PARTICIPATORY SIMULATION AS A TOOL FOR AGENT-BASED SIMULATION

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Abstract: Participatory simulation, as described by Wilensky & Stroup (1999c), is a form of agent-based simulation in which multiple humans control or design individual agents in the simulation. For instance, in a participatory simulation of an ecosystem, fifty participants might each control the intake and output of one agent, such that the food web emerges from the interactions of the human-controlled agents. We argue that participatory simulation has been under-utilized outside of strictly educational contexts, and that it provides myriad benefits to designers of traditional agent-based simulations. These benefits include increased robustness of the model, increased comprehensibility of the findings, and simpler design of individual agent behaviors. To make this argument, we look to recent research such as that from crowdsourcing (von Ahn, 2005) and the reinforcement learning of autonomous agent behavior (Abbeel, 2008).

1 INTRODUCTION

In this paper, we argue that participatory simulation (as pioneered by Wilensky and Stroup, 1999a, 1999b) is a version of crowdsourcing (Wired, 2007) that is relevant to researchers interested in artificial intelligence and multi-agent systems. Crowdsourcing has shown to be useful because it exploits the knowledge, logic, and inherent unpredictability of humans (von Ahn, 2005; von Ahn et al., 2008). In a similar way, simulation with human participants can be used to examine complex phenomena more robustly and facilitate the dissemination of agent-based understanding. As such, we describe the participatory simulation as a crowdsourced design strategy, exploiting the power of the target participants to create solutions to complex problems with dynamic information.

2 PARTICIPATORY SIMULATIONS AND AGENT-BASED MODELS

The growth of the computer as a tool has led to the growth of computer literacy. As such, many recent research and commercial projects have been designed to use the knowledge base of a computer literate population in combination with large computing resources. Wikipedia is the canonical example: millions of individuals use Wikipedia as their primary encyclopedia, and many thousands of those users are also primary content creators (Wikipedia, 2008). For Wikipedia, the power of the crowd is the power of the site; a critical mass of reader/producers is necessary for its continued relevance. The knowledge in Wikipedia is crowdsourced, in that the content of Wikipedia derives from the "crowd" of untrained users rather than a cadre of explicitly trained users.

The central implications of crowdsourced content are that it has a low resource cost and a low training cost; the quality of the data, however, is highly variable. We argue that participatory

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simulation, as a form of crowdsourced simulation, has myriad benefits for designing agent-based simulations. The benefits are the resulting accessible models of human behavior data in the context of the simulation, and the improved comprehensibility of the model due to its interactive nature. Moreover, the high variability of the crowd data, which is problematic in some crowdsourcing applications, can be valuable in participatory simulations since it adds robustness to the designed simulation.

2.1 What is an Agent-based Simulation?

An agent-based simulation (ABS) is a simulation in which independent agents with local or incomplete information interact with one another. Agent-based simulations are often used to model human behavior or ethology, but they can also be usefully applied to a variety of target domains, such as physics (Bar-Yam, 1997), geography (Parker et al., 2003), and biology (Griffin, 2006). A typical ABS might consist of sets of individual agents; each of these agents has some local intelligence and the ability both to evaluate and act on the environment and agents around it. The simulation also contains tools to monitor the behavior and conditions that emerge from the interactions of the agents. For instance, a modeler creating an agent-based simulation of the food distribution in an ant colony might design behaviors for individual ant roles (e.g., worker, queen), generate hundreds of independent agents with behaviors that correspond to their roles, and run the simulation in a virtual space in which the ant-agents can interact by collecting food, distributing food, and consuming food. See Figure 1, below, from a NetLogo simulation (Wilensky, 1997).
ABS is a particularly powerful abstraction not only because of its lucid metaphor and parallelism and ease of encapsulation, but also because it is more easily comprehensible than many competing metaphors and strategies (Wilensky & Reisman, 2006). This comprehensibility stems from the similarity of the ontology of real world to the ontology of ABS, as contrasted with the ontology of a differential-equation-based model, for example. Latour (1987) argues that good academic science must be inherently communicative, but relatively little effort has been spent optimizing models for comprehensibility. This, then, is an exemplary power of ABS: it is easier for an untrained observer to understand an ant colony in terms of individual ant behaviors than in terms of differential equations.
Due to the nature of local simulation, however, it

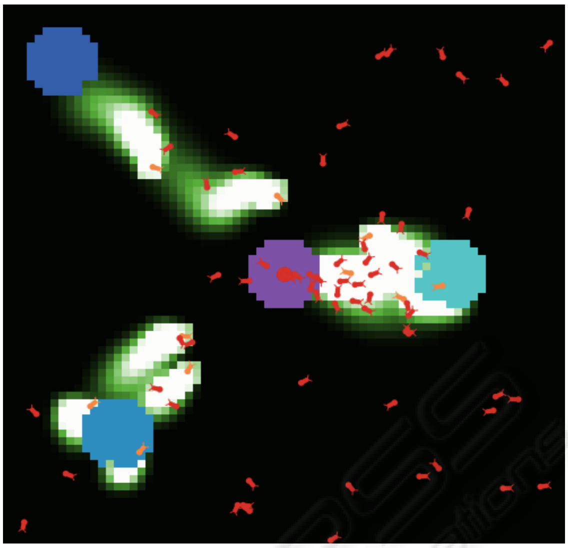

Figure 1: ABM of ant foraging.

is often difficult to design programs (or “rule-sets”) for individual agents such that the solution to a global goal emerges (Wilensky & Resnick, 1999). Much like biological ecology, changing one small aspect of an ABS often results in larger, global changes. As a result, the ecology of the emergent agent systems often becomes deeply unpredictable. Solving problems indirectly and designing intelligence for localized agents can exhibit several of the difficulties of general search problems: many local maxima; behaviors that cause negative or hard to predict side effects; and often the emergent path is effectively incomprehensible.

2.2 What is a Participatory Simulation?

In a participatory simulation, each human designs or controls an individual agent in an agent-based simulation rather than having a single designer (or group of designers) who control the whole simulation. A participatory simulation (PS) can be used to make the agent-based simulation even more understandable; to aid the design of agent rules; to disseminate the methods of agent-based simulation; and to make the simulation of human behavior more accurate.

A popular PS in use in elementary and high schools is Gridlock (Wilensky & Stroup, 1999c). In one version of Gridlock, 25 or fewer individuals each control a stoplight at the intersections on a 5x5 road-map grid. If there are exactly 25 participants, each stoplight is controlled by one and exactly one human. If there are fewer than 25 participants, some of the stoplights will be controlled by the simulation itself. The humans involved must collaborate effectively to control the flow of traffic in the simulation (see Figure 2, below).

The overarching purpose of Gridlock is not to develop optimal traffic light patterns, since an optimized ABS could certainly do a better job than the humans working with the ABS. Instead, the value of the PS is two-fold: the PS outputs an accurate model and record of human behavior in various traffic settings; and the humans involved gain a more comprehensive understanding of the difficulties involved in constructing a complex traffic model.

The adoption of participatory simulations has increased in recent years with the spread of video games. According to a Pew Research study (2008), Almost 97% of people aged 12 to 17 play video games regularly, and the PS model works as a kind of research-oriented video game due to its interactive nature. Indeed, many recent participatory simulations draw the connection to video games explicitly, and the phrases “serious games” and “game-based learning environments” are often used to describe systems that are advanced participatory simulations (e.g., Squire & Jenkins, 2004).

2.3 How Does the ABS+PS Model Relate to Crowdsourcing?

Wikipedia, ReCAPTCHA (von Ahn, 2008), and Facebook are inherently crowdsourced, and they rely on the interaction of the target agents. Crowdsourcing is a relatively new term applied to a very old idea: groups of humans can work in parallel to achieve goals that are too large or complicated for individuals working either alone or serially. The idea comes from the reversal of the typical AI paradigm in which a computer is given the intelligence to achieve a task that humans cannot.

The relevance of a link is in part determined by how many users over time find the link relevant to a particular search. By using millions of searches a day as data, Google can ensure relatively reliable search results. A more manageable and relevant example is ReCAPTCHA (von Ahn et al., 2008): in ReCAPTCHA, humans solve picture-to-text translation problems in order to earn rewards (such as registration for a website, see Figure 3, below).

Participatory simulations are similar to crowdsourcing in that they rely on a critical mass of untrained users to gather relevant data. For instance, a war game in which soldiers use paint guns instead of bullets is a participatory simulation in the sense that results are an emergent process of the actions of

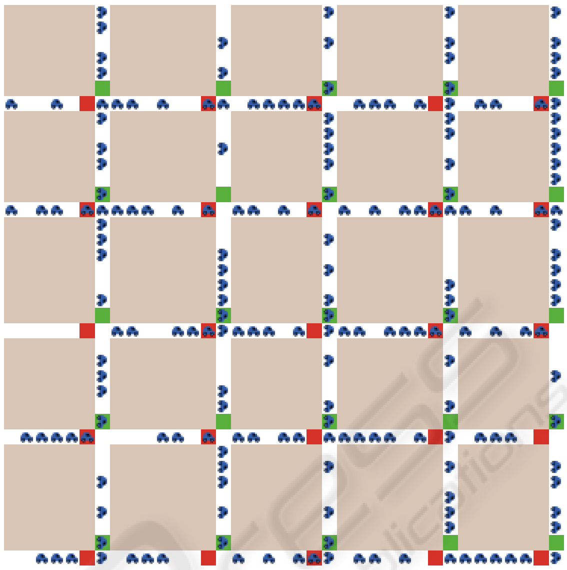

Figure 2: Gridlock Participatory Simulation.

the crowd: these simulations would not make sense without the crowd. A scrimmage soccer match could be considered a participatory simulation. Novel to the ABS+PS, however, is the use of modern computer-based communications towards the running, recording, and evaluation of the simulation. In this sense, ABS+PS is a type of crowdsourcing, the data and content of ABS+PS is created out of the actions of a multitude of users. Thus, research into the methodology of ABS+PS can learn from the crowdsourcing research and vice versa.

2.4 What Does This Have to do With AI?

The recording and simulation of the participating human-agents makes the simulation very relevant to AI/Agent research. Some participatory simulations (such as Berland, 2008; Collela, 2000; Klopfer & Squire, 2005) require the participant to formalize herbehavior (in the form of program code, diagrams, etc.) in order to fully participate. With a variety of behaviors formalized or mathematized, the behaviors can be reused, retested, and subdivided to test for different outcomes based on different behaviors. Recent research into SVM’s (Hearst, 1998) and inverse reinforcement learning (Ng, & Russell, 2000) has found them to be powerful tools in generating behavior models from data such as these. Most of the rules of agents in an ABS are currently designed by humans, but ABS+PS can take advantage of tools like SVM to data mine the results

Figure 3: reCAPTCHA.

of human participants in order to generate the rules of an agent such as in an ABS (such as the helicopter agents in Abbeel, 2008). In addition, since these rules are extracted from real-time decisions that human participants make in response to complex environments, an ABS that is built upon the results of a PS will be more robust than a simulation that was hand-engineered. In this way, we can use the PS to develop a better ABS using modern AI methods.

2.5 What's the Value of More Comprehensible Simulations to AI Researchers?

Communication and education occupy relatively small niches at computer science conferences, perhaps because the work is not easily quantifiable and rarely approaches the rigor or applicability of other work in the field. There are, however, numerous benefits to constructing simulations and models comprehensibly. For instance, equations are hard to parse even for experts in the target field (Wilensky, 1993). Furthermore, statistical descriptions can be misunderstood and improperly generalized even by good statisticians (Kahneman & Tversky, 1973). Clearly, equations and statistics, while unambiguous, are suboptimal tools for reporting findings. These difficulties have been repeatedly acknowledged in data design and visualization subfields as well as learning theories, but the findings have not been widely disseminated (ironically). Several learning theories have shown that interaction with and motivation around target content material dramatically increases uptake and comprehension (Papert, 1980; diSessa, 2000). Participatory simulations are inherently interactive, and often that interactivity proves motivating for participants. Indeed, Wilensky & Stroup (1999a) give examples in which complex target material is more quickly learned through the deployment of a participatory simulation.

2.6 So What's the Problem?

Though participatory simulations can improve the robustness and comprehensibility of agent-based simulations, they are relatively underutilized. Very few of the papers at top conferences on multi-agent systems, such as AAMAS, use participatory simulations, and even fewer take advantage of the participatory simulations to further improve their own agent-based simulations and methods. We have identified a few possible reasons why the PS has been under-utilized in the ABS community. We list these reasons and some suggested responses below:

Problem: Human subjects are expensive and time-consuming.
Rebuttal: With the growth of the web and the relatively low cost of deploying PS to social networking software (such as Facebook), this is becoming increasingly less true. However, it remains the most obvious and meaningful impediment to the widespread use of the PS. The upside is that, with a larger community building participatory simulations, the community could easily create repositories where people collaborate.
Problem: Humans are unreliable.
Rebuttal: In many cases in which agent-based simulations are employed, the target agents are expected to generally act in their own interest, whether they represent humans or not. Often some degree of randomness is added to evaluate the robustness of the model. Humans produce this self-interest with randomness effectively, and the unpredictability that they introduce rarely follows traditional random distributions (these are discussed further in Wolfram, 2002). Thus, humans can test the robustness of the model effectively, and by examining the results of human actions we can develop more robust models.

Problem: Education, learning, and communication are not serious scientific research topics or do not closely relate to the target scientific field.
Rebuttal: Every field must communicate its ideas effectively. A finding is useless if its target audience cannot understand the finding. The PS provides researchers that use the ABS a relatively easy, low-cost way to ensure meaningful engagement with the target material.

3 CONCLUSIONS

We have highlighted the benefits of utilizing participatory simulations in combination with agent-based simulations to examine questions in artificial intelligence. We present these techniques as a form of crowdsourcing, and show how research into crowdsourcing can gain from understanding ABS+PS and vice versa. Crowdsourcing solves machine-difficult problems by harnessing the power of crowds of humans. PS can harness the power of crowds to solve difficult ABS design problems. Thus, ABS+PS can be used to create more refined and robust models of complex phenomena.

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