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"WHERE'S THE TEA?" – SIMULATING HUMAN BEHAVIOR

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ABSTRACT

In this paper we examine the adequacy of simple computer models in simulating human behavior. We survey existing literature on models of evacuation & pedestrian flow, product pricing, the spread of disease, changes in agriculture & land use, and social interaction, and we show that relatively simple models can perform well in these areas, although they may require large datasets such as census data. We also summarize a taxonomy of model-building techniques due to Smajgl *et al.*, and briefly discuss issues related to modeling human decision-making, particularly when models become more complex.

1 INTRODUCTION

In Douglas Adams' famous comic novel *The Hitchhiker's Guide to the Galaxy*, some of the characters discuss the removal of Arthur Dent's brain and its replacement by an electronic one:

> " 'Yes, an electronic brain,' said Frankie, 'a simple one would suffice.'
> 'A simple one!' wailed Arthur.
> 'Yeah,' said Zaphod with a sudden evil grin, 'you'd just have to program it to say *What?* and *I don't understand* and *Where's the tea?* – who'd know the difference?' "

***The Tea*, Mary Cassatt, c. 1880**

But is that true? Can simple computer models adequately simulate human behavior? In this article we survey some approaches to the modeling of human behavior, explore the "state of the art," and illustrate some situations in which relatively simple computer models do indeed perform well.

2 EVACUATION AND PEDESTRIAN FLOW

Whether simple computer models are adequate depends on the goal of the simulation at hand. In models of pedestrian flow, work by Dirk Helbing and others has shown that quite simple models can perform very well, particularly in simulating evacuation dynamics and similar panic-driven scenarios. In these situations, simulations not much more sophisticated than simple fluid-dynamics models can reveal the benefits of, for example, zigzag designs for evacuation routes (Helbing & Johansson, 2009). This approach uses vector addition of social forces, calibrated using video footage of real pedestrians, and is able to replicate phenomena such as the spontaneous formation of "lanes" in the pedestrian flow (Ball, 2009). In typical situations, speeds of individual pedestrians follow a normal distribution, with a mean of 1.34 m/s and a standard deviation of 0.37 m/s (Daamen

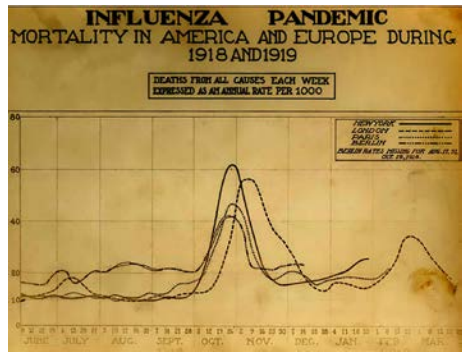
What will a crowd of panicked humans do when they reach this sign?

& Hoogendoorn, 2006). In more extreme situations, simulation of people flows has greatly assisted in, for example, improving the safety of the annual Hajj in Saudi Arabia (Helbing *et al*., 2007). A number of tools exist in this area (Zhou *et al*., 2010), and past SCS conferences have explored progress in the field (Longo, 2010).

3 ECONOMIC AND EPIDEMIOLOGICAL MODELS

Adding more sophisticated decision-making allows us to build agent-based models of economic behavior. Will people purchase a particular product from a particular vendor? Will vendors alter their prices up or down to match other vendors? Alison Heppenstall and co-workers provide a nice example of such modeling, by simulating the spatial variability in petrol (gasoline) prices (Heppenstall *et al*. 2006). In a similar vein, Perugini *et al*. (2011) use agent-based modeling to predict community water usage with greater than 95% accuracy.

A related approach can be used for epidemiological modeling. Combining relatively simple rules about people's work and other movements with very detailed census data and knowledge of disease biology allows the spread of an infectious disease to be predicted (Eubank *et al*., 2004; Stroud *et al*., 2007; Manfredi & D'Onofrio, 2013). In December 2012, a *Workshop on Verification and Validation of Epidemiological Models* was held in Washington D.C., as part of *ASE International Conference on Biomedical Computing*. Speakers included several researchers from the Oak Ridge National Laboratory, which has an impressive track record in this field. Two approaches to the validation of epidemiological models are the use of historical data (Sukumar & Nutaro, 2012) and "sanity checks" on aspects of the model (Skvortsov *et al*., 2007; Ramanathan *et al*., 2012). The better epidemiological models appear to perform quite well under such validation.



Historical data: records of the 1918–1919 "Spanish Flu" pandemic

4 ARCHAEOLOGICAL AND LAND USE MODELS

Agent-based economic models can be extended to include spatial data about agriculture, rainfall, land use, etc. One of the most well known examples of this approach is the insightful study, by Robert Axtell and others, of ancient Anasazi population dynamics in the Southwest USA (Dean *et al*., 2000; Axtell *et al*., 2002; Janssen, 2009). In this case, behavior in the model was synthesized from archaeological evidence, anthropological data, and rational decision-making – households will pack up and move out if they've seen too many bad harvests in a row. The model itself was relatively simple, though including nontrivial datasets on estimated crop yields, etc. over a period of five centuries. It succeeded in matching historical population fluctuations quite well, though not perfectly (Dekker, 2012).


Anasazi ruins, Southwest USA

Related modeling methods are used in studies of present-day land use. Will farmers switch the crops they've been planting? Will they fell trees in the neighboring forest? Will they abandon farming altogether and move to the city? Alex Smajgl and colleagues discuss approaches to such modeling in a recent paper (Smajgl *et al*., 2011). They break down the modeling process into five steps (M1, M2, M3, M4, and M5), and outline techniques are appropriate to each step. Table 1 summarizes these techniques. Smajgl *et al*. further describe 12 cases of modeling, and discuss the most appropriate techniques for each case.

Table 1: The Five Steps of Smajgl *et al*. (2011)

M1 Identify distinct agent classes & their sequences of actions	M2 Specify values of agent attributes	M3 Determine parameters for behavioral rules	M4 Develop agent types	M5 Assign agents to agent types, possibly with cloning
• Expert knowledge (EK) • Participant observation (PO) • Lab experiments • Interviews • Role-playing games (RPG)	• Survey • Census • GIS data	• Survey • Interviews • Field experiments • PO • RPG • Time-series data • EK	• Clustering & regression • Correlation & EK • EK alone • PO • Detailed spatial data combined with aggregated census data	• Proportional assignment • Census/GIS-based assignment • Monte Carlo assignment

An important aspect of agent-based models of this kind is their internal decision-making. How can the complexity of real human decision-making be reduced to a simple algorithm, yet not lose they key attributes of the human decision-making process? For one thing, it cannot necessarily be assumed that humans will always make the "best" decision, nor that human decision-making is necessarily rational (NATO, 2009). There are essentially two approaches that can be used here (Villamor *et al*., 2012a). The first approach is to determine heuristic decision rules, using techniques such as those in Table 1. This can be difficult, but several of the techniques in Table 1 permit validation of the rules, which builds confidence in the result of the model. The second approach is for agents, in their simplified agent world, to optimize their behavior, and hope that this optimal decision-making in the simplified world accurately represents the more complex and less predictable human decision-making process in the real world. Techniques used here include optimization methods such as neural networks or genetic algorithms, and artificial-intelligence methods such as machine learning, planning, or game-tree analysis (Dekker, 2010; Villamor *et al*., 2012a). A degree of randomness and/or bounded rationality may be incorporated within these methods in order to better represent real human decision-making, much as chess-playing software is sometimes "scaled back" to the level of ordinary players. However, any attempt to add randomness and/or bounded rationality should be guided by empirical data on real decision-making by human beings, and a number of other pitfalls exist in the modeling of human decision-making (Villamor *et al*., 2012b).

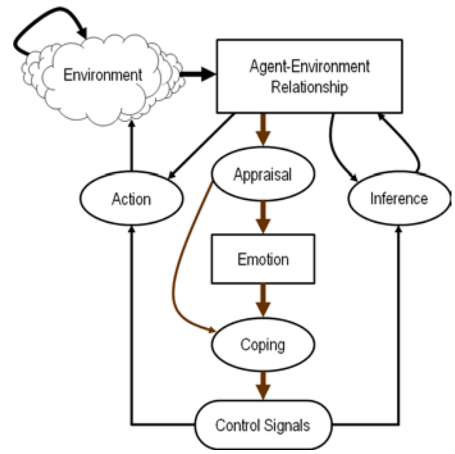
A large number of commercial and academic land-use modeling tools exist (EPA, 2000), and research on better tools is ongoing. Heppenstall, *et al*. (2012) provide a recent book-length collection of papers in this area.

5 MODELS OF EMOTION AND SOCIAL INTERACTION

Emotions expressed in a Japanese Nō mask

The choice between heuristic and optimal decision-making in models is complicated even further when we consider that "Society is not composed of neutral actors but of emotional beings… Social life is rooted in emotion" (Hamburg, 1963, pp. 316–317). Many human decisions – such as whether a drought-stricken farmer will sell the family farm – cannot be divorced from human emotion. However, human emotions can also be simulated, and Stacy Marsella and his colleagues at the University of Southern California have had considerable success in modeling human emotion (Gratch & Marsella, 2005; Marsella & Gratch, 2009; Marsella, 2013). The essence of their approach is to formalize the ways in which human beings emotionally appraise their situation, and to incorporate purely emotional goals in the agent's decision-making process – both in making inferences about the agent-environment interaction, and in deciding on actions to perform.

One very successful use of the approach developed by Stacy Marsella and his colleagues has been the tactical language training software marketed by Alelo, which also incorporates game technology (Johnson & Valente, 2009; Alelo, 2013). This software combines training for Arabic, Pashto, Swahili, and other languages with appropriate cultural training. Human participants interact with agents who react emotionally to the conversation, and express their emotional responses using body language and other actions. The successful student should able to accomplish a mission (such as locating and interviewing a village chief) without offending anybody. Further development of this approach is likely to have several interesting applications.



Theoretical framework used by Marsella & Gratch (2009) for modelling emotion (redrawn)

Modeling human emotion can also improve the accuracy of crowd models, particularly where panic is involved (Tsai *et al*., 2013). Social reactions to military activity often involves emotions such as fear and anger, and simulations of such social reactions can also benefit from explicitly modeling emotion (Dekker, 2010). However, the greater complexity of such models does pose several challenges (Crosbie, 2010; Numrich & Tolk, 2010).

6 DISCUSSION

We can see that, for many practical purposes – such as modeling evacuation & pedestrian flow, product pricing, the spread of disease, changes in agriculture & land use, and social interaction – we **can** simulate human brains by relatively simple (though not trivial) electronic ones. However, this is far from modeling the full complexity of human behavior. For models which attempt to answer more complex questions – such large-scale social models, particularly those with a military flavor – the "need to develop simulations of systems that include human behavior" remains one of "the grand challenges facing us" (Crosbie, 2010). Research in this area is ongoing, as reflected in, for example, the regular *Behavior Representation in Modeling and Simulation* (BRiMS) conferences. In some cases, the motives and mechanisms underlying specific human behaviors are not fully understood, and hence cannot (yet) be modeled.

Tolk *et al*. (2010) suggest that the formalization of a *body of knowledge* is an important part of the way forward for the development of complex social models, as is the development of a true "science of M&S" (Dekker & Suarez, 2013). The interdisciplinary research programs called for by Zacharias *et al*. (2008) also remain necessary, and, at least initially, a federation of multiple simple models – of the kind discussed above – may be more appropriate and more successful than larger monolithic models, since "it is highly unlikely to be able to address all problems with one common approach" (Tolk *et al*., 2010).

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