Agent-based modelling. History, essence, future

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Introduction

In many areas of the social sciences the technique of agent-based modelling (ABM) becomes more and more popular. For many researchers not specialized in computer simulation this catchy term seems to provide a way between Scylla and Charybdis, between the arcane dream worlds of mainstream, general equilibrium economists and the jungle ofsociological singularities that leaves us in a forest of contradictory case studies. Of course, the former - due to their mathematical language and despite their mostly trivial content – are much harder to read; but the mass of the latter has the disadvantage to become even more boring soon. Once it is decided to construct an ABM, this immediately implies that at least a vague idea of what an ABM looks like has to exist. As in most other areas, this idea usually is based on imitation: Take a look at what others did. This is what happened in the last twenty years,and as could have been expected a large set of quite different types of software applications and corresponding customers emerged. Today, still a clear picture of what is characteristic for ABM remains controversial[1].

This paper is just another brief attempt to contribute to the understanding of this not so new approach. It starts with some selected historical steps in the emergence of agent-based modelling. There exist much more comprehensive treatments, which include many details that here due to the needed brevity of the argument are omitted. But by these omissions my argument highlights what I consider to be important.

What follows is a concise sketch of the essence of ABM for novices and those unsatisfied with many of the more restrictive definitions of the field. The part ends with a recipe for building an ABM.

The last part discusses the future of ABM. It is organized along the lines of the three aspects of a language: syntactic, semantic, and pragmatic evolution. This part on the future necessarily contains several more speculative elements, it should be read as a collection of possible visions.

1 –History of ABM

Agent-based modelling is only a fashionable new name for the use of computer simulations in economics, which exists almost as long as computers. When in the fifties and sixties large US universities installed computer centres to support researchers in the natural sciences, there soon were also economists showing up, eager to transfer tedious calculations to the new machinery. Before that, large amounts of data as well as larger difference equation systems built on the then

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[1] E.g. compare the views of Nigel Gilbert [Gilbert, 2008] andChen and Wang[Chen and Wang, 2010].

new analytical technique of input-output tables were using up a lot of intellectual effort that now could be delegated to computers. The advent of computer simulation therefore can be considered as the appearance of ‘an economists little helper’, a calculating machine.

Then came a shift of focus that was initiated by the computer firms acting in anoligopoly, and that quickly was taken up by the scientific interpreters of the new machines. The growth of demand for computers coming from military and other state institutions was starting to slow down, and to revive it in the ‘age of high mass consumption’ [Rostow, 1960] made smaller and more flexible devices necessary. Small firms and households did not need extreme calculation power, like research in theoretical high-energy physics. What they would buy was a small machine that offered a large diversity of different uses, from simple household accounting via writing letters to computer games for children and idle employees. In the early eighties, the personal computer was born, and as an educational add-on the teaching of informatics in schools was introduced. Scientists like Alan Newell and Herbert Simon quickly saw that with this diversity of uses the old calculator had become a ‘symbol manipulating device’, see [Newell and Simon, 1972]. Indeed, whatever one can consider as a symbol can easily be translated in a bit stream and then can be manipulated in many more ways than just adding and subtracting[2].At that time another fashionable term was invented to attract research money: ‘artificial intelligence’. Its success was built on the surprise of computer illiterates about the speed of machines searching in databases. This looked ‘intelligent’, though it had little to do with the traditional meaning of the word[3]. Till today ‘artificial intelligence’ haunts software applications, including economic simulations.

The early fields of application quite naturally followed the divide of economics into microeconomics and macroeconomics. On the one hand, simple oligopolistic markets were mirrored, while on the other hand early Keynesian macroeconomic models were simulated. Of course, contrary to abstract general form models of economists these models first had to be econometrically estimated to fill in parameter values into the behavioural equations. Without using the word ‘agent’ such a behavioural equation already was meant to capture the behaviour of an economic entity, of economic agents. In microeconomics they were firms, households, or individuals, in macroeconomics they were more abstract aggregates of ‘all households’ (e.g. consumption function), ‘all firms’ (e.g. investment function), or ‘several state institutions’ (e.g. tax function). With the increasing technical abilities of hard- and software soon there emerged first attempts to combine micro- and macroeconomic computer simulations, a task paralleling the more conventional efforts of mainstream economic theory to provide a microfoundation for macroeconomics. In the late eighties, it more or less became clear that the latter task had failed since it needed very implausible restrictions on the micro-level to allow for aggregation at all. Moreover, the convenient trick only to consider stable equilibria, or equilibrium paths, became less and less useful in a world that was governed by amplifying disequilibria, e.g. in the labour market. But the human capital stock of academic economists built up by this type of research was already too large to be easily given away. The alternative to use computer simulations would have needed too much investment in learning the new techniques for the established community; it became a territory for mavericks only[4].

Outside standard economic theory, economic simulation got a***first boost from*** a completely different side.In ***biology*** mathematical modelling, in particular game theoretic models were applied with increasing success, see e.g. [Maynard-Smith, 1980]. Darwin’s idea of evolutionary dynamics was

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[2] Quite to the contrary, it is somewhat complicated to perform adding with the processes most elementary to computers, e.g. ‘copying’, compare [Hanappi, 1992].

[3] See [Hanappi and Egger, 1993] for some thoughts on artificial intelligence.

[4] The Scottish economist Brian Arthur, the modeller of the famous ‘Inductive Reasoning and Bounded Rationality. The El Farol Bar Problem’, is such a case [Arthur, 1994].

simulated by computer programs and the results were compared to the developments in actual biological populations. This inspired two economists, Sidney Winter and Richard Nelson, to use computer simulation to mirror market dynamics. Their ‘animals’ were firms and instead of Darwinian traits they were characterized by a set of ‘routines’ they used. And then a simulation of market dynamics was used to study how the worst ‘routines’ were weeded out by some kind of ‘survival of the fittest’. This type of dynamics, now a simulation exercise, of economic processes never coming to rest in an equilibriumhad been described by Joseph Schumpeter 70 years earlier [Schumpeter, 1911]. Richard Nelson in his early life indeed had been a famous representative of standard microeconomics and always had longed for an inclusion of Schumpeterean thought in economic theory. With their book, which they called ‘Evolutionary Economics’, Nelson and Winter started an economic school of the same name [Nelson and Winter, 1982]. And this school still heavily relies on the techniques of computer simulation, today under the label of agent-based simulation.

A whole group of scientists then tried to find new foundations for the social sciences with the help of computer sciences. The ‘New Foundations’-movement spread out over a wide disciplinary range, starting on the more formal end already in 1959 with Stephen Wolfram’s ‘A New Kind of Science’ and reaching into the most prestigious research journal of economists, the ‘American Economic Review’, where Robert Axtell and Joshua Epstein published an article on ‘Artificial Life’, see [Wolfram, 2002], [Axtell and Epstein, 1996], [Axtell et al., 2012]. Models of the ‘artificial life’-variety usually had homogenous small agents that resembled ants: They commanded only very few instruments (e.g. moving and eating) and very few goals (e.g. food consumption), but a huge number of them (e.g. ten thousand) were positioned on a common landscape and the simulation then started. The result waited for was a specific, reproducible pattern of aggregate outcome of the enormous amount of interactions on the micro-level. These artificial ants’ worlds still followed the quest to derive emerging patterns on the macro-level from the simple, archaic behaviour of micro-agents – now, of course, with the help of simulations. So it basically was still the old research program of methodological individualism now dressed up as the fancy new fashion ‘artificial life’. To break this spell ABM had to move on heterogeneous agents and the ability of their internal models to allow for more or less sophisticated forecasts. Only then communication processes could bring about some countervailing macro-foundation[5] of micro-behaviour, and finally the more adequate possibility to dissolve the unhealthy opposition between micro and macro in a simulation with full interaction between all levels.

The ***second important external boost*** to economic theory buildingthat was almost completely ignored by mainstream economists came ***from the study of complex systems*** with the help of ***network theory***. Its roots can be traced back to the scientific revolution in theoretical physics that led to quantum theory. With this new knowledge of basic rules that govern physical processes at the smallest scale the validity of the older Newtonian mechanics could be understood as a special case that can describe behaviour if one looks at statistical averages occurring ifan enormous mass of small units interact. The mathematician and physicist Erwin Schrödinger, who gave this theory the analytical waveform, arguing from this new perspective in 1943 asked a surprising old question: What is Life[6]? This took the natural sciences to the next level. The old atomism of ancient Greek philosophy had assumed a mass of homogenous atoms, the new quantum theory had discovered a

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[5] An intermediate step thus was to construct computer simulations of the interaction of macroeconomic agents, compare [Hanappi, 1995]. The next logical step then is to open up the ‘black boxes’ of lower level agents and turn them into simulated ‘white boxes’ in the sense of Norbert Wiener, see [Hanappi and Hanappi-Egger, 1998].

[6] See [Schrödinger, 1943].

diversity of ever smaller heterogeneous particles interacting in strange looking ways. Asking now how these processes could be formally described stretched the analytical capabilities to their limits[7].

Applying the new finite diversity ideas to the human species meant to depart from the image of a unique homo economicus. Even with the old analytical apparatus of mathematics, heterogeneity could be envisaged, compare [Casti, 1989]. The transdisciplinary genius John von Neumann, who after a talk with the eminent economist Nicolas Kaldor had produced an elegant economic growth model, realized that a deep change in formalisation techniques was inevitable. To support new analytical techniques he revived the old concepts of Charles Babbage and Ada Lovelace, and together with some, outstanding US engineers invented the modern computer. As it turned out, this device was able to accommodate heterogeneity to a previously unimaginable extent. In a daring attempt to imagine the future abilities of this 'new combination' of theory and technical support – note the importance of Schumpeter's characterisation of innovation - Doyne Farmer and Aletta Belin early on tried to grasp the implications, see [Doyne and Belin, 1990].

And then, in 1944, John von Neumann even proposed to invent a new mathematical language for social processes – game theory, see [Neumann, 1944]. It took 40 years until his ideas arrived at least in biology, when Maynard-Smith successfully applied it toanimal systems. But already in 1962 a researcher in the area of weather forecasting, , played around on his computer with the parameters of simple dynamic systems and discovered that these deterministic systems were able to produce time series that could not be distinguished from random series, e.g. from white noise. The methodological impact was severe: Once a historical time series is given and looks like an economic law heavily disturbed by exogenous shocks, it might as well be completely deterministic. A new set of methods to deal with that question had to be developed, and since it soon was found out that the probability of these 'deterministic chaos systems' rises with the size of the system it was evidently necessary to use simulation methods. Strict mathematical arguments often start by assuming to opposite extreme situations. In the case of many endogenous variables one extreme can easily by fixed: assume that everything depends on everything. An opposite extreme would be that the dynamics allow to derive the second variable from the first only, the third from the second only, and so on until the first variable then depends on the last only. The Hungarian mathematician Paul Erdös saw that these two extremes have a geometrical representation as graphs, the nodes are variables and the links are dynamic equations. While the first extreme thus displayed a graph with direct links between all nodes, the second extreme is ring with two links at each node only. Erdös' own innovation was to assume that links might sequentially emerge between variables, following a random process that can be described by well-known stochastic processes. Erdös' random graph theory was just the beginning of the boom of network theories. In the 90-ties Laszlo Barabasi and his team discovered that in a surprising number of living systema special structure could be found empirically – the so-called 'small world'-structure, compare [Barabasi, 2014],[Watts, 1999]. How a sequence of link emergences can be algorithmically specified to lead to such an empirically found structure since then is a vivid field of scientific research. One such procedure is built on the assumption of preferential attachment, i.e. the probability of a node to be part of the next link that is dropped on the network is proportional to the number of links that it already has. It is evident that nodes could also be interpreted as agents, and this is exactly what is assumed in so-called 'games played on networks'. Strategic decisions of agents using their internal models of other agents (in the

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[7] In an attempt to describe network evolution as a learning process Stuart Kaufmann started to apply Boolean networks early on too, see [Kauffman, 1993]. The idea to use networks seemed to be in the air and quickly led to the emergence of another fancy term: Complexity. It turned out to be at the centre of the research program of the most creative research institute in the field, the **Santa Fe Institute**. This institute was also the place where the agent-based modelling simulation package SWARM was developed and applied by Robert Langton and his team. In a sense, the worldwide success story of ABM started there.

sense of Neumann's game theory) then lead to actions, which are the links between nodes[8]. It is clear that the size and content of internal models as well as the number of links that an agent can perceive and deal with is crucial. The limits of these modelling elements determine how adequate a network can mirror an object of investigation.

The agent-based models developed in the last decade therefore collect innovative developments in the recent history of sciences and provide a transdisciplinary focus[9]. The next part will sketch how ABM deviates from mainstream economic modelling and what is needed to produce an agent-based model.

2 - Essential features of ABM

The basic idea of ABM is that agents, living entities using internal model-building, are mimicked by computer programs. Immediate consequences of this starting point are that

a) An agent's structure has to be described by a program that is sophisticated enough to allow for the sequence (i) perception – (ii) embedding in an internal model – (iii) choice of an action (including the action 'communicate');
b) Agents and the programs representing them will typically different, i.e. the standard case of ABM typically will be heterogeneous ABM.
c) There has to be a main program, which is not an agent, and which provides a description of the environment in which the agents can perceive and influence this environments dynamics by their actions.

By disentangling the material world outside the internal consciousness of an agent from what goes on within its internal information processing ABM can describe model-driven behaviour of agents that use models, which differ markedly from the actual dynamics of their environment. The most important task in this respect is to explore how the selection of *what* is observed, *how* it is embedded in an internal model, and *how* finally actions are *recognized* and *chosen*, how this whole process is developing over time. Again it must be emphasized that for each agent this perpetually repeated process can and will be different.

The scientist constructing an agent-based model evidently has to know a lot about the empirically observed agents that shall be described by the ABM. Contrary to most of mainstream economic model building there is not the same necessity to simplify agents' behaviour according to the technical requirements of analytical methods. In particular assumptions that some processes can be ignored because they are so fast that it is sufficient to include only the result of their convergence in the form of *equilibrium equations are superfluous*. There is also not the same need to simplify matters by assuming that the heterogeneity of agents shall be ignored and a common representative type of agent, the *homo economicus* or the '*representative firm*', is good enough for an adequate picture of reality. Moreover the somewhat metaphysical assumption that agents are born with *innate preference orders* - which in more advanced versions of mainstream economic models might allow for slow modification – that guide their choice of instrument variables, this 'heroic' assumption can be replaced by an answer to the underlying question: Where do incentives for actions come from? The answer of ABM is less simple.Incentives are a mixture of signals sent directly from the body of the agent (e.g. 'feeling hungry', 'low revenues', 'political instability', etc.) and of the interpretation of perceptions with the help of the internal model that produces indirect signals.

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[8] Note that actions can either be in the world of information, i.e. communication, or physical processes outside language.

[9] Compare [Hanappi, 2014] for an embedding of the new approach in history of traditional economic modelling.

Perception thus means that impressions are routed to theinternal model that structures them into a vector of need levels. With the increased influence of internal models, the focus on communication processes, i.e. the exchange of models between agents, is strengthened.

The ***shift of methodology*** also concerns the ***choice of thescope of models***.When after the marginalist turn of economic theory - initiated by Walras, Menger, and Jevons in 1874 – mathematical methods started to dominate economics, it seemed to be immediately evident that (following theoretical physics) one had to start with the smallest and easiestunit to model economic dynamics. This unit was assumed to be the physical human individual and the approach was labelled methodological individualism. Later, including micro-units of the production sphere that conceptually were socially neutralized (being called 'firms' rather than 'firm owners') the entire discipline was dubbed microeconomics. Though the mathematical model for a single unit was strikingly simple, copying natural science formalisms and adding some psychological hypothesis was good enough,it proved to be much more difficult to combine them to derive a kind of aggregate 'social thermodynamics'. From Léon Walras to the Arrow-Hahn model of 1967 this effort proved to be manageable only with an increasing amount of implausible additional assumptions. Keynes work in the interwar period had been the theoretical answer to the impotence of marginalist theory in the face of the Great Depression of the 30-ties. Marginalism simply could not explain how such self-amplifying disequilibria in all markets could can happen, and as a consequence it could not propose any remedies. Keynes success thus was built on the methodological innovation to bring aggregates back into the picture that constituted economics. Aggregates, like total consumption of a nation or total labour demand of all firms of a nation, were combined in an accounting framework mirroring national aggregates, this is the essence of macroeconomics. Of course, this accounting framework nevertheless needs agents that drive it. On the one hand these 'aggregate agents' were constructed using socio-psychological constants characterising average microeconomic behaviour, e.g. a propensity to consume of individuals or a propensity to invest of firms, on the other hand some aggregates important for national accounting asked for the re-introduction of an agent that was neglected in marginalism: the state. With this latter methodological innovation a second improvement of standard theory was possible. The exogenously determined agent 'state' could be used to prescribe remedies for the apparent, welfare-decreasing disequilibria. But the methodological gap between marginalist microeconomics and Keynes' macroeconomics could hardly be deeper. While the former claimed that general equilibrium ruled in the long-run and re-established itself quickly if non-economic events disturbed it, the latter focussed on the short-run and emphasized the need of state intervention, of an exogenously added political agent necessary to stabilize capitalism, to fight self-amplifying,endogenous disequilibrium processes. The restriction to consider only the short-run was due to the obvious variations of the aggregate agents' socio-psychological 'constants' across different nations and across time. The disparate methodology between micro- and macroeconomics produced different sets of mathematical toolboxes used by the two sub-disciplines. While microeconomics still followed calculus as it was developed for physics by Isaac Newton, substituting 'economic principles of man' for the laws of physics, macroeconomics typically fell prey to the use of simple linear models developed by early followers of Keynes. This inconsistency of methodology obviously was a challenge for mathematically inclined economists like Paul Samuelson. His so-called 'neo-classical synthesis' – a dramatic misnomer – aimed at providing a set of mathematical links smoothening the jump from microeconomics to macroeconomics. In retrospect these efforts were not too successful. Most of them needed even stronger restrictions on the functional forms to be used and ever more implausible assumptions on expectation processes performed by microeconomic units[10]. With the focus of economics, which in the meantime had become microeconomics *plus* macroeconomics, shifting to questions of consistency and losing any

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[10] An outstanding example is the rational expectations hypothesis, compare [Sargent, 1979].

responsibility for being adequate with respect to the world outside of their models, the scope of the science was redefined: It became dominated by mathematical requirements of elegance and solvability, i.e. the syntax of the formal apparatus.

Parallel to these changes in economic methodology computers had been developed. First, they were used in many rather profane domains, like administrative counting procedures and calculating gun fire directions on warships. In mathematical economics of the after-war period they made their appearance as little helpers for problems still formulated by standard mathematical modelling of the type described above, in particular providing approximations in some econometric areas. But in the late 60-ties finally proper simulation models of economic interactions were emerging. Their goal rarely was to check consistency, or to provide the most simple 'heroic' assumption that still can be solved analytically; they typically tried to come as close as possible to the actual dynamics of the physical economic process of the process they tried to imitate, the process outside the domain of their own language, the singular process in the material, physical world. In short, instead of being syntax-driven, they were semantics-driven.The scope of ABM therefore relies on the observation of specific economic processes that can be good enough covered by observations, and can be good enough isolated from their respective environment. Whenever these requirements are met the algorithmic language is almost unrestricted in its ability to mimic a scientifically suggested essential dynamics. It is not syntax that drives this process, but the attention that the scientific community of ABM modellers gives to events happening outside the world of the language they use.It is thus this scope that makes ABM particularly interesting for practical questions, coming from economic policy or any other field. Unfortunately there also is a downside of this astonishing flexibility implicitly included in the scope of ABM: Once an object of investigation is chosen and its essential features are pinned down by the model builder, there is no way to prove that simulation runs prove *semantically* correct results. In a sense an ABM is just another way to tell the model builder's story in a different language, it is formal story telling producing narratives[11]. The critique that multiple, partially contradicting narratives of the same object of investigation can be told therefore also applies to agent based models. Nevertheless, it is possible to compare the relative adequacy of different agent-based models. The standard procedures to do so can be borrowed from econometrics applied to a comparison between simulation runs and observed data in an ex-post simulation. So there is no 'everything goes' freedom of different models but a 'something is more adequate than something else' that governs progress in ABM.

Finally, the phenomenon of ***emergence*** of patterns of aggregate behaviour often is mentioned as a particular feature of agent-based modelling, and deserves indeed some attention. In these questions there is a deep issue at stake. Finding a pattern in observations of repeated behaviour lies at the heart of every cognitive process, it is a major building block of internal model-building of all living systems and indeed – applied to the agent's own history – constitutes self-consciousness. In the first instance pattern recognition clearly is not an act that takes place in the solitude of an individual member of a species. Thanks to Charles Darwin we know that knowledge can be accumulated in a species by evolutionary processes that work with a combination of (slightly disturbed, i.e. mutated) copying of behavioural traits and weeding out of some of them by forces of the environment[Darwin, 1859]. The agent, which is the subject of the pattern recognition process, of knowledge accumulation, therefore is the species, at least from a biological perspective. A special property of the human species - for many scientists its characteristic property– is its ability to distribute the knowledge of the species across its members. This process needs several preconditions. First,

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[11] If formalization is syntax driven, it is always possible to check if a theorem is syntactically true or false. But here the disadvantage is that the distance to the object of investigation can easily produce the illusion that the derived truth concerns areas outside the language.

individuals need a brain that allows to communicate, i.e. to translate physical processes into symbol systems that can be stored, reactivated and re-translated into physical utterances. Second, there must be a physical medium of exchange between individuals that carries the symbols, transports them from one brain to the next, e.g. air for voices, papyrus for written text. Besides several other preconditions for the somewhat illusionary impression of individual pattern recognition it also needed the special catalyst called recursion to initiate the particular human process: Recursion means that a sequence of copies, each one called by its predecessor, can produce the experience of time. More precisely, this primal experience is the contradiction between the constancy of re-appearing copies, of consciousness, and its opposition of a permanently changing environment. With this feature knowledge accumulation in human societies in principal is freed from learning appropriate behavioural answers to changing environments the hard way: It is not necessary that the part of the population that acts inappropriate dies to allow for the survival of the fittest. The French Enlightenment had already anticipated and proclaimed this goal when Darwin worked on its biological roots.

Some two hundred years earlierRené Descartes had specified some rules for the scientific method that the part of society specialized in discovering the patterns that govern the world, i.e. the scientists, should use[Descartes, 1637]. For him the task to discover scientific laws had to start with the observation of a problem at an aggregate level, and then to proceed by taking the big question apart in ever smaller problems that can be solved easier. According to Descartes this is the essence of analysis in its original sense. What emerges in the end of this process are the atoms,which once they are revealed provide the emergence of their synthesis, this is what Descartes calls the scientific method. The parallelism to the actual discoveries of the natural sciences in his time is evident. Analytical investigation of ever smaller sub-problems necessarily involves an increasing amount of division of labour between different sub-disciplines, and this clearly makes the moment of synthesis, of the emergence of an overarching understanding of a larger phenomenon more difficult and demanding. It simply will happen less often. Today we command an overwhelming amount of highly specialized knowledge in a similarly overwhelming diversity of different sub-disciplines. The latent force of synthesizing this knowledge is enormous, but the intellectual capacity needed to do so, to transfer it from latent knowledge of the species to a manifest emergence, is enormous as well.

With the technique of agent-based modelling there seems to be the possibility to invert Descartes' traditional methodology. The scientist starts with a set of simply modelled micro-agents and works bottom-up by letting them interact on what is called an (interaction-) landscape. Since this interaction is just computer simulation it is easy to experiment with different sets of axiomatic micro-agents. Eventually then aggregate results of these interactions after some time can produce simple patterns in aggregatedvariables that surprise the scientist. This is the moment of emergence of knowledge for ABM research – at least according to the advocates of this argument. The argument certainly touches on an important methodological point but still falls short of its forceas long as it neglects the following consideration: Assumptions on micro-agents that play the role of axioms from which the aggregate patterns are derived need not – and indeed never should – be the end of ABM research. A first move from bottom upwards is just the starting point for deriving better assumptions on a modified set of heterogeneous micro-agents, and a next simulation run. ABM research is a never-ending cycle of repetitive, adapted derivations alternating between running bottom up and running top-down. Moreover, this oscillating movement supports the formalization of three extremely important elements of political economy: ***expectations***, ***power***, and ***institutions***. On the way from bottom upwards, micro-agents use internal models that include expected future values of variables that emerge on the top-level only, e.g. unemployment rates, inflation rates, budget deficits. This process links the two levels from below. On the other hand, political power on the top level restricts the action space of the micro-agents and thus acts as a link from above. Power can be exerted in two formats: either as directly coercive physical power or as information-power that distorts the expectation process of micro-agents. If the social reproduction is taking place over a longer time-period this interplay between the two levels resembles a repeated strategic game played by the scientific community of ABM researchers. To solve the conflict between the opposing forces of expectation modelling and power modelling certain conventions will develop, instituted views what to assume. A typical auxiliary mediator in models of market mechanisms would be an auctioneer managing a tâtonnement process. A more refined example would be social partnership oriented state committee guiding the development of wage structures. It is typical for the channelling of conflicts into institutions that these institutions over time become new intermediate levels between the micro-agents and the top-level political entity. Computer simulation, of course, can and should mimic all essential intermediate levels, i.e. institutions, which are run through by the oscillatory process. Creating models for the interaction between expectation-building of agents, exertion of power by higher-level agents and the resulting institutional solutions of conflicts therefor mirrors what goes within the methodological process of ABM itself. It leads the researcher directly into the dynamics of its object of investigation. This indeed is a particular strength of agent-based modelling. Note that from this perspective a sudden emergence of knowledge not only happens when a one-shot bottom up modelling is reaching the aggregate view, ***emergence of knowledge can happen at all levels and at any time of the repetitive modelling process***.

Though from this point of view, knowledge accumulation as the central project of the human species is unlimited a single ABM research project always has a finite time horizon. And again, computer programs representing agents can as easily be equipped with finite expectation horizons, shortened memory capacities and finite anticipation depth in game-theoretic settings, just as the modelling scientist can and will regulate the effort that is spent on the different details of the project given a hard deadline for project accomplishment. It thus makes sense to provide a short recipe on how cook an exemplary heterogeneous agent-based model:

Step 1: ***Choose a topic*** that is closed enough with respect to its environment to allow for an independent consideration of its internal dynamics. There shall be links between the topic and its environment but the force from outside, from exogenous variables into the model, should be much stronger than the influence of the model on its environment. This can be difficult in the beginning if too many things seem to be fully interdependent. The art of the scientist consists to a large extent in the choice of neglecting less important elements and keep the essential ones. Additionally the time frame of the model, see above, has to be fixed. The result of step 1 is the scope of the model.

Step 2: ***Identify the major agents*** in your model. Agents at every level within the scope of the model can be considered. Each agent has at least one goal variable and at least one instrument variable, which define its embedding within the model. The set of variables of the ABM therefore consists of four types of variables: goal variables, instrument variables, auxiliary variables, andexogenous variables. The first three types are called endogenous variables, auxiliary variables are all those variables that help to formulate relationships either in material processes or in internal models and which are neither goals nor instruments.The result of step 2 are two linked lists, one with agents and one with all variables.

Step 3: ***Construct the internal models*** of the agents. A minimal internal modelof an agent has to consist of a suggested relationship between its single instrument and its single goal variable. Of course, most mental models are more sophisticated and include conflicting goals, multiple instruments, and auxiliary variables. At this stage a close inspection of the empirically observed physical agent is mandatory leading almost necessarily to a heterogeneous set of agents. As an important part of this step it has to be suggested which variables the agent does ***perceive*** and in which way they are perceived – and used in the internal model. Acentral part of perception concerns information coming from other agents, i.e. the endogenous instrument variables (communication elements[12]) set by other agents. The result of step 3 is a non-quantified logical blueprint of the model that contains all agents, all variables, and links showing which ones are related.

Step 4: ***Empirical data***for all used variables has to be found. Since important parts of ABM concern internal model building processes, which are rarely covered by official statistics, this can be a tedious task; in some cases some crude assumptions will be the only possibility. The result of step 4 is a table with historically observed values of all variables.

Step 5: ***Econometric estimation*** of the suggested relationships.The quality of these estimations will vary according to the quality of the available data, in extreme cases just guesses of some parameters will have to be used.The result is a quantitatively specified blueprint of the ABM.

Step 6: ***Software implementation*** of the model. There is a broad range of simulation tools, from the use of procedural computer languages to highly specialized simulation packages. Since the first implementation of a new model usually is considered as a preliminary toy model that can be iteratively used to improve steps 1 to 6, it is very important that this model can be easily handled. A simple software tool with some graphic capabilities therefore should be the result of step 6.

Step 7: ***Systematic result generation***by a large number of steadily improved simulation runs. Since the repeated improvement process of step 1 to step 6 after some time has to reach an end – either because improvements are becoming arbitrarily small, or because the deadline of the research project is approaching – some time before this endpoint the overall emerged new knowledge has to be collected and interpreted and condensed in a report.

3 - Future perspectives of ABM

The perspectives of ABM will be discussed along three dimensions: syntax, semantics, and pragmatics.

The ***syntax of ABM*** certainly is still waiting for some substantial structural improvements, not to speak of standardisation. The variety of software support of ABM will certainly persist in the future, and this is to be welcomed[13]. But nevertheless some particularly important features will be identified (e.g. support graphic capabilities), while others will peter out (e.g. too rigid syntactical restrictions). One important improvement will concern reproducibility of results of simulation runs: The same ABM implemented with different software shall produce the same simulation results. As a precondition for this future task transparency of what happens inside software packages is an immediate imperative.

A more daring goal is the development of a new arrangement of the set of operations that are in the action set of agents. Assigning values to variables and copying/imitating are certainly operations at least as basic as adding and subtracting. Moreover actions in the area of perception, which to a large extent relies on pattern recognition combining external sensors with memory, will experience some special treatment as fundamental elements of syntax. Even more challenging is a type of behaviour observed in real cognitive processes that performs switching between a seemingly stable background

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[12] A communication element can be a whole model, which an agent posts in the hope to influence the actions of other agents in a way that furthers its own goal achievement.

[13] Software development since the times of SWARM has been tremendous with respect to the amount of the available packages, though rather modest with respect to their fundamental capabilities. Currently most popular packages include Anylogic, Repast, NetLogo, and Python; for system dynamics a survey can be found at https://dsweb.siam.org/Software.

and movements in front of this background: If a sensitivity border is reached, sometimes it is only the feeling to be bored, then the moving foreground is taken as stable and the focus is redirected to the dynamics of the background. This switch in the mode of perception occurs more often than commonly understood and adds a new dimension to perceptions. In the moment there exists no syntax element that supports it in ABM[14].

The future challenges of the ***semantics of ABM*** are straightforward extensions of the characteristics provided in the previous part of this paper. The semantic relations are the links between language elements and the elements outside language to which they refer. ABM, the language, in the future will probably change along the lines of its object of investigation. Since – as explained above – the scope of its application is adjusted to a well-defined object, better ABM will mean that there will be a diversity of tailored languages for different areas. An evolutionary economics approach asking for the simultaneous treatment of micro-, meso-, and macro-processes will be supported by a very special type of ABM. In another area dealing with communication processes the features of ABM that concern manipulations of internal models will be particularly well supported to support ideas of learning and manipulating across agents. In a third example market processes of information commodities with high fixed cost and zero variable cost can be supported with software allowing for more sophisticated arrangements of public-private production and more refined preference modelling – fashion effects and communication are essential. This broadening of ABM language into different jargons at first sight looks like a counter-movement to the streamlining effects of syntactic innovations. But how far this diversification produces feedbacks on syntax innovation on a higher ground – both working in the same direction – remains an open question.

It is evident that an argument analogous to domain specification can be made with respect to agent specification. For agents specific forms of perception could be the starting point, or characteristic sets of instrument variables. Another dimension along which the object of investigation of ABM could frame its form will be the respective environment, which surrounds it. Modelling agents acting within a market regulated environment will look different to modelling a free-wheeling bargaining process outside market institutions. In all these cases innovations of the ABM language will come from a close inspection of its respective object of investigation.

The most interesting future prospects of ABM become visible if one looks at the ***pragmatic aspect***. In their simplest form future agent-based models can be used as ***extensions of the 'brain' of an agent***. Anticipation of future interactions between multiple agents, e.g. as modelled in game theory, easily go beyond the information processing capabilities of the agent. In that case an appropriate ABM can help.

Consider another pragmatic example, the conflict between actions optimizing short-run goals and those being necessary for long-run goal achievement. Information processing constrains usually make it more difficult to anticipate long-run implications than advantages in the short-run. With the help of ABM an old goal of enlightenment can be realized: Decisions that in the short-run appear as sacrifice can be made incentive compatible because long-run implications are better understood. This clearly concerns the whole area of global environmental questions.In many cases short-run profit maximization of micro-units, e.g. firms, contradicts the long-run survival of the landscape within which they operate.

This idea leads straight into the most interesting pragmatic aspect of agent-based modelling, the study for intervention into large scale social evolution. It is the limited extent of landscapes, the

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[14] In everyday language this process typically is reflected as an exchange of the roles of verb and noun, or of adjective and noun; a procedure typical for the dialectical textsof the German philosopher Hegel.

predictable borderlines of possible extensions, of extensive growth, of globalisation, which necessitates considerations of deep re-structuring of prevailing dynamics[15]. Since dynamic forces in the mixture of national and continental human populations are driven not only by the respective governance systems – the different ruling classes –but also are characterized by the spread of culture-specific internal mental models that form partially contradicting class forces, it becomes mandatory to gain some insight into this highly complicated process with the help of ABM; hopefully this will be possible in the future. The build-up and vanishing of classes, on national as well as on a global level badly needs a scientific investigation combining the study of economic, political and ideological (mental model oriented) forces. By and large overall welfare increase that also avoids exploding inequality and is to take place in a limited environment can only emerge if the rules of interaction between the different parts of human society that were tailored to conditions prevailing 200 years ago, are changed. There are probably only a handful of feasible new combinations, of new rule sets, i.e. global/local democracy mechanisms, new information sphere governance, modes of organization of production, which could be envisaged. To produce visions of them, to detect them, and to find ways to transform the current setting to the most preferable vision is certainly the most ambitious, but also the noblest goal to which agent-based models can contribute.

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[15] Compare[Hanappi, 2016].

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