Meta-ABS
Recursive Agent-Based Simulation

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Abstract

In this paper we ask what influence recursive simulations has on the dynamics of an Agent-Based Simulation. We investigate the famous Schelling Segregation and endow our agents with the ability to project their actions into the future by recursively running simulations. Based on the outcome of the recursions they are then able to determine whether their move increases their utility in the future or not.
We investigate the dynamics when using recursive simulations and compare it to the dynamics of the original model and our optimizing movement-strategy where agents are not projecting into the future. We hypothesize that in the case of a deterministic future this approach allows the agents to increase their utility as a group but we hypothesize that this is not the case when the future is non-deterministic as the power to predict is simply lost in this case. Further we hypothesize that a deterministic future endogenously turns into a non-deterministic one if the fraction of anticipating agents reaches a given threshold, rendering the predictive power in effect useless. This implies that MetaABS is only useful for optimization if not the whole system is trying to anticipate. We put strong emphasis on the point that MetaABS is *not* another optimization technique but that this research was investigated to raise and address interesting philosophical questions and implications: determinism, computational complexity, simulation argument,... TODO
The main contribution of this paper is the introduction of recursive agent-based simulation, a completely new method in ABS, which we termed MetaABS.

1 Introduction

The 'meaning' of MetaABS is not really clear: how can it be interpreted? It is not so much about the dynamics but more on the philosophical questions it raises.
But also we wanted to check if the same happens as in the recursive simulation paper [1]: deterministic vs. non-deterministic AND one-agent recursion or all-agents recursion
We implemented our Meta-ABS in Haskell using the functional reactive programming paradigm following the Yampa library. We believe that pure functional programming is especially suited to implement Meta-ABS due to its lack of implicit side-effects and copying of data. [1]

2 Background

2.1 Schelling Segregation

We follow in our implementation the original paper of Schelling as in [3] where we focus on the *Area Distribution* section (Schelling starts with movement in a linear, 1-dimensional world where agents are able to move to the nearest point which meets the agents satisfaction but this is not what we follow here). One assumes a discrete 2-dimensional lattice-world with NxM fields. Each field is either occupied by an agent of a given color (e.g. Red or Green) or is

[1] Code available under `https://github.com/thalerjonathan/phd/tree/master/coding/papers/metaABS`

free. Each field has 8 neighbours, which denotes a Moore-Neighbourhood. In Schellings original work the lattice-world is limited at its borders but we assume a torus world which is wrapped around in both the x- and y-dimensions resulting in 8 neighbours also for fields at the border. The occupation density was set by Schelling to be about 70%-75% which he identifies as being a setting which allows the agents to move around freely without making the lattice-world too sparse. Now the agents make their move sequentially one after another. In each move an agent calculates the number of neighbours which are of equal color. If the number satisfies the agents needs about the neighbourhood then the agent is regarded as being 'happy' and will stay on this field. On the other hand the agent moves to the nearest unoccupied field which within its neighbourhood satisfies its needs. Schelling assumed the 3x3 square around the agent to be its neighbourhood, we generalize this in the following way. An agent which moves selects an unoccupied place randomly relative from its current place within a rectangle of side-length 2r where its current place is at the center.

2.1.1 Optimizing behaviour

TODO: define utility

The original schelling model didn't have a move-optimizing behaviour, meaning agents are just binary: if it is happy it will not move, if it is unhappy it will move but they won't care where they move. We introduce local move-optimizing behaviours which can be interpreted as being realistic in the real-world. It is important to note that we focus on *local* instead of *global* move-optimization: the agents are limited in their reasoning-capabilities and have limited information available: they cannot check out *every* place and pick the globally best one.

2.1.2 Anticipating behaviour

Schelling explicitly mentions in [3] that nobody anticipates moves of others. This is what we introduce using the recursive simulation.

TODO: is this optimizing behaviour in the spirit of schellings original work?

Optimizing future Agents pick an unoccupied random place and move to it if it increases their utility in the future. The interpretation for that behaviour is: agents heard about a place which will be cool in the future.

Optimizing present & future Agents pick an unoccupied random place and move to it if it increases their utility in the now and in the future. The interpretation for that behaviour is: agents heard about a cool spot in town, check it out and move to it if they like it but they also anticipate the coolness of the place in the future and if it seems that the place is going down then they won't move there.

2.2 Related Research

TODO: [2] mention kirman complex economics where he investigates the model more in depth

3 Meta ABS

Informally, Meta-ABS can be understood as giving the agents the ability to project the outcome of their actions into the future. They are able to halt time and 'play through' an arbitrary number of actions, compare their outcome and then to resume time and continue with a specifically chosen action e.g. the best performing or the one in which they haven't died.

3.1 Formal description

explain the level two levels of recursion

when an agent is running a recursion, then we need to restrict the other agents otherwise we will end up in an infinite regress.

we are spanning up 3 dimensions: recursion-depth, replications, and time-steps

3.2 Deterministic vs. Non-Deterministic future

The model as described in Background section is completely deterministic once it is running because it makes no use of a random-number generator and there are no other sources of non-determinism - the next move of an agent is always completely predictable. If we introduce randomness through a random-number generator into our model then the future becomes non-deterministic *if the state of random-number generator when running recursive simulations is different from when the simulation is run non-recursively.*

3.3 Computational complexity

the computation power grows exponentially with the number of recursion: give a formula depending on number of agents, recursion depth, independent moves of an agent and number of time-steps problem: need to escape infinite regress by preventing simulated 'other' agents to simulate themselves: what would be the outcome in a zeno machine/accelerated turing machine?

3.4 Philosophical implications

3.4.1 Omega Point

tiplers omega point and paper about god and the simulation argument accelerating turing machine: finishes after 1 time steps

3.4.2 Emergent Non-Determinism

the prediction may work for a single agent but what if more and more agents predict their future? within the prediction no recursion is run so no 2nd level anticipation. hypothesis: increasing the ratio of predicting agents will decrease the effectiveness of the predictions because the future becomes then in effect non-deterministic =¿ non-determinism as emerging property? is there a limit e.g. up until which ratio does the average utility of the predicting agents increase?

the agent who is initiating the recursion can be seen as 'knowing' that it is running inside a simulation, but the other agents are not able to distinguish between them running on the base level of the simulation or on a recursive level

3.4.3 Perfect Information

The main problem of our approach is that, depending on ones view-point, it is violating the principles of locality of information and limit of computing power. To recursively run the simulation the agent which initiates the recursion is feeding in all the states of the other agents and calculates the outcome of potentially multiple of its own steps, each potentially multiple recursion-layers deep and each recursion-layer multiple time-steps long. Both requires that each agent has perfect information about the complete simulation *and* can compute these 3-dimensional recursions, which scale exponentially. In the social sciences where agents are often designed to have only very local information and perform low-cost computations it is very difficult or impossible to motivate the usage of recursive simulations - it simply does not match the assumptions of the real world, the social sciences want to model. In general simulations, with no direct link to the real world, where it is much more commonly accepted to assume perfect information and potentially infinite amount of computing power this approach is easily motivated by a constructive argument: it is possible to build, thus we build it. What we are ultimately interested in is the influence on the dynamics. Note that we identified the future-optimization technique as being locally. This is still the case despite of using global information for recurring the simulation - the reason for this is that we are talking about two different contexts here.

4 Results

In this section we report and discuss the results of our experiments with Meta-ABS. In Table 1 we give the configuration of the model which is the same for all experiments. For the future move-optimization additional parameters are set, which are mentioned

Table 1: Model Configuration

Dimensions	50 x 50
World-type	Torus
Density	0.75
Similarity required	0.8
Agent-distribution	50% Red, 50% Green
Local-movement distance	5
Find-free-place retries	4

in the respective section.
What we are interested in are the following dynamics

1. Global happiness (Yes / No) over time
2. Global similarity over time
3. Global change of similarity between steps

4.1 Non-optimizing

Agents move to the nearest free spot
Hypothesis: very slow convergence, can't solve high density with high similarity requirements.

4.2 Optimizing

Agents move to the nearest free spot which satisfies their requirements
Hypothesis: should have much faster convergence than non-optimizing, areas act as attractors

4.3 Anticipating

TODO: how many agents are predicting? fraction between 0.0 and 1.0 TODO: compare the performance of the predicting-agents to the non-predicting ones
Prediction-Ratio hypothesis: increasing the ratio of predicting agents will decrease the effectiveness of the predictions because the future becomes then in effect non-deterministic
Deterministic future: Hypothesis without present optimizing: same as Optimizing Hypothesis with present optimizing: fastest convergence of all
Non-Deterministic future: Hypothesis without present optimizing: complete breakdown, falling back to dynamics of non-optimization Hypothesis with present optimizing: same as present-only optimization

5 Conclusion and further research

So far we only looked at recursive simulation in a simulation with a strictly sequential update-strategy where agents are updated in sequence after each other as defined in TODO: cite my Art-Of-Iteration Paper. We leave the question of how Meta-ABS would apply to the parallel update-strategy and whether it is reasonable to extend it to that strategy or not for further research.

References

[1] Gilmer, Jr., J. B., and Sullivan, F. J. Recursive Simulation to Aid Models of Decision Making. In *Proceedings of the 32Nd Conference on Winter Simulation* (San Diego, CA, USA, 2000), WSC '00, Society for Computer Simulation International, pp. 958–963.

[2] Kirman, A. *Complex Economics: Individual and Collective Rationality.* Routledge, London ; New York, NY, July 2010.

[3] Schelling, T. Dynamic models of segregation. *Journal of Mathematical Sociology 1* (1971).