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A COMPLEX LENS FOR ECONOMICS, OR: ABOUT ANTS AND THEIR ANTHILL

1. *Basics*

The complexity manifesto is mostly identified with Anderson's paper *More is different* (1972), where we read:

> The reductionist hypothesis may still be a topic for controversy among philosophers, but among the great majority of active scientists I think it is accepted without questions.
>
> (…) The main fallacy in this kind of thinking is that the reductionist hypothesis does not by any means imply a "constructionist" one: The ability to reduce everything to simple fundamental laws does not imply the ability to start from those laws and reconstruct the universe.
>
> (…) The constructionist hypothesis breaks down when confronted with the twin difficulties of scale and complexity. The behavior of large and complex aggregates of elementary particles, it turns out, is not to be understood in terms of a simple extrapolation of the properties of a few particles. Instead, at each level of complexity entirely new properties appear, and the understanding of the new behaviors requires research which I think is as fundamental in its nature as any other. (p.393)

This is the key starting point: the economic world is made of interconnected layers populated by more and more complicated agents (people, families, firms, banks, central banks, international institutions, multinationals, …). People make economies, but each of us is as far from understanding and controlling the economic system as a humble ant with respect to the anthill. Economics, as a science, has been simply ignoring that "detail" for about two hundred years. In Anderson's words, complexity is the big trap generating the current paranoiac situation for which the crisis (2007-2012, at least) has no room in perfect models, but … it exists in the actual world.

How to work with the lens of complexity? We need models, for us and … for the ants.

From the wonderful list of foundational papers about complexity, which we can find at http://www.santafe.edu/library/foundational-papers-complexity-science, let us have a second basic reference, related to the model building perspective. In Rosenblueth and Wiener (1945), the founders of cybernetics, we read:

> A material model is the representation of a complex system by a system which is assumed simpler and which is also assumed to have some properties similar to those selected for study in the original complex system.
>
> (…) Material models are useful in the following cases. a) They may assist the scientist in replacing a phenomenon in an unfamiliar field by one in a field in which he is more at home.
>
> (…) b) A material model may enable the carrying out of experiments under more favorable conditions than would be available in the original system. (p. 317)

Being cybernetics a root of all our contemporary work in complexity and agent-based simulation, it is important to underline the analogy between the "material model" above and the artificial artifact we can construct in a computational system, so as to examine our problems in a closer way, while we are also studying them in a theoretical way.

Why is this more and more important in social sciences and economics?

2. *A historical perspective*

A sound reply can be found in a historical perspective (where history can be also contemporary). I had the privilege of being the co-editor, with David Lane, of a special issue of the journal *History of Economic Ideas* (Lane and Terna, 2010), devoted to *Complexity and the Organization of Economic Life*.

I extract from there some references to the historical paths of the complexity ideas. I owe this wonderful quotation from Keynes to Marchionatti's paper (2010):

> Professor Planck, of Berlin, the famous originator of the Quantum Theory, once remarked to me that in early life he had thought of studying economics, but had found it too difficult! Professor Planck could easily master the whole corpus of mathematical economics in a few days. He did not mean that! But the amalgam of logic and intuition and the wide knowledge of facts, most of which are not precise, which is required for economic interpretation in its highest form is, quite truly, overwhelmingly difficult for those whose gift mainly consists in the power to imagine and pursue to their furthest points the implications and prior conditions of comparatively simple facts which are known with a high degree of precision.(Keynes [1924], Collected Writings, X, 1972, 158n)

Again, what appears here is the opposition between the material model (the artifact of the system) that we need to build taking into account randomness, heterogeneity, and continuous learning in repeated trial and error processes, and the "simple" theoretical model.

What kind of theoretical model~~s~~? Not a too simplistic one: following Louçã (2010), already in the work of important economists of the last part of the nineteenth century we clearly have:

> (…) some cases of revolt against such (note: too mechanical) paradigm that turned out to be early intuitions of complexity and emergence in economics. Without the mathematical and conceptual tools of complex systems and even as ignorant as they were of non-linear systems, these economists voiced their doubts, hesitations or critiques against the mainstream and, in most cases, did so looking at the frontier between economics and other sciences, physics or biology, the most fashionable inventors of modern science. These frontiers became the place to vindicate a new strategy for economics.

Finally, quoting Arthur (2010), the construction of our material model has to take into account the cognitive side of the agents. From the season of early innovation at the Santa Fe Institute,

> (…) a second theme that emerged was that of making models based on more realistic cognitive behavior. Neoclassical economic theory treats economic agents as perfectly rational optimizers. This means among other things that agents perfectly understand the choices they have, and perfectly assess

the benefits they will receive from these. If there is uncertainty, they evaluate it probabilistically, revise their evaluations in the light of new information, and choose the course of action that maximizes their expected utility. Where there are multiple parties involved, each agent is usually assumed to have common knowledge about the others' possible choices and assessments of these. Our approach, by contrast, saw agents not as having perfect information about the problems they faced, or as generally knowing enough about other agents' options and payoffs to form probability distributions over these. This meant that agents need to cognitively structure their problems—as having to "make sense" of their problems, as much as solve them.

In contemporary terms, following Holt et al. (2010), we move closer to material models if we take into account also the details of complexity:

> Since the term complexity has been overused and over hyped, we want to point out that our vision is not of a grand complexity theory that pulls everything together. It is a vision that sees the economy as so complicated that simple analytical models of the aggregate economy—models that can be specified in a set of analytically solvable equations—are not likely to be helpful in understanding many of the issues that economists want to address. Thus, the Walrasian neo-classical vision of a set of solvable equations capturing the full interrelationships of the economy that can be used for planning and analysis is not going to work. Instead, we have to go into the trenches, and base our analysis on experimental and empirical data. From there *we build up*, using whatever analytic tools we have available. This is different from the old vision where economists mostly did the opposite of starting at the top and then built down. (p. 5)

Technically, with Holt et al. (2010), we can remember Simon (1962):

> Roughly by a complex system I mean one made up of a large number of parts that interact in a non simple way. In such systems, the whole is more than the sum of the parts, not in an ultimate metaphysical sense, but in the important pragmatic sense that, given the properties of the parts and the laws of their interaction, it is not a trivial matter to infer the properties of the whole. In the face of complexity, an in-principle reductionist may be at the same time a pragmatic holist. (p. 267)

3. *Moving to models*

We can now move to models: the material models of the founders of cybernetics, or the computational artifacts of the agent-based simulation perspective.

Following Ostrom (1988) and, to some extent, Gilbert and Terna (2000), in the social sciences we traditionally build models as simplified representations of reality in two ways: (i) verbal argumentation and (ii) mathematical equations, typically using statistics and econometrics. The first way (i) is absolutely flexible and adaptable, as in the case of a historical book reporting an analysis of past events; but mere descriptions and discussions, by their nature, preclude tests and verifications of hypotheses. In contrast, the second way (ii) allows for computations and verifications, but suffers from severe limitations in flexibility and adaptation, especially with respect to how agents are expected to operate within the model and when accounting for their heterogeneity and interactions.

There is a third way to build models, (iii) computer simulation, especially when agent-based. Computer simulation can combine the extreme flexibility of a computer code –

where we can create agents who act, make choices, and react to the choices of other agents and to modification of their environment – and its intrinsic computability. This allows us to use jointly the descriptive power of verbal argumentation and the ability to calculate the effects of different situations and hypotheses. From this perspective, the computer program is a form of mathematics. In addition, from our models we can generate time series and analyze them by employing statistics and econometrics.

However, reality is intrinsically agent-based (ourselves or … the ants), not equation-based (for a short, but illuminating discussion of this consideration, see Weinberg [2002] in his review of Wolfram's book, *A New Kind of Science*). At first glance, this is a strong criticism. Why reproduce social structures in an agent-based way, following (iii), when science applies (ii) to describe, explain, and forecast reality, which is, per se, too complicated to be understood?

The first reply is that, with agent-based models and simulation, we can produce artifacts of actual systems and "play" with them, i.e., by showing the consequences of perfectly known ex-ante hypotheses and agents' behavioral designs and interactions; then we can apply statistics and econometrics to the outcomes of the simulation and compare the results with those obtained by applying the same tests to actual data. In this view, simulation models act as a sort of magnifying glass that may be used to better understand reality.

Considering the analysis of agent-based simulation models as a source of knowledge, there is another "third view" of these kinds of tools. In Axelrod and Tesfatsion (2005):

> Simulation in general, and ABM in particular, is a third way of doing science in addition to deduction and induction. Scientists use deduction to derive theorems from assumptions, and induction to find patterns in empirical data. Simulation, like deduction, starts with a set of explicit assumptions. But unlike deduction, simulation does not prove theorems with generality. Instead, simulation generates data suitable for analysis by induction. Nevertheless, unlike typical induction, the simulated data come from a rigorously specified set of assumptions regarding an actual or proposed system of interest rather than direct measurements of the real world. Consequently, simulation differs from standard deduction and induction in both its implementation and its goals. Simulation permits increased understanding of systems through controlled computational experiments.

The considerations above act in a way similar to abductive reasoning, or inference to the best explanation, where one chooses the hypotheses that, if true, give the best explanation for the actual evidence. Note that in the agent-based model perspective, the hypotheses are also related to the rule that determines the behavior of the agents.

The second reply is that, relying again on Anderson (1972), we know that complexity arises when agents or parts of a whole act and interact, and the quantity of involved agents is relevant. Furthermore, following Villani (2006), "Complex systems are systems whose complete characterization involves more than one level of description" (p. 51). Therefore, in order to manage complexity, one needs to build models of agents. As a stylized example, consider ants and an anthill: Two levels need to be studied simultaneously to understand the (emergent) dynamic of the anthill based on the (simple) behaviors of the ants.

We can also imagine building models based on multiple layers of agents, where the agents of each layer compose – in a collective sense – the more complicated agents of the upper stratum. Here, each layer could be considered to be a swarm, which is also the name of the first standardized tool used to build this kind of models, i.e., Swarm, from the Santa Fe Institute (Minar et al., 1996).

This interpretation of the agent-based paradigm corresponds to the "second use – partially soluble models: artificial agents as complementary to mathematical theorizing –" and to the "third use – models ostensibly intractable or provably insoluble: agent computing as a substitute for analysis" considered in Axtell (2000). Axtell's first use occurs "when models can be formulated and completely solved: agent models as classical simulation."

The first use quoted above is mainly related to Monte Carlo simulations and to numerical solutions of equation models. The second use relates to the cases of existing equilibria that can be: incomputable; not attainable by bounded rational agents; known only for simple network configurations; less interesting than transition phases, fluctuations, and extreme events. The third use is related to intractable models (my addendum to Axtell's considerations) when we believe that agents should be able to develop self-generated behavioral rules.

After this positive introduction, we have anyway to note that agent-based simulation models have severe weaknesses, primarily arising from:

(d) The difficulty of fully understanding them without studying the program used to run the simulation;

(e) The necessity of carefully checking computer codes to prevent the generation of inaccurate results from coding errors. As Epstein and Axtell (1994) pointed out, it is necessary to develop new ways to control software and avoid bugs. In addition, thanks to the object-oriented structure that is intrinsic to agent-based programs, it is also possible to create a class of internal agents charged with observing the behavior of the actual agents of the simulation and with reporting anomalies. Anomalies that can be interesting to analyze and do not necessarily always arise from errors, but it is necessary to carefully explore that possibility. If an accounting procedure produces strange results, the users search for an error; if a simulation program produces anomalous results, the user may have discovered an interesting new result, that can emerge too … from a coding error;

(f) The difficulty of systematically exploring the entire set of possible hypotheses in order to infer the best explanation, in accordance with the previously introduced perspective of abductive reasoning. This is mainly due to the inclusion of behavioral rules for the agents within the hypotheses, with a space of possibilities that is difficult if not impossible to explore completely.

The difficulty of communicating the results, which is implied in (a), can be overcome by the diffusion of standardized tools to develop agent simulation models and by the introduction of a protocol to be applied to those tools. The first example, introduced in the mid-1990s (Minar et al., 1996), is Swarm (www.swarm.org), a project that started within the Santa Fe Institute, but then grew independently. Swarm was not a program in the classic sense, but a library of functions to build agent-based computer models. More specifically, it was a library of particular functions that are useful in the handling of a collection of agents, populating spaces or organizing events in time. Swarm has been a milestone in simulation, thanks to the protocol suggested for using those functions, combining them with its own code written in Objective C (a language combining C and SmallTalk); successively, also Java has been added as connective code. The Swarm development team's original purpose was to create a *lingua franca* for agent-based model development; that goal has only been partially achieved if one considers only the library of functions. With modern languages such as Python, a large part of the Swarm library is now unnecessary, thanks to the tools offered natively by the language itself. On the contrary, when considering the protocol defined within the project, Swarm has been highly successful, since that protocol is intrinsically the basis of several recent tools. For interesting considerations on the use of Python in agent-based programming, one should refer to Isaac (2008, 2011) and for an application of the Swarm protocol to Python, one should see SLAPP.[1]

Many other tools have been built upon the Swarm legacy, such as Repast, Ascape, JAS, and now SLAPP. Important tools, such as NetLogo and StarLogo, use partially different protocols, but always with links to the Swarm one. StarLogo TNG is a recent innovative version of StarLogo. We program it by moving on the screen small differently shaped cards, as in a jigsaw puzzle. A second important innovation of StarLogo TNG is the capability for generating animations very similar to video games, easily understood.

We can deal with the second weakness introduced in (b), i.e., the risk of using codes with "bugs" that corrupt the results, both by employing the standard tools reported here (but this is in some way insufficient) and by duplicating the code using independent tools programmed by different scholars. The result is never the same, due mainly to the use of random numbers when determining sequences. However, if the emergent phenomena are substantially similar in both constructions, we can be reasonably sure that the results are not the consequence of coding errors. This significantly heavy work is suggested for important and critical applications.

The third weakness, that described in (c), i.e., the difficulty of exploring the whole set of possible hypotheses (including the behavioral rules of the agents, where the full rationality and perfect information hypotheses represent only one of the possible choices and not the more plausible) is determined by the dimension of the space of possibilities. When analyzed in a detailed way, this space is necessary for computations where no black boxes are allowed, but it generates an unmanageable set of possible paths. As a reply, we can propose the use of neural networks so as to memorize behavioral choices in an automatic way, using the reinforcement of learning to extract the same rules from experience, via a trial and error procedure. In this way, we can move from the wide search of hypotheses about behavior to a procedure to calculate artificially generated, but plausible, rules. We find something close to this idea in an application related to NetLogo, using genetic algorithms to explore the space of the parameters: http://behaviorsearch.org.

Generating behavioral rules to achieve the capability for emulating cognition is anyway a step that is both highly difficult and challenging. Consider Sun (2006):

[1] Swarm Like Agent Protocol in Python at http://eco83.econ.unito.it/terna/slapp/.

> What makes computational social simulation, especially computational cognitive social simulation (based on detailed models of cognitive agents), different from the long line of social theories and models (such as utility theory and game theory) includes the fact that it enables us to engage with observations and data more directly and test various factors more thoroughly. In analogy with the physical sciences (…), good social theories may be produced on the basis of matching theories with good observations and data. Cognitive agent based computational social simulation enables us to gather, organize, and interpret such observations and data with cognition in mind. Thus, it appears to be a solid means of developing social–cognitive theories. (p. 17)

As a comment, let us quote Lave and March (1975): "The best way to learn about model building is to do it" (p. 10).

4. *Moving to computation*

Finally is the importance of calculating: our complex system models live mainly in their computational phase and require more and more powerful calculating facilities.

Schelling's model and random mutations

Schelling verified the well-known segregation model by moving dimes and pennies on a board. The emergence of segregation, due to the desire of each kind of agent to be surrounded by a given quota of similar beings, can be simulated in any way, also with paper and pencil,[2] as in Fig.1.

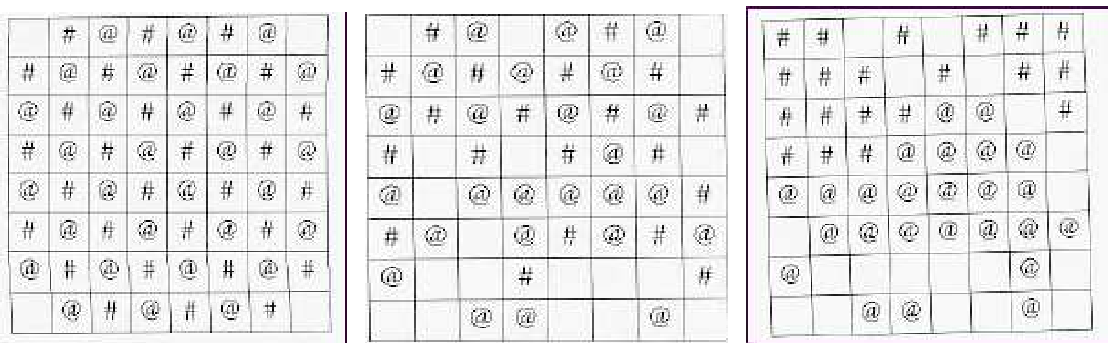

Fig.1 – You do not need a computer here …

However, if you want to check the survival of the segregation islands in the presence of random mutations in agents (from an idea of Nigel Gilbert), as in Fig. 2, you need to use a computer and a simulation tool (NetLogo in this case, see above).

[2] These pictures are from a presentation of Eileen Kraemer, http://www.cs.uga.edu/~eileen/fres1010/Notes/fres1010L4v2.ppt.

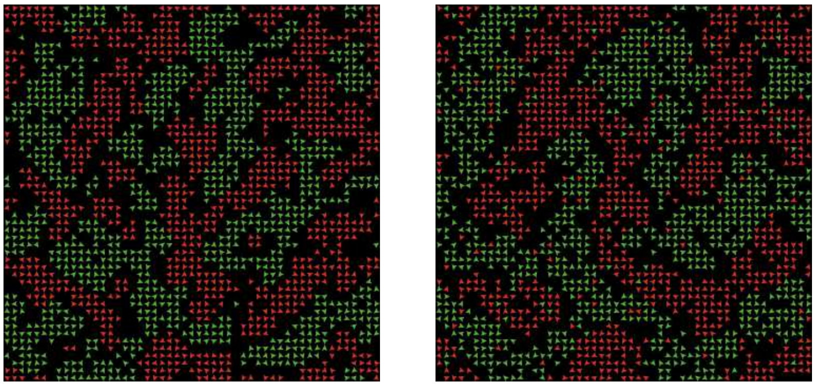

Fig. 2 – Survival of segregation islands with random mutation in the Schelling model population.

Swarm HeatBugs model and different agents' preferences

In the case of the test model of Swarm (see above), the so called HeatBugs model, you can have agents with a preference for high temperature; moving, they generate warmth ; when they are comfortable, they reduce movement; alternatively, some of them can have a preference for low temperature. You have to make a lot of computations to obtain the first and the second emergent results of Fig. 3.

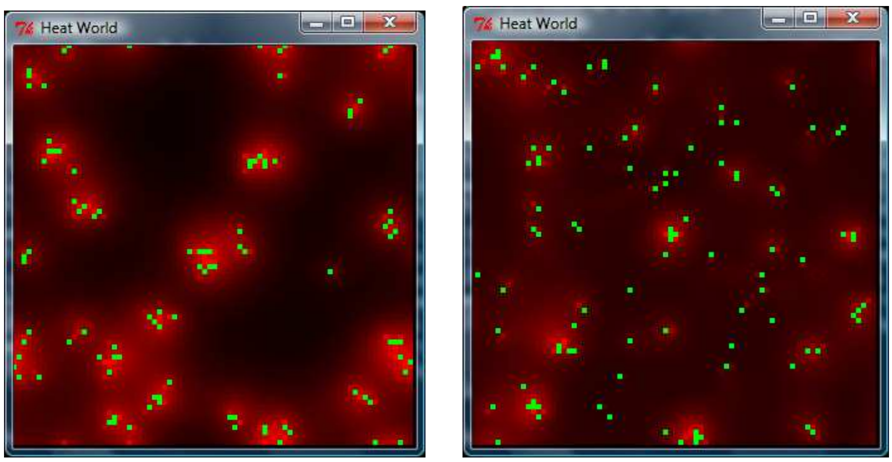

Fig.3 – Emerging isles of agents comfortable with a warm habitat … or same result but with unhappy agents moving around searching for a cold habitat.

Learning chameleons

In Terna (2009a, 2009b) you can find, finally, agents requiring a lot of computational capability for learning and behaving. They are chameleons that change color when they get in touch with another one of a different color; they can learn strategies, via trial and error procedures, to avoid that event, as in Fig. 4.

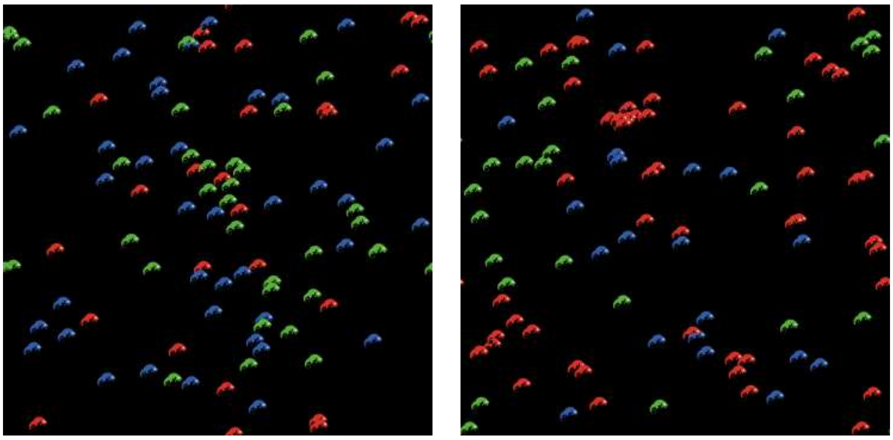

Fig. 4- The chameleons: on the left, acting randomly and,
on the right, learning to survive (the red ones).

We can "play" on line with this model at http://goo.gl/MpS9F.

5. *A tentative conclusion*

Complexity, as a tool to understand reality in economics, comes from a strong theoretical path of epistemological development; to be widely accepted, however, it still requires a significant step ahead of the tools we use to make computations about this class of models, with sound protocols, easy interfaces, learning tools, computational facilities … but it also requires a deep and humble acceptation of the idea that each of us is as far from understanding and controlling the economic system as an ant is with respect to the anthill.

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