The History of Agent-Based Modeling in the Social Sciences

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Abstract. Agent-based modeling is a powerful technique that allows modeling social phenomena ab-initio or from first principles. In this paper, we review the history of agent-based models and their role in the social sciences. We review 62 papers and create a timeline of developments starting from 1759 and Adam Smith into the recent past of 2020 and efforts to model the Covid-19 pandemic. We reflect on model validation, different levels of model complexity, multi-scale models, and cognitive architectures. We identify key trends for the future use of agent-based modeling in the socials sciences.

Keywords: Literature review · Agent-based models · System Dynamics · Complex systems · Disease modeling · Model evaluation

1 Introduction

Agent-based modeling (ABM) is an increasingly popular modeling type that allows researchers to let virtual agents interact with each other. By defining a set of simple rules on the micro-scale, complex behavior at the macro-scale can emerge. The ant hive for example is a highly complex building with a faceted hierarchy and interaction, which emerges from the interaction of the very basic instincts of individual ants.

The agents-based approach is inherently bottom-up, facilitating understanding of how complex phenomena emerge from seemingly simple interactions at the micro-level. ABM is a relatively young modeling technique from the 1970s and deeply connected to the social sciences. ABM focuses, much like the social sciences, on how individual behavior produces larger patterns. This explains why some of the most important contributions to ABM are tied to social phenomena like the neighborhood segregation (Axelrod 1980) or the spread of opinions (Hegselmann and Krause 2002).

Current applications of ABM can be found in biology and infection modeling, finance and market models, robotics, and cargo routing. With the growth of the Artificial Intelligence field, especially with Machine and Deep Learning approaches, the capabilities of cognitive architectures for individual agents changes, and further applications like generating training data are being investigated.

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2 Research Methods and Result Structure

This paper is focused on explaining the history of ABM models and its major influences. As main body of this paper, the most significant authors and their contributions to the field of ABM are detailed. The choice of the selected contributions is influenced by the number of citations on Google Scholar as well as the scope of influence on other contributions. To exemplify the application of ABM in different fields, fewer cited papers are also taken into account.

In overall, 62 contributions are included in this paper to create a comprehensive overview. Four main epochs of ABM were identified, ranging from 1970 to 2021 and described. A central result of this paper is Fig. 1, which provides an overview of the different epochs of Agent-Based Modeling, its predecessors and main contributors.

3 History of ABM and Social Sciences

As Engbert et al. (2020) stated, one of the drawbacks of conventional disease-modeling techniques such as SIR is their assumption of homogeneous population mixing, which does not reflect the behaviour of individuals in the real world. A technique that allows to incorporate this kind of behaviour is Agent-Based modeling. The concept of ABM is the simulation of multiple individual agents whose behavior is described by simple rules. By describing the autonomous behavior and properties of the discrete agents on micro-scale, complex behavior at the macro-scale (in the following also referred to as macro-behavior) can be modeled (Rand and Rust 2011). An ABM usually is set in a given space, which is then used to simulate and track the movement of individuals alone and between social groups. This allows to further investigate the spatial aspect of the transmission of diseases, which was a limitation of classic differential equation based models (Perez and Dragicevic 2009).

Railsback and Grimm (2011) name other examples that show the benefits of ABM, such as in the modeling of biological systems (Railsback et al. 2013), the finance market or cargo routing. Buchanan (2009) states that disasters such as the financial crisis from 2008 are partially due to untested political measures that set off unforeseen consequences, and recommends testing the impact of those measures on the market using ABM before deploying them.

Heath (2010) traces the history of the ABMs back for hundreds of years, when complex phenomena, applied to vastly different systems, were captured with mechanisms at micro-scale by ground-laying works of the like of Adam Smith, Donald Hebbs and Richard Dawkins.

In Adam Smiths Invisible Hand of 1759, individual agents take self-interested actions, which result in mutual advantage an unintended social benefits for the community (Smith 2002). The phenomena of the Invisible Hand is the central justification for neoliberal theories of free markets (Binkley 2002).

Donald Hebbs theory of Cell Assembly of 1949 states that the complex phenomenon of memory is created by the comparatively simple interaction of individual neurons in certain hierarchy patterns (Attneave et al. 1950), and is often summarized as “Neurons wire together if they fire together” (Löwel and Singer 1992).

Dawkins coins the term “memes” in 1976 as a self-replicating, cultural unit, that is subject to the pressures of evolution as observed in biological systems, and results in the complex cultural patterns that can be seen in the real world (Dawkins 2014).

What all of these works have in common is the idea of simple, individual agents that, by interacting with each other, generate some observed pattern, just as the Agent-Based Models aim to. But an important intermediate step between the underlying concept of emerging patterns and the computer-based ABMs we see today, is the Cellular Automata (CA).

3.1 Roots of ABM

The concept of a CA is based on Von Neumannm, who constructed the theory of a self-reproducing machine in 1950. This theoretical machine carries a blueprint and tools to reproduce itself, and also allows its offspring to again be able to reproduce even further. This machine was very complex, resulting in 29 different logical states of the machines components to reproduce itself successfully (Langton 1984). Von Neumann was convinced that complex patterns required complex mechanisms, and adhered to the top-down approach of understanding the global system before investigating the constituents of it.

Von Neumanns colleague Ulam added the idea of a cellular automaton (CA) to the self-replicating machine, which is composed of individual cells on a checkerboard field that interact with each other. This idea also introduced parallelism to the automaton, which allowed to model global behaviour based on the interaction of single agents, and represents a change from the top-down to bottom-up approach. It also accounted for the parallelism often observed in nature (Heath 2010).

Scientists began to use CAs when investigating the complexity of nature and observed patterns. One of the most famous uses of CA was introduced by Conways “Game of Life”, which was using very simple rules to generate a virtual world (Gardner 1970). From these simple rules, patterns such as “gliders” can emerge, and eventually even patterns were found that allow the self-replication of objects, alluding to complex life forms that are composed of simple atoms joined together (Aaron 2010). What separates CA from ABM is that in cellular automata, agents are stationary, whereas agents can move freely (according to their programmed behaviour) across their given space in ABM, which allows to represent and model a much wider variety of phenomenons (Wilensky and Rand 2015).

Another important factor in the development of ABMs were Complex Adaptive Systems (CAS). CAS are rooted in biological systems and take factors like diversity (i.e., different reactions to the same stimulus) and information flow between agents into account. They are, for example, used to gain insights into the formation of complex behaviour and the creation of biological systems as a whole, and were an important base for the design of ABM (Macal and North 2006).

Another important influence was the System Dynamics approach by Forrester which models the nonlinear behaviour of a system with feedback loops, signal delays, and other complex behaviour. It is for example known for its application in the "Limits to Growth" model from the Club of Rome where the exponential growth of economy and population and linear growth of available resources is simulated (Turner 2008).

In the previous paragraphs the deterministic and stochastic modeling techniques were compared. Adding to this comparison, the System Dynamics approach allows the precise study of a complex system, but requires that the rules are stated at macro-level, which is not always feasible (Rand and Rust 2011).

3.2 Evolution of ABMs and the Influence of Social Sciences

What the hereinafter discussed models have in common is that they aim to generate some of the emerging behaviours observed in complex systems from a simple set of rules. This makes it possible to observe and understand the behaviours of complex systems without knowledge of the entire system and with limited computing resources (Heath 2010). While Multi-Agents Systems (MAS) are more often applied with a focus on solving a specific scientific problem (Abdallah and Lesser 2007), ABMs are used to examine and understand systems and patterns from the bottom up. Helbing and Balietti (2011) names heterogeneity (individual behaviour can vary between agents) and stochasticity (the system can exhibit random variations) as two important properties of ABMs. Figure 1 was created to provide an overview of the evolution of ABMs with a timeline of important contributions to ABM and its influences.

One of the first ABMs was the Segregation model, presented by Schelling in 1971. Schelling shows how in a shared space, agents with individual preferences for neighbours of the same type can generate segregated neighbourhoods, much like those that can be observed in the real world. The first versions of this model were paper-based, but still embodied the agent-based approach of individual agents on a shared space, creating a complex outcome based on the agents behaviour and preferences (Schelling 2013).

In the 1970s and 1980s, many other ABMs were developed, such as the Prisoners Dilemma Tournament and Culture Dissemination model from Axelrod. Both show how the application of ABMs became more common, facilitated by advanced computing powers and software. The Prisoners Dilemma model was intended as a tournament, where different strategies for the famous prisoners dilemma were used to investigate which behaviour would prove most beneficial to an individual agent. Surprisingly, the winning strategy was the simplest strategy, "Tit for That", which mimicked the last action of the opposing player, and showed how altruistic behaviour (termed "niceness") can be in the long run favourable for an individual (Axelrod 1980).

The model of Culture Dissemination is based on the tendency of individuals to exhibit some kind of cultural convergence, that is to adapt the traits (be it beliefs, attitudes, or behaviour) of neighbours. Axelrod (1997) aims to model the social influence of others and the emerging patterns such as a global differences despite local convergence. An important feature is that the exchange of traits is not sequential but parallel, allowing interaction between different traits, which is also an important aspect in real-life behaviour (Axelrod 1997).

The next steps towards modern ABMs were facilitated by the development of different modeling software in the 1990s, which enabled easier creation and configuration of ABMs. Software such as Ascape enabled SugarScape, a multi-purpose ABM from Epstein and Axtell which inspired many generative social science models and was used to investigate and model different social phenomena (Wilensky and Rand 2015). Axtell and Epstein also provided several implementations of the SugarScape model and showed how collective behavior like cultural transmission, exchange of goods, and fighting between agents emerges from simple rules and behaviors (Epstein and Axtell 1998). Other widely used software was NetLogo (1999), Swarm (1997), Repast (2000) and MASON (2003), as reviewed by Railsback et al. (2006).

Of course, most of these tools have their own focus on a certain field. Whereas Repast focuses on large-scale simulation and social science aspects, Swarm was specialized on the simulation of biology. Together, these different tools allowed ABM to be applied in vastly different contexts, such as the study of social systems, ecology, economics or geography (Samuelson and Macal 2006).

(Jackson et al. 2017) find that ABM is especially useful to study the emergence of phenomena, which is a subject often studied in social psychology. The idea that aggregation of small-scale individual behavior leads to different collective behaviors is often reflected in real-world phenomenons like traffic jams and human consciousness. The authors furthermore point out that often, the magnitude of emergence furthers the impact the ABM—that is, to explain a lot of complexity with simple rules.

The advantages of ABM, especially for the application to social sciences, are a large statistical power since experiments can be scaled up easily and be well controlled, opposed to real-world experiments. Also, nonlinear dynamics can be introduced and mechanisms isolated, which poses a significant problem in conventional experiments.

As (Calero Valdez and Ziefle 2018) points out, these advantages could be applied to many modern problems where human interaction with technology leads to the emergence of a variety of extremely nonlinear phenomena. In the field of social simulation, the effect of social bots, fake news and filter bubbles could be explored since ABMs could account for the complexity of interaction as well as provide the controlled environment for such experiments.

An example application in the field of social science is the model of Opinion Dynamics of Hegselmann and Krause (2002). It investigated the formation of opinions in interacting groups and whether consensus, polarization or fragmentation emerged from this interaction. In this non-spatial model, bounded confidence emerges as the most important parameter, which describes the phenomenon that the opinion of an agent can not be influenced by a source when he disagreed strongly with it. The factor of opinion distance describes this difference, and if the difference becomes too great, opinion change does not occur.

Other recent contributions to the social sciences and the modeling of epidemics were made by Epstein, such as the technique of growing phenomena of interest in a society of agents (Epstein 2012), introducing fear and flight as important factors in agent behaviour during an epidemic (Epstein et al. 2008) and refining agent behaviour by endowing them with modules for emotional, cognitive and social reasoning (Epstein 2014).

Another example for the application of ABM in recent times is the finance sector. As Franke and Westerhoff (2012) find, ABMs are better suited to explain the stochastic volatility on the pricing dynamics of assets. Fagiolo and Roventini (2017) evaluate that ABMs have become a valid alternative to conventional Dynamic Stochastic General Equilibrium models in macroeconomic policies. After the financial crisis of 2008, many present models that predicted an general equilibrium in the financial sector were reevaluated since they failed to predict the significant crisis that occurred. Since ABMs can provide an alternative to the present model, many models have emerged that studied the impact of regulations on the financial market or warning signals of future crises (Buchanan 2009).

An interesting project at the intersection of financial and social model is the EURACE model, an European project that attempts to generate an ABM of the European economy. The model is devised as massively parallel ABM, containing a large agent population and a complex economic environment. It is based on the philosophy of the research on Generative Social Science from Epstein and Axtell (1998) and one of the first successful attempts to build an ABM of a complete economy, integrating mechanisms of the economy and its most important markets into it (Cincotti et al. 2010).

To support such a complex model, the Flexible Large-scale Agent modeling Environment (FLAME) was developed, which allowed performant parallel computation and the big scale of agents (Deissenberg et al. 2008). From computational experiments with the model, many publications about macro-economic effects resulted, such as about the importance of the lending activity of regulating banks (Raberto et al. 2019), the relevance of credit (Cincotti et al. 2010) or housing market bubbles (Erlingsson et al. 2014).

In the highly influential work of (Bonabeau 2002), Bonabeu names four main areas where ABMs can be applied to business processes in the real world: diffusion, market, organizational, and flow simulation. He emphasises the importance of social aspects of these models and their use as learning tool, which can help better understand marketplaces and customers.

ABMs provide a new approach to the presented methods (deterministic, stochastic, cellular automata, system dynamics, multi-agent system). Agents can behave deterministic or random, based on their programmed behavior, since they allow the modeler to select which behavior to employ. Random behavior can be a good choice when not all aspects of the model have to be specified for reasons of complexity, and still achieve a passable approximation of real world concepts (Wilensky and Rand 2015).

ABMs can provide a micro-level view of the disease spread instead of the population-level view of the SIR model, which allows to better explore behavior at the individual-level and the resulting large-scale patterns. To construct an equation-based model, knowledge of the global behaviour is required so that the model can be verified against the real-world phenomenon, which is not always the case. Oftentimes, insight into the global behavior is even the goal one wants to achieve with the model, which makes ABM a valid candidate for disease spread simulation (Wilensky and Rand 2015).

This approach however also introduces three difficulties as stated by Keeling and Danon (2009): understanding the individual behavior with regard to disease spread, required data at individual rather than global level, and finally complexity and computational requirements.

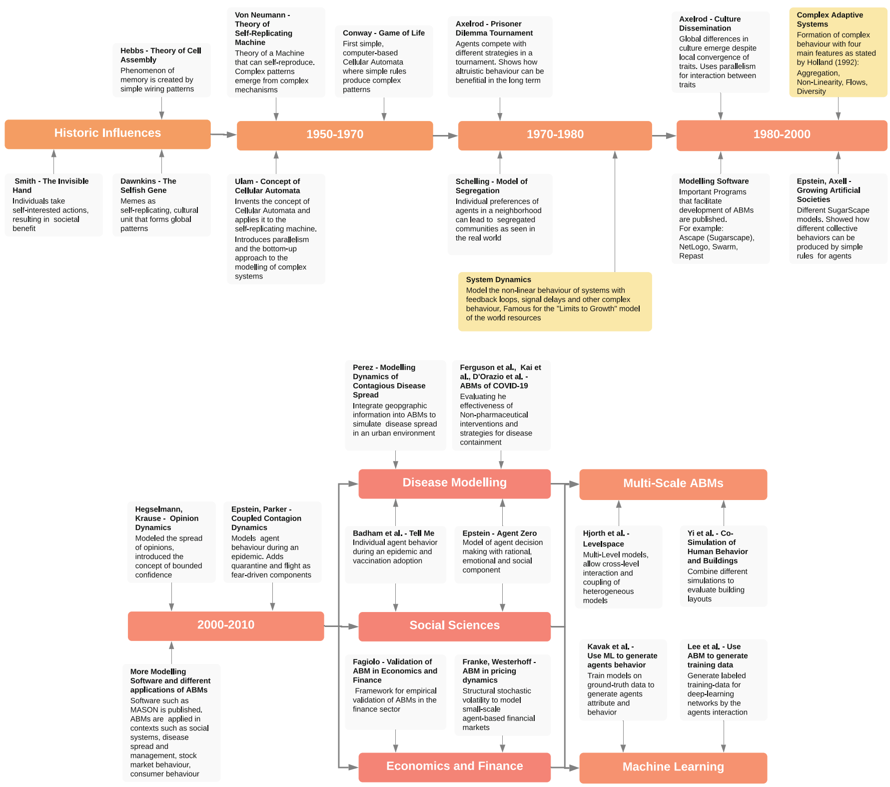

Fig. 1. Timeline of the evolution of ABM and its influences. ABM started in the 1950s and is now applied to fields like disease modeling, social sciences and economics. ABM was influenced by approaches like Complex Adaptive Systems and System Dynamics. For a larger version of this figure, got to https://osf.io/8jk9h/

3.3 Current Topics in ABM

Two major and ongoing research topics in the field of ABM are model-validation and verification and the modeling and realistic replication of human behavior (Kennedy 2011). A third noteworthy topic is the lack of influence of ABM, especially with regard to the Social Sciences. Regarding the validation of ABMs, Windrum et al. (2007) identified four major issues: a lack of a core set of modeling frameworks, issues in regard to the comparability of ABMs, no unified standard procedures for the construction of ABMs, and a difficult empirical validation. This leads to the first of the two most recent trends: model validation.

The validity of a model shows whether the model output is consistent with the results seen in the real world and if the developed, conceptual model represents the modeled system adequately. Through the process of calibration, the model parameters are adjusted with the aim to increase the model accuracy (Xiang et al. 2005). The conventional method for validation is the result validation approach, which simply compares the results of the ABM simulation with data from the real-world system. This validation method motivates the requirement for accurate data of the real-world system, which might not be always available or otherwise infeasible to obtain (Olsen and Kaunak 2016). Windrum et al. (2007) published an influential study about development approaches and the empirical validation of ABMs for economic models which highlighted the need for empirical model validation techniques for the reasons mentioned above. The study compared empirical validation procedures and found the "Indirect Calibration Approach" to be the most popular.

In 2019, Fagiolo et al. (2017) did a renewed survey of validation methods based on the review of Windrum et al. and evaluated the Indirect Calibration Approach as still most widely adopted approach. It consists of four steps (Fagiolo et al. 2017, pp. 3–5):

1. Identification of real-world stylized facts
2. Specification of model behavior
3. Validation and hypothesis testing
4. Application of the model for policy analysis

These steps provide a comprehensive guide for the validation of an ABM and will be taken into account in the model validation of this paper.

The second major development in ABMs was the progress in the development agent behaviour, based on abstractions of real cognitive processes. As Caillou et al. (2017) state, the biggest obstacles for cognitive architectures in ABM are limited processing power and the added complexity of modeling the behaviour.

Kennedy (2011) categorizes three different cognitive approaches for modeling human behavior in ABMs: mathematical, conceptual and cognitive. The mathematical approach generates the agent behavior by mathematical simplifications, for example by comparing a threshold against an input value. The conceptual approach takes concepts like the emotional state and intentions of the agent into account, but is still just a conceptual framework that abstracts cognitive functioning. The cognitive approach aims to model the cognitive function of the target agent, the basic cognitive system of the agent does not change during the model execution.

The mathematical approach was the first architecture that was used in ABM and can be seen in examples such as Schellings segregation model (Schelling 2013) or Axelrods model of culture dissemination (Axelrod 1997). These models have in common that the behavior of the agent is represented by a very simplified reasoning captured in an intuitive mathematical model. The conceptual approach to ABM introduces more complex agent reasoning process with concepts such as beliefs, desires, or emotional states, which was facilitated by advancing computational resources that allowed to simulate this behaviour. An example is the introduction of the Beliefs Desire Intentions or BDI architecture to the modeling language GAML (Caillou et al. 2017), or the architecture of the Agent Zero agent with an emotional, rational, and social component (Epstein 2014). These models provide a middle ground between the simple rules of the mathematical models and the complexity of a model of human cognition of the cognitive approach. They allow for a more realistic, complex agent behaviour while keeping computational costs and model complexity so far in check as to allow sizeable models.

The cognitive approach uses cognitive architectures that model human behaviour. Since human behavior is not fully understood by now, different architectures implement different mechanisms to partially or fully replicate human behavior in different aspects (Ritter et al. 2019). As of now, cognitive models are mainly employed in controlled environments, since they can be unnecessary complex for tasks where simpler agent models could lead to a similar behaviour fit with less complex cognitive models (Reitter and Lebiere 2010). The drawback of high complexity manifests in a lower number of active agents for simulations with complex cognitive architectures, so that with the application of SOAR of Naveh and Sun (2006) no more than ten cognitive agents are active at a time, while the work of Bhattacharya et al. (2019) with a simpler cognitive architecture employs up to three million simultaneous agents. These agent numbers are not objectively compared, but rather serve to exemplify the magnitude of difference.

This performance drawback was reduced over time with advancements in computational power and the steady development of high-performance cognitive models such as ACT-UP (Reitter and Lebiere 2010) or Matrix (Bhattacharya et al. 2019), which aim to make these models more accessible, easier to develop and faster to compute. Especially ACT-R and SOAR are well-established and have an active community (Kennedy 2011). Examples of the application of cognitive architecture are the implementation of Naveh and Sun, which implement the CLARION model to simulate academic science and publications (Naveh and Sun 2006).

Reitter and Lebiere (2010) demonstrated up to 1000 active agents in their model ACT-UP, in the Matrix model up to three million agents were simulated on computing nodes with 30+ cores (Bhattacharya et al. 2019). Salvucci (2009) modeled the dangers of using a telephone while driving a car, based on the cognitive model ACT-R with a vision and motor system connected to a driving simulator, while the same cognitive agent was instructed to go through the steps of dialing a telephone. However, the overall evolution of cognitive models still proves challenging. Modern AI has made a lot of improvements in this direction, but the long-promised unified theory of cognition is, more than 30 years after its conception, still just within reach Ritter et al. (2019).

A third current non-topic is the lack of major impact on mainstream social science research of ABMs (Bruch and Atwell 2015). The most influential examples, the neighborhood segregation and prisoners dilemma models, were mentioned in the history of ABM. The lack of communication between experts in social science research and the ABM modeling community is identified as central reason for the discrepancy between the advantages stated earlier and the lack of significant works. However, this gap is closing with the growing accessibility of ABM and general prevalence of software in all aspects of our lives, and ABMs have found more use in recent times.

More recent examples of the application of ABMs can be found in the Social Epidemiology. Cerdá et al. (2018) investigate the influence of interventions on development of violence in urban neighborhoods. An explanation of group formation in homogeneous populations, where in-group cooperation is observed even though no clear-cut definition of in- and out-members and self-evident group identity, is presented by Gray et al. (2014).

A significant recent application is found at the intersection of disease and social modeling with the COVID-19 epidemic. Since 2020, 1300 articles were published according to Google Scholar, indicating great interest in the topic. Since Non-Pharmaceutical Interventions form a central aspect of every COVID-control strategy and rely on the acceptance of the population, modeling the uptake and upkeep of such measures is of great interest (Hoertel et al. 2021). Furthermore, modeling the social networks itself is of importance since these form an essential part of disease transmission Hinch et al. (2020). These aspects could be much improved when applying the expertise of social scientist familiar with the intricacies and mechanisms of risk perception and reaction to it.

3.4 Future Trends

On a model level scale, the adaptation of multi-scale models is a noteworthy trend. The level-space extension of Hjorth et al. (2020) adapts the concept of multi-level agent based models. This approach allows to connect and integrate multiple models and levels, allowing cross-level interaction, adapting the level of detail dynamically and generally coupling heterogeneous models to simulating interacting systems. This ultimately allows researchers to investigate causality across different levels and complex phenomena. Though not explicitly stated, the approach of Yi (2020) also uses a similar approach by combining different simulations with each other, integrating human behavior with thermodynamic building properties.

A trend that at first sight lends itself for strong consideration with respect to cognitive models lies in cooperation with the broad field of Machine Learning. Most recent AI research has been in the field of Machine Learning, especially, much so that it is often used synonymously. In general however, Deep Learning approaches have not been widely adopted due to the inherent lack of explainability, which often constitutes the most important research goal. This explains the tendency for application in industries, where Deep Learning models are treated as black-boxes that "just work", which is of course no option for research. In contrast, rule-based approaches are often better understandable. Furthermore, the computational effort is often significant and provides a hindrance for model development and testing. However, computational advances and modeling breakthroughs have removed some of these barriers and facilitated recent applications.

Kavak et al. (2018) propose an integration of Machine Learning and ABMs by training models on ground-truth data and applying these models at individual-level to the agents to generate attributes and behavior, ultimately developing better empirical ABMs.

A second approach is proposed by Lee et al. (2020), which generate the labeled training-data for their deep-learning network, resulting in accurate predictions of emerging spatial patterns and proving the applicability to complex interactions. Other authors recommend the combined application of ABMs and ML models to economic problems and policy analysis by emulating micro-scale behavior of economic agents or data-generation with full-scale ABMs (van der Hoog 2017).

The paper of Yi (2020) adapts a ML approach by using a Gaussian Process Classifier, a ML classification approach, to find optimal spatial positions for their agents in a building, enabling designers to receive direct feedback on the predicted usage of a building. This shows how cognitive architectures will receive more and more input from ML approaches, presumably shifting away from the manual expert-systems of SOAR and ACT-R. Thanks to the development of ML libraries such as SciKit Lean and PyTorch, these processes become more and more accessible and therefore find their way into more publications.

However, the use of one or the other does not have to be exclusive. (Johora et al. 2020) recommend the combination of expert-systems (another approach for AI by making complex, manually generated rule-sets) and Deep Learning approaches into a single ABM predicting the interaction of mixed road traffic.

4 Conclusion

The journey of ABM has been a long one as there is no end in sight, yet. The bottom-up approach of ABM gains more and more traction, focusing on the explainability of phenomena and facilitating insights into complex problems. Impactful works of Axelrod (1980, 1997) and Epstein et al. (2008) show how simple rules can produce the emergence of complex phenomena and generate insights into the workings of societies.

Several applications in the areas of social sciences, finance, infection modeling and robots show how the concept of ABM can be transferred to other disciplines and help with understanding emerging behavior. However, there is still a lack of mainstream research (especially in the social sciences) with ABMs, mainly as product of a lack of communication between the ABM modeling and social sciences community.

This communication gap seems to be closing, helped by the growing prevalence and acceptance of software in the researchers' everyday life and the growing evidence of successful applications. Also, the current trend of improved model validation helps building trust in ABMs. The development of cognitive models is also progressing, allowing researchers to build agents with more detailed and realistic behavior patterns.

In the future, multi-scale models enable ABMs to simulate even more elaborate models, connecting different scales of detail and phenomena. The combination with Machine Learning approaches enables researchers to generate the ever-needed data sets for training ML models and integrate smarter, self-learning cognitive architectures and agents, ultimately facilitating research in a variety of fields and understanding of complex phenomena.

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