Human Subjects Experiment Data Collection for Validating an Agent-based Model

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ABSTRACT

The difficulties of validating an agent-based model (ABM) are well documented. Due to the complexities of the phenomenon that are traditionally modeled using ABM, it is difficult to obtain the necessary data to conduct an empirical validation of the resultant simulation. This difficulty means that a modeler is forced to validate through other means, either sensitivity analysis or white-box validation (also known as expert validation). In this paper, we describe a methodology to obtain human subjects data through an experiment for use in empirical validation of an ABM. The experiment will be conducted using a web-based version of a market economy game. These data are collected from a situation where a software agent from the simulation is replaced by a human agent. The remaining agents are independent and autonomous utility-maximizing software agents. Data collected will comprise the actions and decisions of the human agent during a series of game iterations. The proposed experiment will include just one participant per game to allow more control over potential confounders associated with actions from other players. The proposed modeling context is considered a variation of the market economy game known as the glove game. Agents in the game try to form coalitions that maximizing their revenue from selling pairs of gloves; with each agent starting with a different number of left and right gloves. The experiment was web-deployed in JavaScript. This paper discusses the methodology, issues encountered, and initial results from the prototype experiment.

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INTRODUCTION

Modeling human behavior, in a valid manner, is the next frontier for agent-based modeling (ABM) (Cheng et al., 2016). One aspect of human behavior that has not been readily explored, in a simulation context, is group or coalition formation (Bonnevay, Kabachi, & Lamure, 2005). It has been established that individuals join or leave collectives based on the benefit or payoff that the resulting association brings to them based on utility theory (Jackson & Watts, 2002). Strategic coalition formation can be modeled using cooperative game theory, an analytical approach, but cooperative game theory is both normative and computationally intractable. To overcome the later issue, there have been recent attempts to incorporate strategic coalition formation within agent-based simulation through the use of heuristic algorithms (Collins & Frydenlund, 2018). These heuristic algorithms find a reasonable solution much faster than solving a cooperative game numerically. It is those recent algorithm developments that are of interest to this proposed research. The algorithm iteratively searches for better coalitions, for the players, by generating new coalitions, in a prescribed stochastic, manner which are evaluated by the player involved. In this study, we purpose an experiment to determine the validity of these algorithms, as they compare to the game outcomes generated by human subjects as opposed to theoretical players. This research intends to determine whether and to what extent algorithms can replicate human behavior, in a strategic coalition formation context. If the results show a high mathematical correlation between the simulated and human behavior, then this provides some validity to using the algorithm in future simulations of human group behavior, at least for the game considered in our experiment.

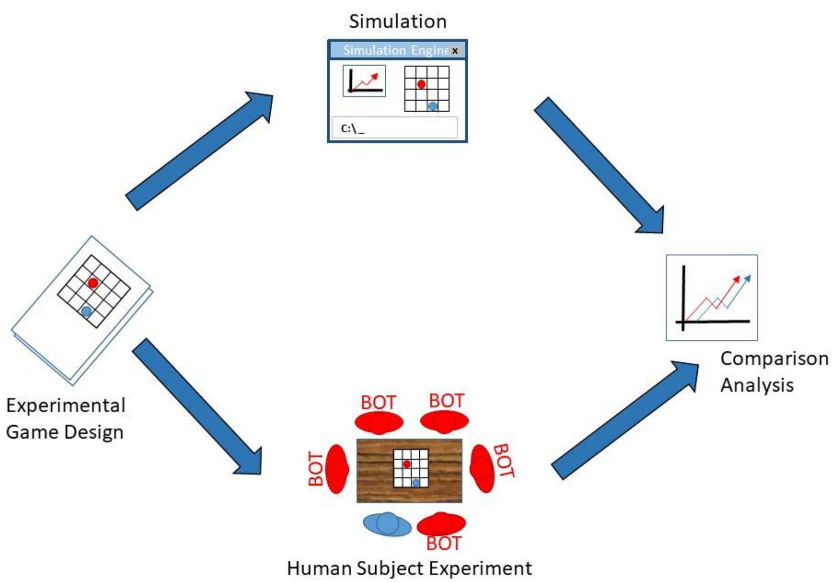


Figure 1. Flow-diagram of proposed experimental steps

The experiment consists of four separate steps, which are shown in Figure 1. First, a series of games will be generated for use in both the human experiment step and simulation step; these two steps will occur simultaneously. In the simulation step, the game will be played several thousand times by autonomous agents (bots), and the resultant distribution of coalition structures will be recorded. A coalition structure is a collection of disjoint coalitions that includes all agents. A given coalition structure can include singleton, dyads or larger coalitions. In the human subject experiment step, one of the simulated agents will be replaced by a human subject playing the game; the human's players actions will be recorded as well as the final coalition structure. In the final step, the results from the simulation and human subject experiments will be compared as well as the actions of the human subjects to those of the bots.

If the bot-only version produces similar results to when a human player is present in the game, we can conclude that the algorithm replicates human behavior and the algorithm is valid, in this context. As such, there is potential for the algorithm to be used for simulating coalition formation in a host of different human modeling scenarios involving coalition formation. Our approach to validation is inspired by ligtenburg et al. (Ligtenberg, van Lammeren, Bregt, & Beulens, 2010) though our focus is on a single human subject playing a game as opposed to roleplaying of all the bots.

The algorithm discussed above has already been developed and has been used in the modeling of farmer cooperatives (Collins & Krejci, 2018). This research is designed to find the validity of the algorithm as it relates to replicating human behavior in a context of coalition formation in an exchange economy game and, if necessary, modify the algorithm to increase its validity.

The next section discussions some validation approaches to agent-based modeling and simulation. This is followed by an overview of the experiment's methodology and some preliminary results. Finally, the paper finishes with conclusions.

BACKGROUND

The validation of ABS is notoriously difficult (Heath, Ciarallo, & Hill, 2012; Ligtenberg et al., 2010) and there have been numerous attempts to develop validation methodologies. Most of these approaches are a combination of existing validation methodologies. For example, McCourt, Ng, and Mitchell (2012) advocate an approach that combines face validation, model-to-model comparison, and statistical testing; Klügl (2008) advocates an approach that combines face validation, sensitivity analysis, and statistical testing.

The only one truly novel approach advocated in the literature is Gore and Reynolds (2010) which looks to validate the emergent behavior of an ABMS. This is done using computer program slicing and causal analysis. The novelty of this approach is that it focuses on emergent behavior, which is one of the key elements of an ABM. Another, slightly novel approach is Champagne and Hill (2009), who advocate the using of bootstrapping sampling of any comparison real-world data.

There are those that advocate the use of Subject Matter Experts (SME) as the main approach to validating ABMS, for example, Niazi (2011). The closest related of these approaches, to the method outlined in this paper, is that developed by Ligtenberg et al. (2010). Their approach is that human players roleplay the agents and see what becomes the resultant outcome. The human actors are given the same options and information; they are told to roleplay the desires and goal of the agents. If the results of role-played agent and computer agent are roughly same then it is concluded that the simulation's agent processes are valid. What is interesting about this approach is the authors advocate the of use stakeholders as the agent actors to encourage their engagement in the simulation development. The main differences between Ligtenberg et al. approach and ours are that we use only a single human player that interacts with actual computer agents; we also are not asking the human player to roleplay but just to simply play.

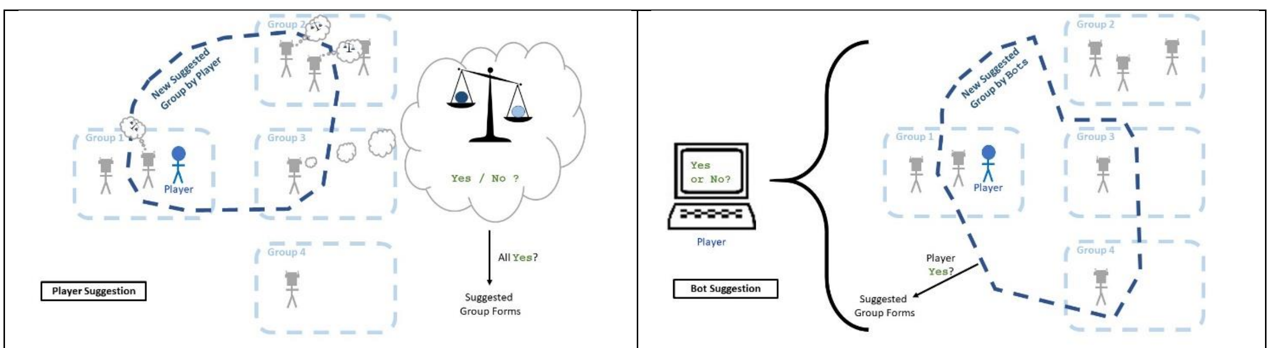
EXPERIMENT METHODOLOGY

A computer-based experiment using a known utility game has been designed to compare human actions to those generated by a computer algorithm for strategic coalition formation. The experiment will be conducted using two different settings, one where the game is driven by a tested computer algorithm (Vernon-Bido & Collins, 2018) and another that incorporates a human player into a computer-based version of a known utility game. This comparison is done by running each scenario with only bots driven by the computer algorithm and each scenario with a single human player. Collectively, the human subject and bots are called the players (or the agents). Due to the stochastic nature of the algorithm and variation amongst human's reactions, multiple samples will be collected from each scenario so that statistical hypothesis can be made and tested using that sample data. We anticipate the use of three scenarios will be used and each human subject will play all three games. The scenarios will increase in complexity, that is, they will increase in the number of agents in the games. The design and development of the game scenarios will be considered in the first step of the research.

STEP 1 - Design of Experimental Game: The basic game design used for this work will be drawn from the cooperative game theory literature as they are already well studied. The particular game that we used is the glove game, which is a simple type of exchange economy (Hart, 1985). In this game, the players are trying to maximize their utility by selling pairs of gloves. Each player starts with a random number of left gloves and a random number of right gloves. At the end of the game, players' in a coalition pool their gloves to create the most pairs which are sold and the coalition members evenly share the revenue. This revenue cannot be transferred among players (known as non-transferrable utility or no side payments). The game is played over multiple rounds where the players join and leave various coalitions to try to maximize their profit at the end of the game. Each round involves the players suggesting different coalitions; if new suggested coalitions are acceptable to all players in that new coalition then it forms. The game will conclude after a fixed number of rounds.

STEP 2 – Game Simulations: The game is played repeatedly with only bots and will be simulated using the agent-based modeling (ABM) paradigm. Each round of each game, the bots suggest new coalitions. The bots' suggestions are based on a heuristic algorithm which tries to emulate the core concept form cooperative game theory. The algorithm involves randomly selecting coalitions or bots, who then make new coalition suggestions: bot leaves the coalition, bot kicked out of their coalition, the joining of two coalitions, a coalition splits, a new pair of bots forms, and a bot defects to another coalition. If the new coalition suggestion is acceptable to all the bots involved, then it forms (i.e., if all the bots in the new suggested coalition would see an increase their utility then the new coalition is formed). The algorithm was developed by Vernon-Bido & Collins (Vernon-Bido & Collins, 2018), which is an improvement on the algorithm developed by Collins & Frydenlund (Collins & Frydenlund, 2018).

STEP 3 – Human Subject Experiments: Each human subject experiment involves a single human player replacing a bot. In each experiment, the same human player will participate in each experimental game. Only one human player will be used per game to decrease variability amongst the results because if multiple human players were used then we would need to account for the interaction between human players in our analysis, which could be quite complex. Each round of the experiment game involves the player then the bots making suggestions of new possible coalitions; the resultant decision-making processes is depicted in Figure 2.



(a)	(b)

Figure 2. Graphical depiction of the decision-making process around (a) player or (b) bot coalition suggestions

First, the player suggests a new coalition; if this coalition is acceptable to all the bots in this potential new coalition then the coalition forms. The human player can suggest any combination of players to be in the new coalition, but it must contain themselves. Secondly, the bots suggest new coalitions, as per the algorithm, if the new coalitions do not involve the human player, then the same approach to decision making as in Step 2 is used. If the suggestion does involve the human player, then first all the effected bots check to see if the new coalition is acceptable. If it is, the human player is then asked to join the new coalition. This step, of asking the human players choice, allows us to directly compare the human players' reaction to those generated by an actual bots' reaction.

STEP 4 – Comparison Analysis: After both the simulation and experiment have been repeatedly played the same game enough times (as determined by a factorial experiment design; we currently have not decided on the numbers of factors we will use), comparisons can be made between their results. There are five key comparison metrics in this game, namely, a comparison of human's reaction to suggested coalition, the average utility outcome of human player compared to its bot counterpart, the final coalition size of the human player to its bot counterpart, the distribution of coalition sizes from the games, and, finally, comparing the average social welfare of the game. There is no direct comparison for the human player's coalition selections due to complications in the game, so this is indirectly compared using the other metrics. The metrics under consideration are the human players' utility and social welfare. The metrics provide a way to determine if the human player's action result in outcomes that are better, worse or the same as if the bots (algorithm) played on their own. The coalition structures can be directly compared using hamming distance (Rossi, 2015). From these metrics, statistical tests will be conducted and conclusions made as to whether the algorithm accurately replicates human behavior and, therefore, validated for use within simulations that involve coalition formation.

PRELIMINARY RESULTS

To give the reader a better understanding of the underlying game that will be used in this experiment, we present a simple game example. When considering a game of only three players, the algorithm produces the same results as most human players. In our example game there are three players (X, Y, and Z), where < . , . > is an ordered pair indicating the number of left and right gloves each player has:

- X = <1, 2>
- Y = <6, 2>
- Z = <2, 6>

On their own, X can sell one pair for a profit of one; Y and Z can both sell two pairs. Neither Y or Z have an incentive to be in a coalition with X as the game has non-transferrable utility, so they would only receive an even split in revenue of the sold pairs (maximum three), which is less than selling two pairs on their own (so joining with X is not individually rational). The only non-singleton coalition that increases the revenue is when Y and Z join as this results in eight pairs being sold, so each receives the revenue from four pairs of gloves. Thus, the rational solution for this game is {X}{Y, Z} (which is in the core of the cooperative game).

Playing with both versions of the game, simulated and human subject experiment, result in this outcome for all cases; a formal experiment was not conducted. The human subject played agent Z. In games of more players and different glove allocations, the results coalition structure is not so obvious; for example, consider the glove allocation: <1, 2>, <6, 2>, <3, 2>, <4, 2>, and <3, 3>. It is not obviously clear what coalitions will form in this example and we leave it to the reader to determine the solution (note: there is more than one solution).

For a reader familiar with cooperative game theory will notice that our glove game is super-additive, as the grand coalition does result in the highest overall revenue, but since this game is non-transferrable utility, cooperative game theory concepts, like imputation, have little meaning. Thus, our game can be categorized as a hedonic game (Chalkiadakis, Elkind, & Wooldridge, 2011).

The proposed algorithm has already been applied to in different contexts. The version of the algorithm to be used in this research (Vernon-Bido & Collins, 2018) has been applied to modeling farmer cooperatives to explore the impact of farmer's preference for autonomy (Collins & Krejci, 2018). An earlier version of the algorithm (Collins & Frydenlund, 2018) has also been applied to refugees movement (Collins & Frydenlund, 2016) and El Farol bar problem (Collins, 2017).

CONCLUSIONS

Agent-based simulation (ABS) provides a way to model interacting heterogeneous autonomous agents and a means to model complex adaptive systems like human group formation (Miller & Page, 2007). ABS is particularly powerful at finding unexpected emergent behavior in the human system. However, the validation of ABS is notoriously difficult (Heath et al., 2012; Ligtenberg et al., 2010). The approach proposed in this paper provides a novel approach to validating models of coalition formation, within an ABS context, though the use of a game involving a single human subject. The proposed experiment might provide insight into this type of coalition formation, that occur amongst humans, and, more importantly, provide insight into the differences between simulated and human agents. Understanding these difference will provide the researcher a better understanding of the limitations of simulated agents (bots), in the context of coalition formation; thus allowing for a more valid and useful simulation to be built.

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