Using Agent-based Modeling to Understand Complex Social Phenomena - A Curriculum Approach

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Abstract. Agent-based modeling (ABM) is a powerful tool for studying complex systems that involve multiple agents interacting with each other and their environment. However, there is a lack of comprehensive and easily accessible resources for learning about ABM and its applications. To address this issue, collaboration on developing an open curriculum on ABM for university seminars is proposed. An open curriculum would allow for the sharing of expertise and knowledge across disciplines and institutions, be more accessible to a broader audience, and foster greater collaboration and cooperation among researchers and practitioners in the field of ABM. This would ultimately improve the accessibility and impact of ABM as a tool for understanding and predicting the behavior of complex systems. We propose a curriculum comprising six modules covering the introduction to ABM, building an ABM, analyzing and interpreting results, real-world applications, advanced topics, and future directions.

Keywords: Agent-based modeling · Second keyword · Another keyword.

1 Introduction

In today's world, phenomena are becoming increasingly complex due to the interplay between people and technology, which can result in **emergent behavior and feedback loops**. Understanding and predicting these phenomena require the use of complexity-enabled methods, which combine empirical and theoretical elements. One such method that has gained popularity in recent years is agent-based modeling (ABM).

ABM is a computational method that **simulates the behavior of individual agents and their interactions within a complex system**. It allows researchers to model complex systems and analyze the emergent behavior that arises from the interactions of individual agents. ABM has been used to model a wide range of complex systems, including social, economic, and environmental systems.

Despite the growing popularity of ABM, it is still **not widely incorporated into university and school curricula**. This is because ABM requires knowledge from multiple disciplines, and interdisciplinary education is still lacking in many institutions. However, there have been some efforts to develop curricula that incorporate ABM into social science education.

For example, the Center for the Study of Complex Systems at the University of Michigan offers a graduate-level course in agent-based modeling for social science research. The course covers the basics of ABM, including agent behavior, agent interactions, and model validation, and **introduces students to the NetLogo programming language**, which is commonly used for ABM.

Similarly, the Santa Fe Institute offers a short course on agent-based modeling for the social sciences, which covers the fundamentals of ABM and its applications in various fields, including economics, sociology, and political science.

To demonstrate the effectiveness of ABM in understanding complex phenomena, researchers have used it to model a wide range of systems, including the spread of infectious diseases, the dynamics of financial markets, and the behavior of social networks.

For example, Epstein and Axtell in 1996 [10] used the emergence of residential segregation in a city **constructed from first principles**, demonstrating how individual preferences for neighborhood diversity can lead to the formation of segregated neighborhoods. Another study by Eubank et al. in 2004 [11] used ABM to **model the spread of infectious diseases**, showing how different control strategies can affect the spread of disease.

ABM is a powerful tool for modeling complex systems and understanding emergent behavior. While its interdisciplinary nature presents challenges for incorporating it into social science curricula, there have been efforts to develop ABM-focused courses and resources to support its adoption. To support these efforts, we propose an open curriculum for teaching ABM in the social sciences.

2 Related Work

This section briefly overviews agent-based modeling (ABM) as a tool and its historical development. Additionally, it discusses the essential aspects that must be considered while developing a curriculum for ABM. A proposed content outline is also presented, along with a discussion of the significance of collaboration in creating an Open Curriculum for ABM.

2.1 Agent-based Modeling

An agent-based model comprises **three essential components** [10]. The central element of an agent-based model is the **agent** itself. An agent has internal states that change dynamically upon interaction with other agents or the environment. The second component is the **environment**, representing the space the agents populate. In Epstein and Axtell's words, the environment is "a medium separate from the agents, on which the agents operate and with which they interact" [10]. The last component is a **set of rules** that links the agents with their environment by defining how they change their internal states and environment in the simulation.

One of the **first agent-based models** that gained traction in the social sciences was put forward by Schelling in 1971 [16], who described a model intended to depict **racial segregation in urban areas**. In its most basic layout, the model consists of two types of agents (e.g., conceptualized as blue and orange agents) that live on a square lattice. Based on the fraction of similar agents in their Moore neighborhood [13], agents determine whether they are satisfied or unsatisfied with their current "home" in the network. The condition for s**atisfaction is given by a global threshold**, which defines the fraction of agents in an agent's neighborhood, which must be similar. Unsatisfied agents relocate to a random empty square on the lattice. When this model is played out for a sufficient amount of simulation steps, **segregated neighborhoods of agents of the same color emerge**. The most striking property of Schelling's model was that this **segregation is even observable for high tolerance values** as defined by the satisfaction threshold.

Schelling's approach would later heavily influence a series of modeling attempts that can be summarized under the umbrella of **generative social science** as described by Epstein and Axtell[10], and Epstein [7]. The authors argue that specific macroscopic system-level patterns should be investigated from the bottom up. The distinguishing element of this approach is a shift in focus from the particular **individual strategy to the macroscopic pattern**. If a measure of fit between the simulated and the (empirically) observed pattern can be developed, the new paradigm is to generate candidate rules that give rise to emergent patterns. The fitness with regard to the observed patterns becomes the quality metric of the model [7]. To our knowledge, there is still no consensus about a formal metric of this kind. In many modeling attempts, **the fit of the simulated pattern with the observed phenomena was mainly determined qualitatively**, predominantly through visualization.

One early example that explicitly adhered to the paradigm put forward by Epstein and Axtell [10] was Axelrod's model of the **dissemination of culture** [1]. The model aimed to generate candidate explanations for a conundrum Axelrod puzzled over. If one assumes that **people that are close to each other converge in their views and opinions**, why does everyone not become the same eventually, and **how can global polarization still occur**?

In the model, agents are organized on a fully populated square lattice, meaning each agent is connected to its four neighbors (think north, east, south, and west). Each agent has a "culture", which is represented by a vector of fixed length whose elements are instances of an arbitrary categorical alphabet. The **cultural**

similarity between two agents is calculated as the fraction of cultural traits they share (i.e., dimensions of the vector that are identical).

In each step of the simulation, one agent is chosen at random. This agent then applies one simple rule to update its internal state represented by the culture vector. He calculates the similarity with one randomly chosen neighbor. Then he **changes one of his dissimilar cultural dimensions to that of the other agent with a probability equal to their similarity**. When these rules are played out sufficiently long in a simulation, **regions of cultural similarity that are entirely separate from each other emerge**.

The crucial detail that led to this global pattern was that Axelrod made the **local convergence of culture conditional on the ex-ante similarity** of the two agents. That is to say that locally proximal individuals do not unconditionally converge in their views and opinions but only do so if they already share certain traits.

On a related note, Epstein [8] studied the opposite phenomenon of why some behaviors are widely adopted by the majority of a population, i.e., **the emergence of social norms**. In this model, agents inhabit a one-dimensional lattice and possess the **two attributes of norm and radius**. The norm is a binary factor whose states are represented by the letters L and R (for driving on the left or the right side of the road, respectively, which Epstein uses as an example norm). The **radii are heterogeneous between agents**, and they determine the number of agents that an agent samples to both of their sides when updating their internal norm.

As in the model of the dissemination of culture, the state updates in this model happen asynchronously and randomly. In each simulation step, the agents are activated in random order and update their norm according to a set of simple rules. First, an activated agent checks the predominant norm in her neighborhood as defined by her internal radius attribute. Then, the agent checks **if the resulting norm would change if the radius were increased by one**. If this is the case, the agent increases her radius by one. If the norm does not change, the agent determines whether the norm would change if she decreased her radius by 1. If it does not, the agent decreases her radius by one. Otherwise, she leaves her radius at the original value.

Epstein describes this kind of normative perception with the **intuitive conceptualization of "lazy statisticians."** The agents will reduce the size of the samples they use to determine the predominant social norm if this does not change the result, and they only increase their sample sizes when the results do change. Put differently, they are "lazy" in the sense that they minimize their samples to determine the predominant norm.

Running a series of experiments with this model, Epstein was able to produce **patterns that exhibit local conformity and global diversity**, meaning that the model allows for both local convergence of behavior as well as regional emergence of different norms.

There are several available software options to implement agent-based models. The recent improvements and broader accessibility of computational resources have made the approach of ABMS significantly more viable. A **well-established and popular option is the NetLogo software** [18] introduced by Wilensky in 1999 that provides a simple programming language based on the educational language Logo along with an integrated visualization framework for agent-based models.

More recently, the programming language **Julia** [3] **has been considered to be a promising option for agent-based modeling**. Burbach et al. [4] compared both options and concluded that each of them has favorable properties. However, they prefer Julia as a more reliable option for more computationally and conceptually complex models. A framework for agent-based modeling in Julia is provided by a software package called Agents.jl [17] which implements a domain-specific language for ABMs and includes data collection and visualization capabilities.

3 Designing Curricula

Developing a curriculum is a complex and multifaceted process involving several different factors and considerations. In general, **a well-designed curriculum should be based on a clear understanding of the program's goals and objectives**, the students' needs and interests, and the latest research and best practices in the field, which in our case, will be agent-based modeling.

Recent literature on curriculum development emphasizes the importance of a **learner-centered approach**, which focuses on the needs and interests of the students and the development of their **critical thinking, problem-solving, and communication skills** [2]. This approach can involve a range of pedagogical strategies, such as active learning, collaborative learning, and problem-based learning, which can help to engage students and promote their learning and development.

In the specific case of a university seminar on agent-based modeling, the curriculum would need to cover the fundamental principles and concepts of this approach, as well as the latest developments and applications in the field. This could include topics such as the basics of agent-based modeling, the benefits and limitations of this approach, and how to implement and evaluate agent-based models.

Overall, developing a curriculum is a dynamic and ongoing process that requires careful planning, research, and collaboration. By taking into account the **latest research and best practices** and by involving experts and stakeholders in the process, it is possible to **develop a curriculum that is effective, engaging, and relevant for students** [12].

4 Curriculum Development

ABM is a computational approach for modeling and simulating the actions and interactions of autonomous agents within a system. It is **a powerful tool for understanding and predicting the behavior of complex systems**, particularly those that involve multiple agents interacting with each other and their environment [6].

In the following, we present an outline for an empirical-based curriculum on ABM for a university seminar using six modules:

1. Introduction to Agent-Based Modeling. The first module of a course on Agent-Based Modeling (ABM) should introduce students to the **key concepts and principles** of this tool for studying complex systems. In the first session, the course should start with an overview of ABM, including its definition and key characteristics. It should discuss why ABM is useful for studying complex systems, using examples such as social networks, traffic flow, and economic systems. A second session should focus on the basic **concepts and terminology** of ABM. Students will learn about agents, which are the individual entities that make up the system being modeled, and the rules and interactions that govern their behavior. They will also explore how agents can be programmed to interact with each other and the environment and how these **interactions can give rise to emergent behavior** at the system level.

2. Building an Agent-Based Model. In the second module, students should learn how to define **agents and their properties**, specify the rules and interactions among agents, and implement the model in a programming language. They will also learn how to validate and calibrate the model to ensure that it accurately represents the real-world system being studied.

3. Analyzing and Interpreting the Results. The third module should focus on analyzing and interpreting the results of the model. Students will learn how to visualize and analyze the output of the model, interpret the results in the context of the real-world system being modeled, and evaluate the robustness and sensitivity of the model.

4. Applications of Agent-Based Modeling. In the fourth module, students should explore **real-world applications** (e.g., disease dynamics [15]) of agent-based modeling and the role of ABM in **policy and decision-making**. They will also discuss the ethical implications of using ABM to model complex systems.

5. Advanced Topics in Agent-Based Modeling. The fifth module should cover advanced topics in agent-based modeling, such as incorporating **spatial and temporal dynamics**, modeling **networked systems** (see Fig. 1 or [5]), and incorporating **machine learning and data analytics** into ABM.

6. Conclusions and Future Directions. Finally, in the sixth module, students should summarize the key takeaways from the course and discuss emerging **trends and challenges** in ABM research and practice. By the end of the course, students will have the skills and knowledge to create and analyze agent-based models of complex systems and will be prepared to **apply these techniques in their own research** and professional practice.

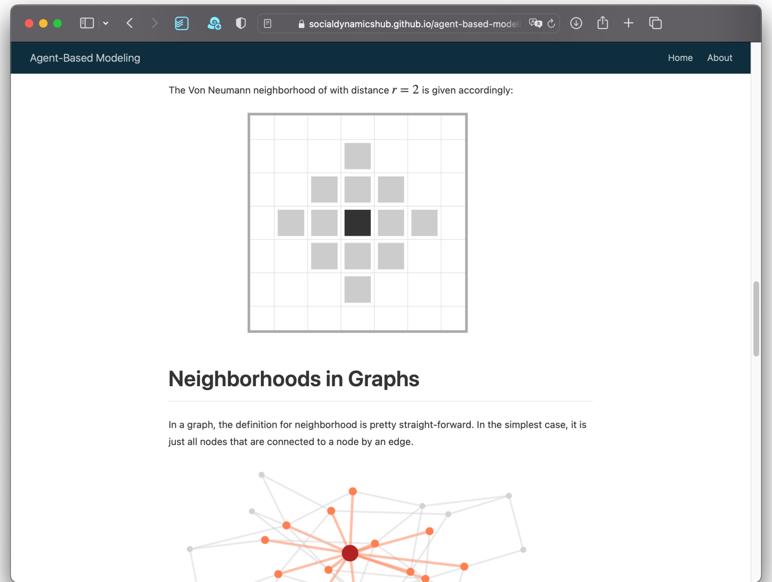

Fig. 1. Comparing different types of spaces in ABM

5 Call for collaboration on the Open Curriculum

ABM involves the creation of computational models that simulate the actions and interactions of autonomous agents within a system and has been applied to a wide range of fields, including e.g., economics, biology, and sociology, among others. Despite its growing importance, however, there is a **lack of comprehensive and easily accessible resources for learning about ABM** and its applications. This is particularly true for university seminars, where students and researchers may not have access to specialized courses or textbooks on the subject. This is where collaboration on the development of an open curriculum on ABM for university seminars becomes crucial. Such a curriculum, created through the collective efforts of researchers and practitioners from diverse disciplines and backgrounds, would **provide a valuable resource for students and researchers** seeking to learn about ABM and its applications.

There are several potential benefits to this type of collaboration. First, an open curriculum would allow for the **sharing of expertise and knowledge across disciplines and institutions**. Researchers and practitioners from different fields could contribute their unique perspectives and experiences, resulting in a more comprehensive and diverse resource.

Second, an open curriculum would be more **easily accessible to a broader audience**, including students and researchers who may not have access to specialized courses or textbooks. This could help to expand the reach and impact of ABM as a tool for understanding and predicting the behavior of complex systems.

Finally, an open curriculum could **foster greater collaboration and cooperation** among researchers and practitioners in the field of ABM. By working together to create a shared resource, researchers and practitioners could foster a sense of community and collaboration that would benefit the field as a whole.

In conclusion, collaboration on the development of an open curriculum on ABM for university seminars is an important step towards improving the accessibility and impact of ABM as a tool for understanding and predicting the behavior of complex systems. By bringing together researchers and practitioners from diverse disciplines and backgrounds, such a curriculum could serve as a valuable resource for students and researchers seeking to learn about ABM and its applications.

5.1 Social Dynamics Hub

We propose to organize such an open curriculum in a way that directly supports the decentralized creation of documents as used in the open-source community, i.e., GitHub. For this purpose, we have created a Github organization SocialDynamicsHub (`https://github.com/socialdynamicshub`) were individual repositories contain either content of modules or interactive notebooks for teaching ABM. One repository automatically renders to a website (see Fig. 2 and Fig. 3) that can serve as a starting point for interested researchers at `https://socialdynamicshub.github.io/`.

We would be happy to welcome collaborators on this platform.

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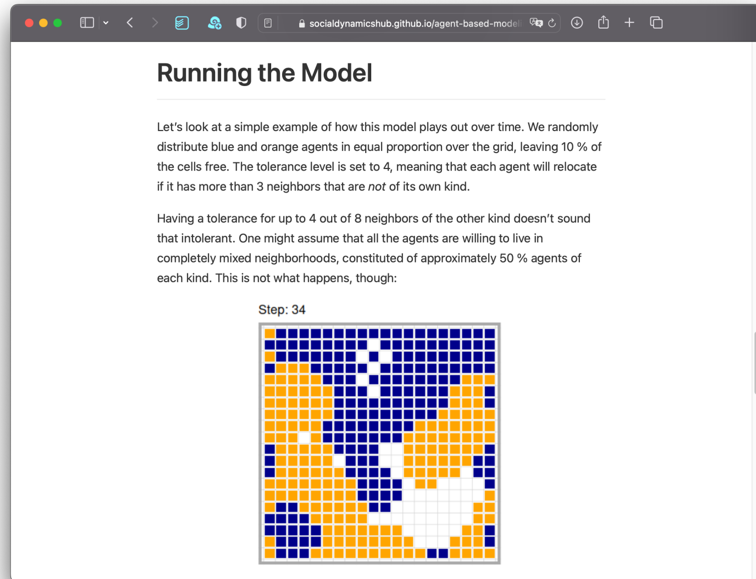

Fig. 2. Screenshot from the website tutorial on the Schelling Model

Fig. 3. Screenshot from the website tutorial on the Forest fire model

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