Model of anti-conformist intention based on perception biases. ODD protocol

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The model was developed in R and libraries such as Hmisc, Hexbin, and PerformanceAnalytics have been used for data analysis and data visualization. The model is described based on ODD protocol which is a standard protocol for documenting agent-based models [1]. The document contains three main sections including overview, design concepts, and details which are explained in the rest of this document.

1 Overview

1.1 Purpose

The main purpose of the model is to investigate how anti-conformist intentions could be related to some biases on the perception of attitudes. It starts from two case studies, related to the adoption of organic farming, that show anti-conformist intentions. The observation from case studies show the negative correlation between the intention and the perceived group norm for respondents with high attitudes (anti-conformism behavior), while there is positive correlation between intention and the perceived group norm for respondents with low attitudes. It proposes an agent-based model which computes an intention based on the Theory of Reasoned Action and assumes some biases in the perception of others' attitudes according to the Social Judgement Theory[2]. It investigates the conditions on the model parameter values for which the simulations reproduce the features observed in the case studies.

1.2 Entities, State Variables and Scales

There is only one key agent in the model called farmer agent. This agent is the representation of farmers who have not converted to organic farming but intend to, or people who tend to be organic farmers in future. The agent has state variables including attitude (att), perceived attitude of others (patt), the network of agents (Net), subjective norm network (snNet), perceived group norm network (pgnNet), , subjective norm (sn), perceived group norm (pgn), and intention to convert to organic farming (int). The table 1 explains each variable and values they take in the simulation:

Each agent at the beginning selects a random at size N = 35 (in our simulation) randomly which includes also the network of subjective norm (N=5). The rest of computing are based on these two networks which are explained in details section.

We Approximate Bayesian Computing (ABC) in order to determine parameter settings for which the model shows the features found in the cases-studies: conformist intention for low attitudes and anti-conformist intention for high attitudes.

1.3 Process Overview and Scheduling

The agent decision-making process is simple in this model since the idea is to investigate the anti-conformism behavior of agents. At the beginning n number of agents are created (n=1000), and n attitude are generated based on Gaussian distribution and each agent takes one attitude. The following steps show the agent-decision process:

- Agent selects its own network randomly (Net).
- Agent compute the perceived attitude of other agents based on social judgment theory.
- Agent selects its own subjective norm network or in other word important others network based on the probability which the closer agents (closer perceived attitude) get higher chance to be selected (snN).
- Agent computes the perceived group norm and subjective norm considering the agents in its associated network.
- Agent computes the intention to convert to organic farming based on Theory of Reasoned Action (TRA).

Name	Meaning	range	Computation
a_i	Agent i takes one attitude at the beginning of simulation	[-1, 1]	The attitudes of all agents are created by Gaussian distribution
$p^i(a_j)$	perceived attitude of agent j by agent i	[-1, 1]	The social judgment theory is used to compute how agent perceive others attitudes. The attitude of the agent plays the key role on how to perceive others.
R_g^i	Agent i selects its own all acquaintances network	35 (30+5)	This general network is selected randomly for each agent
R_c^i	Agent i creates its own close agents (subjective norm network)	5	The agents whom their attitudes are closer to agent's attitude have more chance to be in selected as subjective network of the agent. This network of agents are selected from total network of agent (Net)
N_c^i	The value of subjective norm computed by agent i	[-1, 1]	The average of attitudes of agents in the subjective norm network
N_g^i	The value of perceived group norm network computed by agent i	[-1, 1]	The average of attitudes of agents in the perceived group norm network
I_i	The intention of agent i toward organic farming	[-1, 1]	Theory of Reasoned Action is used to compute the intention as the average of attitude and subjective norm

Table 1. State variables

2 Design Concepts

Basic Principles: The basic principles of this model rely on social judgment theory that drives the model of perception biases, and Theory of Reasoned Action that drives the model of intention [3].
Emergence: Anti-conformist intention is a phenomenon which emerges at macro level for agents with high attitudes. It is characterised by a negative correlation between intention and perceived group norm (PGN). However, for agents with a low attitude the intention os positively correlated with the PGN.
Stochasticity: Selecting the first large network by each agent is totally random. The subjective norm network is randomly chosen with high probability for agents with similar attitudes and this probability decreases by difference between attitude of given agent and attitude of other agents. Therefore, the results of each run are different from one to another.
Interaction: No direct interaction is included in the model, however, agents has her own perception of others' attitude, which can have an impact on her intention.
Observation: Attitudes, social norms, perceived group norms, and also regression of intention by perceived group norm for low and high attitude are stored in a csv file for further analysis.

3 Details

3.1 Initialization and Input Parameters

Besides state variables that are explained before, there are parameters that are used as input to the model. Table 2 shows the model parameters ad the values they take in simulation.

3.2 Submodels

Agent Model

The model includes n virtual agents and each agent i is then characterised by an attitude a_i. In practice, we draw the attitudes a_i at random from a Gaussian distribution of mean $0 < \delta < 0.5$ and of standard deviation σ. The scale of attitudes is continuous on the segment $[-1, 1]$ (attitude -1 being very against while 1 is much in favour of the issue). Only the values drawn from the Gaussian distribution that fall within the segment of attitudes $[-1, 1]$ are kept. Therefore, the average attitude $\bar{a}$ of the population is generally a bit different from δ.

The attitude a_j of agent j perceived by agent i is denoted by $p^i(a_j)$ and it is ruled by threshold τ_i, as follows:

Symbol	Definition	Range
n	Size of the population	1000
δ	Mean of attitude distribution	[0, 0.75]
σ	Standard deviation of attitude distribution	[0.2, 0.6]
α	Coefficient ruling probability to be in close other set R_c^i	[0, 6]
β	Slope of the perception threshold function τ_i	[0, 1]
τ_M	Maximum perception threshold (for attitude equal 0)	[1, 2]
ρ	Coefficient ruling the difference between attitude and perceived attitude	[0, 1]

Table 2. Break-down of model parameters.

- If the difference between a_i and a_j is lower than τ_i then the perception $p^i(a_j)$ of a_j by agent i is closer to a_i than a_j is;
- If the difference between a_i and a_j is on the contrary greater than τ_i, then the perception $p^i(a_j)$ of a_j by agent i is further from a_i than a_j is;

The threshold τ_i depends on the extremity of attitude a_i. It is assumed to increase linearly for a_i between -1 and 0 and to decrease linearly for a_i between 0 and 1. More precisely (β and τ_M being parameters of the model), we have:

$$\begin{cases} \tau_i = \tau_M(1 + \beta a_i), \text{ if } a_i < 0; \\ \tau_i = \tau_M(1 - \beta a_i), \text{ if } a_i \geq 0. \end{cases} \tag{1}$$

Then, $p^i(a_j)$, the attitude of j perceived by i, is given by (ρ being a parameter):

$$\begin{cases} p^i(a_j) = a_j + \rho(a_i - a_j) \text{ if } \tau_i > |a_i - a_j|, \\ p^i(a_j) = a_j - \rho(a_i - a_j) \text{ otherwise.} \end{cases} \tag{2}$$

To be compatible with the extreme ends of attitude's scale, $p^i(a_j)$ is blocked in the range [-1, 1].

Subjective norm, perceived group norm and intention

For each agent i we draw uniformly in the population a set R_g^i of agents that represents the acquaintances of agent i in the whole group and gives the agent an idea of the average attitude in the group which is the perceived group norm (PGN). The size s_g of this set is assumed the same for all the agents. The PGN N_g^i of agent i is modelled as the average of the attitudes in the set R_g^i as they are perceived by agent i:

$$N_g^i = \frac{1}{s_g} \sum_{j \in R_g^i} p^i(a_j). \tag{3}$$

A subset R_c^i of R_g^i that represents the important others (close to the considered agent) who are the base for the computation of the subjective norm (SN). We assume that the attitude of the important others is likely to be close to the one of the considered agent, especially if the issue at stake is important. Indeed, important others are likely to have a background which is similar to the one of the considered agent which increases the probability to be aligned on important issues. Therefore, the set R_c^i is built by drawing at random s_c agents j in the set R_g^i with a probability decreasing with the difference between a_i and a_j:

$$\mathbb{P}(j \in R_c^i) = \exp\left(-\alpha |a_i - a_j|^2\right); \tag{4}$$

The SN is finally computed as the average of the attitudes of important others (in set R_c^i) as perceived by agent i. It is denoted N_c^i:

$$N_c^i = \frac{1}{s_c} \sum_{j \in R_c^i} p^i(a_j). \tag{5}$$

The intention I^i of agent i to act (e.g. intention to convert to organic farming) is approximated from the TRA as the sum of the agent's attitude and SN:

$$I_i = \frac{1}{2}(a_i + N_c^i). \tag{6}$$

3.3 Parameter selection by Approximate Bayesian Computing (ABC)

Approximate Bayesian Computing [4,5,6,7] is a class of methods rooted in Bayesian statistics that is used to estimate the distribution of model parameter settings for which the model satisfies some criteria. Starting from a large number of parameter settings, each drawn uniformly in a chosen interval (prior distribution), we select the parameter settings for which the simulation shows the features identified in the case studies and this determines the approximation of the posterior distribution. Figure 1 represents the conceptual model of the system based on ABC. The figure describes the main steps of the process:

- 1) Generate $N = 25$ million parameter settings p using the Latine Hypercube Sampling (LHS) package in R
- 2) Run the model for parameter setting p.
- 3) Compute the regression coefficients $c_l(p)$ and $c_h(p)$ of the intentions as a function of the perceived group norm for respectively the low and the high attitudes, derived from the simulation run with parameter set p.
- 4) Compute the acceptance criteria:

$$c_l(p) > 0.2 \text{ and } c_h(p) < -0.2. \tag{7}$$

  These criteria ensure the conformist intention of agents with low attitude and anti-conformist intention for agents with high attitude.
- 5 and 6) If criteria 7 are satisfied, then parameter set p is accepted (stage 5), otherwise it is rejected (stage 6).

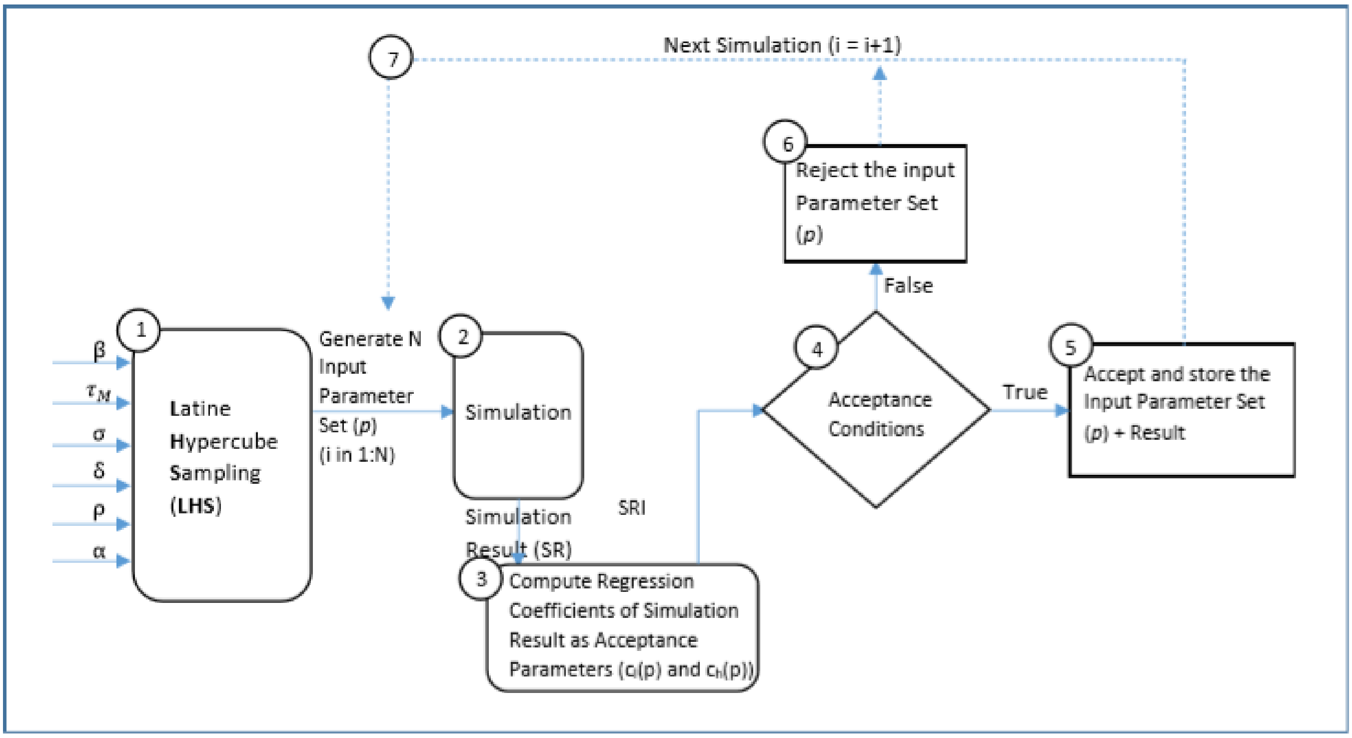

Fig. 1. Distribution of Attitudes of Eastern European farmers

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