Visualizing the workings of agent-based models: Diagrams as a tool for communication and knowledge acquisition

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ABSTRACT

One of the biggest challenges in developing agent-based models (ABMs) is the acquisition of domain knowledge. Interviews, or other types of face-to-face communication, are one of the ways of doing it but problems might arise if we deal with tacit knowledge and if the interviewee and the interviewer come from a very different cultural and educational background. This research proposes a visualization approach to be used in the interaction between domain and modeling experts that will facilitate communication in these kinds of situations. The approach is based on the findings of knowledge visualization and related fields, as well as on a firm understanding of ABMs. Three important aspects of ABMs that need to be visualized in order to facilitate understanding were identified. In a case study, performed in relation to a project where a spatial ABM was developed, three node-link diagrams were created according to the developed approach. They visualize the conceptual structure, the simulation process, and the data model of the ABM. These diagrams were positively received by the stakeholders of the project and they improved workflow and communication in the project.

1. Introduction

One of the biggest challenges in developing agent-based models (ABMs) is the acquisition of domain knowledge. This knowledge is held by the domain experts but as they are seldom familiar with the ways of representing knowledge in computer programs they cannot add it to the models themselves. Thus, the knowledge has to be collected, which is both laborious and time-consuming, resulting in applications that often are technically advanced but poor in terms of substance. In short, domain knowledge is often lacking in ABMs, something which Crooks, Castle, and Batty (2008) also observe.

Various methods for knowledge acquisition exist, both theoretical, such as literature reviews (e.g., Bennett & Tang, 2006), and empirical, of which, e.g., Robinson, Brown, Parker, et al. (2007) give a review, such as direct observation (e.g., Miller, Breckheimer, McKeary, et al., 2010), and GPS measurements (e.g., Torrens, Nara, Li, et al., 2012). The applicability of these methods varies, depending on the domain and the kind of knowledge needed. Literature reviews work well for well-studied domains, direct observation for observable phenomena, and GPS measurements for studying the spatial behavior of living agents. When none of these methods are applicable, e.g., for innovative, non-observable, and non-measurable application domains, such as, e.g., urban planning, the best solution might be to use interviews (e.g., Saqalli, Bielders, Gerard, et al., 2010).

In an interview, knowledge is constructed in the interaction between the interviewer and the interviewee (Kvale, 2007). For this to work well, the interviewee needs to be able to express his or her knowledge verbally and the interviewer and the interviewee need to be able to understand each other. Problems of communication might arise if we deal with knowledge that is difficult to verbalize and if the interviewer and the interviewee, or, in our case, the modeling experts and the domain experts, have very different backgrounds, which is not uncommon.

In our research, we try to find solutions to this problem in the domain of Knowledge Visualization (KV), which tries to “improve the transfer and creation of knowledge between at least two persons” (Eppler & Burkhard, 2005, p. 551) through “the collaborative use of interactive graphics” (Eppler, 2013, p. 3). Visualizations facilitate communication as they can be “mentally assessed and rearranged in multiple ways that contribute to understanding, inference, and insight” (Tversky, 2014, p. 4). Crooks et al. (2008) also acknowledge this as they explain that visualization is one of the keys to sharing the structure of digital models.

KV is not about representing explicit data, which information visualization is, but about representing experiences, insights, instructions, and assumptions (Burkhard, 2005). This kind of highly personal knowledge, which is hard to formalize and verbalize, is also called tacit knowledge (Nonaka, Toyama, & Konno, 2000). Acquiring this kind of knowledge requires a shared cognitive and social context (Novak & Wurst, 2005); it cannot simply be passed on through text or similar media. KV offers tools, such as different kinds of diagrams, which facilitate the creation...
of this kind of context. A similar approach can be found in, e.g., database design, where conceptual diagrams are used as a communication tool when trying to find a compromise in terms of database contents (e.g., Routledge, Bird, & Goodchild, 2002).

Thus, the goal of this research was to develop diagrams that can be used as a communication tool by modeling experts and domain experts in the process of designing an ABM. The goal was not to develop a standardized and rigid way of visualizing these aspects but to demonstrate a flexible and straightforward approach to the problem. These diagrams would work both as a way for modeling experts to gain domain knowledge from domain experts and also as a means for making the system architecture and the operational logic of the model accessible to the potential users, i.e., the non-modeling experts, enabling them to verify the model. Furthermore, this research paid special attention to the spatial aspects of ABMs and utilized research on spatial and temporal relations from the field of Geographic Information (GI) Science.

This research responds to one of the key challenges in agent-based modeling for geo-spatial simulation identified by Crooks et al. (2008, p. 420), namely how to “communicate and share agent-based models with all those who we seek to understand or work with the model based on the field of Geographical Information (GI) Science.

The research consists of a literature review and a case study.

1.2. Materials and methods

The research consists of a literature review and a case study. Section 2 reviews three well-known and simple graphical representations as a starting point for the case study: the concept map, the flowchart, and the entity-relationship (ER) diagram. Concept maps are used to organize and express knowledge in an easily understandable way, flowcharts show step-by-step progression through a procedure or system, and ER diagrams are mainly used for database design. These were chosen as a representative subset of the myriad of node-link representations that can be used for knowledge construction and sharing, of which Eppler (2006) lists many. After this review, ABMs are discussed and defined in Section 3 and then the implications of the findings of the literature review for the case study are summarized in Section 4.

The case study, which is presented in Section 5, was performed in relation to a project that aimed at developing a spatial ABM for the simulation of urban planning. The model was intended to help urban planners in the initial stages of designing a new residential area by giving them quick and easy answers about the consequences of certain planning decisions. By changing certain parameter values in the model the planner would be able to perform sensitivity checks on his or her plans. In the case study a set of diagrams was developed in parallel with the model based on the findings from the literature review, with the goal of communicating the operational logic of the model to non-modeling experts. To evaluate how well the diagrams succeeded in their goal a survey was conducted. This survey is presented in Section 5.3, the developed diagrammatic approach is discussed in Section 6 and conclusions are drawn in Section 7.

The case study suited our research purposes well. In the project, which included both city planners and architects, as well as GI scientists and computer scientists, communication was not only hampered by the fact that the principles of planning that the model needed to apply, those used by urban planners in their daily work, were a highly tacit form of knowledge, but the different background of the members of the project was equally problematic. Specifically, the design background of the urban planners and the engineering background of the modeling experts proved to be a difficult combination. This resulted in a project where two groups with different cultural and educational backgrounds, mindsets, concepts, and problem approaches tried to communicate with each other about a very difficult topic.

2. Node-link diagrams for knowledge visualization

This section presents three well-known graphical node-link representations and their origins: concept maps (Section 2.1), flowcharts (Section 2.2), and ER diagrams (Section 2.3). Common to all three is that they are developed to facilitate understanding and communication between humans.

2.1. Concept maps

Concept mapping is a graphical method for organizing and representing knowledge that was invented in 1972 by Joseph D. Novak and his research team at Cornell University as a means of representing children's knowledge about scientific concepts (Novak & Cañas, 2006). At first, it was mainly marketed as an educational tool (e.g., Novak, 1984) but has since been found useful in numerous other contexts, such as KV (e.g., Cañas, Carff, Hill, et al., 2005; Coffey, Hoffman, & Cañas, 2006; Eppler, 2006) and expert knowledge acquisition (e.g., Coffey, Hoffman, Cáñes, et al., 2002; Ford, Coffey, Cáñes, et al., 1996; Hayes, Eskridge, Saavedra, et al., 2005). An example of a simple concept map is given in Fig. 1.

Concept maps comprise concepts, represented by labeled nodes or boxes, and relationships between pairs of concepts, represented by labeled directed links. The relationship labels are often verbs forming phrases for each pair of connected concepts, e.g., grass-is-green (concept-relationship-concept). Concepts are defined by Novak and Cañas (2006, p. 177) as “perceived regularities or patterns in events or objects, or records of events or objects, designated by a label”. Concept maps are arranged hierarchically, going from the most general concept at the top to the most specific concepts at the bottom. They also include crosslinks showing relationships between concepts in different areas of the map and manifestations of concepts.
2.2. Flowcharts

A flowchart is a diagram that shows a step-by-step progression through a procedure or system (Merriam-Webster, 2015), and thus it has an inherent temporal structure. The steps are usually represented by boxes of various kinds and their temporal order by arrows connecting the boxes. Flowcharts showed up as early as 1921 (Gilbreth & Gilbreth, 1921) and have since been used extensively and in a variety of forms and contexts, ranging from the management of patients with paracetamol poisoning (Wallace, Dargan, & Jones, 2002) to algorithm comprehension (Scanlan, 1989). An example of a simple flowchart is given in Fig. 2.

Flowcharts have also been used frequently in agent-based modeling. They are usually used to depict the flow of the simulation from initialization to termination (e.g., Azar & Menassa, 2011; Crooks & Wise, 2013), to depict the structure and dynamics of a time step (e.g., Sleeman, Boggs, Radford, et al., 2005; Wise & Crooks, 2012), or to depict the decision-making process of an agent (e.g., Berger, 2001). Usually, different kinds of boxes are used to differentiate between different kinds of steps, such as input, output, processes, decisions, start points, and stop points.

2.3. Entity-relationship diagrams

The ER diagram was introduced as a tool for database design in 1975–76 by Peter P. Chen alongside the ER data model (Chen, 1976, 2002). The ER data model models the world as consisting of entities and relationships. Entities can be distinctly identified, e.g., a person or a company, and relationships are associations between entities, e.g., a father–son relationship or work-for relationship. The original ER diagram notation depicts entities as rectangular boxes and relationships as diamond-shaped boxes with connecting lines defining the entities for which a relationship holds. The diagram also distinguishes between 1:1, 1:n, and n:m cardinalities. The attributes of entities can be displayed in circles (e.g., Khatri, Ram, & Snodgrass, 2004). An example of a simple ER diagram is given in Fig. 3.

Several extensions of the ER diagram have been proposed (e.g., Harel, 1988; Teorey, Yang, & Fry, 1986); a comparative analysis of some of them can be found in Song, Evans, and Park (1995). Special effort has also been put into developing temporal extensions, of which Gregersen and Jensen (1999) give a survey. Spatial extensions also exist, e.g., Parent, Spaccapietra, Zimanyi, et al. (1998) and Khatri et al. (2004).

Fig. 1. A simple concept map depicting knowledge about ABMs.

Fig. 2. A simple flowchart depicting an agent’s decision and its consequences during a time step. The agent evaluates whether its goals are fulfilled and, depending on the answer, it takes different actions.
3. Agent-based models

An ABM can be defined as “a simulation model that employs the idea of multiple agents situated and acting in a common environment as central modeling paradigm” (Siegfried, 2014, p. 18). As such, it is more of a mindset than a technique (Bonabeau, 2002). It is an approach that is mainly used to model complex systems consisting of autonomous and interacting agents (Macal & North, 2010). One of the main benefits of this approach is that it allows the simulation of emergent behavior, i.e., behavior that emerges from the interaction of the components of a system (Wooldridge, 2009).

The agent is the central idea on which agent-based modeling builds. There is no general agreement on a precise definition of the term but definitions tend to agree on more points than they disagree on (Chen, 2012; Siegfried, 2014; Wooldridge, 1999). The definition given by Siegfried (2014, p. 18), which is similar to that of Wooldridge (1999, p. 29), is suitable for our purposes: “An agent is an entity that is situated in some environment, and that is capable of autonomous action in this environment in order to meet its objectives.” To put it simply, an agent perceives its environment (percepts) and, on the basis of this, usually according to some condition-action rules, acts within the environment (actions), in order to meet its objectives. This is illustrated in Fig. 4.

What is meant here by environment is the simulated environment, a goal-directed abstraction of the original environment, which contains what the agents can perceive and manipulate (Klügl, Fehler, & Herrler, 2005; Siegfried, 2014). The environment consists of both active entities, usually represented by agents, and passive entities, which do not exhibit any behavior, e.g., a road network. A global state variable, or environmental property, can also be connected to the environment, e.g., temperature. Thus, an agent’s percepts and actions can be directed towards both active entities, i.e., the other agents, and passive entities, as well as the environment itself through environmental properties. Here we presuppose a spatial environment, although there can be non-spatial variants (Klügl et al., 2005), and spatial agents, which Rodrigues and Raper (1999) define as agents who can reason over the representation of space.

4. Diagrams for understanding agent-based models

Something that is common to all three of the diagrams reviewed above is that they are node-link diagrams showing relationships (links) between parts (nodes). Most of the relationships have an arrow specifying some kind of order and, in general, are labeled in a descriptive way, if they are not purely sequential or attributive. What, then, are the parts and relationships that are important in communicating the workings of an ABM?

Understanding how an ABM works is ultimately about understanding the behavior of the agents. According to Batty (2007, p. 211), an agent, and thus its behavior, can be understood through its environment, percepts, and actions (see also, e.g., Russell & Norvig, 1995). To this list we would like to add the agent’s objectives, as an agent’s behavior cannot be fully understood without taking its objectives into consideration. Furthermore, to understand an ABM it is not enough to understand how a single agent behaves; it is necessary to understand how they behave in concert.

The diagrams thus need to cover the agents and their environment, i.e., the active and passive entities of the model, and their relationships. Additionally, there might be other conceptually important elements in the model that are not realized as active or passive agents, but those still need to be covered, e.g., elements that are an important part of the output of the model. As for the relationships, we argue that they can be divided into behavioral, semantic, temporal, spatial, and causal relationships. Behavioral relations describe the behavior of the agents in the light of their objectives. The two most basic semantic relations can be argued to be the is-a and the part-of relations (Kuhn, 1999) and they are important in relating the entities of the model to each other. Spatial and temporal relations are important in describing how space and time are taken into consideration and in what order things happen. In particular, spatial and temporal relations that govern agent behavior

![Fig. 4. A schematic view of typical agent behavior.](image-url)
need to be covered. Causal relations describe cause-and-effect relationships, e.g., what percepts cause what actions and effects. Additionally, the data model, including the conceptually important parameters and values, and their relationships, needs to be described.

As these diagrams will work as a communication tool between modeling experts and domain experts of varying fields, the relations should be expressed in an as much as possible intuitive and straightforward way. A standardized approach expressing relations in a very formal, perhaps mathematical, way would be detrimental as it would have to be less human-oriented and less adaptable to different domains and cultures than what we are proposing here. The topics covered by these five different types of relationships—behavior, categorization, space, time, and causality—are all cognitively important concepts for us as humans when we try to make sense of the world around us (e.g., Egenhofer & Mark, 1995; Galton, 2009; Kosslyn, Chabris, Marsolek, et al., 1992; Levinson, 2003; Pinker, 2009; Sloman, 2009). Therefore they are well suited to our diagrams.

As we see it, all of this cannot be done in a single type of diagram. Instead we propose three different diagrammatic approaches that together will cover the necessary aspects of the model: the conceptual structure, the simulation process, and the data model. The conceptual structure diagram should display the conceptually important elements of the model and describe how they interact through their behavioral, semantic, and spatial relationships. It resembles a concept map. Temporal relations are essential to understanding ABMs and the behavior of agents; therefore they get their own diagram, of a flowchart type, called the simulation process diagram. It focuses on how the agents act as the simulation proceeds by explicitly visualizing their percepts and actions. In particular, it maps the causal relations between different percepts and actions. It also includes the start and stop conditions for the simulation, as well as information on how agents enter and exit the simulation. Finally, the data model diagram covers the data model, including the conceptually important parameters and values, and their relationships. It is similar to an ER diagram.

4.1. Spatial and temporal relations

As special attention is paid to spatial aspects in this research, and as ABMs are inherently temporal, spatial and temporal relations are presented in greater detail than the other types of relations. Spatial and temporal relations are either metric or topological. In space, the metric relations distance and direction form together with topology a set of three basic types that cannot be broken down to simpler relations and that do not duplicate the meaning of any other relation (HALL & AHNEN-RAINIO, 2014; Nystuen, 1968). The same set can be formed for temporal relations although there the fundamental difference between distance and direction is less evident, as in a one-dimensional environment positive and negative distance values express direction. Spatial and temporal relations do not exist in the real world but in representations of the real world (MARK & FRANK, 1989), and, in the case of agent-based modeling, they relate active and passive entities to each other, and these may be modeled as points, lines, or polygons.

Topological relations are defined as those properties of geometrical figures that are invariant under continuous deformation (McDonnell & Kemp, 1996); they describe such things as adjacency, connectivity, containment, and overlap. Simple topological relations are Boolean properties, while distance and direction are metrical relations defined in relation to some frame of reference (Mark, 2005). Mathematically, a Boolean domain is a set consisting of exactly two elements, true or false, while in a metric case there is an infinite continuum of possible values between any two entities. E.g., two polygons, or intervals, either overlap or they do not overlap, while the possible values for the distance between two points are infinite.

Topological relations are qualitative, while distance and direction can be given in both qualitative and quantitative terms. Human reasoning is mainly qualitative and works by qualitative categorical terms such as ‘near’ and ‘far’ in a spatial context (e.g., Egenhofer & Mark, 1995; Galton, 2009; Kosslyn et al., 1992; Renz & Nebel, 2007) and ‘before’ and ‘after’ in a temporal context (Galton, 2009). Computers, on the other hand, are good at fast and accurate quantitative processing, i.e., reasoning with metric values. However, through various formalizations developed in the field of computer science, computers are also able to reason qualitatively about both space and time (see, e.g., Galton, 2009).

5. Case study: visualizing the workings of an agent-based model

The case study was performed with a spatial ABM for the simulation of resulting solutions for the locations and compositions of new buildings in an area. The model includes three types of agents, houses, apartments, and households, and a simple environment consisting of a road network. A detailed description of the model is beyond the scope of this article but it is briefly described in the next section. The results of the case study are presented in Section 5.2.

5.1. An agent-based model for simulating urban development

The model simulates: (1) the placement of houses; (2) the types of apartments needed in those houses, and (3) the number of parking places needed for each house. The model uses empirical data on apartment sizes, household sizes, car ownership, and the apartment size preferences of households from a real city and combines them with certain given boundary values, such as the distances allowed between buildings and buildings and roads. The model produces buildings that have an apartment size distribution and a number of parking places that match the empirical distribution, i.e., the real demand, and that are reasonably located in the environment.

The model was developed by Jyrki Vanamo from Aalto University and implemented with the GAMA platform, which allows the building of spatially explicit ABMs, and empirical data on the city of Helsinki from Statistics Finland. A screenshot of the model can be found in Fig. 5. To the left is a map showing the environment. The lines are the road network, the gray circles are buildings, the smaller green, yellow, and red circles are different kinds of apartments, and the blue circles are households. To the right is various numerical data visualized: the distribution of apartments, the distribution of households, the amount of people and cars, the percentage of populated apartments, and the target percentage.

The model uses a semi-random approach when generating apartment and household agents. For apartments, the number of rooms is randomly generated but the size of the apartment is based on the empirical data, e.g., the size of a one-room apartment is allowed to vary between a minimum and maximum value based on the actual distribution of the sizes of one-room apartments in Helsinki. In the same way, the model generates different kinds of households (the size is allowed to vary from one to five or more persons) on the basis of the actual distribution of households in Helsinki. Each household is also given 0–3 cars and an apartment size preference based on its size and on the empirical distribution of car ownership and apartment sizes for households in Helsinki. In this way, each household agent gets its own unique profile. The model places all kinds of different apartments into the environment but only those that meet the needs of the households remain when the simulation is over.

5.2. The visualization approach put into practice

Based on the findings from the literature review, three diagrams were created in the case study, according to the three proposed diagrammatic approaches (Section 4), with the goal of making the operational
logic of the model accessible to non-modeling experts. The first diagram, which is meant to be read first, gives an overview of the model, while the two following diagrams go into more detail. This kind of approach is also endorsed by Shneiderman’s visual information-seeking mantra (Shneiderman, 1996). Next, the three diagrams will be described in detail.

5.2.1. The conceptual structure

The first diagram, Fig. 6, focuses on the conceptual structure of the model. It includes the conceptually important entities of the model and their behavioral, semantic, and spatial relationships. The model includes three different agents, buildings, apartments, and households, and one passive entity, the road network. In addition to these, parking

Fig. 6. A diagram describing the conceptual structure of the ABM of the case study.
places and cars, which are implemented as attributes of agents, are also conceptually important, as parking places are one part of the output of the model. Therefore, they are also included. The visualization builds on the agent-environment duality and uses two different colors, orange and blue, to amplify it. Furthermore, the semantic relations is-a and part-of clarify the differences between the three types of entities. E.g., by inspecting the building box it is directly clear that it is an agent and that a parking place is implemented as an attribute of it.

From the behavioral relationships it is possible to gain an initial understanding of the agents’ behavior. They describe the objectives and needs of the agents. Both direct relationships, e.g., a household wants to have an apartment to live in, and indirect relationships, e.g., a household with a car needs an apartment that is situated in a building with a free parking place, can be read from the diagram. The spatial relations visualize how space affects the interactions between the agents. E.g., a building wants to have another building within 12–100 m and a road within 4–100 m of its own location. This diagram makes it clear that the spatiality in this model is quite simple, with the distance between buildings and between buildings and roads actually alone defining the suitable locations for all three agents. Each type of

Fig. 7. A diagram displaying the simulation process of the ABM of the case study.
relation is visualized with its own color to make it easier to separate them from each other.

5.2.2. The simulation process

This diagram, Fig. 7, displays the simulation process of the model. It is temporal to its nature. From it, both the start and end conditions of the whole simulation, as well as the lifespan of individual agents, become clear. It also shows how many new agents are introduced to the simulation in each round (one building, 20 apartments, and 10 households). It explicitly visualizes how the agents act as the simulation proceeds by visually separating, with different colors and boxes, each agent’s percepts (blue) and actions (green), and how these relate to the agents’ objective, which in this case is, somewhat simplified, to become happy. A yellow tint is used for the boxes related to the happiness and the start and end points are visualized with green and red circles. The more detailed objectives of each agent type can also be read indirectly from this diagram by studying how different percepts affect their happiness.

The arrows between the boxes describe causal relationships, especially how percepts relate to actions. The textual descriptions give the conditions that decide what kinds of actions follow from what kinds of percepts, if there are such conditions. If we take a closer look at, e.g., the building agent, we can see that each building each round perceives how close the closest other building is, how big its growth area is, i.e., does its current location allow it to grow, how close the closest road is, and how many apartments it has. After perceiving how many apartments it has it also perceives their combined area and the number of parking places it has by dividing the area of the apartments with a constant. From the diagram it is apparent that if the closest other building is less than 12 m away the building will move to a new location and if it is more than 100 m away the building’s happiness will decrease with a random value between zero and ten. If the closest other building is between 12 and 100 m away, this percept will not have any direct consequences. As can be read from the diagram, the building agent’s other percepts have similar consequences.

From the diagram it can be seen that the lifespan of an agent is decided by their happiness. At initialization, each agent’s happiness is 100. In this model, agents’ percepts either affect their happiness negatively or do not affect it at all. When an agent’s happiness drops below zero the agent exit the simulation. To counterbalance this, each agents’ happiness grows with a random value between zero and five each round (as stated in the diagram). This means that if all the agent’s percepts are satisfactory, i.e. they do not affect the happiness negatively, the agent’s happiness is allowed to grow each round, which means that the agent will not exit the simulation.

5.2.3. The data model

This diagram, Fig. 8, focuses on the data model behind the ABM. It visualizes the agents’ different parameters (round boxes) and values (sharp boxes) and how these are interrelated. It identifies three different types of parameters: input parameters (dark blue) stay unchanged during the lifetime of an agent, derived parameters (light blue) depend on the value of other parameters and they change during the lifetime of an agent, and output parameters (red dotted border) are the output of the whole simulation. The values have four different origins in this case: they can be given by the user (gray user input boxes), randomized from a uniform distribution (red circles), randomized from an empirical distribution (green cylinders), or dependent on other parameter values. Additionally, one parameter is a given constant. The dependencies between different values are made clear using arrows connecting the boxes in the diagram.

This diagram makes explicit both the input and output parameters of the model and their values. It distinguishes between static parameters, which do not change, and dynamic parameters, which do change over time, in a similar way to that in which Macal and North (2010) distinguish between static and dynamic attributes. More importantly, the diagram makes clear how the values of the parameters are calculated, e.g., the value of the parking places parameter of buildings depends only on the amount of floor space in the building and on the parking place constant. All the conceptually important parameters and relationships are included in this diagram. It works as a supplement to the two earlier diagrams by, among other things, specifying the objectives of the agents. The idea is that through this diagram it is possible to trace the origin of each value that affects the output of the model.

5.3. Evaluation of the visualization approach

To evaluate the diagrams a simple survey was conducted among the non-modeling experts of the project where the ABM was developed (these were mostly members of the project management group). Strictly speaking the survey consisted of only two questions: the respondents were asked to describe their understanding and ability to discuss the ABM before and after the diagrams were introduced. The survey was sent out to nine people out of whom seven answered. Of these, four where architects, two had similar or higher level technical education and one was a lawyer. None of them had experience of using or designing ABMs.

An analysis of the survey results revealed that all seven respondents thought that the diagrams facilitated their understanding about the ABM and three explicitly mentioned that the diagrams facilitated their ability to discuss the ABM. However, the better you understand a topic the easier it is to discuss it, therefore the conclusion is that the diagrams facilitated understanding and communication for all respondents. As one of the architect respondents put it: “Only after the diagrams were presented to the stakeholders there was a real discussion and even enthusiasm about the possibilities of the method.”

6. Discussion

As earlier concluded, communication had been a problem throughout the project in which this research was performed. With the introduction of the diagrams, the workflow and communication improved. Furthermore, the diagrams were positively received by the stakeholders of the project. This can also be seen in the survey which shows that the diagrams facilitated understanding and communication for all seven respondents. The diagrams helped to explain the workings of the ABM to the non-modeling experts and thus improved the communication in the project.

The diagrams enabled an understanding of the ABM of the case study through visualizing: (1) the conceptually important elements of the model and their semantic, behavioral, and spatial relationships; (2) the percepts, actions, and objectives of the agents and their causal relationships, and (3) the conceptually important parameters and their values, relationships, and origins. We argue that any ABM can be understood by visualizing the same elements and relationships. Possibly, temporal relations need to be added to the conceptual structure diagram (1) in some cases. In our case, the only temporal relations of importance were the order in which things happen, and they are readable from the causal relations of the simulation process diagram.

The diagrams did not include all the elements of the model, or all the parameters, only the conceptually important ones, i.e., those that are relevant to understanding the behavior of the agents, and through that the simulation as a whole. In choosing the conceptually important elements, it is important to bear in mind the purpose of the model, as well as the input and output of the model. In our case, both parking places and cars were important elements of the model, although they were not agents, because the former was part of the output and the latter was closely related to the output.

In this project, the diagrams were only used as a means to facilitate the non-modeling experts’ understanding about the model and to

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3 Translated from Finnish by the first author.
make the communication between the modeling and non-modeling experts easier. However, the idea is that diagrams like these could be used already in the model development phase both as a tool for acquiring domain knowledge and as a means to create a common understanding. E.g., they can be the basis for an iterative group work process: first, the modeler visualizes his draft model through these kinds of diagrams and gets feedback from the domain experts. Then, on the basis of the feedback, the modeler modifies the diagrams and gets new feedback. In this way it is possible to have a continuous discussion about the model between the modeling experts and the domain experts.

Compared with ODD and UML our approach is aimed at laymen not familiar with ABM or software engineering. Therefore, we do not give
any strict formal rules on the design of these diagrams as it would demand the laymen to first learn the standard before using the diagrams. What we have focused on, instead, is a new kind of approach to visualizing ABMs that is flexible and straightforward. The exact implementation, e.g., what colors and types of boxes to use, is of secondary importance and should be decided on a case-by-case basis. What is important is that these diagrams go from an overview to details and that they show the conceptually important elements. However, when there are no formal rules it is important to always include a legend in the diagrams. The diagrams also need to be explained, but as they are to be used in inter-human communication this will not be a problem. At present, the ODD protocol lacks any instructions on how to graphically present the structure of an ABM. Our approach does not fill this gap but could work as a basis for the development of a graphical ODD.

Although the case study dealt with a spatial ABM the amount of meaningful spatial relations was quite small. The agents’ spatial reasoning could actually be described through only two topological and two distance relations (Fig. 6). Therefore, all four spatial relations were here visualized in the same way. In another case, it might be beneficial to visually differentiate between, e.g., distance, direction, and topological relations. In the same way, there might be cases where it is beneficial to differentiate between different temporal relations. Fig. 6 used a mix of quantitative and qualitative terms to describe the spatial relations. We are not giving any strict rules on what kinds of descriptions to use but urge the fact that human reasoning is mainly qualitative and works by qualitative categorical terms is borne in mind when creating these kinds of diagrams.

7. Conclusions

This research set out to develop diagrams that can be used as a communication tool by modeling experts and domain experts in the process of designing an ABM. Based on the basis of a literature review a visualization approach was proposed and applied in a case study. According to this approach, the workings of ABMs can be visualized through three different types of diagrams. The first visualizes the conceptual structure of the model and relates the conceptually important elements to each other through semantic, behavioral, spatial, and possibly temporal relationships. The second visualizes the simulation process through the life-cycle of the agents. It covers the percepts and actions of each agent type and the causal relations between these. The third diagram visualizes the data model of the ABM; it covers the important parameters, their values, and their interrelationships. These three flexible and easily understandable diagrammatic visualization approaches are the main contribution of this research.

The diagrams build on the recognition that the workings of an ABM can only be understood through the behavior of the agents, and that the behavior of the agents can only be understood through their percepts, objectives, and actions. We argue that the five types of relationships covered by the proposed diagrams, behavior, categorization, space, time, and causality, which are cognitively important concepts for us as humans, enable a sufficient understanding of how the elements of an ABM interact.

The diagrams are based upon a visual language shared by all humans. They use a simple node-link structure that anyone can understand and that, with appropriate software, anyone can create. Their strength lies in the fact that they visualize the relevant elements and clarify how these are interrelated by explicitly stating their relationships. A survey was carried out showing that the diagrams facilitated learning and communication in the case study.

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