the individual actions that take place over time during the first four negotiations. Then, we observe the final round to confirm the effects of cueing on the single-game case.

We hypothesize that Pareto optimality will be discovered specifically by players that actually accept requests for favors. We seek to show that human players that engage in repeated favor exchange are more likely to discover Pareto optimal solutions over time when available (when good offers are present).

For players that accept favor requests in the first negotiation, we run a χ^2 analysis to determine how many subsequently discover the Pareto optimal over time solution for the third and fourth negotiations. We find a significant positive effect of favor framing on Pareto optimal discovery, χ^2 [1, N = 73], = 14.93, $p < .001$. This distinction is visible as the large difference between the first and second columns in Figure 3.

Additionally, a log-linear analysis confirms an interaction between favor framing and offer quality, indicating that agents that promise favors but fail to return them are discovered easily by players. The player is less likely to accept offers if the human has been betrayed by the agent (χ^2 [4, N = 73], = 16.88, $p = .002$). Thus, even when Pareto optimal solutions are unavailable due to the actions of the agent, betrayals lead to a far lower rate of offer acceptance than can be explained by the mere quality of offers. This difference is expressed by the depressed rate of acceptance seen between columns 3 and 4 in Figure 3.

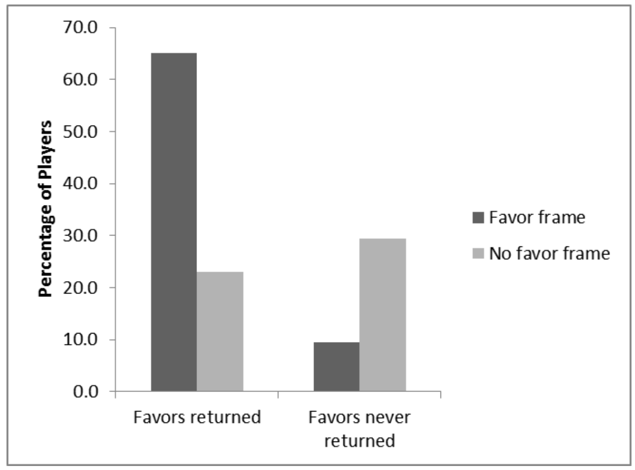

Figure 3: Percentage of players that accept both ultimatums in negotiations 3 and 4

Decomposing the exact relationship between betrayal and offer acceptance requires examining the particular sequence of offer acceptances in the rounds leading up to the betrayal. Although the "betrayal" agent consistently asked for favors and never returned them in subsequent negotiations, it is noteworthy that this behavior may not necessarily be interpreted as betrayal in the eyes of the player. If, after asking for a favor in the first negotiation, the player refuses to cooperate, then the agent's subsequent action to offer a poor deal in second negotiation should not be interpreted as betrayal, but rather as a "tit-for-tat" strategy. To accurately measure this true cost of betrayal, we specifically want to examine those participants that both accepted an offer in the first negotiation that was framed as a favor, and then subsequently received a poor offer in the second negotiation. Our 2x2 conditional design was thus decomposed into 8 cells by further conditioning on offer acceptance in the first negotiation. This decomposition of state from negotiation 3 onwards is summarized in Table 5.

To examine the betrayal distinction, we looked specifically at the third negotiation, which is the first place in which a betrayal could have occurred (the agent didn't return a promised favor in the previous negotiation). A 2x4x2 log-linear analysis of condition versus acceptance rate, dependent on the player agreement in the first negotiation revealed a significant effect of condition on acceptance rate, χ^2 [10, N = 167], = 29.98, $p = .001$.[6]

Table 5: Betrayal condition decomposition

Favor asked in negotiation 1?	Player agrees to offer in negotiation 1?	Good offer given in negotiation 2?	Description of state
Yes	Yes	Yes	Favor returned
Yes	Yes	No	Betrayal
Yes	No	Yes	Altruistic
Yes	No	No	Tit-for-tat
No	Yes	Yes	Tit-for-tat
No	Yes	No	Competitive
No	No	Yes	Altruistic
No	No	No	Tit-for-tat

To decompose the results of our 3-way log-linear analysis, we conducted two follow-up 2x2 χ^2 analyses—one among participants who chose to accept the offer in round one, and one among those who chose to reject it. This subsequent χ^2 analysis showed that this effect was driven by the betrayal cell; that is, the situation in which the player conceded to agent demands for a favor early on but never received any favor in return (Figure 4)[7]. For players that did accept the first offer, and were thus capable of being betrayed, the effect was significant, χ^2 [1, N = 73], = 12.17, p < .001, whereas for players that did not accept the first offer, there was no significant effect, as predicted: χ^2 [1, N = 94], = 4.67, p = .198.

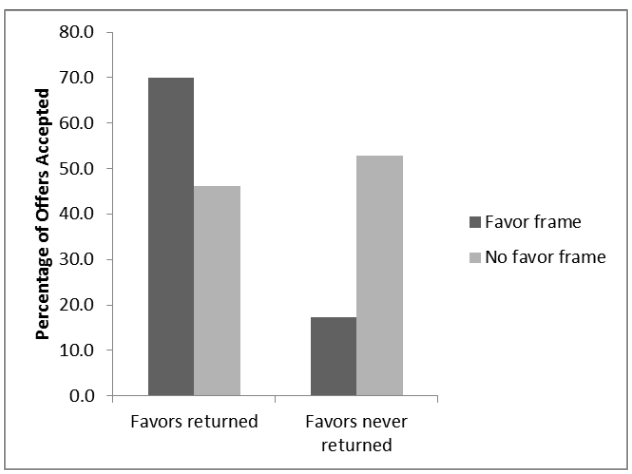

Figure 4: Acceptance cost of betrayal as measured in negotiation 3

Our analysis has revealed not only that human participants are very aware of the language used in negotiations, but also that this language can translate into real costs for the agent employing them.

Many situations create an apparent conflict between efficiency and self-interest, but this conflict can be reconciled if value is exchanged across time, and specifically, favor language can enhance self-interest by cuing parties to search for and discover more efficient solutions. Having shown that human players are more able to discover complex Pareto efficient solutions over time when appropriately primed (and are willing to punish their partners for betrayal), we now examine the final negotiation in our study, in which the player takes on the role of proposer. The final game is structured so that initially, the resources of each player would allow the player to receive 8 points. Solutions exist where one or both players can achieve a result as high as 16 points. The joint value in this game can thus be represented by the combined total points from each side, with 32 being the maximum combined utility. If this joint value is indeed elevated following a favor-language framing, we can extend our results to include Pareto efficient solutions even in negotiations that do not have an "over time" optimal solution.

We performed a univariate analysis of variance (ANOVA) to examine the effect of the experimental condition on the joint value discovered in the final round. The effect of the language chosen in the preceding rounds was found to have a significant effect on the joint value discovered, with the presence of favor language increasing joint value, $F(1, 163) = 5.15$, $p = .025$, $d = 0.36$.[8] Without using favor language, the player was only able to discover 22.19 points of value, but this increased to 25.03 points when engaging in previous negotiations in which the agent specifically asked for favors (see Figure 5). This effect was found regardless of the quality of the offers received by the player; indeed in the condition characterized by the "betrayal" agent, the player would have received no good offers at all. The main effect of the favor framing on joint value discovered is in line with our previous hypothesis regarding cueing: by being made aware of the presence of potential tradeoffs within negotiations, human players are more able to discover joint value *regardless* of the helpful or betraying nature of the agent up to this point.

Having established this creation of joint value, we then wish to examine the effect of the qualities of the offers made in previous negotiations on its distribution. As the concept of joint value explicitly collapses the distribution of points between participants, we wished to examine specifically the points garnered by each side in the final negotiation. To examine more closely this relationship, we ran two subsequent univariate ANOVAs to see the effect of the differing agent strategies used on the player's points and the agent's points in the final round, respectively.

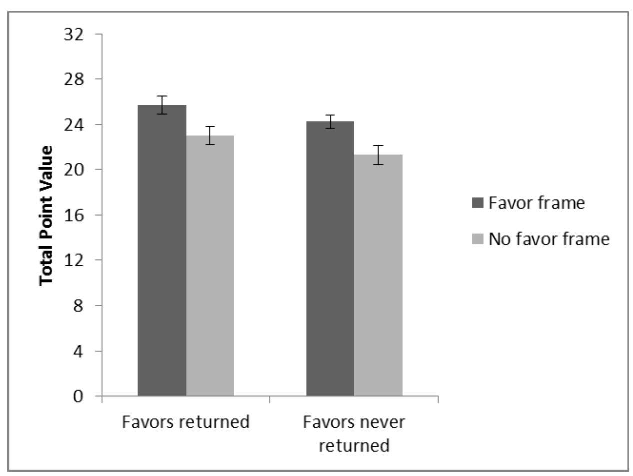

Figure 5: Total joint value discovered by the user in the final negotiation

The points retained by the player in the final round were found to positively correlate with the agents that used favor language, suggesting that at least some portion of the additional value discovered was being retained by the player, $F(1, 163) = 5.94$, $p = .016$, $d = 0.37$ Player points were on average 1.83 points higher when they had been exposed to the favor language than when they had not. There was no significant effect of the quality of offers received (competitive vs. cooperative condition), $F(1, 163) = 1.52$, $p = .220$, $d = 0.18$. These results are summarized in Figure 6.

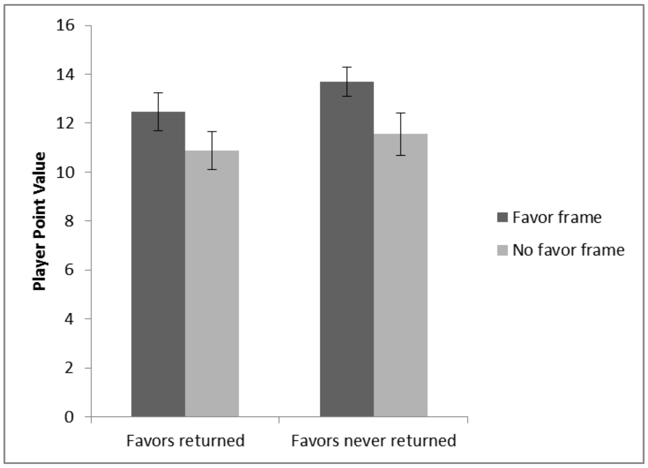

Figure 6: Value retained by the user in the final negotiation

The amount of points the agent received however, was certainly dependent on the quality of offers it had made in previous interactions. Agents that had given some good offers in previous negotiations generally scored higher than their more competitive counterparts, $F(1, 163) = 5.35$, $p = .022$, $d = -0.37$. Thus, agents that either explicitly returned favors (favor-seeking agent) or were simply altruistic (cooperative agent) did indeed see returns to this strategy in the final round (Figure 7).

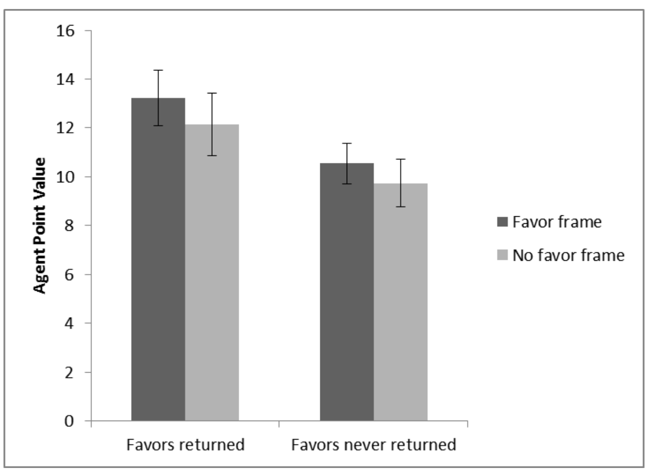

Figure 7: Value retained by the agent in the final negotiation

We can therefore state that while merely manipulating the language used by the agent is enough to prime the discovery of joint value, thus increasing the total value, failing to "practice what you preach" and give good offers resulted in most of this value being captured by the player, rather than the agent.

6. CONCLUSIONS

Repeated negotiations are highly dependent on the history of actions taken by each party. Robust virtual agents should capture this complexity, and to reflect it accurately when interacting with human participants. Since the concept of integrative potential taking place over multiple negotiations is relatively untested in automated negotiation, it is also critical that agents be able to enact methods that allow this potential to be captured using effective measures. We believe that the favor-seeking agent proposed can be used to excel at this class of negotiation, in which multiple issues are discussed over multiple negotiations, and the lessons learned can be applied in a general way.

Inducing human partners to discover integrative potential in repeated negotiations is the first step in both an effective pedagogical training agent, and in a competitive agent that seeks to capture value by increasing the total value available to all parties. By signaling intention using simple alterations to natural language that cue parties to the possibility of favor exchange, we have shown that joint value can be discovered more readily. Furthermore, ensuring a match between signaling using language and signaling using actions has many additional benefits. By effectively following through with the implications of the favor exchange by returning those favors, agents can encourage their negotiation partners to give a fair allotment of value in later negotiations. Failing to do so is associated with a cost of betrayal in which value is retained by the player.

While it may not be the case that this cost of betrayal is enough to warrant generous favors early in the negotiation, in domains with approximately equal power across parties and time, and especially in domains with increasing negotiation power in the hands of the player, it seems key to avoid signaling betrayal to the agent's partner. Furthermore, following through with favors signaled through language may interact positively with user-reported measures of trust, which is often a critical (and sometimes sole) goal of rapport-based agents.

In the future, agents should be designed with these signaling principles in mind, as agents that utilize favor language in a positive way are likely to achieve superior results for both parties than those that do not. Virtual humans that are aware of the potential benefits and tradeoffs of favor exchange can increase the internal validity of studies that involve a confederate; by utilizing virtual humans, we can better isolate factors that increase joint gain.

Furthermore, virtual humans that successfully emulate and improve on face-to-face negotiation strategies like favors and ledgers can become an important tool in both mediated negotiation and negotiation education, both of which require ample training and practice in order for humans to succeed. We have demonstrated that a simple virtual agent that makes use of natural language framing and an awareness of human negotiation behavior can establish relationships that bear substantial effects on subsequent interactions over time, and we hope to extend these benefits in other human-agent interactions.

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8. NOTES[9]

[1] The fable of the orange involves the additional inference that what seemed to be a single issue (orange) could be decomposed into multiple issues (juice and peel).

[2] Some cultural effects may also affect the rate of favor exchange: members of collectivist cultures may discover joint value without the need for cueing; to mitigate this risk, we examine only US participants.

[3] In the absence of favor framing in language, the favors returned condition is more accurately termed “some good offers”, while the favors never returned condition is “all poor offers”. However, this distinction is purely notational, as the quality of the offers in the favors-returned/favors-never-returned conditions is independent of the language used to frame them.

[4] The agent’s language is also conditional on user choice: for example, when the player accepts an offer, the agent might say “Sounds good!”, but say “Oh that’s too bad” upon a rejection.

[5] This favor language was only used by the favor-seeking agent, and only if the previous offer had indeed been accepted. Otherwise, the generic language is used.

[6] χ^2 [degrees of freedom, sample size] = Pearson’s χ^2, p = significance

[7] Each group as divided by condition is an independent sample. With this between-subjects design, percentages do not sum to 100%.

[8] F(between-groups DoF, within-groups DoF) = F statistic, p = significance, d = Cohen’s d

[9] This work was supported by the National Science Foundation under grants IIS-1211064 and BCS-1419621, and the U.S. Army. Any opinion, content or information presented does not necessarily reflect the position or the policy of the United States Government, and no official endorsement should be inferred.