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TUTORIAL ON AGENT-BASED MODELING AND SIMULATION: ABM DESIGN FOR THE ZOMBIE APOCALYPSE

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ABSTRACT

Agent-based modeling (ABM) and simulation is an approach to modeling systems comprised of autonomous, interacting agents. Computational advances are making it possible to develop agent-based models in a variety of application areas, including areas where simulation has not been extensively applied. ABM applications range from supply chains, consumer goods markets, and financial markets, to predicting the spread of epidemics and understanding the factors responsible for the fall of ancient civilizations. Progress suggests that ABM could have far-reaching effects on the way that businesses use computer models to support decision-making and how researchers use models as electronic laboratories to identify promising research directions. Some contend that ABM "is a third way of doing science" and could augment traditional discovery methods for creating new knowledge. This brief tutorial introduces agent-based modeling by describing key concepts of ABM and addressing toolkits and methods for developing agent-based models.

1 INTRODUCTION

Agent-based modeling and simulation (ABM) is an approach to modeling systems comprised of autonomous, interacting agents. ABM has gained increasing attention over the past several years as evidenced by the increasing numbers of articles appearing in modeling and applications journals, funded programs that call for agent-based models incorporating elements of human and social behavior, the demand for ABM courses and instructional programs, and the growing number of conferences that feature agent-based modeling, such as the Winter Simulation Conference (WSC). By autonomous, we mean that software agents have programmed behaviors that give them the capability to decide or act within the context of the simulation, depending on the situations in which the agents find themselves. There is no central authority or overall objective function that dictates agent behaviors or actions. Agents act on their own according to the prescribed instructions programmed for their behaviors.

An agent is a general concept having broad applicability. Agents often represent people, or specific groups, such as producers and consumers in an economic ABM. Agent-based simulation is commonly used to model artificial societies, or organizations, that include models of individual decision-making and social and organizational behavior (Epstein and Axtell 1996; Bonabeau 2001; Gilbert and Troitzsch 2005; Railsback and Grimm 2013; Wilensky and Rand 2015). Agents could also represent nations and sub-national groups, animals and plants, bacterial cells or cells in the human body, smart devices that have intelligence built into them, such as smart meters in an electric power gird, or even molecules and nanoparticles. Agent relationships represent interaction processes among agents. For modeling people, these would be social interactions. For modeling molecules, interactions consist of physical relationships. For example, an individual's daily activities are explicitly modeled in an ABM of infectious disease transmission to understand transmission patterns arising from person-to-person contact and the infectivity of a disease pathogen. In a supply chain ABM, agents are firms that have decision-making behaviors about

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material sourcing and ordering, stocking, shipping, and capacity expansion. In an ABM composed of artificial agents, collaborating swarms of robots search the landscape and communicate information to collectively accomplish a task. The development of agent-based modeling tools, the availability of micro-level data on agent interactions, and advances in computers and simulation modeling technology have made possible a growing number of ABM applications across a variety of domains and disciplines. The notions of agent behavior, decision-making, interaction and diversity of individuals across a heterogeneous population apply to many kinds of system that people are interested in modeling.

Table 1 lists some publications in a variety of disciplines that make the case for ABM as being a valuable approach to advancing the respective fields. ABM originated and developed independently of traditional Monte Carlo simulation, discrete event simulation (DES), and system dynamics approaches. Interest in ABM at the WSC has steadily grown since the first ABM tutorial presented in 2005 (Macal and North 2005) to 2014 (Macal and North 2014). The current paper provides background and focuses on the design of agent-based models, illustrated through a simple example – modeling the zombie apocalypse. Thinking through the model design is an important step, separate from implementing the model in a computer language or ABM toolkit. We refer the reader to previous papers, and the references therein, on other introductory topics in ABM not covered here, such as the history of ABM and its relationships to other modeling and simulation techniques (Macal et al. 2013; Heath and Hill 2010; Macal and North 2010; Heath et al. 2009).

This paper is organized as follows. Section 2 is on how to think about ABM. Section 3 is on how to do ABM. Section 4 is a practical guide on how to get started in ABM. Section 5 steps through an example ABM for modeling a zombie apocalypse.

Table 1: Some publications introducing ABM to various disciplines.

Discipline	**Key References**
Supply Chains	Chen et al. 2013; Swaminathan et al. 1998
Intelligent/Distributed Manufacturing	Leita 2009; Monostoria et al. 2006; Shen and Norrie 1999
Queueing	Sankaranarayanan 2011
Economics	Hamill and Gilbert 2016; Farmer and Foley 2009; Tesfatsion and Judd 2006
Finance	Bookstaber 2012; LeBaron 2005
R&D (Pharmaceuticals)	Hunt et al. 2013
Marketing	Rand and Rust 2011
Tourism	Nicholls et al. 2016
Environmental Planning and Policy	Zellner 2008
Land Use	Parker et al. 2003
Urban / architecture	An 2012
Transportation	Bernhardt 2007
Geography, Geo-spatial Analysis	Heppenstall et al. 2012; Crooks and Heppenstall 2012; Crooks et al. 2008
Cognitive Science	Bedau 2003
Psychology	Smith and Conrey 2007
Archaeology	Cegielski and Rogers 2016; Wurzer et al. 2015; Lake 2014
Healthcare	Maglio et al. 2014; Luke and Stamatakis 2012;
Epidemiology/Infectious Diseases	Auchincloss and Diez Roux 2008; Epstein 2009

2 HOW TO THINK ABOUT AGENT-BASED MODELING

2.1 Structure of an Agent-based Model

A typical agent-based model has three elements:

- *Agents*, their attributes and behaviors.
- A*gent relationships* and methods of interaction. An underlying topology of connectedness defines how and with whom agents interact.
- *Agent environment*. Agents live in and interact with their environment, in addition to other agents.

2.2 Agents

There is no universal agreement on the precise definition of the term *agent* in the context of ABM. It is the subject of much discussion and occasional debate. The issue is more than an academic one, as it often surfaces when one makes a claim that their model is *agent-based* or when one is trying to discern whether such claims made by others are valid. There are important implications of the term agent-based when used to describe a model in terms of the model's capabilities or potential capabilities that could be attained through relatively minor modification. In the literature, some modelers consider any type of independent component, whether it be a software component or a model to be an agent (Bonabeau 2001). Some authors insist that a component's behavior must also be adaptive in order for it to be considered an agent. Others argue that agents should contain both base-level rules for behavior as well as a higher-level set of "rules to change the rules." The base-level rules provide responses to the environment, while the rules-to-change-the-rules provide adaptation. Jennings' (2000) computer-science-based view of agent emphasizes the essential agent characteristic of autonomous behavior.

For practical modeling purposes, we consider agents to have certain properties and attributes, as follows (Figure 1):

- *Autonomy*. An agent is autonomous and self-directed. An agent can function independently in its environment and in its interactions with other agents, generally from a limited range of situations that are of interest and that arise in the model. When we refer to an agent's *behavior*, we refer to a general process that links the information the agent senses from its environment and interactions to its decisions and actions.
- *Modularity*. Agents are modular or self-contained. An agent is an identifiable, discrete entity with a set of characteristics or attributes, behaviors, and decision-making capability. The modularity requirement implies that an agent has a boundary, and one can easily determine whether something (that is, an element of the model's state) is part of an agent or is not part of an agent, or is a characteristic shared among agents.
- *Sociality*. An agent is social, interacting with other agents. Common agent interaction protocols include contention for space, collision avoidance, agent recognition, communication and information exchange, influence, and other domain- or application-specific mechanisms.
- *Conditionality.* An agent has a *state* that varies over time. Just as a system has a state consisting of the collection of its state variables, an agent also has a state that represents its condition, defined by the essential variables associated with its current situation. An agent's state consists of a set or subset of its attributes and its behaviors. The state of an agent-based model is the collective states of all the agents along with the state of the environment. An agent's behavior is conditioned on its state. As such, the richer the set of an agent's possible states, the richer the set of behaviors that an agent can have.

Agents often have additional properties, which may or may not be considered as requisite properties for agency. An agent may have explicit *goals* that drive its behavior, not necessarily objectives to maximize as much as criteria against which to assess the effectiveness of its decision and actions. An agent may have the ability to *learn and adapt* its behavior based on its experiences. At the individual level, learning and adaptation can be modeled as agent behaviors. Individual learning and adaptation requires an agent to have memory as a dynamically updated attribute of the agent. At the population level, adaptation can be modeled by aggregate changes in individual behaviors or by allowing agents to enter and leave the population, with the more successful agents increasing their relative numbers in the population over time.

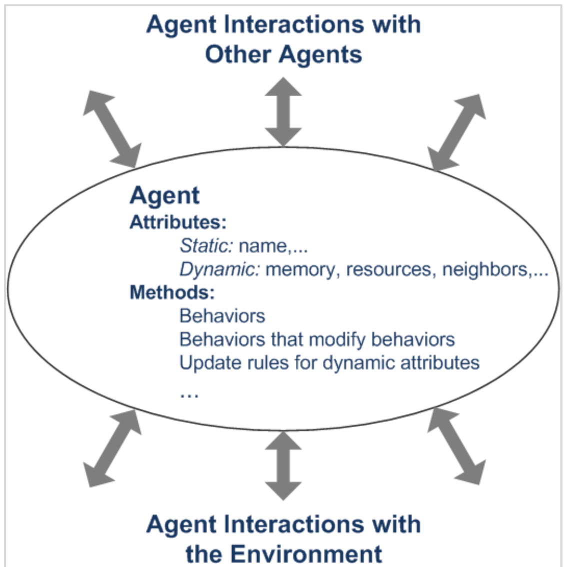

Figure 1: A typical agent.

2.3 Agent Relationships

Agent-based modeling concerns itself with modeling agent relationships and agent interactions as much as it does with modeling agents and agent behaviors. The primary issues of modeling agent interactions are specifying who is, or could be, connected to whom, and the dynamics governing the mechanisms of the interactions. For example, an agent-based model of Internet growth would include mechanisms that specify who connects to whom, why, and when.

Common topologies for representing social agent interactions include: (1) *Soup*: A non-spatial model in which agents have no locational attribute, (2) *Grid or lattice*: Cellular automata represent agent interaction patterns and available local information by a grid or lattice; cells immediately surrounding an agent are its neighborhood. An agent's location is the grid cell index. (3) *Euclidean space*: Agents roam in 2D or 3D spaces. An agent's location is its relative or geospatial coordinates. (4) *Geographic Information System* (GIS): Agents move over and interact with realistic patches of geo-spatial landscapes. An agent's location is a geographical unit (e.g., zip code) or geospatial coordinates. (5) *Networks*: Networks may be static (links pre-specified) or dynamic (links determined endogenously by relationship-creating mechanisms). An agent's location is the relative node location in the network.

No matter what agent-interaction topology is used in an agent-based model to connect the agents, the essential idea is that agents only interact at any given time with a limited number of other agents out of the population. This notion is implemented by defining a local neighborhood (possibly a network) and limiting interaction to a small number of agents that happen to be in that neighborhood. This is not to say that agents need to be located in close proximity to one another spatially to be able to interact. The network topology allows agents to be linked on the basis of relationships in addition to proximity. For example, an agent may be a member of many networks, e.g., proximity, social, familial relationship, ideological, etc.

3 HOW TO DO AGENT-BASED MODELING

3.1 Thinking Through an Agent Model

Agent-based model development follows the general steps of developing any model with the additions of agent-related tasks of modeling agent behavior and connecting the agents to an environment. It is useful to ask a series of agent-specific questions before developing an agent-based model (Table 2). The answers to these questions help define the scope and level of detail, granularity, appropriate to modeling the system. They imply the resources required for successfully completing the project and can be used to help identify likely bottlenecks to development.

Table 2: Questions to ask before developing an agent-based model.

Number	Category	Question
1	Model Purpose / Value-added of Agent-based Modeling	• What specific problem is the model being developed to address? • What specific questions should the model answer? • What kind of information should the model provide to help make or support a decision? • Why might agent-based modeling be a desirable approach? • What value-added does agent-based modeling bring to the problem that other modeling approaches cannot bring?
2	All About Agents:	• Who should be the agents in the model? • Who are the decision makers in the system? • What are the entities that have behaviors? • Where might the data come from, especially for agent behaviors?
3	Agent Data	• What data on agents are simply descriptive (static attributes)? • What agent attributes are calculated endogenously by the model and updated for the agents (dynamic attributes)? • What is the agents' environment? How do the agents interact with the environment? Is agent mobility in space an important consideration?
4	Agent Behaviors	• What agent behaviors are of interest? • What decisions do the agents make and what information is required to make such decisions? • What behaviors are being acted upon? • What actions are being taken by the agents? • How would we represent the agent behaviors? By If-Then rules? By adaptive probabilities, such as in reinforcement learning? By explicit heuristics? By regression models or neural networks?
5	Agent Interactions	• How do the agents interact with each other? • How do the agents interact with the environment? • How expansive or focused are agent interactions?
6	Agent State	• What are the states the agents could find themselves in at some point in time, in the model? • Under what conditions do agent states change?
7	Agent Recap	• How do we design a set of experiments to explore the importance of uncertain behaviors, data and parameters? • How might we validate the model, especially the agent behaviors and the agent interaction mechanisms?

3.2 Documenting Agent-based Models

Several formats have been proposed for describing agent-based models. Chief among these standards is Grimm et al.'s (2010) Overview, Design Concepts, and Details (ODD) protocol. According to Grimm et al. (2010, p. 1) "The primary objectives of ODD are to make model descriptions more understandable and complete, thereby making ABMs less subject to criticism for being irreproducible." ODD describes models using a three-part approach: overview, concepts, and details. The model overview includes a statement of the model's intent, a description of the main variables, and a discussion of the agent activities and timing. The design concepts include a discussion of the foundations of the model, and the details include the initial setup configuration, input value definitions, and descriptions of any embedded models (Grimm et al. 2006). Examples of using the ODD protocol include Polhill et al. (2008) and Schreinemachers and Berger (2011). More guidelines continue to emerge for agent-based modeling documentation, in addition to ODD (Monks et al. 2018).

3.3 ABM Software and Toolkits

Agent-based modeling can be done using general, all-purpose software or programming languages, or can be done using specially designed software and toolkits that address the specific requirements for modeling agents. Agent modeling can be done in the small, on the desktop, or in the large, using large-scale computing clusters, or it can be done at any scale in-between. Projects often begin small, using one of the desktop ABM tools, or whatever tool or programming language the developers are familiar with, or the approach that one finds easiest to learn given their background and experience. The initial prototype then grows in stages into a larger-scale agent-based model, often using dedicated ABM toolkits.

We distinguish several approaches to building ABM applications in terms of the scale of the software that one can apply according to the following continuum:

- Desktop Computing for ABM Application Development: (i) Spreadsheets: Excel using the macro programming language VBA; (ii) Dedicated Agent-based Prototyping Environments: Repast Simphony, NetLogo; and (iii) General Computational Mathematics Systems: MATLAB, Mathematica
- Large-Scale (Scalable) Agent Development Environments: Repast, Swarm, MASON, AnyLogic, Simio
- General (Object-Oriented) Programming Languages: C++, Java, Python

Desktop ABM can be used to learn agent modeling, prototype basic agent behaviors, and perform limited analyses. Desktop agent-based models can be simple, designed and developed independently in a period of a few days by a single computer-literate modeler using tools learned in a few days or weeks. Desktop agent modeling can be used to explore the potential of ABM with relatively minor time and training investments, especially if one is already familiar with the tool.

Spreadsheets, such as Microsoft Excel, are in many ways the simplest approach to modeling. It is easier to develop models with spreadsheets than with many of the other tools, but the resulting models generally allow for limited agent diversity, restrict agent behaviors, and have poor scalability compared to the other approaches designed specifically for agent modeling. Agent-based modeling in spreadsheets requires some macro-programming to be done in a language such as Visual Basic for Applications (VBA), the macro programming language for Excel and other Microsoft Office applications. Complex agent models have been developed entirely using spreadsheets. In previous WSC papers, we described a spreadsheet implementation of a spatial agent-based shopper model (Macal and North 2007).

General-purpose desktop computational mathematics systems (CMS) with integrated development environments (IDEs), such as MATLAB and *Mathematica*, can be used to develop agent models, although the agent-specific functionality has to be written by the developer from scratch, as there are no dedicated libraries or modules that focus on agent-based modeling. The basic requirement is knowledge on how to program in a scripting language. CMS environments have rich mathematical functions and, in some cases, the tools even support symbolic processing and manipulation. If a CMS environment is already familiar to a developer, this can be a good place to start agent-based modeling (Macal 2004).

Swarm was the first ABM software development environment, launched in 1994 at the Santa Fe Institute. Swarm was originally written in Objective C and was later fitted with a Java interface. Special-purpose agent tools, such as NetLogo, provide facilities for agent modeling (Wilensky 2013). The most directly visible common trait shared by the various prototyping environments is that they are designed to get first-time users started as quickly as possible. NetLogo uses a modified version of the Logo programming language (Harvey 1997) and was originally developed to support ABM education at all levels, but it can be used to develop a wide range of applications. Following the original Swarm innovation, the REcursive Porous Agent Simulation Toolkit (Repast) was developed as a pure Java implementation (North et al. 2006), and Repast Simphony (Repast S) is the latest version of Repast, designed to provide visual point-and-click tools for agent model design, agent behavior specification, model execution, and results examination. Repast Simphony 2.0 also includes ReLogo, a new Logo-like interface for specifying agent models (Ozik et al. 2013). Reviews of Java-based agent modeling toolkits are provided by Tobias and Hoffman (2004) and Nikolai and Madey (2009).

Scalable ABM software environments are now freely available or open source. These include Repast (North et al. 2006; North et al. 2013), Swarm (Minar et al. 1996), NetLogo (Wilensky 2013) and MASON (GMU 2013) among others.

AnyLogic (XJ Technologies 2014; Borshchev 2013) and Simio (Simio 2014; Pegden 2014) are leading commercial simulation environments that include agent-based modeling capabilities. AnyLogic features "multimethod" modeling, i.e., has the capabilities to structure models that combine all three simulation paradigms: agent-based, system dynamics, and discrete event. Simio is a simulation modeling framework based on "intelligent objects" and supports a seamless use of multiple modeling paradigms including event, process, object, and agent-based modeling.

As computational capabilities continue to advance in both hardware and software, new capabilities are continuously being incorporated into the latest versions of ABM toolkits. The field is advancing rapidly toward highly scalable, high productivity agent development environments that are easy to learn and use.

4 HOW TO GET STARTED WITH AGENT-BASED MODELING

Many people ask how to get started with agent-based modeling. A good background in simulation modeling in the traditional fields of discrete-event simulation, Monte Carlo simulation, or even system dynamics is an excellent prerequisite but is not essential, as the field of agent-based modeling was not originally founded on these fields or the software that supports them. Some universities offer courses on agent-based modeling, but not very many at this time. There is not even a generally agreed-upon agent-based modeling curriculum for the modeling and simulation community, but Macal and North (2013) attempt to get that discussion rolling through their experiences with workshops and tutorials such as this one. Many people have found success at becoming agent-based modelers, including the authors, by independently following a path such as this:

1. Read about introductory agent-based modeling,
2. Review some good, simple applications in the literature,
3. Download, play with, and inspect some available pre-built ABM demonstration models,
4. Attend conferences devoted to agent-based modeling or that have significant focus on ABM,
5. Define a problem meaningful to you to address with agent-based modeling (see Table 2), and
6. Develop some simple agent-based models (prototypes) in available ABM toolkits.

Going through these steps positions one to start thinking about how to develop larger-scale and serious agent-based models. The most important point to make is that *there is no substitute for learning about agent-based modeling than to get one's hands dirty and actually build an agent-based model*. This is true even if the ultimate goal is not to become a full-time agent-based modeler. Steps 5 and 6 were discussed in the previous section. Steps 1 – 4 are discussed below.

A background in computer programming is very helpful but not absolutely essential to get started with agent-based modeling, as ABM environments may offer high-level languages that are relatively easy to learn (e.g., NetLogo, ReLogo) or visual environments that simplify ABM specification (e.g., AnyLogic, Repast Simphony). However, developing an ABM with advanced capabilities (GIS, database connectivity, etc.) often requires programming, typically in Java or another object-oriented language such as C++. There is a natural relationship between ABM and object-oriented programming, as agents may be regarded as objects with behaviors, i.e., intelligent objects (Macal and North 2007).

A single comprehensive source for reading all about ABM does not exist. Good introductions to ABM include the web sites by Axelrod and Tesfatsion (http://www2.econ.iastate.edu/tesfatsi/abmread.htm), the ACE web site also by Tesfatsion (http://www2.econ.iastate.edu/tesfatsi/ace.htm), and the new web site by Railsback and Grimm (http://railsback-grimm-abm-book.com/). The book by Epstein and Axtell (1996) is often regarded as launching the field of social agent simulation in a sustained way. It includes simple, but elegant, models of various social processes that are still being elaborated upon. The early paper by Bonabeau (2001) remains one of the most cited and readable papers on the motivations for ABM. The book by Gilbert and Troitzsch (2005) is widely read and provides a highly readable overview of the field including how to construct simple ABM. Our book (North and Macal 2007) is designed to provide a broad non-technical introduction to ABM in terms of how to think about and do ABM as well as providing terminology and language for becoming conversant in agent-based modeling.

There are several recurring issues that are often raised by newcomers to ABM including how agents handle resource contention and allocation, how time is taken into account, etc. There are common approaches in ABM to address these and other issues that are beyond introductory ABM. The SIMSOC Archive (https://www.jiscmail.ac.uk/cgi-bin/webadmin?A0=simsoc) and SIMSOC listserv are good places for information on various introductory and advanced ABM topics.

Good ABM applications are scattered throughout the literature across many disciplines. There is no single publication source for ABM applications, but the online *Journal of Artificial Societies and Social Simulation* (JASSS) has provided a consistent outlet for agent-based models for many years (http://jasss.soc.surrey.ac.uk/JASSS.html).

Disciplines often produce their own overview publications on agent-based modeling specific to their discipline. These can serve as valuable resources for understanding the value of using ABM in a discipline and include key references for the domain. For example, disciplinary ABM overview and survey papers include: marketing (Rand and Rust 2011), economics (Cristelli et al. 2011), financial economics (LeBaron 2005), transportation (Bernhardt 2007), electric power markets (Weidlich and Veit 2008), geographical information systems (GIS) (Brown et al. 2005), and many other areas. Simple Google searches on "agent based model" or multi agent system model" yield many application papers.

It can be very useful to visit the web sites for the ABM toolkits and download the software (NetLogo or Repast, for example) or trial versions (AnyLogic, for example). Demonstration examples are provided that give a good idea of how agent-based models are constructed and of the software's capabilities.

Several conferences have a focus on agent-based modeling or tracks devoted to ABM. The annual Winter Simulation Conference tends to have a full track of proceedings papers devoted to agent-based simulation and applications. The annual MABS (Multi-Agent-Based Simulation) workshop, which is part of IAAMAS (International Conference on Autonomous Agents and Multi-Agent Systems), focuses on agent-based modeling "from the standpoint of the multiagent systems community of engineering and the social/economic/organizational sciences" (https://sites.google.com/site/mabsworkshop/). The annual Computational Social Science Society of the Americas (CSSSA) conference, formerly NAACSOS, focuses on "Computational Social Science (CSS), a scientific discipline where computational methods and simulation models of social dynamics are employed to offer new insights into social phenomena beyond what is available with traditional social science methods" (http://computationalsocialscience.org/csssa2013). SwarmFest (www.swarmfest2014.org) is a conference devoted to agent-based modeling and simulation. Other conferences such as the annual INFORMS meeting (https://www.informs.org/) and the annual MORSS (Military Operations Research Society Symposium, http://www.mors.org/) often have significant numbers of presentations involving agent-based models, and this number has steadily grown over the past 10 years.

5 MODELING THE ZOMBIE APOCALYPSE

5.1 System Analysis

We consider the steps in designing an agent-based model of a zombie apocalypse. A large-scale version of such a model has actually been developed and applied on a city-scale to simulate possible outcomes of a zombie invasion to the City of Chicago (Macal 2016). In the description of the model design that follows, we separate the model design from its implementation. In other words, the design contains all the information to be able to be implemented in any computer programming language or ABM toolkit. We take a watered-down object-oriented approach to the design of the model, using pseudo-code (actually *Mathematica* code) that includes classes, class templates, characteristics, and methods applied to classes. Other approaches to specifying a model design are possible, whether they be object-oriented or not, but they would be equivalent in terms of the information content specified for the model.

We follow the process for developing agent-based models in Table 2 to illustrate the thought process.

- *Step 1.* Model Purpose and Value-added of Agent-based Modeling: We seek to understand what the outcome of a zombie invasion could be. How many people will be turned into zombies and ow fast will this occur? What intervention could quell the outbreak and prevent the zombies from taking over? Agent-based modeling can uniquely consider the spatial location of individual agents and zombies, and well as consider individual characteristics of humans to defend themselves against a zombie attack, as well as the abilities of individual zombies, and their natural diversity of zombies to overcome humans.
- *Step 2.* All About Agents: The agents in the model should be humans and zombies. Note as an added complication for the model, the identities of the agents are not fixed, humans can be turned into zombies.
- *Step 3.* Agent Data: The zombie genre of movies and literature provides a rich source of possible zombie behaviors and characteristics. For example, some zombie movies feature slow zombies, others fast zombies. Development of valid zombie models could entail watching many zombie movies and shows and categorizing zombie behaviors for many different situations, such as George Romers's movie *Night of the Living Dead* (https://www.imdb.com/title/tt0063350/) and AMC-TV's series *Walking Dead* (https://www.amc.com/shows/the-walking-dead).
- *Step 4.* Agent Behaviors: Humans make decisions consisting of where to move to at any given time, and whether to fight or flee when encountering a zombie. Zombies also has behaviors consisting of where to go next in search of humans. We assume that zombies always attack when confronting a human. Technically, this is a behavior that could be altered in the model. Behaviors for humans could come from imagining what one would do in certain situations when encountering or avoiding zombies. We might want to consider alternate schemes for human behavior and see which one works best and under what circumstances.
- *Step 5.* Agent Interactions: Humans and zombies interact when co-located. Humans and zombies visually see and recognize each other. If a zombie successfully bites a human, the human turns into a zombie after a transition period. On the other hand, a human may flee from a zombie or kill a zombie to avoid being bitten.
- *Step 6.* Agent States: A critical piece of information or the model is the state of the agents. Humans are in normal, transition to zombie, or dead state. Zombies are in normal or dead states.
- *Step 7.* Agent Recap: We consider some interventions designed to change the outcome of human-zombie encounters. Specifically, we consider the effects of better pre-training to increase the odds

that a human would survive an encounter. We might validate the model by having it reviewed by zombie genre experts.

5.2 Model Design

The model design consists of specifying object classes and associated methods. Following the convention that objects with decision-making behaviors are called agents, the agents in the model consist of humans and zombies. In addition, places are objects, as they do not have associated behaviors. The first decision we make is whether humans and zombies should be their own classes or should be subclasses of agents. We choose the latter approach since humans can transition to zombies. We represent whether an agent is a human or zombie by the state of the agent. In addition, the state of a human includes information on (1) transition from human to zombie (implying the human is alive), and (2) dead. The zombie state also includes whether the zombie is normal or dead, how long it has been since the zombie transitioned into the zombie state, and the time of the zombie's last feeding. We have the option of recording an agent's history as transitioning to a zombie state.

Object classes specify the characteristics associated with objects.

```
agent[name/identifier, subclass:{human, zombie}, location: placeID, speed:number }]
```

Sub-classes:

```
human[name/identifier, humanState:{normal, in-transition, dead}, location: placeID,
speed:{slow, fast  (converted to number)], probability of winning encounter with a
zombie]

zombie[name/identifier, zombieState:{normal, dead, time transitioned to zombie, time
of last feeding}, location: placeID, name of biting zombie, time of being bitten,
probability of winning encounter with a human, speed:{slow, fast  (converted to
number)]

place[placeID:name/identifier, placeType, location:{latitude, longitude}]]
```

The model further defines `agents` as a list of all agents in the model*,* `humans` as a list of all human agents, and `zombies` is a list of all zombies in the model. `human` refers to a specific human agent. `zombie` refers to a specific zombie. Agent states are updated for the agents in the lists `humans` and `zombies` as the simulation progresses.

Agents in the simulation decide whether they will stay where they are or move from place to place on an hourly basis. When humans and zombies find themselves in the same place at the same time, that is, are co-located, a series of bilateral contacts occurs between the zombies and the humans. Each contact is defined as occurring between a single zombie and a single human.

Object Methods operate on objects or collections of objects (see Table 3). The methods need to be programmed with the appropriate logic (not shown here).

When fully programmed the zombie apocalypse model allows for understanding the timing of a possible zombie takeover. For example, a base case was run that showed zombies would take over Chicago within 60 days. Interventions were simulated in which the probabilities of zombies vs. humans winning an engagement were varied. One intervention proved highly effective at stalling a zombie takeover.

Table 3: Object methods for the zombie model.

Methods	Decription
`updateAgents[agents]`	Updates the simulation clock. Considers the movement choice of an agent each hour, and updates the agent locations and states. If agent decides to move, schedules arrival of an agent to a destination, a place. Includes agent behavior deciding on where to move to next.
`getHumans[agents]`	Identifies human agents in the model from the list of all agents.
`getZombies[agents]`	Identifies zombie agents in the model from the list of all agents.
`colocatedAgents[agents]`	Identifies co-located humans and zombies in the same place.
`humansDecideToMove[human]`	Human decides on whether to move or stay at a location.
`zombiesDecideToMove[zombie]`	Zombie decides on whether to move or stay at a location.
`encounterOutcomes[agents]`	Given a collection of co-located humans and zombies, determines the outcome of the encounters. Each zombie and human state is updated accordingly.
`logStateChange[]`	Logs any state change for an agent during the simulation. The log is useful for reconstructing the history of the simulation and in post-simulation analysis.

6 CONCLUSIONS

We conclude by offering some ideas on the situations for which agent-based modeling can offer distinct advantages to other simulation approaches. Axtell (2000) discusses several reasons for agent-based modeling especially compared to traditional approaches to modeling economic systems. It is beneficial to think in terms of agents when any of the following criteria are satisfied:

- When the problem has a natural representation as being comprised of agents
- When there are decisions and behaviors that can be well-defined
- When it is important that agents have behaviors that reflect how individuals actually behave (if known)
- When it is important that agents adapt and change their behaviors
- When it is important that agents learn and engage in dynamic strategic interactions
- When it is important that agents have dynamic relationships with other agents, and agent relationships form, change, and decay
- When it is important to model the processes by which agents form organizations, and adaptation and learning are important at the organization level
- When it is important that agents have a spatial component to their behaviors and interactions
- When the structure of the system does not depend entirely on the past, and new dynamic mechanisms may be invoked or emerge that govern how the system will evolve in the future.
- When arbitrarily large numbers of agents, agent interactions and agent states are important
- When process structural change needs to be an endogenous result of the model, rather than an input to the model

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