Foreword

Simulation is a third way of doing science (Axelrod, 1997).

By building on a computer artificial societies using and sharing resources in a virtual landscape, Epstein and Axtell (1996) promoted a new way of thinking for "Social science from the bottom up". Their purpose was to demonstrate that it is possible to explain many concepts from the Social Sciences perspective via computer simulations based on relatively simple models. By designing step-by-step populations of simple agents located in a *Sugarscape*, they contributed, with others, to explain "How does the heterogeneous micro-world of individual behaviors generate the global macroscopic regularities of the society?" (Epstein & Axtell, 1996). *Sugarscape*, the virtual world they have implemented, allows them to experiment various hypothesis on the emergence of social structures such as migratory phenomena, trade exchanges, crisis and wars. In other words, they seek to explain complex social phenomena from simple but dynamic representations.

Thus from the origin, the Agent-Based Model (ABM) paradigm aims at explaining global emergent patterns from individual behaviors of agents interacting with their environment (including other agents). So, to claim such bottom-up approach, it is necessary to conceive our model by designing individual behaviors and by formulizing how the agents interact. Then, by running the model, the simulation time will let the entities evolve and interact. The simulation lets the model to express itself: by activating the agents, the time animates the model (from Lat. *animare*: to give life) and lets us see how global phenomena may emerge. Distinguishing model and simulation is thus of importance. The modeler should conceive agents with restricted skills (local perception, no or partial control on the others, etc.) and similarly, he shouldn't specify how a population of entities must evolve. Therefore, instead of trying to predefine the states of the agents and to fix on how the system must evolve, the modeler should try to find the basic rules that conduct the actors' strategies and may reflect activities observed in reality.

In the frame of ABM applied to Biological and Environmental Systems, it is sometimes tempting for a modeler to design his agents in a very descriptive way. This work is of interest to describe practices observed on the field. But these descriptions can be seen as frozen: a sequential set of facts without explanation. On the contrary, the agents need a kind of liberty in their choices: an emulated autonomy that allows them to take decisions and finally to confer them some adaptation capabilities. Consequently, after having described the practices of the actors, we should gain in abstraction by trying to extract the basic mechanisms and decision points that conduct their behaviors. Hence, when running a simulation (after having translated these schemes in a computer language), the agents are able to act in a more freely way, without a strong control on the sequences of their actions. Then, if coherent patterns are observed at individual and global levels, we can estimate that we were able to acquire a more essential level of understanding of the studied system. From a very descriptive representation, the model has improved its generic nature: with our understanding of the system, we are able to explain the reasons why some social or ecological behaviors occur.

Models, however, are not crystal balls and the resulting simulation is not a prediction (Bradbury, 2002). It is an artifact, which by nature is highly unrealistic. It is nonetheless essential because, it helps us to assess the logical consequences of multiple and interdependent mechanisms. It is a crutch for understanding because our brain is simply not able to anticipate how several joined dynamics produce a global behavior. In this sense, having designed a model doesn't mean to be able to anticipate all its outputs. After having checked the consistency of it functioning (Balci, 1998), we should explore it parameters space. The exploration phase gives us a better understanding of the model significance. This knowledge allows us to better anticipate its reactions, to better explain its results and to provide answers to the questions at the origin of the modeling process. Therefore, the role played by the model is essentially to learn and understand (Grimm & Railsback, 2005).

One advantage of ABM (which should rather be considered as a weakness) is the ability to endlessly complicate a model to work towards a perfect and realistic representation of the world. While mathematical models require condensing knowledge, conciseness isn't a constraint for the design of ABM. One can incorporate more and more elements and details.

Anyway, simplistic versus sophisticated models is always a topical issue. In this debate, some argue it is essential to build complicated models to address social issues. They criticize the excessive simplicity of some ABM with too poor reasoning agents. This approach is also consistent with the ideas of some sociologists, who (when they do not reject any idea of modeling) recommend using cognitive agents to generate social dynamics. In this regard, the BDI architecture often used to model cognitive agents does not rely on robust scientific evidences: it is not derived from precepts of neuroscience nor psychology nor philosophy. In the paper entitled "From KISS to KIDS", Edmonds and Moss (2004) propose an "anti-simplistic" approach for modeling. They criticize the usual KISS (Keep It Simple Stupid) approach, which requires the modeler to make preliminary choices and to eliminate elements that seem unimportant a priori. The risk is to eliminate information that could be fundamental to correctly describe the structure and dynamics of the studied system. In contrast, they claim the KIDS approach (Keep It Descriptive Stupid), which aims to incorporate into a model all available information on the system.

However, even for very simple models, the probability to unintentionally introduce simulation bias is not zero. Given the sensitivity of ABMs with respect to time and interaction management, but also with respect to the initial conditions, and even to the quality of the pseudo-random number generator, not to mention errors related to floating point calculation, there are significant chances of finding results which may be the consequences of biases. Today, we cannot demonstrate the characteristics of an ABM. Then one can legitimately question the reliability of its results since many biases may occur, especially from complicated ABM. Yet these problems are generally underestimated: we usually prefer to improve the agent decision-making or the realism of it behavior at the expense of a clear and unbiased management of their activation or interactions.

Besides the problem of reliability, designing a very sophisticated model means running the risk of not being able to explain its results. If the decisions of the agents are too complex and the processes too intricately linked, it quickly becomes impossible to provide a comprehensible explanation about the simulated outputs. Yet the main purpose of modeling is not to mimic reality nor to simplify complexity, but rather to try to understand it. Even if it looks wonderful, an ABM remains essentially unrealistic and its results remain not provable. Without any explanatory dimension, it becomes useless. Running after the fantasy of the perfect model seems doomed to failure. Consequently, if it is useful to criticize a model, the lack of sophistication should not be blamed.

Between extreme simplicity and endless sophistication, it is obviously necessary to find a balance so that the model can be useful for understanding or decision. However, given the current knowledge on ABM simulation, throwaway models should be preferred to cathedrals models. Instead of seeking complex models (in their structures and mechanisms), it seems preferable to regain a form of complexity through simulation (as explained earlier in this text). At least, studying simplifications of an elaborated model is a necessary stage. "It allows the researchers to establish robust results and stylized facts, which constitute references for the study of more complicated dynamics" (Deffuant, Weisbuch, Amblard, & Faure, 2003).

ABM modeling, like any modeling, should obey the principle of parsimony. This is not to say that simplicity is a guarantee of truth, but rather that looking for concision requires identifying and understanding the basic mechanisms at work in the phenomenon under study. In other words, it is important to say as simply as possible the most complex things as would say William Ockham, the medieval philosopher.

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