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Abstract

Many environments in which people and computer agents interact involve deploying resources to accomplish tasks and satisfy goals. This paper investigates the way that the contextual setting in which decisions are made affects the behavior of people and the performance of computer agents that interact with people in such environments. It presents experiments that measured negotiation behavior in two types of contextual settings. One provided a task context that made explicit the relationship between goals, tasks and resources, The other provided a completely abstract context in which the payoffs for all decision choices were listed. Results show that people are more helpful, less selfish, and less competitive when making decisions in task contexts than when making them in completely abstract contexts. Further, their overall performance was better in task contexts. A predictive computational model that was trained on data obtained in task contexts outperformed a model that was trained under abstract contexts. These results indicate that modeling the way people make decisions in context is essential for the design of computer agents that will interact with people.

1 Introduction

Technology has opened up vast opportunities for computer agents to interact with people in such increasingly diverse applications as online auctions, elderly care systems, disaster relief operations, and system administrator groups Das *et al.* (2001); Pollack (2006). While these applications differ broadly in size, scope, and complexity, they are similar in that they involve people and computers working together in *task settings*, in which the participants fulfill *goals* by carrying out *tasks* requiring the use of *resources*.

Participants may have to cooperate, negotiate, and perform other group actions in order to achieve the goals, requiring their reasoning about the potential and likely behaviors of other participants. For computer agents to interact successfully with people in these mixed human-computer task settings, they need to be good partners, meeting people's expectations of others. In designing computer agents for such settings, it is thus important to understand the decision-making strategies people deploy when they interact with others and to evaluate various computational strategies for interacting with people. Formally modeling the behavior of people, and in particular their decision-making behaviors, raises significant artificial-intelligence challenges.

In this paper, we show that for best performance, computers participating in mixed human-computer task settings must model human behavior in a way that reflects the *contextual setting* that embeds the decisions people face. We demonstrate that different contextual settings influence significantly human decision-making, by presenting to people identical multi-agent decision-making problems framed in different types of contextual settings, and by providing detailed measurements of the outcomes. In addition, we trained computational models on data obtained in these different contextual settings, and evaluated the performance of these models.

Our experiments deploy a conceptually simple but expressive game called Colored Trails (CT) Grosz *et al.* (2004) to provide a *task context* for decision-making. CT explicitly manifests goals, tasks, and resources in a way that is compelling to people, yet abstracts away from a complicated underlying domain. It thereby enables investigators to focus on people's decision-making strategies, rather than specifying and reasoning about individual domain complexities. We used a version of CT that included a one-shot take-it-or-leave-it negotiation round between two agents that needed to exchange resources to achieve their goals.

Experiments in behavioral economics typically use even more highly abstracted contextual settings, such as decision trees or normal form tables, that fully specify payoffs for players from potential strategies and completely hide any underlying relationship between tasks, goals, and resources. The decisions engendered by CT games can be described as a table of payoffs as well. We call this abstract representation the *table context*. Game-theoretic tools can be applied in table contexts to provide an idealized notion of appropriate decision-making behavior.

We show that people presented with identical decision-making problems in these two contextual settings perform strikingly differently, both qualitatively and quantitatively. We analyzed people's behavior in terms of various social criteria, for which we give a precise definition in terms of the CT game. Results show that when making decisions in the task context, people are more helpful and less competitive — less game-theoretic — than when making decisions in the table context. Surprisingly, the results also indicate that the task context improves people's overall performance.

To evaluate the effects of these differences on computer agents, we trained predictive models on data obtained in both types of contextual settings. The models explicitly represented social factors that have been shown to affect people's behavior Gal *et al.* (2004). The model trained on data obtained in the task context outperformed the model trained on data obtained in the table context. These experiments show that for optimal performance, agents need to model how people make task-related decisions *as presented to them in context*. Furthermore, overall performance may be better if that context is task-oriented, rather than payoff-oriented, *even for the same tasks*.

For designers of intelligent agents, the important lesson of these experiments is that the design of computer agents that will operate in mixed human-computer settings must consider how the decisions presented to people will be contextualized and reflect the human decision-making process in that contextual setting, not merely in a purely idealized (even if theoretically equivalent) manner. As much as we might like it, there is no way for AI systems to escape into pure game theory in building agents that will participate in mixed systems.

2 Empirical Methodology

This section describes the two contextual settings, task context and table context, we investigated and the experiments we conducted in those settings.

In the *task* context, a 2-player CT game was played on a 4x4 board of colored squares with a set of chips. One square on the board was designated as the goal square. Each player's icon was initially located in a random, non-goal position. To move to an adjacent square required surrendering a chip in the color of that square. Players were issued four colored chips. They had full view of the board and each others' chips, and thus they had complete knowledge of the game situation.

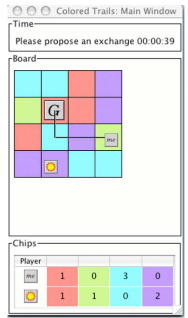
Players were designated one of two roles: *proposer* players could offer some subset of their chips to be exchanged with some subset of the chips of responder players; *responder* players could in turn accept or reject proposers' offers. If no offer was made, or if the offer was declined, then both players were left with their initial allocation of chips. Chip exchanges were enforced by the game controller: after the negotiation ended, both players were automatically moved as close as possible to the goal square.

The scoring function for players depended solely on their own performance: 100 points for reaching the goal; 10 points for each tile left in an player's possession; 15 points deducted for any square in the shortest path between player's final position and the goal-square. These parameters were chosen so that getting to the goal was by far the most important component, but if an player could not get to the goal it was preferable to get as close to the goal as possible. The score that each player received if no offer was made was identical to the score each player received if the offer was rejected by the deliberator. We refer to this score as the *no negotiation alternative* and to the score that each player received if the offer was accepted by the deliberator as the *proposed outcome* score.

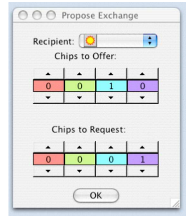
Snapshots of the CT GUI of one of the games used in the experiment is shown in Figure 1. The Main Window panel, shown in Figure 1(a), includes the board game, the goal square, represented by an icon displaying the letter *G*, and two icons, "me" and "sun", representing the location of the two players on the board at the onset of the game.[1] The bottom part of the Main Window panel, titled "chips", shows the chip distributions for the players. In the game shown here, both players lack sufficient chips to get to the goal square. A proposer uses the Propose Exchange panel, shown in Figure 1(b), to make an offer to a responder.

The *table* context consisted of a completely abstract representation of a CT game as a list of potential offers that could be selected by the proposer player. Each offer was represented as a pair of payoffs for the proposer and the responder. Figure 2 shows a

[1]CT colors have been converted to grey scale in this figure.



(a) Main Window Panel (onset of game)



(b) Propose Exchange Panel

Figure 1: Snapshots of Interaction in a Task Context

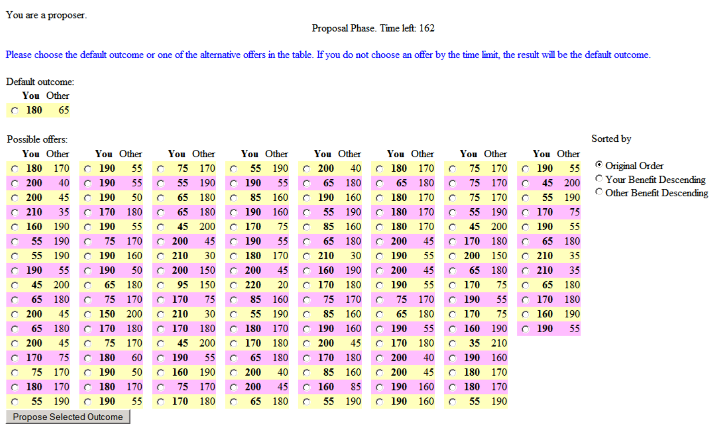


Figure 2: Snapshot of an Interaction in a Table Context

snapshot of a game in this representation as seen from the point of view of a proposer player. Each cell in the table represents an offer, and selecting a cell corresponds to choosing the offer associated with its payoffs. One of the cells represents the no-negotiation alternative, which is presented as the default outcome of the interaction.

A total of 32 subjects participated in the experiment, equally divided between the two conditions. They interacted with each other for 96 rounds. Participants in the task condition interacted with each other using the CT environment, whereas those in the table condition interacted with each other using the payoff matrix representation. Participants only interacted with others in their condition group;they were not provided any information about each other. In both conditions, participants were compensated in a manner that depended solely on their individual scores, aggregated over all rounds of interaction.

For each CT round that was played in the task condition, an equivalent round was played in the table condition, in the sense that the payoff pair at the intersection of each row and column represented the score in the CT round for the corresponding offer and response. For example, the payoff matrix shown in Figure 2 is equivalent to the CT game shown in Figure 1.

3 Results and Analysis

We use the term *table proposers* and *task proposers* to refer to the participants that were designated with the proposer role in the table or task condition respectively and similarly for the responder role. We use the term *offer benefit* to refer to the difference between the proposed outcome for an offer and the no-negotiation alternative score of the round. We measured proposers' behavior in terms of three features: The degree to which proposers were *selfish* or *helpful* was defined in terms of the average offer benefit they proposed for themselves or for responders, respectively; the degree to which proposers were *competitive* was defined in terms of the difference between the average offer benefit they proposed for themselves and the offer benefit provided to responders. Although we have given a psychological interpretation to these features, we do not imply that they are independent. For example, proposers can exhibit both a degree of selfishness and a degree of helpfulness based on the average benefit of their offers.

3.1 The Effect of Contexts on Human Behavior

Table 1 presents the average offer benefit to participants in both task and table condition for each role designation. Table proposers offered significantly more benefit to

Table 1: Average Benefit of Offer

	Offer Benefit to		Num.
	Proposer	Responder	acceptances
Task	82.3	**47.6**	62 (77%)
Table	**98**	36	69 (77%)

themselves than did task proposers (t-test $p < 0.05$). Also, table proposers offered significantly less benefit to table responders than task proposers offered to task responders (t-test $p < 0.01$). Thus, the task context had the effect of making proposers more helpful and less selfish when interacting with responders.

The difference between the average offer benefit to proposers and to responders is positive in both conditions (t-test $p < 0.05$). Although in both conditions proposers are competitive. the offer difference was larger in the table condition than in the task condition (t-test $p < 0.05$). Thus, on average table proposers were more competitive than task proposers. We hypothesized that table proposers made competitive offers more often than did task proposers. To test this hypothesis, we performed a within-round comparison of the offer benefit in both conditions. Table 2 presents the number of rounds in which the difference between the proposed benefit for proposers and responders was positive (column "Proposer $>$ Responder") and the number of rounds in

Table 2: Frequency of Competitive Offers

	Proposer > Responder	Proposer < Responder
Task	26 (27%)	**51** (60%)
Table	**60** (62%)	24 (28%)

which this difference was negative (column "Proposer < Responder"). As shown by the table, table proposers made offers that benefited themselves over responders significantly more often than task proposers (chi-square $p < 0.05$). These results confirm that table proposers are more likely to be competitive than proposers.

Table 2 also shows that 62% of all offers made by table proposers benefited *themselves* more than table responders, while 60% of all offers made by task proposers benefited task *responders* more than themselves (chi-square $p < 0.05$). This striking result indicates that task proposers were helpful more often than they were selfish, whereas table proposers were selfish more often than they were helpful.

Having established that the context in which decisions are made affected the behavior of proposers, we investigated whether it affected the behavior of responders. It is more difficult to perform within-round comparisons of responder behavior across task and table conditions, because the decision of whether to accept or reject an offer depends on the exchange offered by proposers. For the same round, this exchange may be different for task and table conditions. As shown in Table 1, there was no difference in the ratio of exchanges accepted by responders (77%) between conditions. However, this result does not mean that responders were not affected by context; as also shown in Table 1, they were responding to exchanges that were more helpful to them in the task condition. We expected this pattern to hold for accepted offers as well; thus, we expected that the offers that were *accepted* by responders were more helpful to them in the task condition than in the table condition.

Table 3: Average Benefit for Accepted Exchanges

	Proposer	Responder	Total
Task	79.5	**56.4**	135.9
Table	**85.6**	40.7	126.3

Table 3 shows the exchange benefit to proposers and responders averaged over all accepted proposals, as well as the total accumulated benefit in each condition. The benefit to responders from accepted proposals was significantly higher in the task condition than in the table condition, and conversely for the proposers (t-test $p < 0.05$). These results indicated that task responders outperformed table responders, whereas table proposers outperformed task proposers. Interestingly, as the rightmost column shows, the total performance (combined proposers and responders scores) was higher in the task condition than in the table condition. The benefit for accepted exchanges is a measurement of performance, because the outcome of each round of interaction was fully determined by the action of the responder (t-test $p < 0.1$). Although this result was not significant at the $p < 0.05$ confidence interval, the trend it indicates suggests that task context has a positive effect on the combined performance of participants.

To address the question of whether the difference in behavior can be explained by the lack of an explicit representation of payoff in the task condition, we ran an experiment that used the CT game, but allowed subjects to view the payoffs for potential offers for all players. This intermediate representation preserves the task context as well as displaying the payoff function for both players. Results using the same set of games as in the original experiment show that there was no significant difference in the average benefit allocated to proposers and responders in this intermediate representation than in the task condition.

In addition, we ruled out the effect of cognitive demands on subjects by including decision support tools for both modes of decision representation. In the CT game, subjects could query the system for suggestions about the best paths to take given any hypothetical chip distribution. When presented with a table of payoffs, subjects could sort the table by their own, or the other's benefit. In this way, subjects were allowed to focus on interacting with each other rather than the cognitive complexity of the decision-making.

3.2 Comparison with Game Theoretic Strategies

We now turn to a comparison between the offers that were made in each condition and the offers dictated by the exchange corresponding to the Nash equilibrium strategy. We use the term *NE exchange* of a round to refer to the exchange prescribed by the Nash equilibrium strategy profile for the round. This exchange offers the maximum benefit for the proposer, out of the set of all of the exchanges that offer non-negative benefits to the responder. In our scenarios, the NE exchange generally amounted to selfish, unhelpful, competitive offers.

We expected table proposers to be more likely to offer NE exchanges than task proposers. Table 4 shows the number of NE offers made by proposers in both conditions. The proportion of NE offers was significantly higher in the table condition (59%) than in the task condition (15%) (chi-square $t < 0.01$).

Table 4: Frequency of Nash Equilibrium Offers

	Num.. offers
Task	13 (15%)
Table	**57** (59%)

To compare the extent to which the exchanges made by proposers in the two contextual settings differed from the NE exchange, we plotted the average benefit offered by NE exchanges and by proposed exchanges for both task and table conditions, as shown in Figure 3.

The difference between the average benefit to responders from the NE offer and the average proposed exchange was close to zero in the table condition, and large and positive in the task condition (t-test $p < 0.05$). Similarly, the difference between the benefit to proposers from the NE offer and the average proposed exchange was was close to zero in the table condition, and large and negative in the task condition (t-test $p < 0.05$). The Euclidean distance between the two points representing the NE benefit

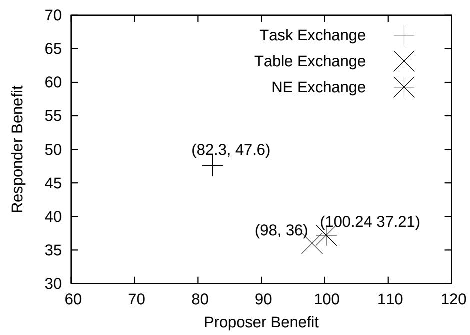


Figure 3: Benefit from Proposed Exchanges vs. NE Exchanges

to proposers and responders was significantly larger in the task condition than in the table condition. In fact, there was no statistically significant difference between offers in the table condition and NE offers. These results are strikingly significant, showing that participants who make decisions in the table condition are more likely to follow the game-theoretic paradigm.

There is a discrepancy between these findings and those of the behavioral economic studies, which show that people do *not* generally adhere to game theoretic equilibria, and display variance within their play. Several differences between the structure of the negotiation scenario used in our experiments and the games traditionally used in behavioral economics may explain this difference. First, our scenario presented participants with some guaranteed reward (the no-negotiation alternative) if agreement was not reached at the end of the interaction. Traditional behavioral economic games do not provide such reward. (For example, if no agreement is reached in the ultimatum game, both players end up empty handed.) It is possible that in table contexts, proposers saw fit to make selfish exchanges, because they could always fall back on their guaranteed outcome if that offer was rejected.[2] Second, each interaction in our experiment varied which player needed the other to get to the goal. In some rounds, both players were mutually dependent on each other. In traditional behavioral economic experiments, players' dependencies are static. It may be case that table participants were more likely to follow game theoretic equilibria in one type of dependency but not in others.

4 The Effect of Contexts on Learner Agents

This section presents results that indicate the effects of task contexts on the performance of computer systems that learn a model of people's negotiation behavior. Using the data collected from the task and table contextual conditions, we trained a computational model for predicting the actions of human proposers. We adopted the model

[2]This phenomena, deemed the "endowment effect", has been documented in the psychology literature Kahneman, Knetsch, & Thaler (1991).

proposed by Gal & Pfeffer (2006) for predicting people's bidding behavior in multi-attribute negotiation. In this model, proposals are generated by converting people's utility functions into a stochastic function that assigns a probability to each potential exchange at each round of interaction. A soft-max function is used to make the likelihood of each exchange proportional to the likelihood of other possible exchanges. This model is well suited for capturing certain aspects of human behavior: The stochasticity of the soft-max function allows for proposers to deviate from choosing the action associated with the highest utility, but in a controlled way. In addition, the likelihood of choosing an exchange that incurs a high social utility will increase if there are few other similar exchanges that incur high utility, and will decrease if there are many other similar exchanges.

For each potential exchange, we defined a "social" utility function for proposers that is a weighted sum of their own benefit from the offer, the benefit to the responder, and the difference in benefit for the proposer and the responder. These features capture the social factors (i.e., selfishness, helpfulness and competitiveness) that we defined in the Results section. The model parameters, represented by the feature weights of the utility function, were trained using supervised learning. The labeled training set consisted of the exchanges made by proposers in the task and table conditions. Each instance consisted of pairs of possible exchanges (x_*, x_j), where x_* was the offer made by the proposer, and x_j is any other possible exchange. To estimate the feature weights of the utility function, we used a gradient-descent technique that learned to predict the chosen offer x_* given any other offer x_j:

$$P(x_* \text{ chosen } \mid x_* \text{ or } x_j \text{ chosen }, \mathbf{s}_*, \mathbf{s}_j) = \frac{1}{1 + e^{u(x_*) - u(x_l)}}$$

Here, $\mathbf{s}_*$ denotes the social factors associated with the offer that was proposed. This probability represents the likelihood of selecting x_* in the training set, given x_j. The error function to minimize is defined as the extent to which the model is not a perfect predictor of this concept,

$$err_j = 1 - P(x_* \text{ chosen } \mid x_* \text{ or } x_j \text{ chosen } .\mathbf{s}_*, \mathbf{s}_j)$$

Taking the derivative of this function, we obtain the following update rule for the features $\mathbf{w}$, where α is a constant learning rate, and $\mathbf{d} = \mathbf{s}_* - \mathbf{s}_j$.

$$\mathbf{w} = \mathbf{w} + \alpha(err_j)^2 \cdot (1 - err_j) \cdot \mathbf{d}$$

We learned separate models for the task and table contexts. In both cases, we trained and tested the algorithms separately, using ten-fold cross validation. We obtained the following average posterior parameter values for the features selfishness, helpfulness and competitiveness in each condition.

Condition	Learned weights
Task	$(5.20, 3.2, 0.40)$
Table	$(8.20, 1.3, 8)$

As shown in the table, both task proposers and table proposers are selfish, in the sense that they place high weight on their own benefit. However, table proposers assign higher weight to their own benefit than do task proposers, suggesting they are more selfish than task proposers. Task proposers also assign a higher weight to helpfulness and significantly lower weight to competitiveness than table proposers. These values align with the trends reported in the Results and Analysis section.

We evaluated both models on test sets comprised of held out data from both task and table conditions. We report the average negative log likelihood for all models in the following table as computed using ten-fold cross validation. A lower value for this criteria means that the test set was given a higher likelihood by the model.

Training / Testing Condition	Average Log Likelihood
Task / Task	0.144
Table / Task	1.2
Table / Table	0.220
Task / Table	1.2

As shown by the table, the model trained and tested on the task condition was able to fit the data better than the model trained and tested in the table condition, indicating that computer agents participating in mixed human-computer task settings must model human performance in a way that reflects the *contextual setting* that the humans are faced with.

In addition, the model trained in the task condition outperformed the model trained in a table context when both models were evaluated in task contexts. (And conversely for the model trained in the table condition.) The extent to which both models under-performed when evaluated in the context they were not trained on was similar for both conditions. These results clearly imply that the context in which decisions are placed affects the performance of computer models that learn to interact with people.

5 Related Work

Our work extends the studies in behavioral economics that measure the behavior of human participants in controlled laboratory experiments. These studies have explored the conditions in which people depart from selfish reasoning and exhibit a varying degree of preference for others' welfare. For example, people have been shown to engage in cooperative behavior in a one-shot prisoners' dilemma game about half the time, despite the fact that their dominant strategy is to defect.

In behavioral economic experiments, decisions are traditionally placed in a table context. There is a direct mapping from participants' actions to their outcomes; all decisions are reduced to choices between explicit utility values; participants interact using a "low band-width" representation, summarized in a payoff matrix or tree format. CT is similar to games used in behavioral economics in that it abstracts away from the real-world, but it abstracts less, removing only domain specific contexts, and preserving the key interaction between tasks, goals and resources. CT can provide a task context in which to place many standard concepts from economic games, such as the ultimatum game and the prisoner's dilemma.

Our work is fundamentally different from research in the decision and management science literature that addresses on the effects of graphical versus tabular representations on people's decision-making Vessey (1991); Jarvenpaa (1989). This work has shown that performance on particular tasks is enhanced when there is a good match between the mode used to represent a task and the cognitive resources required to complete it. It aims to present information in a way that provides good "cognitive fit", a vivid representation that overcomes the constraints of human information processing. In contrast, we examine whether the structural features that are inherent in task contexts, such as the relationship between goals and resources, affect people's decision-making. We are not concerned with the cognitive implications of different context settings or with their mode of representation. In fact, we control for the effects of cognitive load in both task and table context settings by providing participants with decision support tools.

Lastly, recent work on modeling the social factors that affect people's decision-making behavior have concentrated on task contexts only Marzo *et al.* (2005); Gal *et al.* (2004). This work extends these approaches by comparing models of decision-making in task contexts and table contexts.

6 Conclusion and Future Work

We have shown that when making decisions placed in a task context, people behave more helpfully, less selfishly and less competitively than when making decisions placed in a table context. Further, people are significantly more likely to behave according to game theoretic equilibria in table contexts, which has a negative effect on their performance, compared to their behavior in task contexts. Moreover, people do not behave differently in task contexts when they are given access to the possible payoffs for themselves and others. We induced predictive models of the decision-making processes, showing that when learning in task contexts, computer players are better at predicting people's behavior than when learning in completely abstract contexts.

The results reported in this study suggest that when building a system for human-computer interaction, placing the decisions in task contexts will improve the performance of both people and computer agents that learn from people. Therefore, designer of systems that involve people and computers interacting together need to decide how to appropriately contextualize the decisions they present to participants.

While our experiments were performed in a relatively simple and flat task context, the fact that differences were found in this context suggest that it is likely there will be even greater ones in more complex settings. Our results provide a guideline for agent designers, specifically that the right context should be used when investigating human decision-making processes. We have presented an infrastructure for conducting such an investigation, and a methodology for how it might be done.

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