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TYPES AND PRIORITIES OF MULTI-AGENT SYSTEM INTERACTIONS

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ABSTRACT

Multi-Agent Systems may be classified as containing No Direct Interactions, Simple Interactions or Complex, Conditional Interactions between agents. This paper argues and illustrates that models with simple interactions, even though possibly less fascinating for the Multi-agent system theorists than complex interaction models are, deserve more attention in the Multi-agent system community. Simple interaction models may contain social learning and reciprocal relationships. Maybe most importantly, Simple interaction models enable cross-scale connections by linking local to global actors in their local and global 'life worlds'.

KEY WORDS

multi-agent systems, social learning, reciprocal relationships

CLASSIFICATION

ACM Categories and subject descriptors: I.2 [ARTIFICIAL INTELLIGENCE]; Agent Interaction

JEL: C63, C69

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INTRODUCTION

Multi-agent technology is presently moving from supply and theory-driven explorations to applications in a wide array of scientific and societal fields. In the present contribution, we take our examples from applications of multi-agent systems (MAS) in land use science. We hope and expect, however, that our message may be fruitful in many other areas, too.

The background of our paper is formed by the difference between theoretical and empirical fascinations. The ideal-type theorist is fascinated by MAS because of the capacity of a multitude of simple agents to generate system-level evolution, learning, stability and so on. The ideal-type empiricist is fascinated by MAS because of the capacity of simple agents to potentially generate a fit with reality that supports understanding and prediction of that reality. One example is from collective action (e.g., [1]). The theoretical fascination with collective action stems from that within rational choice theory, collective action involves almost insurmountable dilemmas. What models, in game theory or MAS, may resolve this problem? The empirical scientist, on the other hand, finds that in reality, collective action is everywhere, only with strongly varying degrees of success. Could MAS models explain this variety?

In this paper, we propose a three-tiered ladder of MAS model complexity that captures the tension between theoretical and empirical relevance. The rest of the paper is organized as follows. In section 2 we give an overview on the theory behind the Belief-Desire-Intentions (BDI) model and the Action-in-Context (AiC) framework. The classification of the types of MAS models based on their interactions is described in section 3 and we conclude in section 4 with priorities for MAS models with a primarily empirical 'versus' those with a primarily theoretical aim.

AGENTS AND AGENT THEORY

There is no universally accepted definition of the term agent, however some definitions have been suggested depending on the domain used in the sequel:

- "Most often, when people use the term 'agent they refer to an entity that functions continuously and autonomously in an environment in which other processes take place and other agents exist [2]."
- "An agent is an entity that senses its environment and acts upon it [3]". "The term agent is used to represent two orthogonal entities. The first is the agents' ability for autonomous execution. The second is the agents' ability to perform domain oriented reasoning."
- "Intelligent agents are software entities that carry out some set of operations on behalf of a user or another program, with some degree of independence or autonomy, and in so doing, employ some knowledge or representation of the user's goals or desires."
- "An autonomous agent is a system situated within and a part of an environment that senses that environment and acts on it, in pursuit of its own agenda and so as to effect what it senses in the future [4]."
- "An agent enjoys the following properties: (i) autonomy – agents operate without the direct intervention of humans or others, and have some kind of control over their actions and internal state, (ii) social ability – agents interact with other agents (and possibly humans) via some kind of agent-communication language, (iii) reactivity – agents perceive their environment and respond in a timely fashion to changes that occur in it, (iv) pro-activeness – agents do not simply act in response to their environment, they are able to exhibit goal-directed behaviour by taking initiative [5]".

In MAS models, agents are given a structure for decision-making. A well-known agent theory is the Belief-Desire-Intentions (BDI) framework that was first proposed by Bratman [6]. BDI describes ‘beliefs’ as the representation of the agent’s knowledge about the current world/environment and messages from other agents as well as the internal information. ‘Desires’ represent a state that the agent is trying to achieve and ‘intentions’ are the chosen means to achieve the agent’s desires, generally implemented as plans. Thus, an agent is characterised by its beliefs, goals (desires), and intentions – it will intend to do what it believes will achieve its goals given its beliefs about the world. Additional to these three components, a BDI agent is usually assumed to have a plan library – a set of “plans as recipes” that it can use to achieve particular goals given particular preconditions. An intention is formed when the agent commits to a particular plan – a particular sequence of steps to perform – from this set in order to achieve a goal. The steps themselves may be atomic actions, or they may be sub-goals, which can be satisfied by other plans [7]. Because the agent does not need to commit to a particular plan for these sub-goals until the last possible moment, this allows a balance between reactive and deliberative planning. The model is shown in Figure 1.

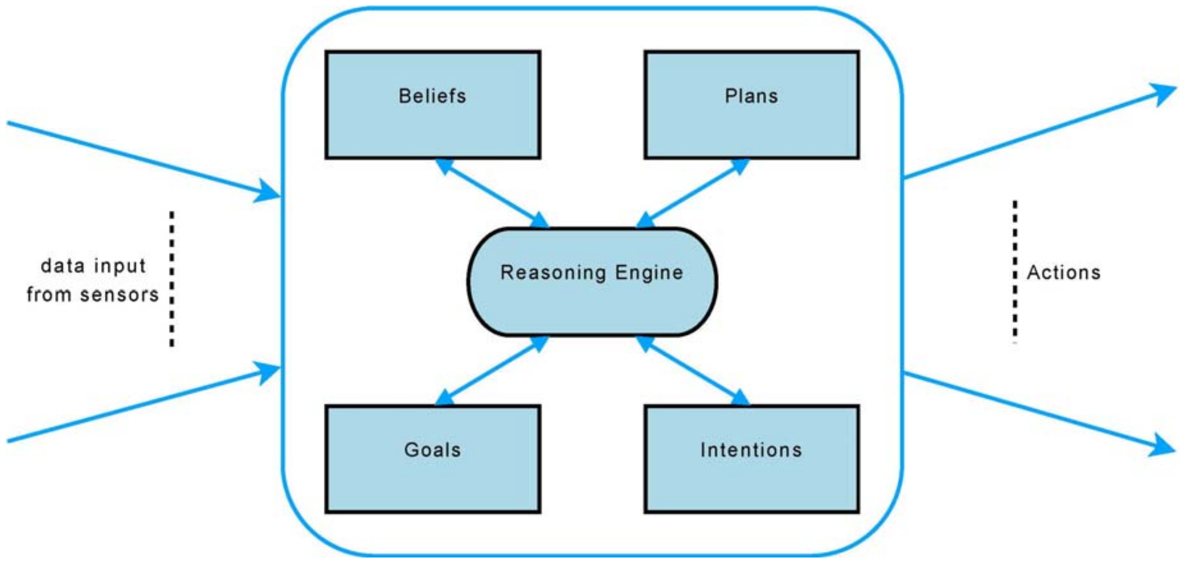

Figure 1. The BDI Model.

Putting together the beliefs, goals, plan library and intentions is the ‘reasoning engine’. This reasoning engine is what drives the agent, updating beliefs, monitoring and updating goals and intentions, selecting plans to achieve goals, and based on the current intentions, selecting the actions to perform. A key feature of the plan library is that although the plans are fixed “recipes” for action, they do not have to be fully specified. For any particular goal, there may be multiple plans to achieve that goal, and while any plan may be fully specified as a sequence of actions, a plan may instead consist of a sequence of sub goals, or a combination of actions and sub goals. In the case that the plan contains sub goals, the agent can delay the choice of how to achieve a particular sub goal until the time that it reaches that stage of the plan. While this does not achieve the full range of adaptability that people display, it does allow considerable flexibility in the agent’s planning, and its resulting behaviour.

Aside from the BDI model is the Action-in-Context (AiC) framework in which De Groot [8] developed an agent structure that expresses a broad rational choice theory just like BDI but contains some differences too, e.g. that the “plans as recipes” are taken up in the core structure (as ‘options’) but that the ‘intentions’ element is skipped in favour of going straight to ‘actions’. Moreover, the structure is multi-layered in order to express the linkages to the

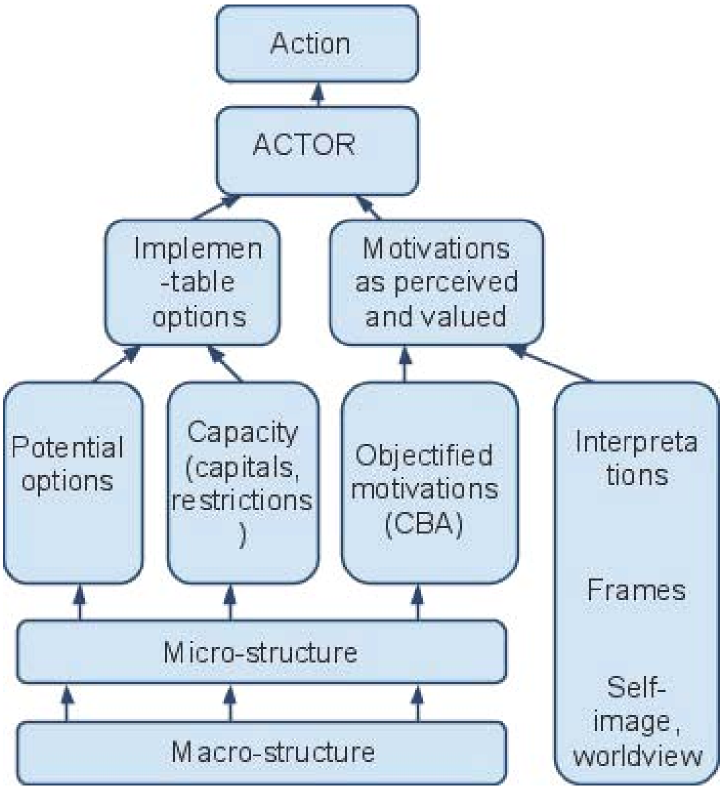

Figure 2. The Agent structure of the Action-in-Context framework (AiC).

structure and culture that the agent is part of. 'Actor' in AiC equals the 'Reasoning Engine' in BDI. The AiC agent model is depicted in Figure 2, describing the agent structure of the Action-in-Context framework (AiC) [8].

Implementable options are all actions the actor has available to reach the action's objective. Motivations as perceived and valued are the criteria (e.g. economic, social and cultural merits) by which the actor evaluates the action. Potential options are all options known by the actor. Capacity is the difference between potential and implementable options and is composed of positive capitals (economic, social, cultural, physical) and negative restrictions (prohibitions, taboos). Objectified motivations are those easily expressible in simple terms such as money, time or calories, often summarized as the actor's cost-benefit analysis (CBA). Interpretations are the cultural and psychological colours (quantitatively: multipliers) that attach to these objectified factors. Interpretations are embedded in more general frames of reasoning (which may be contextual, depending on the micro-structure), which in turn are embedded in self-image and world view (e.g. for a farmer, the image of what is a good farmer). Micro-structures are all structures (environments – physical, social and on the web) where the actor makes a difference. Macro-structures are all structures where the actor does not make a difference (e.g. for most actors, the oil market).

Although we will frame most of our examples in AiC terms here, we will not discuss the comparative merits of the agent definitions or two agent models here. The major point to note, however, is that all agent definitions as well as the two agent models allow no direct interaction of agents in multi-agent systems. In a MAS, variable types of agents may all respond to a variable, physical or economic environment without interacting with any other agent, and the system would still be a MAS.

TYPES OF MULTI-AGENT MODELS

In this section, we will distinguish and illustrate three types of MAS models. This is of course not the only way to make MAS classifications, but ours serves the specific purpose of elucidating the differences between theoretical and empirical fascination. The classification is:

1. NI – No direct Interaction between agents,
2. SI – Simple Interactions between agents,
3. CI – Complex, or Conditional, or Collective Interactions between agents.

What we will call ‘simple’ and ‘complex’ here also relates to our purpose. For multi-agent models that focus on land use decisions, it will for instance be relevant to make the MAS spatially explicit, i.e. taking data from and writing data in a GIS (e.g. the MameLuke framework, [9]). This obviously makes the MAS more complex but this is not the type of complexity we want to capture here. What we will call ‘simple’ is the type of interactions between agents that are basically one-way (although they may become reciprocal if one agent responds to the request of the first agent). What we will call ‘complex’ interaction could also be called ‘conditional’ interaction or ‘collective interaction’. Thus, an interaction of “I move to where I see you sitting” is a simple interaction, while “I move if you move” is a complex interaction.

A MAS that contains no direct-interacting agents is an NI MAS, a MAS that contains at least one simple interaction is an SI MAS, and a MAS containing at least one complex interaction is a CI MAS.

NO DIRECT-INTERACTION (NI) MAS MODELS

Overmars et al. [10] elaborate on the question if empirical land use science should remain caught in its current inductive, econometric paradigm, or try and become more deductive (‘theory-led’), e.g. by assuming an actor theory and testing the degree to which we may explain land use with it. In order to illustrate their case, they apply an inductive inference and a MAS model to land use in a part of the Philippines. Expressed through a simplified AiC structure, the MAS model contained different ethnic groups with varying land use options and different preferences (‘interpretations’) for different crops. The crops have different outcomes depending on markets, slopes and other environmental features. The agents are spread out over the GIS map according to their real demography. The agents do not interact, however. They just do their activities with their land without being aware of, let alone interacting with, any neighbour.

Both the inductive inference and the MAS model (without any calibration, i.e. purely deductive) generated a 70 percent fit between inferred/predicted and real land use in the GIS grid cells. This is empirically fascinating, inter alia because induction versus deduction is a basic question in empirical science and because deduction delivers a superior, namely causal rather than statistical, type of knowledge. This also enhances policy relevance. The response to a new crop, for instance, is easy to predict with the MAS, but out of reach of the inductive model (simply because the new crop, by definition, cannot be found in the dataset to do induction with). From the theoretical point of view of developing MAS models, at the same time, the model is utterly dull. Nothing happens in the model, so to speak. One run does it all.

‘Emergence’ is the hunting ground of theoretical MAS modellers. It may be interesting to note, therefore, that even NI MAS models may generate emergence. Take the well-known case of the Paramecium in an aquarium. Starting from a random distribution, these tiny creatures will be found in one corner of the aquarium after a while. Why? Are they attracted to each other (an SI model)? Or do they see food or smell in one corner and move, somewhat analogously to the NI model of the farmers above? Biological reality is an even simpler NI. The only rule for Paramecium is: “move randomly until you find food”. The pattern emerges out of this simplest of NI rules. For virtual examples, see the Net Logo site, e.g. the termites running about in the Net Logo Termites model [11].

Even some forms of social learning can be modelled in NI MAS. One spatially explicit example is a model written in the AiC-based MameLuke Framework [12]. Farmers here learn from evaluating their own performance but also from those of their neighbours, e.g. looking at how their neighbour’s various crops are doing on slopes comparable to their own, depending on their neighbor’s choices such as the planting date. Thus, farmers learn from each other without direct interaction with each other.

SIMPLE-INTERACTIVE (SI) MAS MODELS

Farmers in the Philippines and anywhere obviously do interact with neighbours and other actors. They discuss crop choices, they are influenced by government and NGO agents; they get news from their children that life in the city is much better than muddling through in the village. Capturing a wider understanding and prediction of land use therefore requires MAS models that contain Simple Interactions such as these.

The interaction that we will give special attention here is how land users are influenced by actions from ‘higher’ actors in a causal chain. These causal chains may be simply called power. We focus on this type of SI because it is strangely neglected in the social sciences and MAS. The usual answer of the social scientist to questions referring to interaction between agents is “social networks!”. Social networks capture a lot, but not power in a straightforward manner, even when networks are constructed of actors that do not necessarily know each other. The president of your university, the government that raises and spends your taxes, the bus company that decides if you have an option to commute by public transport, are they in your social network? Network theory does allow to identify central actors in your network, e.g. through Bonachich’s eigenvector centrality metric, but it does not seem likely that the director of the bus company will be identified as central in your network. Farmers, too, they are influenced by subsidies, by prohibitions, by markets, by extension policies and so on, decided by actors far removed from them. Yet, these actors may often be much more relevant for the explanation of land use than the farmer’s social network that basically contains of other farmers that are in the same boat rather than determining where the boat is going.

Let us have a closer look here, put in AiC terms. We may find farmers all growing maize, while looking at their motivations, growing coffee would in fact be more profitable. It may be the case that the farmers are tenants and that the landlord has prohibited coffee. In AiC terms, the landlord has taken away coffee as an option. The landlord could be called a ‘secondary’ actor behind the farmers as primary ones. Why would the landlord have issued the prohibition? It may be because he fears that allowing any perennial crop implies that legally, farmers have invested in the land, through which they may build up land tenure rights. Who may have influenced this motivation of the landlord? The Ministry of Land may well be a tertiary actor here, refusing as it does to settle the land rights issue either in favour of smallholders or big holders. And in the background of that one may be the World Bank as an actor, arguing that land reform has failed so often and advising to wait for a “willing seller, willing buyer” situation.

Figure 3 depicts the generalized version of this basic idea, called the ‘Actors field’ in the AiC framework. The essence is that actors are connected through actions that influence the options and/or motivations of other actors. Actors expand the range of implementable options of other actors e.g. through Research and Development (R&D) communication such as agricultural extension. They enhance capacities ('empowerment') through supporting organizations or rural credit schemes. They reduce capacities through prohibitions and permit conditions. They influence objectified motivation e.g. through levies, subsidies, bonds, improving circumstances in public traffic, and so on. They work on actors' cultural interpretations through making things 'hot' or declaring them fit only for the losers (like smoking). In all this, actors are not connected directly (in face to-face contact, seeing each other, forming a social network or community). For the sake of simplicity, we have connected the actors through a reduced version of AiC actors' model with simply 'options' and 'motivations'. Taking the full model works the same way – or BDI for that matter, with actors influencing beliefs, optional plans etc.

The action of the primary ('proximate') actor (e.g. a category of farmers) is influenced by one secondary actor through influence on the primary actors' options (e.g. through the action of knowledge dissemination, a credit scheme or a prohibition), by another secondary actor through influence on the primary actor's motivations (e.g. the government through the action of establishing a fertilizer subsidy), which in turn is influenced by a tertiary actor (e.g. the fertilizer industry lobbying and bribing the government for the subsidy).

The AiC agent structure has been simplified into the Action-Actor-Options-Motivations triangles that may be repeated and expanded in any direction as far as empirical significance or theoretical interests go. (See [13] for an example on tropical deforestation).

Actors fields may be forever expanded, following a general rule that "behind every factor, there is an actor". With students, it is always fun to try find the International Monetary Fund (IMF) behind anything. Actual modelling of actors fields depends on choices of empirical, policy or theoretical relevance. Note that the causal routes reach all the way from the local to the global levels. Yet the whole picture remains 'actor-based'. The World Bank is an agent that lives in a 'world system' of global trade flows, national actors and so on from which it takes its options and motivations. Yet, the actor, not the world system, acts. Note that we model cross-scale interaction here, with each actor taking his options and motivations from his own life world scale (local, regional, global).

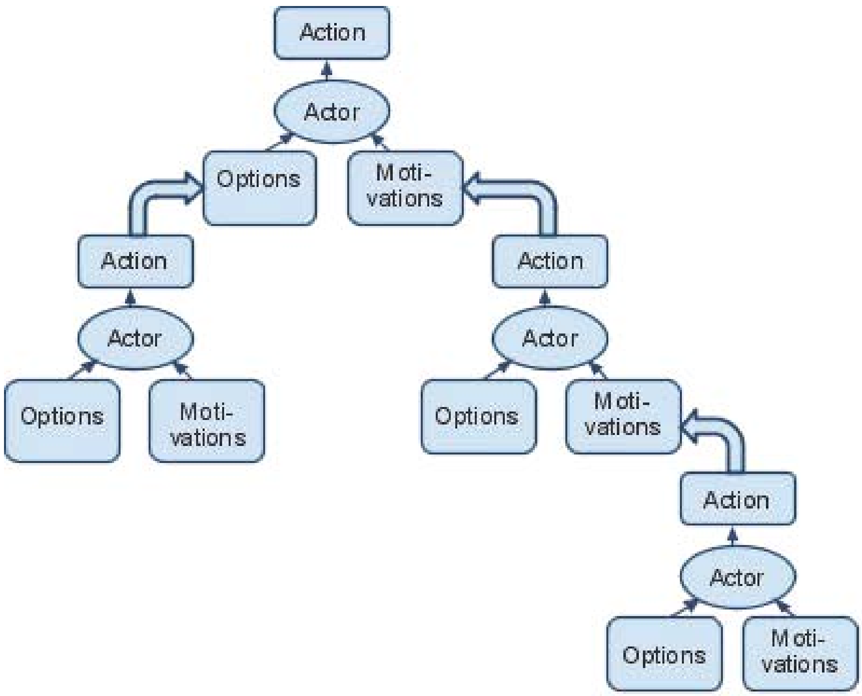

Figure 3. An Actors Field structure in the Action-in-Context framework.

Social learning (from other actors) and the almost endless variety of inter-agent influences captured by the actors' fields are not the only possible types of Simple Interactions. SI MAS models may, for instance, also involve spatial interaction, e.g. a rule of "I settle where I see kinsmen settled" in migration models (e.g., [14]). To a certain degree, also collective action may be taken up in SI models. Not fully, because that will be typically the CI domain, but through simple empirical rules that may be grounded in field work. One such a rule concerning the emergence of farmer cooperative may be, for instance, "if there are fewer than 20 agents, and if these agents have a basic level of trust in each other e.g. through shared ethnic identity, and if their profits through the cooperative are at least twice the total profits of working separately, a cooperative will be formed". Note that this rule contains conditions ('fewer than 20' etc.) but these are not the interactive conditions of the CI MAS models, which in this case might read as 'I will join the cooperative if you do'.

COMPLEX-INTERACTIVE (CI) MAS MODELS

As said, the Complex, Conditional Interactions that characterize the CI MAS models are of the type of "I move if you move" – see for instance the seminal tit-for-tat rule and prisoners dilemma. CI MAS models are typically made to study the emergence of stable societies out of multiple interactions of agents with such rules, preferably without invoking 'non-rational' elements in the actor model such as social norms [15]. The examples and projects here, revolving around concepts such as complexity, trust, self-regulation, agent societies and so forth are too well-known and numerous to necessitate elaboration here.

CONCLUSION AND FURTHER WORK

Complex, conditional agent interactions are the great attractor for MAS and game theorists. And indeed, no-one can be blamed for being fascinated by the intricacies of tit-for-tat, the prisoner's dilemma and the emergence of stable societies out of simple actor rules. Or: what would be a greater achievement than being able to predict the outcomes of multi-country climate negations with a MAS? Giddens' [16] theory of structuration, standing in the perennial 'actor versus structure' debate in the social sciences, may be summarized as that actors create and change institutions (i.e. structure – rules, organizations, societies), and that institutions shape and influence actors. This principle positions the CI MAS and SI MAS models with respect to each other. CI models typically focus on collective action, i.e. how agents build institutions, e.g. through trust, collective social capital, stepwise actions, negotiations, reciprocity in multiple encounters, and so on. SI models typically focus on the reverse causality, i.e. how institutions shape and influence agents.

This pattern is informative in the way the CI and SI models inform and link to each other. CI models can approach how institutions are made, while SI models can approach how institutions, once made, impact on actions in causal chains of agents.

For any empirical problem however, the fact remains that the question must be raised, what is needed most for the given challenge? What direction of causality dominates in the given problem? Hence, with Ockam's razor in mind, the question is: can SI MAS models do the job here? As we saw, cross-scale interactions, with interlinked actors all living in their own life worlds up to the global level, are no problem for SI MAS models, as is social learning with actors interpreting what other actors do. As we saw too, even if some questions of collective action are relevant to the empirical problem to some degree, it might be simulated in an SI model in a reduced form, e.g. a field-based rule.

Our main message at this point is that SI models, if fully explored inter alia through the actors' field concept, hold an enormous empirical potential. Our bet would be that 90 per cent of the land use change in any nation can be approached through SI MAS models that contain the interactions between local, national and global agents. The relatively low level of attention that these models receive, though understandable because of the 'social network' routine in the social sciences and the supply-driven history of MAS, is therefore not an entirely positive thing. If MAS modelling is to live up to its great promise for the empirical social sciences, exploring its potentials to work with simple, SI actor interactions would appear to be of great value.

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VRSTE I PRIORITETI MEĐUDJELOVANJA U SUSTAVIMA MNOŠTVA AGENATA

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SAŽETAK

Sustavi mnoštva agenata mogu biti klasificirani ovisno o tome sadrže li neizravna međudjelovanja, jednostavna međudjelovanja ili kompleksna, uvjetovana međudjelovanja između agenata. Ovaj rad razmatra i ilustrira kako modeli s jednostavnim međudjelovanjima, iako su za teoretičare sustava mnoštva agenata manje fascinantni nego modeli sa složenim međudjelovanjima, zaslužuju više pozornosti u zajednici koja se bavi sustavima mnoštva agenata. Modeli jednostavnih međudjelovanja mogu sadržavati društveno učenje i recipročne relacije. Kao možda i najvažnije, modeli jednostavnih međudjelovanja omogućuju povezivanje više skala putem vezanja lokalnih i globalnih aktera u njihovim lokalnim odnosno globalnim svjetovima.

KLJUČNE RIJEČI

sustavi mnoštva agenata, socijalno učenje, recipročne relacije