Human-Computer Negotiation in Three-Player Market Settings

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Abstract. This paper studies commitment strategies in three-player negotiation settings comprising human players and computer agents. We defined a new game called the Contract Game which is analogous to real-world market settings in which participants need to reach agreement over contracts in order to succeed. The game comprises three players, two service providers and one customer. The service providers compete to make repeated contract offers to the customer consisting of resource exchanges in the game. We formally analyzed the game and defined sub-game perfect equilibrium strategies for the customer and service providers that involve commitments. We conducted extensive empirical studies of these strategies in three different countries, the U.S., Israel and China. We ran several configurations in which two human participants played a single agent using the equilibrium strategies in various role configurations in the game (both customer and service providers). Our results showed that the computer agent using equilibrium strategies for the customer role was able to outperform people playing the same role in all three countries. In contrast, the computer agent playing the role of the service provider was not able to outperform people. Analysis reveals this difference in performance is due to the contracts proposed in equilibrium being significantly beneficial to the customer players, as well as irrational behavior taken by human customer players in the game.

1 Introduction

Many negotiations between consumers and suppliers in the real-world include binding commitments. Examples abound and include cell-phone and credit card plans, as well as publishing and retail. Commitments often have detrimental effects for producers and consumers alike. It is often the case that consumers find themselves locked into long-term commitments to existing contracts that prevent them from switching providers and possibly paying less for the same services. Such long-term commitments also reduce the amount of competition in the market and companies have less motivation to improve their products and services, further decreasing the efficiency and quality of the market. On the other hand, removing commitments altogether may encourage consumers to switch between providers at high rates and burdening suppliers with recurring installation and deactivation costs.

This paper studies these aspects in a controlled experiment involving human players and computer agents playing equilibrium strategies. We defined a new game called the Contract Game which is analogous to a market setting in which participants need to reach agreement and commit or renege from contracts over time in order to succeed. The game comprises three players, two service providers and one customer. The service providers compete to make repeated contract offers to the customer consisting of resource exchanges in the game. The customer can join and leave contracts at will.

We formally define the notion of commitment between service providers and customers in the game and provide Sub-game Nash equilibrium strategies for each of the players. Specifically, because service providers compete over the customer player, the contracts proposed by both service providers and customers are highly beneficial contracts to the customer, but require a commitment from the customer that would prevent it from signing a contract with the other service provider. In addition, the customer player will agree to any contract proposal that provides it with positive benefit, while the service provider will not accept a contract proposal that will not include a commitment from the customer player. These off-the-equilibrium path strategies are shown to be especially relevant to human play in the game which does not adhere to equilibrium strategies. We hypothesized that the focus on commitments in the game will make the equilibrium agents adapt well to play with people in the game.

To evaluate computer agents that use the equilibrium strategies, we conducted extensive empirical studies in three different countries, the U.S., Israel and China. We ran several configurations in which two human participants played a single agent participant in various role configurations in the game. Our results showed that the computer agent using Nash equilibrium strategies for the customer role was able to outperform people playing the same role in all three countries. In particular, the customer agent made significantly more commitment type proposals than people, and requested significantly more chips from service providers than did people. Also, the customer agent was able to reach the goal significantly more often than people. Lastly, in China, people were able to outperform the service provider agent, while in Israel the performance of the service provider agent was similar to that of people. These results suggest that customers making commitment proposals in the face of competition from provers can succeed well when the providers follow equilibrium strategies.

Our paper relates to works studying negotiation and bargaining behavior in economics and artificial intelligence. There are few works that study negotiations in groups comprising more than two participants human-computer settings. Ficici and Pfeffer used machine learning to model the belief hierarchies that people use when they make decisions in one-shot interaction scenarios [4, 3]. Van Wissen at el. [10] studied team formation in human-computer teams in which players negotiated over contracts. None of these works considered an agent-design for repeated negotiation with people. Hoz-Weiss and

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Kraus's prior work has addressed some of the computational challenges arising in repeated negotiation between people and computer agents [7]. Azaria et al. [1], studied negotiation over completing a set of tasks in a crowed-sourcing environment. They implemented an agent which negotiated with people from the USA and from India. Lastly, Peled et al. [8] used equilibrium agents to play with people in a two-round negotiation setting of incomplete information. These agents were outperfomed by agents using machine learning methods that predicted how people reveal their goals during negotiation.

The key contribution of this paper is a first study of negotiation over contracts in three-player market games involving human and computer players in different countries.

A few works have studied negotiation behavior among more than two agents in settings comprising solely computational players. An et al. [2] formalised how uncertainty over deadlines and reserve prices can affect equilibrium strategies in one-to-many and many-to-many negotiation scenarios in which agents follow alternating-offers bargaining protocols and there is a discount factor. Sandholm and Zhou studied equilibrium in negotiation in which agents could opt out of a commitment by a penalty fee [9]. Kalandrakis [6] studied bargaining behavior among three players and formalized a Markov perfect Nash equilibrium that depends on the state of the world using a dynamic game formalism.

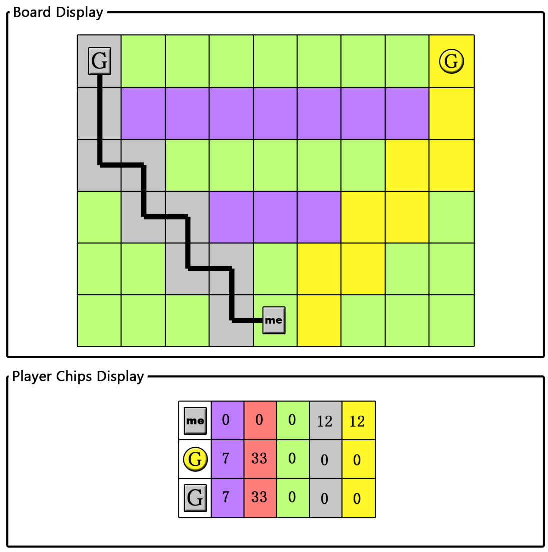

Figure 1. Snapshot of the Contract Game with an outlined preferred path

2 Implementation: Colored Trails

Our three-player market setting was configured using the Colored Trails (CT) game [5]. It consists of a game that interleaves negotiation to reach agreements and decisions of whether to accept or reject an agreement, to whom to propose a proposal, and the movement strategy.

2.1 The Contract Game

There are 3 players, one is the customer (CS) player and two players are the service providers (SPy and SPg) players. The CS player moves on a board of color squares $m \times n$ grid. Figure 1 shows a snapshot of the game from the perspective of a CS player (the "me" player). In this game the SPg player is designated as the square icons located at the far-left corner of the first row, and the SPy player is designated as the oval goal icon on the far-right corner of the first row. These two squares on the board were designated as the goal squares. The board also shows the location of the CS player icon on the last line of the board in the middle column, nine steps away from each goal square.

At the beginning of the game, each player has a set of colored chips, in which the amount and the colors of the chips may differ from one player to another. The game is divided into several rounds. Each round entails a negotiation between the customer and the providers, a movement of the customer on the board. In the negotiation phase, the SP players or the CS can act as a "Proposer" or as a "Responder". The players switch their roles, such that the first proposer in the previous negotiation phase was designated as a responder in the next negotiation phase, and vice versa. When the CS is the proposer, it can send a proposal to only ONE of the Providers. When the CS is the responder, the providers may send him a proposal simultaneously in this phase, but they cannot see each other's proposals. Once the CS receives a proposal, he may accept or reject the proposal, but he can accept only one such proposal in each round. Once the responder accepts a proposal, the chips are automatically exchanged between the proposer and the responder of the proposal.

At the end of the negotiation phase, there is a movement phase, which is analogous to the customer performing individual tasks which take up resources. In the movement phase, only the CS can move. The CS can choose where to move according to the chips he has, and can move any number of squares (up, right or left but not diagonally) according to the chips in its possession.

2.2 Game Termination and Scoring

The phases described above repeat until the game terminates, which occurs when one of the following conditions holds. (1) The CS does not move for two consecutive rounds; (2) The CS reaches one of the goal-squares belonging to one of the providers. The players' scores are computed at an intermediate or terminal point in the game as follows: (1) 150 Points to both the customer and the provider whose goal-square was reached by the customer, if any, and (2) 5 bonus points for any chip left in a player's possession. For example, at the beginning of the game, as shown in Figure 1, the CS player has 24 chips and his score is 125, whereas the SPs has 40 chips each and their initial score is 200 each. The object of the game for the CS is to reach the goal of one of the providers, and to try to use as few chips as possible in order to end the game with a large amount of chips. In this game, there is full information about the board and chips, but both providers repeatedly compete to make contracts with the customer player. The score of each player does not depend on the scores of any of the other players.

2.3 General Formalization

We provide a formalization of the board game as follows using parameters where necessary: A state s of the game is a tuple: $\langle C_{CS}, C_y, C_g, (x, z), r\rangle$ where C_{CS} is the set of chips of the customer player, and C_y and C_g are the sets of chips of SPy and SPg respectively, (x, z) is the location of CS on the board and r is the round of the game. There are two goal locations on the board: $G_y = (x_y, z_y)$ and $G_g = (x_g, z_g)$. An offer O is a pair (O_{CS}, O_i)

$i \in \{g, y\}$ such that $O_{CS} \subseteq C_{CS}$ is the set of chips that customer will send to player SPi and $O_i \subseteq C_i$ is the set of chips that player SPi will send to the CS player.

The game ends in a terminal state $s = \langle C_{CS}, C_y, C_g, (x, z), r\rangle$ in which one of the following holds:

- the CS agent reached the SPy goal, i.e. $(x, z) = (x_y, z_y)$,
- the CS agent reached the SPg goal, i.e., $(x, z) = (x_g, z_g)$,
- the CS player has not moved for two consecutive rounds, i.e., in the two states prior to s, the location of the CS was also (x, z).

A player's performance in the game is measured by a scoring function. Each player obtains b points for each chip he has at the end of the game. If the CS player reached one of the goals G_i then he and the service provider SPi both receive a bonus b^*. In the specific game that we played b was 5 and b^* was 150 points. For a terminal state s we denote by $u_i(s)$ the score of player i at s, $i \in \{CS, g, y\}$. We extend u_i to non terminal states to be $b \cdot |C_i|$.

3 Equilibrium Strategies

In this section we provide an equilibrium analysis of the game. Beforehand we make the following definitions. Given a board in the Contract Game, a location (x_1, z_1) is said to be near location (x_2, z_2) if either $x_2 = x_1 + 1$, $x_2 = x_1 - 1$, $z_2 = z_1 + 1$ or $z_2 = z_1 - 1$. A path P from (x_1, z_1) to (x_k, z_k) is a sequence of locations on the board $\{(x_1, z_1), ..., (x_l, z_l), ..., (x_k, z_k)\}$ such that (x_l, z_l) is near (x_{l+1}, z_{l+1}) for any $1 \leq l \leq k - 1$. For example, in Figure 1, we see a possible path outlined on the board from the current location of the CS player to the SPg service provider.

The set of needed chips to go through a path P is denoted by C_P. A path P is possible in state s if $C_P \subseteq C_{cs}$ and $(x_1, z_1) = (x, z)$. Moving along a path, regardless to its length moves the game to the next round. Let $s = \langle C_{cs}, C_y, C_g, (x, z), r\rangle$ be a state and $P = \{(x, z), ..., (x_l, z_l), ..., (x_k, z_k)\}$ is a possible path of s then the result of CS moving according to P denoted $Res(s, P)$ is the state $s' = \langle C_{cs} \setminus C_P, C_y, C_g, (x_k, z_k), r + 1\rangle$. In Figure 1, if the CS moves on the outlined path, this will reduce from its chip set 9 grey chips.

A *preferred* path for the CS player at s from (x, z) to the one of the goals G_i, denoted P^*_s is a possible path of state s to the goal G_i such that for any other possible path P from (x, z) to one of goals G_j, $j \in \{g, t\}$ $u_{cs}(Res(s, P)) \leq u_{cs}(Res(s, P^*_s))$. The CS has many paths to move on in order to reach a goal-square, for example, suppose the CS has also 3 purple chips. Then, one path is to go directly to the goal-square using 9 chips, and another path is to use 12 chips, then the preferred path is the one that requires the least number of chips. In the board game shown in the figure, the path that is outlined is one of the preferred paths of the customer player.

We extend the Res function when an offer $O = (O_{cs}, O_i)$ is accepted in state $s = \langle C_{cs}, C_g, C_g, (x, z), r\rangle$. If $i = y$ then $Res(s, O) = \langle C_{cs} \cup O_i \setminus O_{cs}, C_y \cup O_{cs} \setminus O_y, C_g, (x, z), r\rangle$; similarly if $i = g$. For example, suppose the CS has 120 points and the SPy has 200 points. Now, the SPy proposes to send 33 red chips and 7 purple chips for 11 grey chips, then after accepting the offer, the resulting score of the CS is 265 and 55 for the SPy.

Recall that the CS player has the needed chips to reach both goals at the beginning of the game. Furthermore, all the paths from the location of the CS at the beginning of the game to G_i, $i \in \{g, y\}$ require specific chips that are not required to reach G_j, $i \in \{g, y\}, i \neq j$. As can be seen in Figure 1, the CS has all the needed chips to reach both goals. To reach the SPy goal square the CS needs to use 9 yellow chips, while to reach the SPg goal square the CS needs to use 9 grey chips. The service provider players do not have these specific chips that are needed to reach the goals. Formally, let $s_1 = \langle C_{cs}, C_y, C_g, (x_1, z_1), 1\rangle$ be the initial state of the game. There are a set of chips C_{G_y} and C_{G_g}, $C_{G_g} \cup C_{G_y} \subseteq C_{cs}$ such that for any possible path P_i from (x_1, z_1) to $G_i \in \{g, y\}$ $C_{G_i} \subseteq P_i$ and for any possible path P_j from (x_1, z_1) to G_j, $j \in \{g, y\}, i \neq j$, $C_{G_i} \not\subseteq P_j$.

3.1 Commitments

The offers that play an important role in the equilibrium are called commitment offers and are defined as follows: We say the CS player is *committed* to player SPi, $i \in \{g, y\}$ in state $s = \langle C_{cs}, C_y, C_g, (x, z), r\rangle$ if for any path P from (x, z) to G_j, $j \in \{g, y\}$, $j \neq i$, $C_P \not\subseteq (C_{cs} \cup C_j)$. That is, if the CS player is committed to player SPi, even if the CS player will get all the chips from SPj, he will still not be able to reach its goal. Thus, to get the bonus, he will need to reach the goal of SPi.

An offer $O = (O_{cs}, O_i)$ made at state s is a *commitment offer* toward SPi if in s the CS player is not committed toward any of the SP players and the resulting state the CS player is committed to SPi. That is, the CS player is committed to SPi in $Res(s, O)$.

As an example, a commitment offer at the beginning of the game shown in Figure 1 is when the SPy proposes to send 33 red chips and 7 purple chips for 11 grey chips.

A *preferred* commitment offer at state s for the CS player toward SPi denoted O^i_s is a commitment offer such that

1. there is a possible path toward G_i at $Res(s, O^i_s)$,
2. it holds that $u_i(Res(s, O^i_s)) + b^* > u_i(s)$,
3. for any other commitment offer O toward SPi that satisfies (1) and (2), it holds that

$$u_{cs}(Res(Res(s, O), P^*_{Res(s,O)})) \leq u_{cs}(Res(Res(s, O^i_s), P^*_{Res(s,O^i_s)})) \quad (1)$$

Condition (3) refers to the score for the CS player score at the end of the game. Once a commitment offer toward SPi is implemented, we assume in the definition that the CS agent will move directly to the goal (as will be specify in the equilibrium below). If so, it is to his benefit that he will move following the shortest path. Since, $Res(s, O^i_s)$ is the state after implementing the preferred commitment offer, the shortest path will be $P^*_{Res(s,O^i_s)}$. As an example, the commitment offer described above for the board game of Figure 1 is the preferred commitment of the CS player for the conditions at the beginning of the game. We denote the set of all preferred commitment offers toward SPi by $\mathcal{O}^i_s$ and set $\mathcal{O}_s = \mathcal{O}^g_s \cup \mathcal{O}^y_s$ and $O^*_s = \text{argmax}_{O \in \mathcal{O}_s} u_{cs}(Res(Res(s, O), P^*_{Res(s,O)}))$.

3.2 SubGame Perfect Equilibria

Before providing additional notations that will be used in the formal definition of the sub-game perfect equilibrium strategies, we will provide some intuition on these strategies. In equilibrium the CS player would like to (1) follow the shortest path toward one of the goal and thus obtain his bonus and keep as many chips as possible; (2) it would like to negotiate with the service providers to make deals that will give him as many chips as possible. Thus, even if SPi sends him many chips, there is no guarantee that the CS player will go to his goal. Furthermore, the CS player will keep asking for additional chips making the overall interaction non beneficial to SPi. However, once a commitment offer toward SPi is implemented the CS must go to G_i in order to obtain his bonus and therefore commitment offers are beneficial.

Both service providers want to reach commitment offers and they compete with each other. In particular, in the first round both of them send commitment offers to the CS. The CS will choose the one that will yield him the highest final score. So, both of them will send the best offer to the CS that is better to the SP than his current score. The CS will accept the highest one and will go directly to the relevant goal. Thus, the game will end after one round. However, the sub-game perfect equilibrium strategies will also specify the off the equilibrium path choices. This is especially needed as the computer players must be able to play with peope who may not adhere to equilibrium strategies.

Next we will define beneficial paths for the CS player. These paths will be used in the equilibrium strategies specified bellow.

Definition 1 (Preferred Paths) *If s is a commitment state toward SPi, the preferred path for CS is P^*_s.*

If s is not a commitment state then (i) if CS has moved in the previous round then it should not move and the path is the empty sequence. (ii) if the CS has not moved in the previous round then he should move according to path $\mathrm{argmax}\{u_{cs}(Res(s, O^*_{Res(s,P)})) \mid P \text{ is a possible path at } s\}$.

We denote the preferred path at state s by P^+_s.

As an example, the path outlined in Figure 1 is preferred for the CS player.

Next we define the values of offers and states if the players follow the equilibrium specified below.

Definition 2 (Value of offers and states) *Let s be a non committed state, O is an offer and $s' = Res(Res(s, O), P^+_{Res(s,O)})$*

- *If O is a non commitment offer at s then $v(O, s) = u_{CS}(Res(Res(s', O^*_{s'}), P^*_{Res(s',O^*_{s'})}))$.*
- *If O is a commitment offer at s then $v(O, s) = u_{CS}(Res(s', P^*_{s'}))$.*
- $v(s) = u_{CS}(Res(Res(s, O^*_s), P^*_{Res(s_i,O^*_s)}))$.

If s is a commitment state then $v(s) = u_{CS}(Res(s, P^*_s))$ and $v(O, s) = u_{CS}(Res(s, O), P^*_s)$.

Theorem 1 *The following strategies form a sub-game perfect equilibrium for the contract game:*

Given a state $s = \langle C_{cs}, C_y, C_g, (x, z), r\rangle$ the strategy for the SPi is as follows:

1. *If it is the negotiation stage of an even round and it received an offer O then*
   - *(a) If (i) O is a commitment offer toward SPi and (ii) there is a possible path toward G_i at $Res(s, O)$, and (iii) $u_i(Res(s, O)) + b^* \geq u_i(s)$ then accept the offer.*
   - *(b) Otherwise (if at least one of the conditions does not hold), if $u_i(Res(s, O)) > u_i(s)$, accept the offer.*
   - *(c) Otherwise, reject the offer.*
2. *If it is the negotiation stage of an odd round (the SP makes the proposal)*
   - *(a) If $\mathcal{O}_i \neq \emptyset$ then make the commitment preferred offer $argmax_{O\in\mathcal{O}_i}(u_i(Res(s, O)) + b^*)$.*
   - *(b) Otherwise make the offer $(\emptyset, \emptyset)$.*

Given a state $s = \langle C_{cs}, C_y, C_g, (x, z), r\rangle$ the strategy for the CS is as follows:

1. *If it is the negotiation stage of an odd round and it received the offers O_g and O_y then*
   - *(a) if $\max_{O_i\in\{O_g,O_y\}} v(s, O_i) \geq v(s)$ then accept $\mathrm{argmax}_{O_i\in\{O_g,O_y\}} v(s, O_i)$ and reject the other offer.*
   - *(b) Otherwise reject both offers.*
2. *If it is a negotiation stage of an even round (the CS makes the proposal)*
   - *(a) if $\mathcal{O}_s \neq \emptyset$, $v(O^*_s, s) \geq v(Res(s, P^+_s))$ and $O^*_s \in \mathcal{O}_i$ then make the preferred commitment offer O^*_s to SPi.*
   - *(b) Otherwise make the offer $(\emptyset, \emptyset)$ to SPi.*
3. *If it is a movement state then move according to P^+_s.*

The proof of this Theorem is omted for brevety. We demonstrate the equilibrium on the board game in Figure 1. In this game, the SPy agent will propose 33 red chips and 7 purple chips and require 11 yellow chips. This proposal provides 265 points to the CS player and 205 points to the SP agent. This proposal is a preferred commitment and will be accepted by the CS player.

4 Empirical Methodology

In this section we describe the evaluation of the equilibrium agents for playing the contract game with human players. We recruited 398 students enrolled in undergraduate degree programs in three different countries: Israel, U.S.A and China. These included 172 students from two Israeli universities (average age of 25; female ratio of 35%), 115 students from the greater Boston area (average age of 22; female ratio of 48%), and 111 students from China (average age of 23; female ratio of 46%). Participants were given an identical 25-minute tutorial on the 3-player market Game (in their native language) as well as a 5-minute quiz about the rules of the game.

We ran two types of configurations, one consisting of all human players and the other consisting of two people and a computer agent playing the service provider or customer role. Games consisting of 3-human players games were denoted as HvsH; the games consisting of an agent playing the customer role (denoted as CSa) and two human players were denoted as HvsCSa; the games consisting of an agent playing the service provider role (denoted as SPa) and two human players were denoted as HvsSPa. In the HvsSPa games, the agent player played the role of the SP yellow player. The initial score of each player is as follows: the CS player had 125 points; and each one of the SP players had 200 points. All the following analysis and results were statistically significant in the $p < 0.05$ range using appropriate t-tests and ANOVAs.

Table 1 shows the number of games played in each game type.

	HvsH games	HvsCSa games	HvsSPa games
Israel	36	15	17
U.S.A	15	15	20
China	15	16	17

Table 1. Number of games played in each country

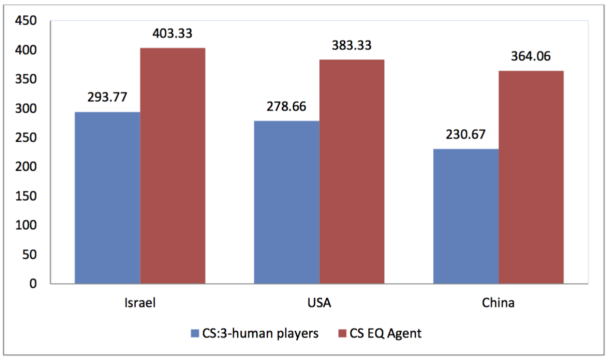

Figure 2. Performance comparison of the CS player

4.1 Analysis of Results for the Customer Role

In this section we analyze results for HvsCSa games in which the CSa agent used the equilibrium strategies to play the role of the customer. We compare the performance of these agents to human players in the respective customer role in the all-human HvsH games.

	HvsH games	HvsCSa games	HvsSPa games
Israel	7.37	**16.36**	5.096
U.S.A	7.1	**21.32**	12.68
China	4.57	**22.52**	9.06

Table 2. CS Proposals competitiveness comparison

As shown in Figure 2, the CSa agent significantly outperformed the respective human player in the HvsH game-type. This result was consistent in all three countries.

To understand the success of the CSa agent, recall that in equilibrium, the commitment proposals made by the customer are highly selfish, in that it requests many chips from the designated service provider. This is because of the inherent competition in the game between the two service providers. To demonstrate this, we define the *competitiveness measure* of a proposal made by the customer to a service provider to equal the difference between the number of chips requested by the customer player and the number of chips provided by the customer player. For example, suppose that the CSa agent player proposes a commitment offer and asks for 40 red chips and proposes to send 11 yellow chips. In this case its competitiveness measure will be 29 chips. Table 2 shows the average competitiveness of the customer player (both human and computer agent) in all games played in the different countries. As shown in the table, the average competitiveness of the CSa agent in HvsCSa games was significantly higher than the competitiveness of people in HvsH games and in HvsSPa games.

Table 3 lists the ratio of games that ended after commitments were made. After a commitment is made, the CSa player proceeds towards the relevant SP player, and the game terminates. As shown in the table, in HvsCSa games (middle column), there were significantly more games in which commitment proposals were accepted than in HvsH games (left-most column).

Lastly, Figure 3 shows the percentage of games in which the customer player reached the goal in each country. This figure also shows that the CSa agent was significantly more likely to reach one of the

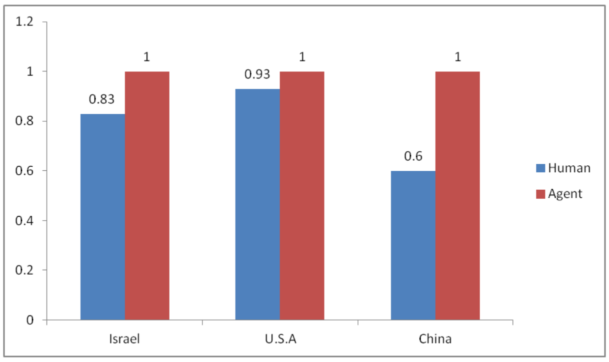

Figure 3. Getting the goal in HvsH games versus HvsCSa games

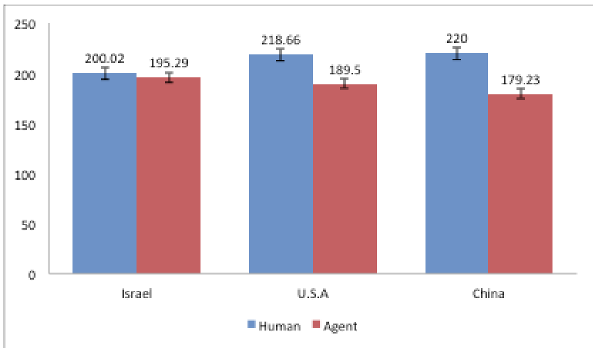

Figure 4. Performance comparison of the SPa player

service providers than human beings. This result is striking, given that the customer players have the necessary resources to reach the goal at the onset of the game, showing that at times people playing the customer role behave irrationally in the game.

	HvsH games	HvsCSa games	HvsSPa games
Israel	13/36 (36.11%)	12/15 (**80%**)	3/15 (64.7%)
U.S.A	3/15 (20%)	10/15 (**66.66%**)	14/19 (73.68%)
China	5/15 (33.33%)	7/16 (**43.75%**)	14/17 (82.35%)

Table 3. Percentage of games ending with accepted commitments

4.2 Analysis of Results for Service Provider Role

In this section we evaluate the HvsH game-type versus the HvsSPa type. Figure 4 shows the performance of the SPa human player in the HvsH games versus SPa equilibrium agent in the HvsSPa games. As we can see in this table, people were able to significantly outperform the SPa agent in China and in the U.S. In Israel, the difference of the average score between the SPa human player was not significant. The reason for this performance is that according to the equilibrium strategy described in Section 3, the SPa proposed commitments that were highly generous to the customer player. In particular, the SPa proposed all of its chips to the customer player

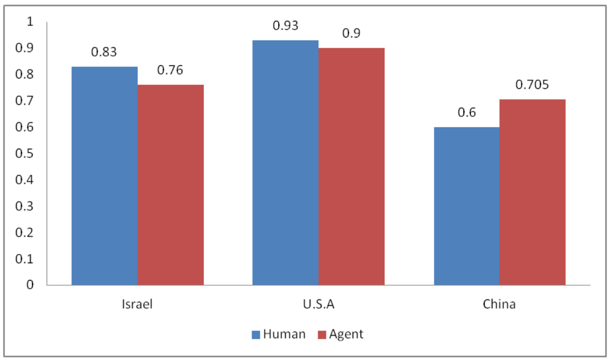

Figure 5. Getting the goal in HvsH games versus HvsSPa games

as part of the commitment. As shown by Table 4, the average number of chips that is offered by the SPa player to customers was significantly higher than people in all three countries. However, the reason for its poor performance was not the generosity of the agent but rather the way people behaved in the game. Interestingly, Table 3 shows that the ratio of games that ended following commitments requested by the SPa agent was significantly lower (right-most column) than commitments requested by the CSa player (middle column). This is another example of irrational behaviour by people, in that they agree to commitments but do not follow through by ending the game.

	HvsH games	HvsCSa games	HvsSPa games
Israel	2.6	2.71	**15.66**
U.S.A	1.53	0.69	**19.33**
China	2.5	0.36	**16.32**

Table 4. SPa Proposals generosity comparison

4.3 Cultural Differences

We end this section with discussing cultural difference between people's behavior in China and the other two countries. First, as shown in Figure 3, In China, people playing the customer role reached the goal significantly less often than in Israel and in the U.S.A. As a result, Figure 2, they accrued significantly less score than their respective scores in Israel and the U.S. In addition, in the U.S.A, the CS reached the goal much more than in China and Israel in both HvsH and HvsSPa game types. Lastly, Figure 5 shows that in Israel and in the US, there was no significant difference between the percentage of games in which people and SPa agents reached the goal. In contrast, in China the percentage of players reaching the goal in HvsSPa games was higher than in HvsH games. Specifically, in China in the HvsSPa games, the CS reached the SPy goal-square in 83% of games, versus 55% of games in the HvsH games. On the other hand, the SPa average score in HvsH was much higher, 220, than the SPa score, 179.23. Again, this is because of the fact that according to the EQ model, the SPa proposed only commitment offers which proposed many chips to send.

5 Conclusions

This paper studied the notion of commitment in three-player contract games consisting of human and computer players. We defined a new game that comprises three players, two service providers and one customer. The service providers compete to make repeated contract offers to the customer consisting of resource exchanges in the game.

We evaluated computer agents that use the equilibrium strategies in extensive empirical studies in three different countries, the U.S.A, Israel and China. We ran several configurations in which two human participants played against a single agent participant in various role configurations in the game. Our results showed that the computer agent using equilibrium strategies for the customer role was able to outperform people playing the same role in all three countries. We are currently developing a risk averse agent for this purpose that uses learning and adaptation to improve the SPa performance.

6 Acknowledgements

This research is supported in part by the U.S. Army Research Laboratory and the U.S. Army Research Ofce under grant number W911NF-08-1-0144, by ERC grant #267523, EU grant FP7-ICT-2011-9 #600854 and Marie Curie grant #268362. We thank Jairui Gan, Jun Lin, Sagi Ohayon, Priel Shmukler, and Yue Yin for their help with conducting experiments in Israel and in China.

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