DeMo: a simple generic model for making decisions influenced by friends

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Abstract

Decisions are rarely made in solitude. Here we present a very simple model that balances the inner drive towards an individual optimum with the influence of the neighbors in a social network. As a third element the model incorporates inertia towards change. The model generates structure from an unstructured initial state by clustering individuals through their social interaction. This clustering is associated with a cognitive dissonance that arises when individuals' states differ from their own optimum due to the influence of their neighbors. We find this cognitive dissonance to

I. INTRODUCTION

A. Social dynamics literature

- pioneering work on the modelling of social behaviour was conducted by e.g. Sakoda [1], Schelling [2] and Granovetter [3]
- one of the first models on opinion formation was proposed by De Groot [4], studying the convergence to consensus in a group of individuals
- we refer to reviews on the benefits of agent-based modelling [5] and for a general summary of the developments in social dynamics modelling [6, 7]
- In the last years, several specialized models where used to show specific aspects of social dynamics. Research topics include coalition formation on networks and network evolution [8, 9], social tipping [10], bounded confidence opinion dynamics extended by a measure of cognitive dissonance [11]
- applied work focused on social dynamics of the COVID-19 pandemic [12, 13] and begins to evolve to include a coupled modelling of social and natural systems with respect to the Climate Crisis [14]
- A recent example of theoretical work on polarization and segregation of opinions [15] shows the challenge and interest to model observed opinion dynamics of the real world in a minimalist approach.
- Our model takes into account the competition between two of the most fundamental human social desires: Belonging to a group and sticking out of the crowd.

– Brewer's optimal distinctiveness theory (ODT) [16] posits the need to balance assimilation and distinction from others.

– Deci's and Ryans's self determination theory [17] also differentiates between individual and collective needs, labelled as "autonomy" and "relatedness"

– more references in chapter 28, pp. 395-410 [18], empirical study on ODT e.g. [19],

– some studies on social distinctiveness theory already used agent-based modelling, e.g. [20] and called for more agent-based research into socio-psychological effects [21]

Our model integrates the strive to be individual and integrated into a collective at the same time in an opinion dynamic simulation, thus bridging the gap between theories of self-expression and models of opinion formation. In the following we present our generic **De**cision **Mo**del. with social dynamics based on as simple as possible assumptions.

II. MODEL SETUP, DESCRIPTION AND ANALYSIS

A. Model setup

This agent-based approach models the decision dynamics on a grid as a competition between personal belief, social influence and a personal need for independence. The model setup and dynamics are visualized in fig. 1

G agents are placed on a regular, periodic grid. Each agent i has two time-invariant attributes: An *avantgarde factor* a_i and a *belief* b_i. The avantgarde factor $a_i \in [0,1]$ expresses the agent's need for individualism with $a_i = 1$ corresponding to independent decisions ("pioneer") and $a_i = 0$ for decisions strongly adapted to the social surroundings ("follower"). The belief $b_i \in [0,1]$ expresses the agent's intrinsic, personal opinion on the matter to be decided. For each agent i both a_i and b_i are drawn from independent random distributions. This can easily be adapted to reflect individualist behaviour and beliefs in the context of a particular application.

Each agent i in the grid interacts with a set of neighbors $N_{i,R}$ where R is the radius of the neighborhood. All agents j with Chebyshev Distance $\leq R$ to agent i are part of $N_{i,R}$.

In our basic model we set $R = 1$ resulting in $|N_{i,1}| = 8$ on a grid with periodic boundary conditions. Each agent i is influenced by all agents j in their neighborhood. The strength of the influence of j on i is determined by the weight $w_{j,i}$. In the basic model, we set $w_{j,i} = \frac{1}{|N_{i,R}|}\ \forall\ i, j$. This is again adaptable to contextually model different influences.

B. Model dynamics

At each timestep t, each agent adjusts a continuous *choice* parameter $c_i \in [0, 1]$ based on the following equation:

$$\frac{\Delta c_i}{\Delta t} = \lambda\left((1 - a_i)W_i + a_i\left(b_i - c_i\right)|W_i|\right) \tag{1}$$

At timestep $t = 0$, for each agent i, c_i is drawn from independent random distributions . W_i describes the overall influence of the neighborhood $N_{R,i}$ and is defined as

$$W_i = \sum_{j \in N_{R,i}} w_{j,i}(c_j - c_i) \tag{2}$$

$$\text{with} \sum_{j \in N_{R,i}} w_{j,i} \equiv 1 \text{ and } w_{j,i} \in [0, 1] \quad \forall j \in N_{R,i} \tag{3}$$

Since $(c_j - c_i) \in [-1, 1]$, it follows that W_i is also bounded:

$$W_i \in [-1, 1] \quad \forall i \in \{1, \ldots, G\} \tag{4}$$

The model equilibrium is given by... DAMIAN ADD ADAPTED EQUILIBRIUM EQUATIONS AND SOME EXPLANATION ON THEM.

simple implications / equilibrium:

$$\begin{aligned} &\Delta o_i \ll 1 \\ &c_i - o_i = \frac{a_i - 1}{a_i}\frac{W_i}{|W_i|} + \frac{\Delta o_i}{a_i|W_i|} \end{aligned} \tag{5}$$

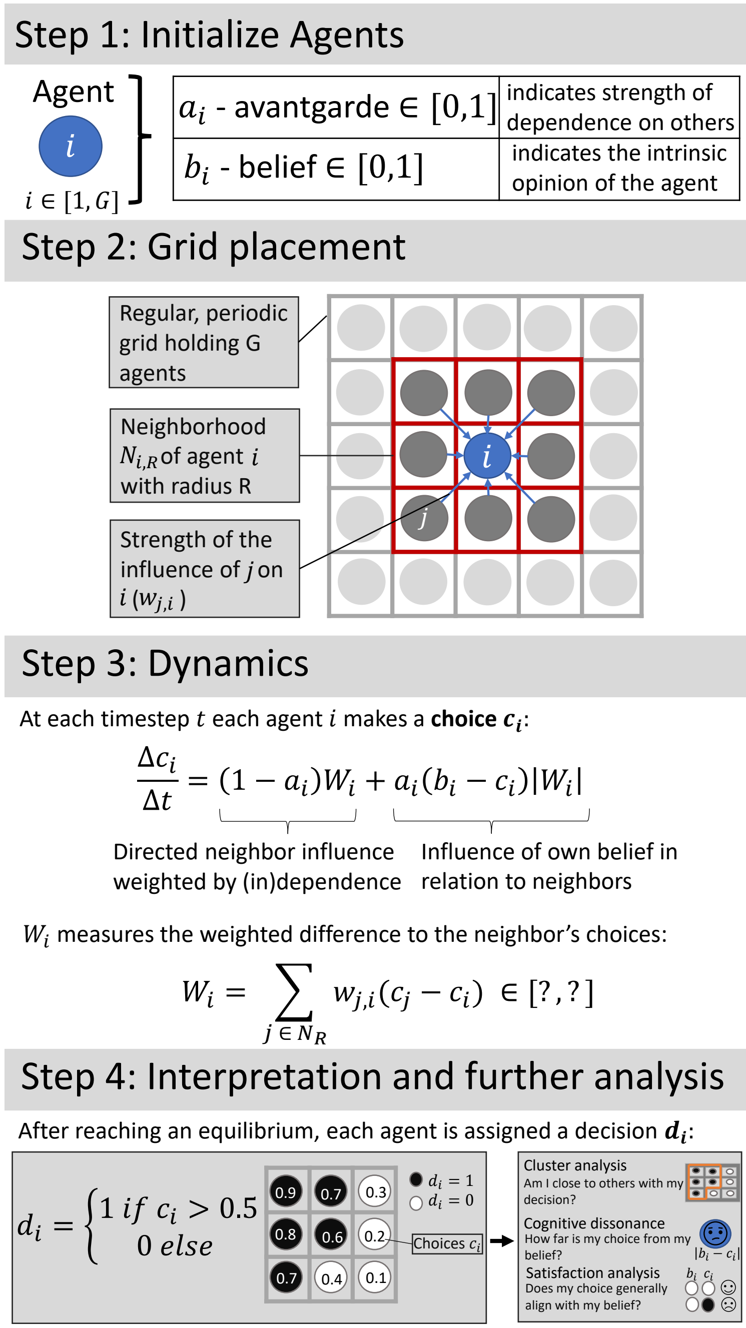

FIG. 1. **Model setup and dynamics.** Agents are initialized with an avantgarde factor a_i, expression individualism, and a personal belief b_i. They are placed on a regular periodic grid and assigned neighborhoods based on a Chebyshev distance. At each timestep, agents make a choice with the dynamics factoring in the need for individualism, the influence of the neighborhood and the striving towards the personal belief. Once the equilibrium is reached, each agent is assigned a final decision and the final parameters are then processed in downstream analysis.

$$|c_i - o_i||W_i| = \left|W_i + a_i^{-1}\left(\Delta o_i - W_i\right)\right| \tag{6}$$

$$|W| \leq \frac{\epsilon}{|(1-a)\mathrm{sign}(W) + a|} \tag{7}$$

Once the model has reached it's equilibrium, each agent is assigned a final decision d_i based on their final choice c_i:

$$d_i = \begin{cases} 1, & \text{if } c_i > 0.5 \\ 0, & \text{else} \end{cases} \tag{8}$$

Based on the final decision and choice we then conduct downstream analysis.

C. Model analysis

We conduct analysis on the individual agents level as well as summarizing clustering analysis based on these.

For individual analysis we consider: First, the *cognitive dissonance* CD_i of agent i, i.e. the distance between belief b_i and choice c_i.

$$\mathrm{CD}_i := |b_i - c_i| \tag{9}$$

This metric summarizes the effects of the neighbourhood on agent i, since deviations from the belief are driven by the choices of neighbours modulated by an agents avantgarde a_i

Second, we define an agents i *satisfaction* S_i as a binary measure based on belief b_i and final decision d_i:

Since beliefs are constant, we define the *endogenous decision* $\tilde{d}_i$ of agent i as

$$\tilde{d}_i := \begin{cases} 1, & \text{if } b_i > 0.5 \\ 0, & \text{else.} \end{cases} \tag{10}$$

If the endogenous decision concurs with the decision finally taken, an agent is satisfied. Vice-versa, if belief and final decision are opposed, an agent is not satisfied:

$$S_i = \begin{cases} 1, & \text{if } d_i = \tilde{d}_i \\ 0, & \text{otherwise.} \end{cases} \tag{11}$$

Thus the satisfaction measures the distortion of the final decision compared to an agents inherent decision.

We define *neighbourhood uniformity* $U_{N_{i,r}}$ for agent i with respect to a neighbourhood N with extent r as

$$U_{N_{i,r}} := \frac{\sum_{j \in N_r} \mathbf{1}\left(\tilde{d}_i = \tilde{d}_j\right) - \sum_{j \in N_r} \mathbf{1}\left(\tilde{d}_i \neq \tilde{d}_j\right)}{|N_r|}. \quad (12)$$

Thus positive uniformity indicates an majority of neighbours with the same decision, while negative uniformity indicates that the majority of the neighbouring agents has contradicting beliefs.

For population level analysis, we consider summary statistics of CD_j and S_j for (sub)groups of the G agents, i.e. for $j \in g \subseteq \{1, \ldots, G\}$.

D. ideas for further analysis

We conduct cluster analysis ...

- connectivity of same decision clusters
- (K-means) clustering by decisions
- similarity of choice in a cluster?! (just an idea, not sure how to measure and if interesting)
- are there clusters of high / low CD resp. satisfatction?

III. RESULTS

Simulation ensemble We run 100 simulations on a 100x100 lattice. Random initialisation draws the avantgarde factor, belief and the initial choice parameter from an uniform distribution $\mathcal{U}([0,1])$ The time-scaling factor is chosen as $\lambda^{-1} = 10$).

We analyze the state after 200 simulation steps, since the model reaches a semi-stable state of small changes of choice parameter. (fig. S2)

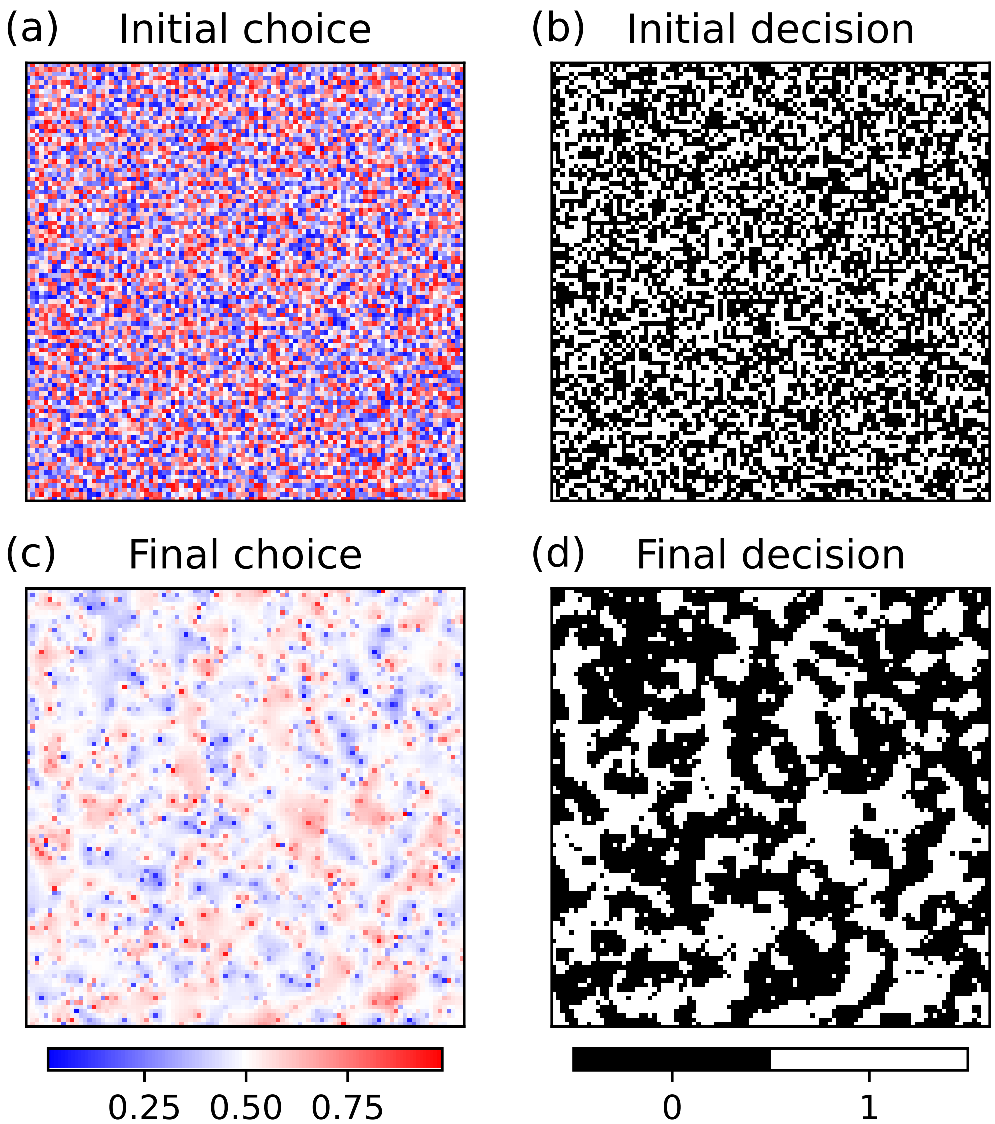

FIG. 2. **Polarization of decisions emerging from random initial configurations.** Sample realization from a single simulation. **(a,b)** show uniform distributed initial choice and the initial decisions. **(c)** shows emergence of clustered choice parameter in the final state. The resulting decisions in **(d)** thus show the emerging polarization of final decisions.

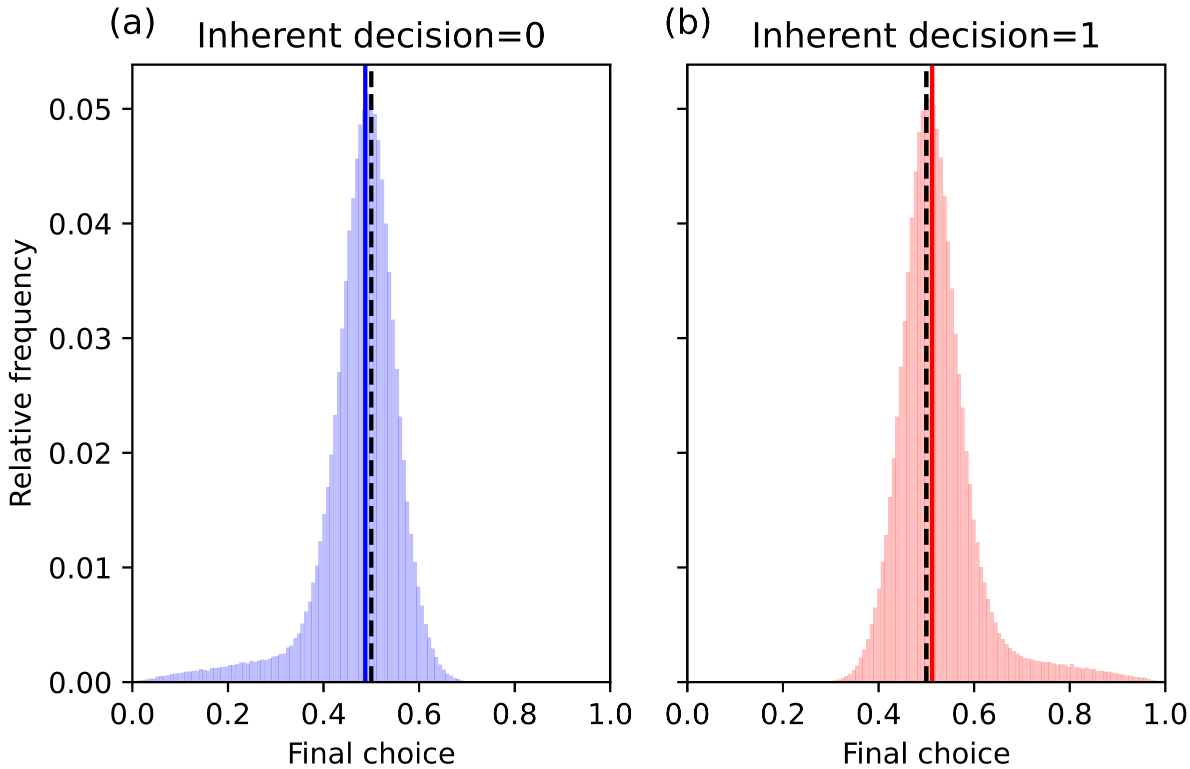

FIG. 3. **Accumulation of agents with choice parameter around 0.5.** A majority of agents (approx. 58%) make a final choice according to there inherent belief.

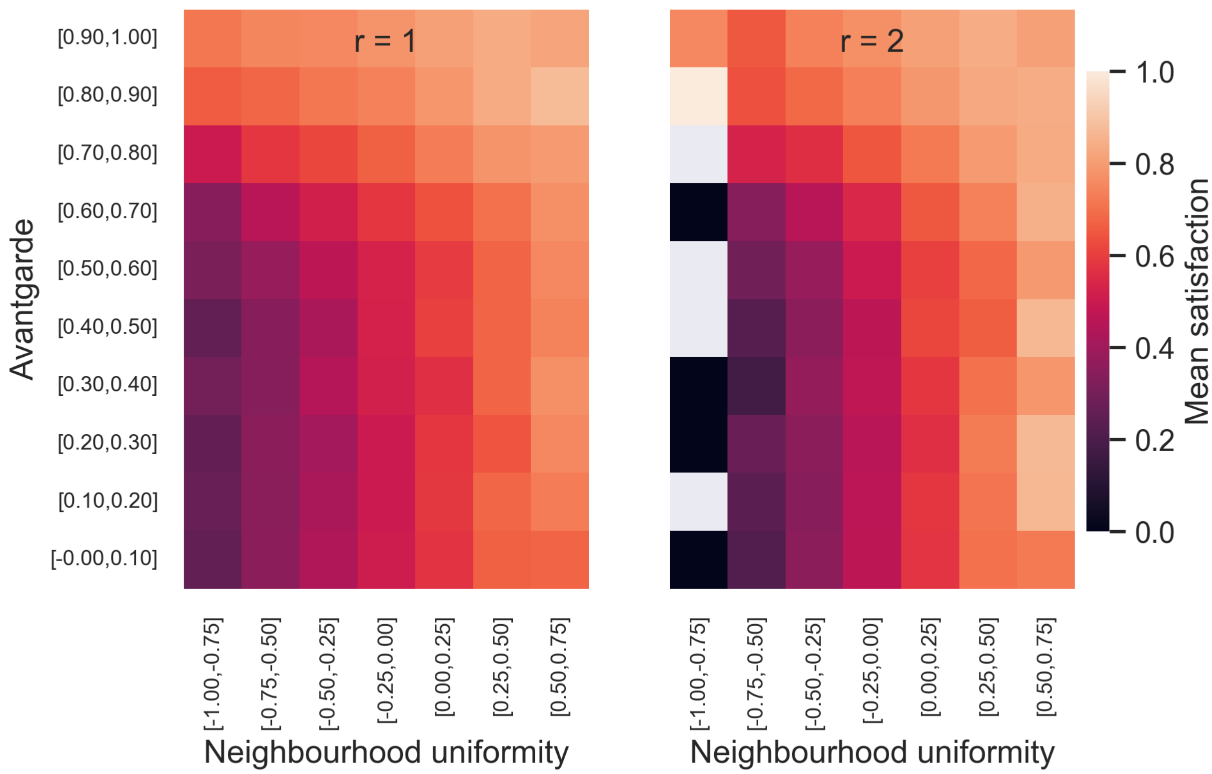

FIG. 4. **Uniformity of neighbourhood leads to higher satisfaction. High avantgarde agents are faster satisfied regardless of their neighbourhood. (a)** shows results for neighbourhood radius $r = 1$, **(b)** for $r = 2$. Satisfaction is averaged over neighbourhood uniformity bins.

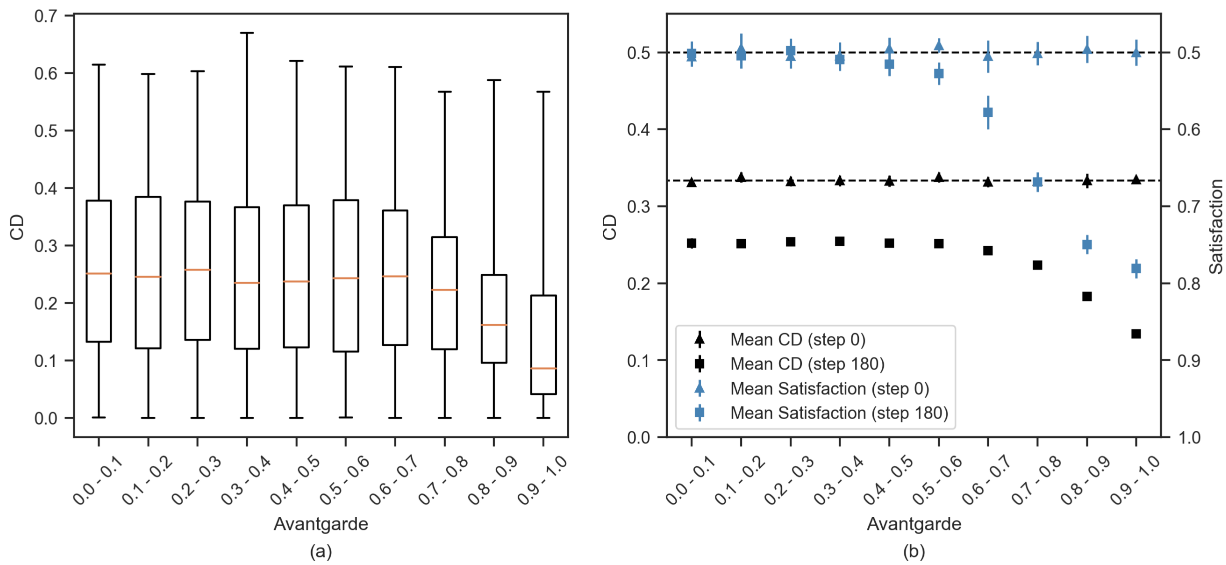

FIG. 5. **Cognitive Dissonance (CD) of agents declines for high avantgarde factors.** For avantgarde factors $a_i \leq 0.6$ we found the average CD to be approximately constant. **(a)** shows the full span of the CD distributions per avantgarde interval including the 25% and 75% ranges. **(b)** shows the mean CD (black) and satisfaction (blue) for the initial and final states and the respective expected value (dashed) for the initial configurations. While the average CD declines with increasing avantgarde factors the average satisfaction lags behind and only changes substantially for $a \gtrapprox 0.5$.

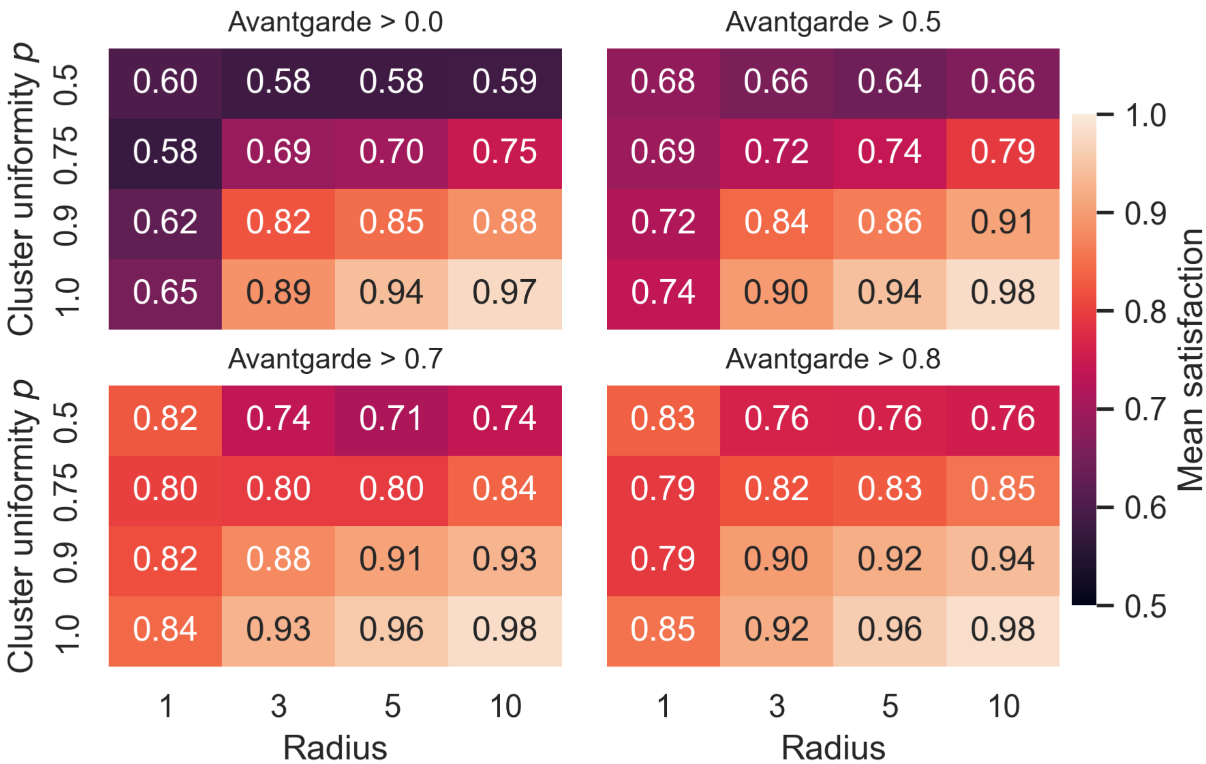

FIG. 6. **Large clusters with uniform conviction lead to higher satisfaction.** Multiple simulations on a 100x100 lattice with isolated positive (negative) conviction clusters of different size and density were used to calculate the respective average satisfaction inside the clusters. Only agents inside the cluster with an avantgarde $a > x$ ($x < 1.0$) were used. For initializing a positive cluster a position was chosen to be the cluster center and p percent of all neighbours within radius r have been assigned a random (uniform distribution) conviction $c > 0.5$ (< 0.5 for the others). All agents outside of the cluster have a conviction $0 < c < 1.0$ (uniform distribution).

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Appendix A: Supplementary information

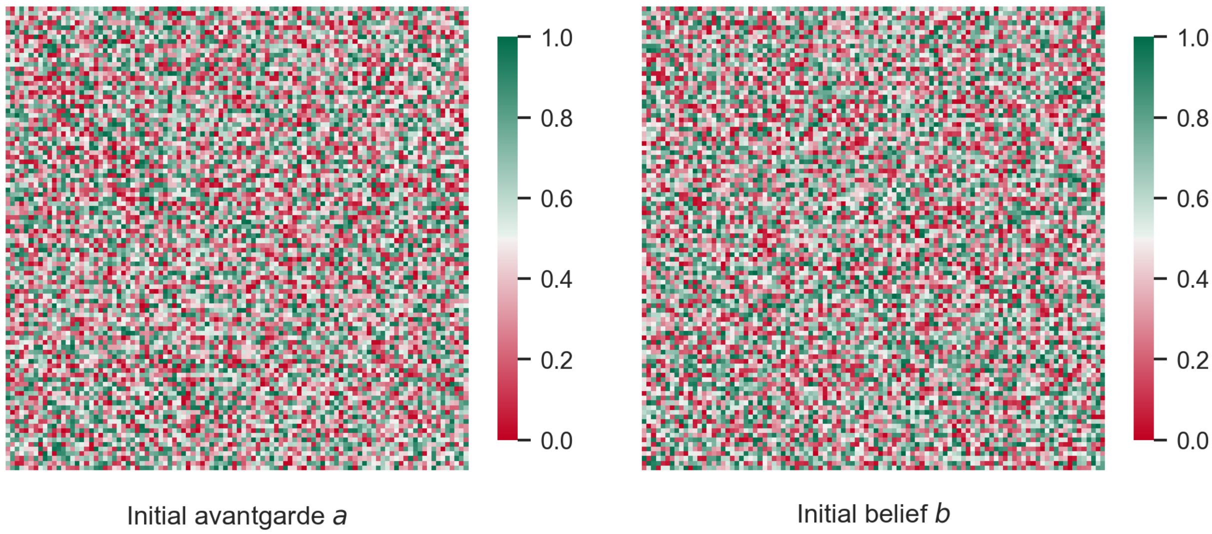

FIG. S1. Initial avantgarde factors and conviction sampled from uniform distributions.

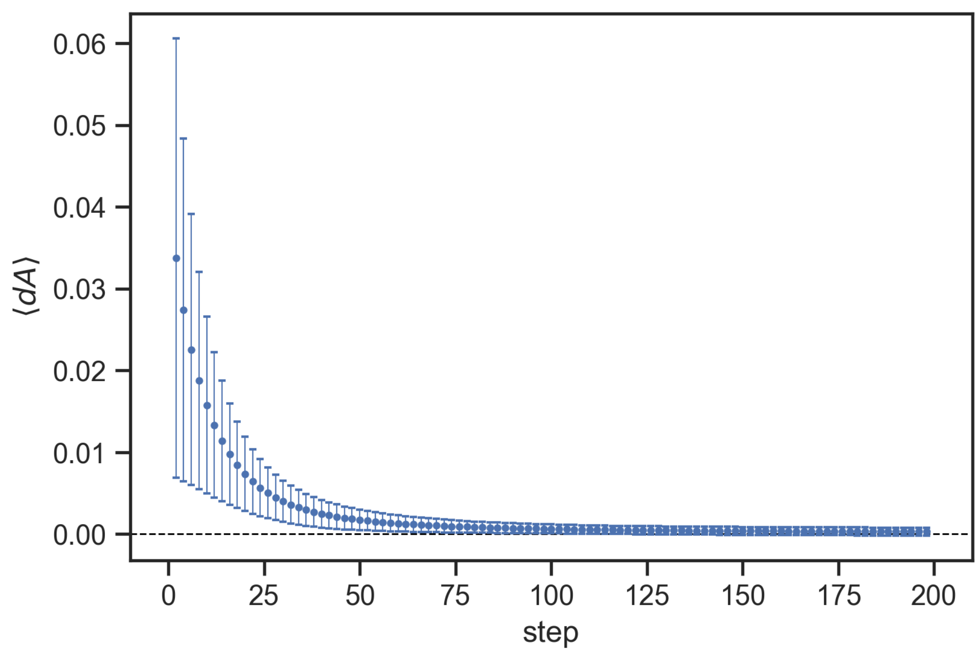

FIG. S2. Convergence of model dynamics. The average change in choice parameters between subsequent model steps declines exponentially indicating the convergenced into a equilibrium state. Here, for better resolution, only every second model step was considered.