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Cultural Differences in Playing Repeated Ultimatum Game Online with Virtual Humans

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Abstract

Efficient interaction between computational agents and users in tasks such as negotiation and bargaining requires recognition and understanding of potential differences in human behavior. Cultural differences in humans bargaining behavior are the focus of this study. We investigate the dynamics of human game playing with a conversational computational agent (Virtual Human). We demonstrate that the cultural background influences their observed behavior in this task. We investigate whether the social values held by the participants from each culture can at least partially explain the observed differences in behavior. We show that it is possible to automatically identify players' cultures from their game behavior and to predict their upcoming decisions in different stages of a repeated game. We employ data collected from US and Indian participants playing repeated rounds of the Ultimatum Game online against a virtual human when low stakes are involved. Our results are comparable to the reported results of similar games played among people in laboratory conditions and with high stakes. The two cultures are different in terms of the statistics and the sequence of offers made in the game and their reported values. The findings of this study are valuable for development of culturally-sensitive computational agents for negotiation and bargaining.

1. Introduction

Online interactions constitute a large portion of our daily communications. Many commercial websites (e.g. AT&T and United Airlines) are already using avatars and virtual agents (an animated character who engages in spoken dialogue and non-verbal communicative behavior) for serving their customers with their initial interactions. It's been shown before [1] that in simple economic interactions with virtual agents, people treat the agents similar to how they'd treat other humans. They make significantly higher offers to the agent than the amount predicted by rational self-interested utility maximizing models and report that they care about the agent. These results suggest that interaction with agents is still posed as a social interaction for people [2] but agents are from ne needs to understand the dynamics of the social interactions in detail. Analyzing the behavior of the people playing economic games with virtual humans and comparing it to those playing against other humans in real life or laboratory settings is essential for developing (virtual) agents that can engage in more complex social interactions with users.

Our focus is on developing interactive agents that can engage in economic decision making scenarios with human users. Therefore, in this paper we present a cross-cultural study of online game playing behavior with computational agents. Players from two cultures (United States and India) are recruited through Amazon Mechanical Turk to play ten-rounds of the Ultimatum Game online opposite a virtual human.

We attempt to address the following questions. How different are players from the United States from players in India? Are there cultural differences in players' decisions and values? Are the results of our repeated Ultimatum game similar to the single shot games previously studied (such as in [1] and [3])? How similarly do people perform in the context of a repeated game when playing with a virtual human online in comparison to when they play with humans in person?

2. Background and related work

Ultimatum Game is a well-studied game used extensively by behavioral economists to study people's decision making behaviors. Ultimatum Game involves allocation of a certain amount of money between two people. One player is asked to

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split a sum between themselves and the other party. In the single shot ultimatum game [4], the first player proposes a partition. If the other player accepts the proposal, then the sum is partitioned to the players according to the proposal. However, if the other player rejects, then both players receive nothing. In the repeated version of the Ultimatum game, the same scenario is repeated in multiple rounds.

Country-level differences have been previously reported in the context of the Ultimatum game. Using the Ultimatum game among others (such as the Public Goods game [6]) Heinrich et al. [5] studied the influence of culture on decision making process in economic domains among 15 small-scale societies. This study not only revealed substantially more behavioral variability across social cultural groups than has been found in previous research but also suggests that group-level differences in economic organization and the structure of social interactions explain a substantial portion of the behavioral variation across societies. This study also provides evidence that the available individual-level economic and demographic variables do not consistently explain game behavior, either within or across groups.

A very good example demonstrating country level differences in the repeated version of the Ultimatum Game (as well as market behavior) is a study reported in [7] in which participants from four countries of Israel, Japan, US and Yugoslavia play ten rounds of Ultimatum Game with other humans.

More recent studies have investigated how humans interact with computers in the context of the Ultimatum game [1][8][9]. In [8] Participants acted only in the role of responder in the Ultimatum Game. Participants played 20 rounds, 10 times with a person (a different person in each round) and 10 times with a computer partner. Significantly higher skin conductance response for unfair offers compared to responses for fair offers, suggests that participants experienced more emotional arousal when confronted with an unfair offer as compared to a fair offer. The participants also showed overall lower acceptance rates of unfair offers from humans as compared to from computers. Several studies have shown that when offers are made by a computer rather than a human player rejection rates are much lower (albeit still significantly higher than zero [10]; [11]).

[9] showed that the subjects tended to choose the same offer again after a win trial, and they tended to change their choice after a loss trial. The subjects would have applied different strategies when they faced human and computer respectively.

The main aim of [12]'s study was to examine how people respond to robotic opponents in the Ultimatum Game as the responder and how this compares to the way people respond to human and computer opponents. This analysis showed that the number of times subjects accepted their opponents' offers was not significantly influenced by the type (human, robot or computer) of their opponents.

We expect that virtual humans would have a similar effect on humans and prompt participants to show giving behavior toward the agents. [1] compares how people make offers to virtual humans in single shot Ultimatum game and Dictator game versus when they play with other people. [3] shows that the results obtained online are comparable to laboratory conditions when people are recruited and compensated for their time according to the amount of time they put in participation.

However, none of the previous studies look into the cultural differences in the dynamics of repeated Ultimatum Game in which a human makes proposals to a virtual human.

In most prior work regarding analysis of behavior in Ultimatum Game, people participate in face to face laboratory conditions. A few recent studies have begun to look into what happens when these games are played online [13][14]. These studies have reestablished the classical findings in previous in-person behavioral studies such as the effect of framing and priming on Mechanical Turk participants [14][15]. [16] and [17] has shown that running economic games experiments on Mechanical Turk is comparable to those run in laboratory setting even when very low monetary stakes are involved. [18] replicates previous results of [19] showing that stakes do not affect offers in the Ultimatum Game. These experiments alleviate concerns about the validity of economic games experiments run online versus ones in the laboratory.

It's important to note that in almost all variations of the Ultimatum Game, a player's behavior does not follow the prediction of the classical economic game-theory accounts of decision-making. In those models a monolithic notion of utility and maximization of self's expected utility as the key to rationality is assumed [20]. Because these models fail to explain a number of observed actual human behaviors in social situations [7][21], researchers have attempted to look for alternative explanations. Some have used models that propose that deciders have goals other than just maximizing their self-gain [22]. [22], [11] and others have tried to elicit related information by directly asking participants to fill out different surveys. [12] compares human rejection behavior in Ultimatum Game towards robots and computer and uses two standardized anthropomorphism questionnaires: `Epley questionnaire' [28] and `Van't Sant questionnaire' [29] to measure the extent to which these agents are seen as humans. [1] and [3] both use a social value survey questionnaire based on the attributes in the MARV model [23] in order to study the relationship between the single shot game playing behavior and social values held by participants. [1] showed that reported values by human players when playing with humans are comparable to the values reported when they play with virtual humans. [3] showed that the held values are different between participants from US and India and that these values can be used to predict the offers in single shot Ultimatum game and Dictator game.

3. Experiments

3.1. Method

In our experiment participants played the proposer role in the 10-shot version of the ultimatum game (Repeated Ultimatum Game). Each round of the game was played to split a sum of 100 points by choosing an offer from the set of possible offers ={ 0, 10, 20, 30, 40, 50, 60, 70, 80, 90, 100}. Players could accumulate points throughout the rounds of the game. The virtual humans played the responder role in the ultimatum game based on a fixed policy. The policy was to accept any offer equal or more than 50 points in all rounds and reject all the others.

Participants filled out a demographic questionnaire before starting the experiment. They received a $0.5 show up fee for participating in the task and were told that they will be playing over points and will earn another $0.05 for each additional 10 points that they accumulate in the game.

Participants were given a description of the game by the virtual human, and then asked for their move as the proposer in the game. Once the participants in the experiment made their decisions in the first round of the game, they were asked to report how much they cared about each of the values in Table 1, on a scale from -5 to 5 (-5 meaning that they were strongly against, 0 meaning that they didn't care at all, and 5 meaning that they cared a lot about achieving the goal).

After this survey, they were given the result of the game for that round (which was determined by their offer and according to the agent's policy). The game would continue similarly for another 9 rounds. At the end of the tenth round the value survey was given to the player again.

We did not control for the effect of language in this study and the instructions were given in English to both populations.

Value	Description Given to participant
V_{self}	Getting a lot of points
V_{other}	The other player getting a lot of points
$V_{compete}$	Getting more points than the other player
V_{equal}	Having the same number of points as the other player
V_{joint}	Making sure that added together we got as many points as possible
V_{rawls}	The player with fewest points gets as many as possible[24]
$V_{lower\ bound}$	Making sure to get some points (even if not as many as possible)
V_{chance}	The chance to get a lot of points (even if there's also a chance not to get any points)

Table 1. Values survey [1][3] based on MARV model [23]

3.2. Agent

The virtual human used in the experiment was developed using the SimCoach virtual human authoring platform, called Roundtable (described in [25]). The platform is built upon a broad set of virtual human technologies that make it easier to create, test and deploy conversational virtual characters on the web. Characters can be developed to understand natural language textual input as well as fixed-choice menu options[26]. The Flores Dialogue manager [27] selects character actions based on the authored policy and the developing context. Finally, the textual form of character responses are explicitly authored and are bound to dialogue acts specified in the policy. Actions can be realized as speech performances, references to web resources or purely nonverbal reactions. The character was launched on the web and once provided the link to the server the participants were able to interact with the virtual character that can interact through audio and text. The character is shown in Figure 1.

Figure 1. Screen shot of the Simcoach character Ellie

The pre-game survey and the values questionnaire were administered by the virtual human as well as the game itself. A sample screen shot of the beginning of the interaction chat box is shown in Figure 2.

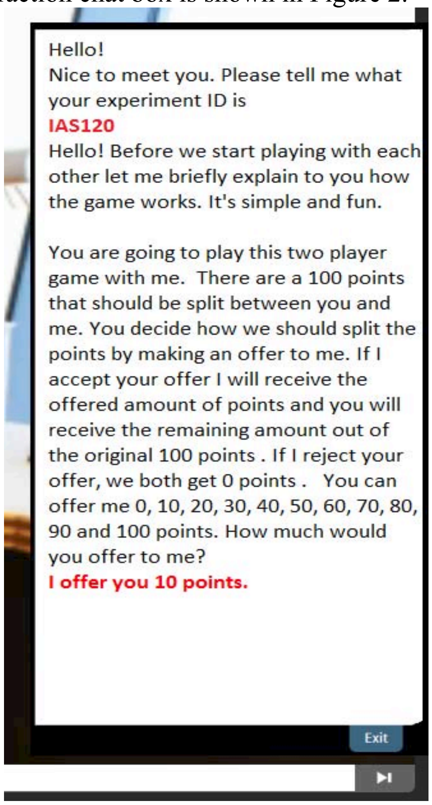

Figure 2. Screen shot of the chat box with Simcoach character Ellie

3.3. Participants

Ninety nine participants were recruited online using Amazon Mechanical Turk. Roughly half of the participants were from the United States (57 participants) while the other participants were from India (42 participants).

4. Cultural differences

In this section we report the results of the experiments. The US and Indian population both played against the same agent which used the fixed policy of accepting offers more than or equal to 50 and rejecting the lower one. We investigate the participants' behavior in the game in the first subsection by looking in to the round to round offer distributions. In the second subsection the differences in reported values is investigated. Section 5 examines the possibility of using the reported values as predictor's for the amount of offers that the players make in the game and their country of origin.

4.1. Round to round behavior

Our results are consistent with previous reports of people playing Ultimatum Game with humans in the laboratory conditions (such as in [21], [4] and [19]), in which a majority of players offer about half of the money to the other player. Similar to observation in the single shot version of the game [1], participants offer significant portion of the points to the virtual human.

Figure 3 shows the overall distribution of offers made by Indians and US players across all rounds. 46% of the Indian players offered half of the points (50 points) to the virtual humans while 70% of the US players made the same offer. We also noticed that about 16% of the offers made by Indians are offers of 100 to the agent. Only 3% of the US players gave all the points to the virtual human.

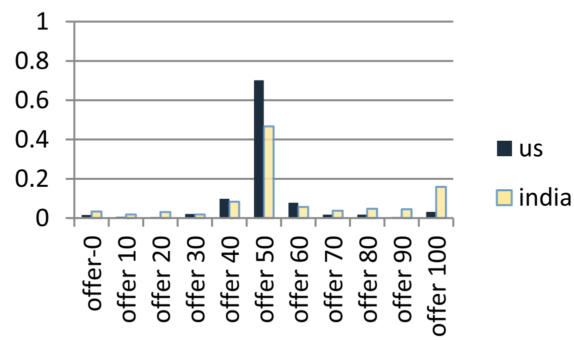

Figure 3. Distribution of offers made across rounds (US vs. India)

Figure 4 compares the average offer during the ten rounds of the game for US and Indian participants.

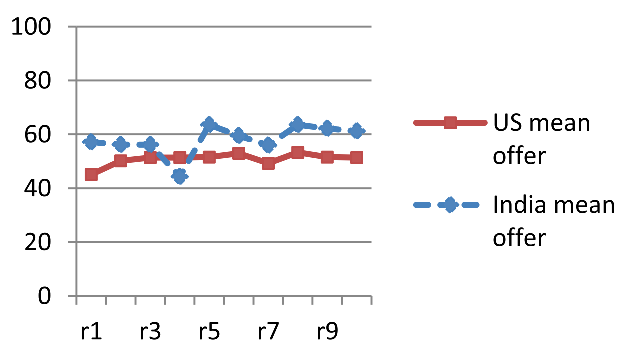

Figure 4. Average offers made in each round by US and Indian players

We use the Ranksum[1] test to compare the two distributions and it shows that the average offers

[1] Rank-sum test (also called the Mann–Whitney–Wilcoxon (MWW), Wilcoxon rank-sum test, or Wilcoxon–Mann–Whitney test) is a non-parametric

made across rounds by US and Indian players are significantly different from one another (p=0.0028).

Although the game is the same across all rounds, it is important to compare the two population by looking into the corresponding rounds because the strategy of the players in each round depends on their decisions in the previous rounds and the policy of the agent. We grouped the offers made by players in each round by their country and ran a one way ANOVA test on offers in each round. The result of the ANOVA test is reported in Table 2.

		Mean offer		ANOVA test (p-value)
		US	India	
Rounds	1	45.08	57.14	0.0105*
	2	50.17	56.19	0.1315
	3	51.40	56.19	0.2161
	4	51.40	44.28	0.0969
	5	51.57	63.57	0.0010*
	6	52.98	59.52	0.0694
	7	49.29	55.95	0.0587
	8	53.33	63.57	0.0137*
	9	51.57	62.14	0.0052*
	10	51.40	61.19	0.0133*

Table 2. Average offer in each round for US and Indian players (Two left columns) and the p-value of the ANOVA test comparing US and Indian offers in each round.

This round to round analysis of the offers shows significant difference between the Indians and US proposers in terms of the offers they made in the first round and the fifth round and the final three rounds of the game.

The detailed information on the frequency of offers made in each round for US and Indian players is shown in Table 3.a and Table 3.b (Next Page).

When studying the data from Indian players two issues were raised. The first issue was the relatively high percentage of 100-point offers by Indian players (16% of the total offers), and the second issue was the mass of 0-point offers at the fourth round. The offer sequences made by Indians were further analyzed and no evidence of a problem in the interface or the set-up of the experiment was found. Although the results reported in previous cultural studies of the Ultimatum Game such as [5] and [7] do not report similarly high percentage of high (100%) offers to the opponent, the offer sequences seemed legitimate and reasonable based on the individual patterns. We did not find any previous reports of Indian behavior in repeated Ultimatum Game. We wonder whether altruism alone can explain those high offers to the agents by Indian players, or if confounding factors, such as language barrier are at play. It's possible that if this study was run in the native language of the Indian speakers the outcome of the experiment would be different.

4.2. Reported values

The players from both US and India reported their decision making values at the end of the first round as well as the last round in order to compare the effect of the game on the values held by the player. The ANOVA analysis on the set of values shows that some values are affected by culture. From the first set of values reported in the first round: V_{self} (p-value=0.043), V_{other} (p-value=0.002), $V_{compete}$ (p-value<0.0001) and V_{chance} (p-value=0.012) showed significance difference between the two cultures. The second set of values reported after the offer made in the final round showed significant difference on V_{equal} (p-value=0.024) as well. However, the T-test analysis for each dimension comparing the two sets of reported values showed no significance difference between the values implying that the values have remained consistent throughout the game. Figure 6 shows the mean values for participants from the US and India (on the MARV Decision-making Values Survey introduced in section 3 and Table 1).

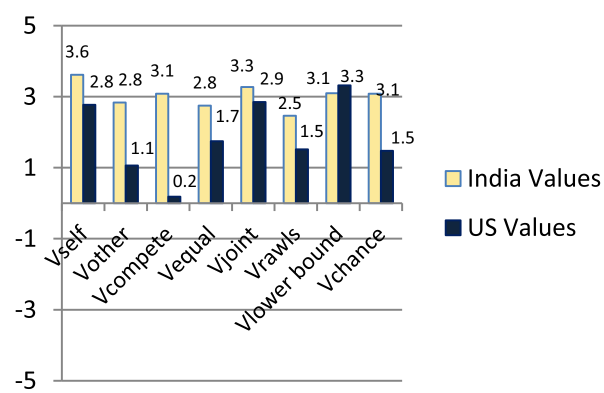

Figure 5. Self-reported values

In order to test the hypothesis that the values affect the amount of offers made in each round of the game, we analyzed the correlation between each value and the offer amount. One-way ANOVA test showed that for US players V_{self}, V_{other}, V_{equal}, V_{joint}, V_{chance} and for Indian players V_{self}, V_{other}, V_{joint} and V_{rawls} showed correlation with the value of offers made in different rounds.

test of the null hypothesis that two populations are the same against an alternative hypothesis.

India		Rounds									
		1	2	3	4	5	6	7	8	9	10
Amount of points offered	0	0.02	0.02	0.02	0.17	0.00	0.02	0.02	0.02	0.00	0.02
	10	0.02	0.05	0.00	0.02	0.00	0.02	0.00	0.02	0.02	0.02
	20	0.12	0.00	0.05	0.07	0.00	0.00	0.05	0.00	0.02	0.00
	30	0.07	0.00	0.02	0.02	0.00	0.00	0.00	0.02	0.02	0.02
	40	0.10	0.10	0.12	0.12	0.07	0.07	0.19	0.02	0.02	0.02
	50	0.31	0.55	0.43	0.38	0.55	0.48	0.43	0.50	0.55	0.50
	60	0.02	0.02	0.14	0.02	0.05	0.14	0.05	0.00	0.02	0.10
	70	0.02	0.02	0.02	0.05	0.07	0.02	0.05	0.07	0.02	0.02
	80	0.02	0.10	0.02	0.05	0.02	0.02	0.07	0.05	0.05	0.07
	90	0.05	0.05	0.05	0.00	0.02	0.10	0.02	0.07	0.07	0.02
	100	0.24	0.10	0.12	0.10	0.21	0.12	0.12	0.21	0.19	0.19

Table 3.a Frequency of offers in each round made by Indian players

US		Rounds									
		1	2	3	4	5	6	7	8	9	10
Amount of points offered	0	0.05	0.02	0.02	0.00	0.02	0.00	0.02	0.02	0.02	0.00
	10	0.00	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.04
	20	0.02	0.00	0.02	0.02	0.00	0.00	0.00	0.00	0.00	0.00
	30	0.09	0.04	0.00	0.02	0.00	0.00	0.04	0.00	0.02	0.02
	40	0.18	0.09	0.18	0.12	0.11	0.12	0.11	0.04	0.04	0.02
	50	0.56	0.67	0.58	0.67	0.75	0.70	0.72	0.79	0.77	0.81
	60	0.07	0.05	0.14	0.11	0.05	0.09	0.11	0.04	0.09	0.05
	70	0.02	0.04	0.00	0.04	0.00	0.00	0.00	0.05	0.02	0.02
	80	0.00	0.04	0.02	0.00	0.02	0.05	0.00	0.02	0.04	0.00
	90	0.02	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.02
	100	0.00	0.04	0.05	0.04	0.04	0.04	0.02	0.05	0.02	0.04

Table 3.b Frequency of offers in each round made by US players

5. Prediction Models

By using the findings described in the previous section we were able to successfully perform different classification tasks and therefore build prediction models for players' game behavior and identification of the culture that they belong to. The details of the tasks are presented in the following section:

5.1. Prediction of culture based on offer sequence and reaction to agent's policy

Given that the number of sample points we had were limited to the data we collected in our experiment (99 sequence of offers), we used a 10-fold cross-validation training/test paradigm. We performed a support vector machine (SVM) classification with parameters C and γ optimized through grid search. For the prediction model, an SVM classifier with the polynomial kernel function was trained and tested. Figure 7 shows the result of the classification of the culture of the player at the end of each round of the game. The accuracy is compared to the "most common class" baseline which is the number of US instances in our dataset (57 out of total of 99 data points).

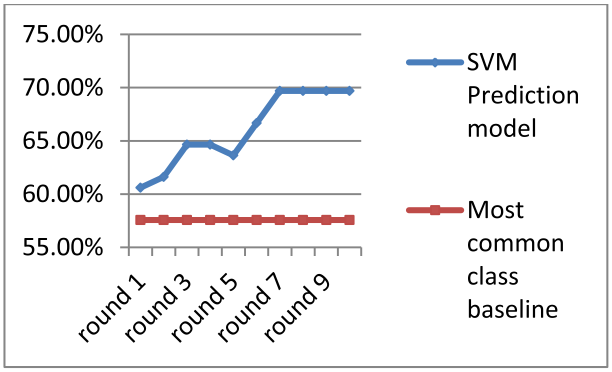

Figure 6. Accuracy of identification of culture based on the sequence of offers made as the multi shot Ultimatum game unfolds.

5.2. Prediction of players' game behavior

In this task, we used the decision values, culture and previous round offers to predict the value of the offer made by the player in each round of the game. Comparable to the overall distribution of offers in the ten-shot game, the distribution of the offers in each round also followed a normal distribution in which about half of the players from both countries would offer 50 points to the virtual human. The details are given in the table below:

Frequency of offers of 50	
round 1	45.45%;
round 2	61.61%
round 3	51.51%
round 4	54.54%
round 5	66.66%
round 6	60.60%
round 7	59.59%
round 8	66.66%
round 9	67.67%
round 10	67.67%

Table 4. Frequency of offers of 50 points per round

In order to deal with the imbalance in the distribution of our training dataset, we divided the data points into three classes:

1) Offers less than 50
2) Offers equal to 50
3) Offers more than 50

We performed the prediction task on these three classes by using an SVM classifier with the polynomial kernel function. Ten-fold cross validation was employed. Table 5 shows the result of our prediction based on the average accuracy of the model over ten folds:

Stage in the game		Percentile (%)	
		Prediction Accuracy	Most Common Class base line
Round	1	43.4	45.0
	2	70.7	61.0
	3	62.6	51.0
	4	60.6	54.0
	5	70.7	66.0
	6	67.7	60.0
	7	69.7	59.0
	8	80.8	66.0
	9	75.7	67.0
	10	80.8	67.0

Table 5. Prediction of the offer in the next round based on previous round

Except for the first round in which the prediction accuracy is below the most common class baseline, in later rounds of the game our prediction outperforms the baseline.

6. Discussion and Conclusion

In terms of the general behavior in this repeated version of Ultimatum game most people tend to offer about half of the points to the other side of the interaction even if the people are playing against a virtual human. The offers in all rounds of the game follow a normal distribution. Even though the structure of the game is fairly simple, significant cultural differences are observed in the offers made over different rounds and the reaction of people to the policy of the virtual human. Since the virtual human .We observed an unusually high percentage of Indian players offering all the points to the virtual agents, Participants' self-reported values also showed significant differences between people from US and India and remained constant for the players throughout the game. It is worth mentioning that the reported values by participants demonstrate that they have more than one valuation criteria when they were making their decisions, and validates the assumption that most are not trying to solely maximize their self-gain in a social interaction. Using these values enables the prediction of the next move of the players in the game. We are able to train SVM-based models that can predict behavior in the games based on national culture or self-reported value of the players. We are also able to determine what culture the participants belong to with higher than chance probability based on the offers and reactions that they make in the games.

In the future we will investigate more complex negotiation scenarios and whether we can make computational agents that use the self-reported values for their policies in the negotiation.

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