Sensitivity to Initial Conditions in Agent-based Models

Francesco Bertolotti, Angela Locoro and Luca Mari

Università Carlo Cattaneo - LIUC, Castellanza (VA), Italy
(fbertolotti,alocoro,lmari)@liuc.it

Abstract. In the last thirty years, agent-based modelling has become a well-known technique for studying and simulating dynamical systems. Still, there are some open issues to be addressed. One of these is the substantial absence of studies about the sensitivity to initial conditions, that is the effect of small variations at the beginning of simulation on the macro-level behaviour of the model. The goal of this preliminary work is to explore how a single modification on one agent affects the evolution of the simulation. Through the analysis of two deterministic models (a simple market model and Reynolds' flocking model) we obtain two main results. First, we observe that the impact of the variation of a single initial condition on the simulation behaviour is high in both models. Second, there is evidence of an at least qualitative relation between some general agent-based model settings (numerosity of agents in the model and rate of connections between agents) and the sensitivity to the modified initial condition. We conclude that at least some significant classes of agent-based models are affected by a high sensitivity to initial conditions that have a negative effect on the predictive power of simulations.

Keywords: Agent-based modeling, Initial Conditions, Sensitivity Analysis

1 Introduction and motivations

Agent-based modelling is a well-known technique for "describing and simulating a system composed of 'behavioral' entities" [3]. Unlike in other kind of dynamic systems models, what is observed in agent-based simulations is not only a behavior of some kind, but also the behaving subjects (ibidem). These subjects may be studied in their interaction topologies and behavioral heterogeneity [5], and with the aim of predicting specific outcomes. For these reasons, initial settings such as the topology of the model and all of those "conditioning assumptions imposed or implicit in the model" [4] may influence the predictive power and accuracy of the simulation.

Although sensitivity analysis is generally considered a fundamental element of the analysis of agent-based models [9,13], to the best of our knowledge the effect of the sensitivity to initial conditions was never investigated in a systematic way [6,7,8], with exception for spatial conditions in geosimulation models [10]. With this study, we propose to fill a gap in the direction of the research questions whether and how the sensitivity to initial conditions in agent-based models impacts their prediction power.

To this goal we analyzed two simple agent-based models, of a simple market and of a simple swarm [11], and we tested the effects of two small changes in the initial conditions: the small increase of a single parameter of one of the agents and the removal of one agent from the model. We show that, in both cases, there is a high impact on the macro-behavior of the system, and a negative relationship between the numerosity of the agents in the model and the sensitivity to the initial condition.

The remaining of the paper is structured as follows: in Section 2 we introduce the two models exploited in the experiments; Section 3 presents the methodology adopted; Section 4 shows the results and discusses them; Section 5 concludes and outlines future research directions.

2 Models and Methods

In this work, we analyzed a simple market model and a variation of traditional Reynolds' flocking, to get information related to their sensitivity to the variation of a single initial condition. These models were selected according the following criteria:

1. the models should be simple, so that it is easier to the detect the effect of the modification of an initial condition;
2. the models should be natively deterministic, or at least it should be possible to remove the stochasticity without modifying neither their macro- nor their micro-behavior, so that the effect of a single variation can be analyzed independently of the presence of noise;
3. the models should differ from each other in topology, rules of interaction and domain, to confer genericity to the results.

In what follows we introduce the two models and show the methodology used to obtain the results.

2.1 A simple market model

To the best of our knowledge, no classic simple agent-based model of a generic market exists in the literature, so we developed one. The purpose of the model is to simulate an elementary dynamical trading system in which heterogeneous individuals produce, exchange and trade one kind of good over time. The agents are connected through each other with a Scale-Free distributed network [2], representing the structure of the market. Hence, the spatial distribution is irrelevant.

Each agent follows the same set of rules in each time step. First, it produces goods. Second, it trades them under these conditions:

- if the level of goods is below a "security threshold" and some of the neighbors has a level of goods beyond a "plenty threshold" (push trading);
- if the level of goods is beyond a "plenty threshold" and some of the neighbors has a level of goods below a "security threshold" (pull trading).

The amount of goods exchanged in every transaction is equal to a “trading quantum” set at the beginning of the simulation. Third, each agent consumes goods at an individual consume rate. If the level of goods is lower than that consume rate, the agent consumes everything. Agents can not to die of starvation. The rate of production and consumption are individual parameters, independent one to each other and randomly generated at the beginning of the simulation.

The Reynold’s flocking model

The flocking model is a traditional agent-based model developed by Reynolds [11]. Its purpose is to show how a collective swarm behavior can emerge from a set of “bird-oid objects” (from now on “boids”) that interact according to three simple rules:

- separation from other boids;
- cohesion with other boids;
- alignment of the heading with the direction of nearby boids.

We adapted the implementation by Wilensky [15], by removing all the stochasticity. In this version separation is the overriding rule, which means that cohesion and alignment are taken into consideration only if a minimum separation threshold is exceeded. Furthermore, all boids flock on a toroidal surface with the same constant speed.

Methods

To the best of our knowledge, in agent-based modelling there is not a well-established method to analyze the sensitivity to the variation of a single initial condition related to a single agent. Therefore, we developed a workflow on three steps: model implementation, measure development, and simulation cycle.

First, we developed a deterministic implementation of the simulation models under study. We wrote the market model from scratch, while we slightly modified the Reynolds’ flocking model from NetLogo library (Wilensky 1998). Both models are implemented in NetLogo, a well-known agent-based simulation platform [1,14]. Second, we defined some functions to evaluate the sensitivity to initial conditions. In the market model, we calculated the percentage difference between the average goods level of each agent at the final step of two simulations with the same seed of the pseudo-random number generator (“seed” from now on), one with the initial modification and one without. In Reynolds’ flocking model, we defined how the initial condition variation impacts on the position of each boid by computing the average distance of the position (in percentage of the size of the world) of the same boid at the end of two different simulations with the same seed, one with the initial variation and one without.
Third, we translated into code the simulation process shown in Figure 1.

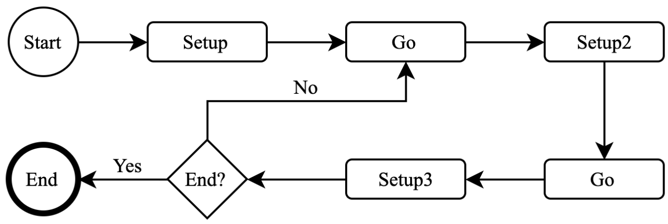

Fig 1. Simulation process developed for testing the sensitivity of a model to the variation of a single initial condition on a sole agent.

The entire simulation (both agents and global variables) was initialized in the "Setup" phase. Then there was a four steps cycle made by two simulation runs ("Go" phases) and two special setup processes: "Setup2" and "Setup3". In "Setup2", the model was reset without changing the seed, agents were created and the target initial condition modified. In "Setup3" the difference between the two simulations (from the "Go" phases) was calculated and saved on an external file with the progressive number of the simulation, the seed and the setup general parameters. Then, the model was initialized with a new seed and the whole model was reset, with exception of global variables designed to take track of the experiment. For every experiment, we executed 75000 pairs of simulations, after which the gate "End?" opens. The number of repetitions was chosen to have reliable results [12].

3 Results and discussion

Simple market model

We performed a total of 150000 simulations on this model, using two kinds of variation of the initial conditions:

1. A 1% increment in the production rate parameter of one of the agents ("IPR experiment" from now on);
2. the removal of one of the agents.

The test was performed on different general parameters of the model, to discover possible relations between them and the sensitivity to the variation of the initial condition. The analyzed parameters were: a) the numerosity of the agents in the model; b) the minimum degree of the scale-free network generator algorithm.

Table 2. Absolute percentage difference of the mean of good level of each agent at the end of the simulation in the IPR experiment.

	Min Degree %					
# Agents	2	3	4	5	6	Total
15	152.9	95.5	87.4	84.8	87.8	101.5
45	105.1	39.0	33.2	33.9	30.9	48.4
135	71.2	19.3	17.0	17.5	17.2	29.7
405	47.1	12.0	10.0	10.1	9.8	17.8
1205	26.5	7.3	5.9	5.8	5.5	10.2
Total	84.1	36.7	33.0	33.0	32.8	44.1

Table 2. Absolute percent difference of the mean of good level of each agent at the end of simulation in the removal experiment

	Min Degree %					
# Agents	2	3	4	5	6	Total
15	121.0	107.0	113.5	108.0	109.6	111.8
45	93.2	92.8	95.6	96.2	96.8	94.9
135	72.3	80.7	90.6	94.7	96.0	86.9
405	55.0	52.4	61.2	72.3	81.9	64.5
1205	36.8	26.9	28.8	33.3	38.4	32.8
Total	75.5	71.9	77.9	80.9	84.5	78.1

Table 1 and Table 2 show that the average value is high, due to a strong sensitivity to the variation of the initial condition. In the IPS experiment, the total and subtotals average percent differences were lower than in the removal experiment. This could be a consequence of the more invasiveness of the second experiment: we expected that deleting a single agent from the model had a greater impact than increasing a single parameter. Furthermore, it was possible to see qualitative relations between the characteristic of the model and the sensitivity to the initial condition.

In both experiments, a greater number of agents implied a lower sensitivity to the initial condition, which could be a consequence of the dilution of the impact in a bigger model. It hinted that it could be possible to lower this phenomenon by developing simulated models with more agents. Furthermore, in the first experiment a higher minimum degree in the network topology of agents brought to a lower effect of the modification of the initial parameters. We suggest that a higher level of connectivity between the agents could have brought to a better compensation of production rate from the market, and then to a lower effect on the macro-behaviour of the model. This relationship was reversed in the second experiment, since the more the network was connected the more increased the probability that an agent lost a trading partner. Besides, a higher connectivity implied also that a greater number of agents were indirectly connected by the removed agent, and since all these links were ended, we awaited a positive relationship between the increment of connection rate and the variation of macro-behaviour. In conclusion, the kind of connection between sensitivity to initial condition and the level of connectivity depended on the kind of modification.

Reynolds' flocking model

As in the previous model, two experiments were performed, each with 75000 simulation runs:

1. a 1% increment of pace of one of the boids ("IPP experiment" from now on);
2. the removal of one of the boids.

Table 3. Average of percentage distance of each boid at the end of the two simulations in IPP experiment.

	Vision Radius (in patches) %					
# Agents	2	3	4	5	6	Total
15	33.5	36.9	37.0	37.0	36.6	36.2
45	37.4	37.8	37.6	37.1	37.0	37.4
135	38.0	37.9	37.3	36.8	35.9	37.2
405	38.0	37.4	36.9	36.1	35.5	36.8
1205	38.0	37.5	37.0	36.6	36.3	37.1
Total	37.0	37.5	37.2	36.7	36.3	36.9

Table 4. Average of percentage distance of each boid at the end of the two simulations in removal experiment.

	Vision Radius (in patches) %					
# Agents	2	3	4	5	6	Total
15	28.5	31.7	32.2	32.6	32.5	31.5
45	35.9	36.2	36.2	36.2	36.0	36.1
135	37.5	37.4	37.2	36.9	37.0	37.2
405	37.9	37.6	37.2	36.8	36.6	37.2
1205	38.0	37.6	37.3	37.1	36.9	37.4
Total	35.6	36.1	36.1	35.9	35.8	35.9

In both cases, the average percentage distance between boids was near 38%, which is the expected distance between two random point on a torus. It means that in both the experiment the modification was enough to completely shuffle the boids' topology during the simulation. As a consequence, in this second model it was not possible to highlight any qualitative relationship between the sensitivity to initial condition and the general parameters of the model. We suppose that this was due to the measure we chose. Since in the majority of the observed cases the impact was near the expected value for a random distribution, it was not possible to observe any clear trend.

4 Conclusions, limitations and future works

Evidence suggests that small variations in single initial conditions strongly influence the global behavior of agent-based simulations. This is relevant because it could have a negative effect on the forecasting power of the technique, which is considered one of the main reasons to develop an agent-based model [6,7]. Furthermore, the results in the market model imply that there could be a negative correlation between the impact of variation and the numerosity of the agents in the model. It suggests that it is possible to mitigate the effect of the sensitivity to initial conditions by performing simulations with a higher number of agents. Still, this is a preliminary study: a statistical analysis on data taken from a wider variety of models is required before to confirm this hypothesis and generalize the results.

Future research could lead to different directions. First, to individuate a class of models for which these findings are valid. Second, to define general rules that link the sensitivity to initial conditions of different model parameters. These rules could depend also by the typology and the size of modification. Third, appraise the relationship between sensitivity to initial conditions and the topology of the agents' network.

References

1. Abar, S., Theodoropoulos, G. K., Lemarinier, P., & O'Hare, G. M. P. (2017). Agent Based Modelling and Simulation tools: A review of the state-of-art software. *Computer Science Review*. https://doi.org/10.1016/j.cosrev.2017.03.001
2. Barabási, A. L., & Albert, R. (1999). Emergence of scaling in random networks. *Science*. https://doi.org/10.1126/science.286.5439.509
3. Bonabeau, E. (2002). Agent-based modeling: Methods and techniques for simulating human systems. *Proceedings of the National Academy of Sciences of the United States of America*. https://doi.org/10.1073/pnas.082080899
4. Boschetti, F., Grigg, N. J., & Enting, I. (2011). Modelling=conditional prediction. *Ecological Complexity*. https://doi.org/10.1016/j.ecocom.2010.06.001
5. Castellano, C., Fortunato, S., & Loreto, V. (2009). Statistical physics of social dynamics. *Reviews of Modern Physics*. https://doi.org/10.1103/RevModPhys.81.591
6. Edmonds, B. (2017). Different modelling purposes. In *Understanding Complex Systems*. https://doi.org/10.1007/978-3-319-66948-9_4
7. Epstein, J. M. (2008). Why model? *JASSS*. https://doi.org/10.1016/s0168-9525(01)02382-4
8. Klein, D., Marx, J., & Fischbach, K. (2018). Agent-based modeling in social science, history, and philosophy. An introduction. *Historical Social Research*. https://doi.org/10.12759/hsr.43.2018.1.7-27
9. Railsback, S., & Grimm, V. (2011). Agent-Based and Individual-Based Modeling: A Practical Introduction. Princeton University Press.
10. Raimbault, J., Cottineau, C., Le Texier, M., Le Néchet, F., & Reuillon, R. (2019). Space matters: Extending sensitivity analysis to initial spatial conditions in geosimulation models. *JASSS*. https://doi.org/10.18564/jasss.4136
11. Reynolds, C. W. (1987). Flocks, herds, and schools. *Computers & Graphics*.

12. Thiele, J. C., Kurth, W., & Grimm, V. (2014). Facilitating parameter estimation and sensitivity analysis of agent-based models: A cookbook using NetLogo and R. *JASSS*. https://doi.org/10.18564/jasss.2503
13. Wilensky, U., & Rand, W. (2015). An Introduction to Agent-Based Modeling: Modeling Natural, Social, and Engineered Complex Systems with NetLogo. MIT Press.
14. Wilensky, U. (1999). NetLogo. http://ccl.northwestern.edu/netlogo/. Center for Connected Learning and Computer-Based Modeling, Northwestern University, Evanston, IL.
15. Wilensky, U. (1998). NetLogo Flocking model. http://ccl.northwestern.edu/netlogo/models/Flocking. Center for Connected Learning and Computer-Based Modeling, Northwestern University, Evanston, IL.