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Leaving the "gothic cathedral" of economics

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Abstract Studies in economics and humanities generally have intrinsic problems that this work illustrates, along with innovations for overcoming them. The main limitations and weak-points of orthodox theory necessitate the use in their stead of other multi-disciplinary approaches, like complexity science, agent-based simulations and artificial life simulations. An example of an artificial life simulation applied in the economics field concerning the exchange process shows the benefits of such new conceptual and methodological instruments.

Keywords Artificial life · Bounded rationality · Computational economics · Dynamic systems · Neural networks · Genetic algorithms · Cognitive science · Cognitive economics · Agent-based social simulations · Exchange process

1 Introduction

Studies in economics and humanities generally have inherent problems. Inadequacies stem from the intrinsic difficulty in viewing the object of study, the manner in which these sciences are studied, and the conceptual and methodological instruments implemented (Parisi 2001, pp.15–25, 110–111). The main causes of structural weakness in the human sciences are a limited dialogue between theories and empirical events, the fragmentation of the various disciplines and the distinction between mind and body, between

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individual and society, and between a synchronic and a diachronic view of time (Parisi 2001, pp. 115–116).

In particular, the traditional view of economics presents some problematic characteristics such as the perfect rationality concept and, in general, the decision-making process. For example, McFadden (1999) illustrates the limits of neoclassical economics using cognitive psychology conceptual instruments. Neoclassical economics and psychology have radically different views of the decision-making process. The primary focus of psychologists is to understand the nature of decision elements, how they are established and modified by experience, and how they determine values. Whereas, the primary focus of economists is the mapping of information from input to choice. For the latter, the decision process is considered a "black box" and so, as McFadden (ibid.) says, "Economists know the price of everything and the value of nothing". Moreover, psychological views of the decision process are dominated by the idea that behaviour is local, adaptive, learned, dependent on context, mutable, and influenced by complex interactions of perceptions, motives, attitudes, and emotions. Conversely, the standard neoclassical economic model presents us with a particular "agent" whose behaviour is driven by information that shapes perceptions and beliefs according to Bayesian statistics. Preferences are considered primitive, consistent and unchangeable. Moreover the cognitive process is equivalent to the maximizing of preferences in given market constraints (ibid.).

Virtually all current theories regarding choice under risk or uncertainty are cognitive and consequential, in the sense that people are held to make decisions only based on an assessment of the consequences of possible alternatives. In fact these theories assume that people act as if they estimate the desirability and likelihood of possible outcomes of alternatives, and integrate this information through some type of expectation-based calculus to arrive at a decision (Loewenstein et al. 2001). However, nowadays evidence is demonstrating the importance of experiential and emotional components in the decision-making process. For example, LeDoux (1996) highlights the fact that emotional reactions to stimuli are frequently more rapid than cognitive evaluations. As he says, "emotions can flood consciousness [...] because the wiring of the brain at this point in our evolutionary history is such that connections from the emotional systems to the cognitive systems are stronger than connections from the cognitive systems to the emotional systems".

The development of economics theories to this point has ignored some important items: the mind and body of the agent, the complexity of interactions between subject and object, the representation and interpretation of real phenomena, the expectations of individuals, the time factor, the possibility of making systematic errors, creativity, and the interaction between individuals and the environment.

This paper aims to redress this situation. The next section discusses some recent attempts made to go beyond neoclassical economics and overcome its inadequacies. The third section introduces dynamic and computational systems as methodological and conceptual instruments for the study of complex systems. In Sect. 4 the properties of economic systems as complex systems are outlined. Complexity science offers a conceptual framework for their study, and Sect. 5 argues that the most useful instruments in this field are agent-based simulations and "artificial life". Section 6 reports on an artificial life simulation that recreates the economy exchange process. The results demonstrate the usefulness of simulations for the social sciences. Conclusions in Sect. 7 close the paper.

2 Beyond neoclassical economics

Ways have been tried to overcome the boundaries of orthodox economics. For example, experimental economics adds a human dimension in the form of the economic agent, but then introduces other difficulties. To take people into the laboratory and observe their behaviour under controlled and ideal conditions is problematical. Usually such experiments are conducted in an academic laboratory, and often the "agents" are themselves economics students inevitably influenced by their studies.

An important contribution to understanding economic phenomena comes from cognitive psychology. Cognitive psychology brings the economic agent nearer to the human being and consequently, as Viale (1997) notes, this new perspective can effectively provide economists with a realistic conceptual instrument for understanding how economic agents judge and make choices in various empirical contexts.

Limits and erroneous suppositions within the concept of perfect rationality are admitted and accepted by some economists. McFadden (1999) underlines the limits of neoclassical economics using the conceptual instrument of cognitive psychology, recuperating emotional components of cognitive processes as illustrated in reports and research (e.g., Tversky and Kahneman 1991). Even so, many economists, and also many cognitive psychologists, consider the heterogeneity of human behaviour a cognitive anomaly, emphasizing instead a normative approach to the economy, and disregarding other important components of the real world like the body and the environment. The necessity to recover or re-discover the body is emphasized by many neurobiologists (e.g., Edelman 1993; Damasio 1995).

Besides, mind and body are not enough to understand the human being. There is a need also to account for and reproduce the environment in which individuals interact and evolve. As Tomasello (1999, pp. 216) notes, genes are an important part of the human being but are not the whole human being. In fact, an important part of phenotype history consists of learning processes, and the interaction between individuals and the environment in the complex context we call "human societies". Therefore, to understand the mind, consideration must also be given to the body, its pathologies, internal states, and interaction with the natural environment, as well as with the cultural and technological environments (Parisi 2001; Piaget 1970; Vygotskij 1978). Recovering mind, body and environment breaches the most important divisions upon which human sciences were founded: mind and nature, individual and society, synchronic and diachronic views of time (Parisi 2001).

In the face of the conceptual and methodological problems inherent in the neoclassical approach to economics theory, two choices are possible. Firstly, discount the problems and continue to study economic phenomena using traditional instruments. Friedman's (1953) hypothesis of the "As is" says, "Truly important and significant hypotheses will be found to have 'assumptions' that are wildly inaccurate descriptive representations of reality, and, in general, the more significant the theory, the more unrealistic the assumption". Alternatively, in order to understand real phenomena and overcome the boundaries of neoclassical economics, there is a need to reclaim the human being, society, history, and context of individual lives. Consequently, new instruments and new methodologies must be found.

3 Cognitive sciences: dynamic and computational systems

Cognitive sciences and their methodological and conceptual instruments have contributed to bringing economics theory nearer to the phenomena of the real world. The study of cognition is traditionally based on two approaches: dynamic and computational systems.

Dynamic systems theories of change and movement favour a continual, temporal change in complex systems. They view temporal changes in a geometric way, in terms of "trajectories", "attractors", "bifurcations", and so on. Historically, such theories have been useful for understanding emergent behaviour in complex systems. More important, however, is their emphasis on how the brain-body-environment system as a whole changes in real-time, and their proposition that dynamics is the best framework for capturing that change. But they also have some weak points. For example, as Mitchell (1998) notes, "it is not completely clear how the approaches being explored for motor abilities, simple perception, simple language processing, and the like will provide complete accounts of 'higher-level' cognitive phenomena such as the recognition of and reasoning about abstract ideas".

Besides, the dynamic systems approach does not explain how the underlying system gives rise to those aspects of behaviour that are functional or adaptive. For example, it does not explain how two adaptive systems with very different dynamic portraits can give rise to similar functional behaviour, or how they will be affected by various sorts of damage. Also, it does not explain what happens when new functional components give rise to improvements in the system (ibid.)

Cognition and computation systems have been profoundly linked for at least fifty years, especially in the field of artificial intelligence. The origin of the digital computer derives from Turing's idea of formalizing the kinds of symbolic logic manipulations that mathematicians perform, later recognized by Newell and Simon (1976) and others as the correct conceptual framework for understanding thought processes. Similarly, von Neumann-style architecture that has dominated computer science for most of its history has been used to model brain function, highlighting information processes, symbolic manipulation, and the functional structure of mental state. As Van Gelder and Port (1995) write about the computational approach, "Cognitive operations are transformations from one static symbol structure to the next".

To summarize, dynamic systems contribute to characterizing continual change in cognitive systems, describing complex couplings among the brain, body, and environment (theories of change), while computational approaches shed light on functional and adaptive behaviour in complex systems (theories of structure).

4 The economy as a complex system

Research on complex systems has contributed greatly to *rapprochement* between the computation and dynamic approaches. The goal of complex systems research is to explain in a multidisciplinary way how complex and adaptive behaviour can arise in systems composed of large numbers of relatively simple components, with no central control, and with complicated interactions (Mitchell 1998; Crutchfield 1994).

Like other social phenomena, the economy is a complex system, and it needs to be defined as such. Arthur et al. (1997) have attempted to so do, highlighting features that present difficulties for traditional economists. These are:

- *Dispersed Interaction* What happens in the economy is determined by the interaction of many dispersed and heterogeneous agents. Moreover, the action of any agent depends upon the anticipated actions of a limited number of other agents.
- *No Global Controller* In the real world there is not a global coordinator that controls the interaction between agents. Controls are provided by mechanisms of competition, coordination and cooperation among agents; e.g., legal institutions, assigned roles, and shifting associations.
- *Cross-cutting Hierarchical Organization* The economy, like any social system, has many levels of organization and interaction. The units at any given level are the building block for constructing units at the next higher level but the overall organization is not purely hierarchical. The units at any level are connected with other units in a complex manner; i.e., by association, and through channels of communication. The overall organization is more similar to a complex network, like the brain.
- *Continual Adaptation* Behaviours, actions, strategies and all else are revised continually as individual agents accumulate experience and learn new things.
- *Perpetual Novelty* Innovation is continuous, creating new technologies, new behaviours, new institutions, new markets and new niches that in turn redefine the behaviour of individuals and the market. The result is perpetual novelty and co-evolution of things.
- *Out-of-Equilibrium Dynamics* Because new niches, new potentials and new possibilities are continually created, or co-evolve, the economy operates far from any global equilibrium. Improvements are always possible and indeed occur regularly.

Complex systems with the above features can be described as "adaptive non-linear networks" (Holland 1988) because they are capable of learning on the basis of both physical and social events. There are many kinds of adaptive non-linear networks in nature and society; e.g., nervous systems, immune systems, and ecologies, as well as economies. An essential element of such systems is that they do not act in terms of stimulus and response. Rather, adaptive non-linear networks emphasize aspects like expectations and predictions brought about through interaction between agents and from continuous learning. The existence of this ability to learn is important for economics to acknowledge, as it enables the elaboration of a truer representation of the world, and more realistic expectations. Learning is ignored in orthodox economics since it is reduced to a mere upgrade of some information variables, rather than as producing structural change.

Adaptive and non-linear "systems" highlight complex interactions that are scarcely comprehensible with standard instruments like mathematics. To understand the emerging "structures" and "processes" of social phenomena, and to overcome the dichotomy between computational and dynamic systems, there is a need for new instruments, new mathematical models and new stochastic models, all united with the potential of computer modelling.

5 Agent-based simulations and "artificial life"

In complexity science the focus is not on the final results of a particular process or phenomena but, rather, on the underlying processes and the emerging structures. Here, agents have a pluralistic vision, and make sense of a particular object or event each in their own way, as opposed to the concept of perfect rationality where every agent has the same vision. Agents have bounded cognitive resources but can learn new behaviours and new strategies. They live in an environment where information is asymmetrical, knowledge is limited, new information categories can be developed, and interaction networks are tangled.

In this context the need for new instruments becomes evident. Agent-based simulation is one such needed instrument, and is also a new symbolic system. In fact, as Ostrom (1998) notes, there are three symbolic systems for understanding social phenomena. The first is description and argument; the second is mathematics; while the third symbolic system (not yet completely accepted) is computer simulation, where the model of phenomena is contained in a computer program. Simulation is a new method for expressing scientific theories (Parisi 2001, pp. 27) and goes beyond the simple concept of a model. A model describes any phenomena whether concrete or abstract, while a simulation is a method by which scientists rebuild the mechanisms and processes underlying the object or phenomena simulated. A model does not consider the underlying processes, whereas a simulation reproduces these processes as relative emerging structures.

Simulations are intrinsically multi-disciplinary and, consequently, they enable a more complete understanding of social phenomena. They are virtual laboratories where variables can be manipulated in order to learn more about the processes and structures underlying the real world. Simulations allow the exploration of hypothetic worlds, and may be used as an instrument to improve learning (Parisi 2001). In practice, simulations are computer programs that make possible the recreation of phenomena such as agents, environment, and rules of interaction. Besides, for computer programs to run they must be exact and detailed, and so theories too must be rigorously formulated.

But what are the characteristics of agents? Do agents have a complex form of mind, or function with simple rules? Can use be made of the same kind of simple agents that Axelrod (1997) notes, or ought they should be *BDI* (*beliefs, desires, intentions*) *agents*? The answer seemingly is that both types are applicable. As Terna (2000) notes, a simulation can be created with different kinds of agents, and even with simple "no-mind" agents emerging structures, or complex patterns, can be observed.

In particular, Terna (ibid.) has performed experiments using three different kinds of simulations. The first used agents lacking a symbolic rule system ("no-mind") in a completely unstructured market, that also lacked rules and operating mechanisms. The second kind used artificial adaptive agents with a mind and the ability to learn, in an unstructured market. The third kind of simulation used simple "no-mind" agents in a strictly structured market, like the stock market.

In the first experiment was observed chaotically emerging phenomena caused by the collective behaviour of the mindless simple agent. Also observed in the completely unstructured market, with agents incapable of adaptation, were a rigidity of behaviour, and eventually the absolute instability of the market itself. On the other hand, when agents had a mind a different situation emerged. In the second experiment, the agents' adaptive abilities gave rise to stability in the unstructured market.

Finally, the third simulation showed "it is possible to generate complex patterns (as bubbles) without using BDI agents, if the structure of the market is highly sophisticated, and consequently able to generate internally sequences of prices linked to the agent's actions in a non linear way" (ibid.). Terna's work does not generalize the capabilities of "no-mind" agents but outlines the possibility that complex patterns can emerge from the interactions between different kinds of agents and their environment.

Another important item in agent-based social simulation is the level of detail in the simulations. While neural networks (Floreano 1996; Rumelhart and McClelland 1986) and genetic algorithms (Holland 1992) can be used to describe and recreate social phenomena, these conceptual instruments can be surpassed with "artificial life". Artificial life simulations also use neural networks and genetic algorithms but are more complicated since agents have a physical body, a neural system, and a genetic heritage, and they live in a real or imaginary environment where they reproduce other individuals, produce food and other assets, and where they die. In short, artificial life simulations reproduce real or imaginary life and, additionally, reclaim anthropological and historical perspectives. They allow the understanding of both simple and complex phenomena, including the possibility of observing emerging social phenomena, even more so than expected (Waldrop 1992; Parisi 1999; Langton 1995) and as noted in Ugolini and Parisi (1999) and in Parisi and Ugolini (2002).

6 Understanding exchange processes in artificial life

To this point the paper has addressed agent-based simulations as methodological and conceptual instruments for understanding emerging structures and processes of social phenomena. This section examines an artificial life simulation in the economics field concerning the exchange process (Ugolini 2004).[1] The intention is to show how this methodology can be usefully applied in analysing economic phenomena and social phenomena in general, consistent with the features of complex systems identified in Sect. 3.

To describe the exchange process simulation an "islands" metaphor is used. There are three islands: *W*, *O* and *M*. On island *W* the inhabitants produce wheat, and on island *O* the inhabitants produce olive oil. On island *M* the inhabitants are merchants. Wheat producers obtain olive oil by exchange, and olive oil producers obtain wheat by exchange, through the merchants. Producers cannot travel between islands. Merchants, on the other hand, have the means to sail between islands and, therefore, to make exchanges.

On each island, *W* and *O*, the initial producer population is 140–150 individuals randomly positioned. These numbers were derived from the steady state reached in other simulations that determined ability to produce food (Ugolini 2004). The initial population of merchants is 100 individuals randomly positioned on island *M*. Each initial producer is allocated a set number of food units, randomly selected in the interval between 10 and 30.

Producers and merchants store food in their individual store (*IS*). To survive, every individual must eat at least one kind of food. If an individual eats both kinds of food more energy is gained and, consequently, that individual has a better chance of survival. Conversely, if an individual eats only one kind of food (i.e., only wheat, or only olive oil), less energy is accumulated and chances of survival reduce. The transformation rule for food to energy is:

$$\begin{aligned} &1\,\textit{wheat unit} \text{ and } 1\ \textit{olive oil unit} \Rightarrow 15\ \textit{energy units} \\ &2\,\textit{wheat units} \text{ or } 2\ \textit{olive oil units} \Rightarrow 10\ \textit{energy units} \end{aligned} \tag{1}$$

The maximum age of any individual is 300 time-steps, and with every time-step an individual consumes 1 energy unit. When an individual's energy level is under the threshold equal to 10 energy units they must eat. Individuals die when they exhaust their wheat and olive oil supplies, or at the maximum 300 time-steps. All individuals, every 50 time-steps, generate offspring who inherit 20% of their parent's wheat and olive oil supplies.

The behaviour of each individual is controlled by neural networks and by rule-based cognitive agents. In particular, neural production networks (*PN*) regulate food production on islands *W* and *O*, while a rule calculates the demand for food at each trade. Similarly exchange rate networks (*ERN*) determine the exchange rate (*ER*) to be applied by merchants during a trade, and a separate rule calculates the supplies on offer.

*PN*s have two input units encoding the presence and location of the nearest food element, two output units encoding one of four possible actions ("move one cell forward in the current facing direction", "turn 90 degrees to the left", "turn 90 degrees to the right" or "do nothing"), and three hidden units linking the input to the output units. At each time-step an individual is

[1] The simulation model can be obtained directly from the author.

informed about the position of the nearest food element and must respond with some movement. When the movement causes the individual to enter a cell containing a food element, the food is transferred to their *IS*.

*ERN*s have two input units encoding the *ER* and the percentage of resources exchanged during the previous trade, one output unit encoding the *ER* to be used during the next trade, and three hidden units linking the input to the output units.

Each merchant has two *ERN*s for determining *ERs*. One rate, ER_w,, is used on island *W* where merchants trade wheat for olive oil. The other rate, ER_o, is used on island *O* where merchants trade olive oil for wheat. The *ER* is set at a value in the continuous interval from 1:2 to 2:1, so individuals also may exchange fractions of food units. The worst-case scenario occurs when a merchant yields two food units in exchange for one, while the better exchange is to yield one food unit in exchange for two.

The initial *PN* connection weights were derived from the steady state reached in other simulations that determined ability to produce food (Ugolini 2004), while the initial *ERN* connection weights were determined by randomly selecting a value in the interval between -3 and $+3$. Producer offspring inherit their parents' current connection weights slightly mutated by adding a quantity randomly selected in the interval between -0.1 and $+0.1$.[2] Merchant offspring inherit their parents' current connection weights slightly mutated by adding a quantity randomly selected in the interval between -0.3 and $+0.3$.[3] Therefore, the global behaviour of the neural networks is determined by a change in the value of connection weights as a result of learning inspired by biological evolution. In short, *PN*s and *ERN*s improve their abilities through artificial selection (genetic algorithms) on the basis of best performance in regards to either producing food or making exchanges.

Every 25 time-steps merchants start an exchange round according to the following rules:

- Merchants are randomly picked, one by one, to go to islands *W* and *O*.
- Each merchant randomly chooses the island to visit and make exchanges. During the exchange process each merchant offers their entire supply (*S*) of food in their *IS* ($S_w = IS_w$ and $S_o = IS_o$) at exchange rates ER_w and ER_o as determined by two *ERNs*. Each merchant meets producers individually and randomly chosen. Producers on islands *W* and *O* demand either wheat or olive oil according to the following rule, where *D* is demand, and *w* and *o* are respectively the wheat and olive oil in their *IS*:

$$D_o = \frac{w - o}{ER_o}, \quad D_w = \frac{o - w}{ER_w}, \tag{2}$$

As such, individuals aim to balance the quantity of wheat and olive oil in their *IS*s. If a producer needs food ($D > 0$), then the exchange is made,

[2] The interval between -0.1 and $+0.1$ is determined following the simulative models described in Ugolini and Parisi (1999) and Parisi and Ugolini (2004).

[3] The interval between -0.3 and $+0.3$ is determined by empirical tests to ensure variability in the merchant's behaviour.

otherwise the merchant will bypass to another producer, again randomly chosen. The exchange is done as follows:

- If $D \geq S$ then the merchant yields all their food supply on offer and leaves island W or O.
- If $D < S$ then the merchant yields the food demanded by the producer and randomly chooses another to offer their residual supply of food.

The simulation was run with two different sets of "game" rules. In the first simulation (*s1*) the exchange round ended when the merchant had yielded their total supply of food, or had met 10 consecutive producers with no demand for food. In the second simulation (*s2*) the number of opportunities to trade was increased from 10 to 20 consecutive producers with no demand, before the exchange round ended. In *s2* merchants had the potential to remain on islands W and O longer to execute a greater number of exchanges. With their potentially wider sampling of producers these merchants were more likely to acquire greater information about the market. A merchant that had to leave an island after 10, rather than 20, unsuccessful trades (*s1*) was less likely to know if there might be other producers interested in exchanging.

Both simulations *s1* and *s2* were run 10 times with 10 different seeds. Each simulation was terminated after 25.000 time-steps. The results, summarised in Table 1, are as follows.

At the end of *s1* (steady state) 63 merchants remained on island M, and each possessed on average 34 food units. The food possessed by the most successful merchant was 310 units, while the most unsuccessful had only 0.32 units. The average amount of food possessed by the best 20% of merchants was 110 units, and by the worst 20%, an average 1.61 units.

Different results emerged from *s2*. At its end 60 merchants remained on island M and, on average, each possessed more food compared with those in *s1*. On average each merchant in *s2* had 39 units, while the most unsuccessful had 0.29 units. Moreover, the best 20% had 135 units, while the worst 20% of merchants had 1.52 units on average.

In other words, comparing results of the two simulations, these trends emerged:

- increased wealth, on average, of the surviving merchants;
- increasing social differences between merchants and, specifically, a greater difference between the best (more food) and the worst (less food) merchants;
- a decreasing number of merchants on island M.

Table 1

Merchant's parameters	*s1*	*s2*
N of individuals	63	60
Average amount of food units	34	39
Food units possessed by the best individual	310	388
Ave. food units possessed by the best 20% ind.	110	135
Ave. food possessed by the worst 20% ind.	1.61	1.52
Food possessed by the worst individual	0.32	0.29

To explain, in *s2* merchants could stay longer on the producers' islands to trade more often and, thus, potentially satisfy the demands of more producers, as well as gain more information on market demand. In *s1* merchants who had to leave a producer's island after 10 unsuccessful attempts ($D = 0$), could not know if there were other producers wanting food ($D > 0$). Calculating how many merchants executed at least one exchange in both *s1* and *s2* confirms this. The percentage of merchants who executed at least one exchange in *s1* was 47%, while in *s2* this percentage decreased to 38%. In other words, the first merchants to trade effectively skimmed the market, leaving less opportunity for others, and brought about the decreasing population of island *M* as a consequence. Imperatives in *s2* evidently are to reach the producers quickly, and to have the most food to exchange.

The results in *s2* are related not only to having greater opportunity to trade but also are a consequence of the amount of information available to merchants. Where merchants have potentially less information about market demand – as in *s1* where merchants were limited to a smaller sample during the random selection of producers – then there is a notable reduction in selective pressure on the merchants. Conversely, where merchants gain more information through greater sampling, then selective pressure increases and the more successful merchants gain a competitive edge.

Merchants who owned technologies that enabled them to reach a producer's island before others, and who possessed more food (were wealthier) skimmed the market, causing increasing social differences. This result is consistent with the findings of Vercelli (2002) who notes, the empirical evidence examined by some economics historians shows that in the absence of distribution policies (e.g., of wealth) the market tends towards increased social inequalities.[4]

As such the simulations can be said to well represent certain aspects, emerging processes and structures, of the real market and, therefore, are most relevant for economics. Focusing on content, *s1* and *s2* reveal the dynamic nature of the relationships between individuals relative to the information they possess. For example, if merchants possess more information about the context, then the model shows the emergence of greater social inequalities, an increased selective pressure and a consequent reduction of population on island *M*. Hence, the increasing availability of information is not a simple informative update of some variables in an economic model but, on the contrary, it is a structural change and an out-of-equilibrium dynamic.

Simulations, particularly artificial life models, are important also from methodological and conceptual viewpoints. They can recreate social phenomena, such as the economy exchange process, reproduce real or imaginary life, and recover anthropological and historical perspectives that are usually missing elements in neoclassical economics approaches. Moreover, by changing their variables and with repetition, artificial life simulations can reveal patterns in interesting social behaviour. Processes and structures can be seen emerging from interaction between individuals and between

[4] See also Brandolini (2002), Bourguignon and Morrisson (2000) and Sen (1999).

individuals and their environment. Neural networks allow these interactions to occur naturally, without the need for a global controller, while genetic algorithms assure continual adaptation of behaviours, actions and strategies. Therefore artificial life simulations are best placed to recreate social phenomena and bring economics theories closer to real life, going well beyond the limits of the orthodox view of the economy.

7 Conclusions

Nowadays many economists are aware of the intrinsic limitations of neoclassical economics, although perhaps equally as many still hold fast to this outdated view. Awareness of its limitations has been the inspiration for some economists to forge new conceptual instruments, applying insights gained in cognitive psychology research. An offshoot has been the creation of a new area of research called cognitive economics. This new approach in turn has increased awareness of the gap existing between the neoclassical economics concept of "perfect" rationality versus a more realistic view, and the standard "black box" economic agent versus real individuals.

Cognitive science has further contributed to overcoming problems with neoclassical economics. Dynamic systems characterize the continuous change in cognitive systems and in the interaction of body, mind and environment, while computational systems underscore the functional and adaptive sides. Complexity science helps bridge the divide between dynamic and computational systems, and agent-based simulation excels as a multidisciplinary instrument for bettering understanding of complex phenomena.

Agent-based and artificial life simulations overcome the limitations of orthodox economics by providing agents with a body and neural system, and inserting them into an environment where they can all co-evolve, similarly to real life. Such simulations can be used to describe complex phenomena like the economy exchange process, emphasizing the nature of structure and the processes through which it emerges across different levels of organization, satisfying the six features of complex systems described in Sect. 4.

In the past, "gothic cathedrals had the purpose to take the believer into alternative and sacred space, outside of reality" (Bettetini and Colombo 1993). Now, artificial life and agent-based social simulations may be considered the new conceptual and methodological instruments for guiding economic studies out of the *gothic cathedral* that is orthodox economics.

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