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A spatially explicit agent-based model of opinion and reputation dynamics

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***Abstract*—Key in spatial planning are opinion dynamics (the exchange of opinions between agents and the consecutive updates in opinions by individual agents). A number of possibly relevant factors that are commonly excluded in well-known models of opinion dynamics are peer pressure, localized opinion formation through isolation, and the reputation of the agents involved. We present a model of agents with a fixed spatial location (e.g., a household) in a "village" who are capable of only local interactions with their neighbours. There exist nonlinear feedbacks between updates in opinion and reputation, which are described by smooth mathematical functions. Sensitivity analysis is used to quantify the contributions of different factors to the convergence of opinions within the "village".**

I. Introduction

Spatial planning is aimed at land use development that fulfills current and future societal needs. Traditionally spatial planning is considered to be a linear process in which selected actors have to obtain consensus about common goals. In practice, spatial planning is a non-linear, dynamic process involving many, heterogeneous stakeholders. Actors have diverse and changing goals and motivations, and influence each other via direct and indirect communication. Opinion dynamics - the exchange of opinions between social agents - thus play a crucial role in spatial planning [1].

Models of opinion dynamics are commonly based on physical diffusion principles which average neighbouring quantities [2], [3], [4], [1]. An 'if-then-else' condition is implemented to operationalize the concept of a 'social distance' between interacting agents, i.e., if two agents disagree too much then no opinion averaging is occurring. There are however a number of factors that may be relevant in spatial planning which may significantly influence opinion dynamics, such as:

- *Reputation*, i.e., 'higher' ranking agents will also more likely be more dominant in their interactions, resulting in biased opinion exchanges.
- *Peer pressure*, i.e., solitary agents with one opinion confronted with two or more agents that share a different opinion will also often change their opinion more than the group of agents.
- *Empathy*, i.e., the 'ease' with which an agent listens to others and is willing to accept their opinion.
- *Isolation and spatial effects*, i.e., in a spatial land-use context agents are often fixed at a spatial location (e.g., a farm or household) with a limited action radius. They are thus more likely to interact with neighbouring agents than with others agents (even in the current Internet era).

We present a spatially explicit agent-based model of a "village" of limited size consisting of agents with a fixed spatial position (e.g., a "household") and no outside contacts. Agents can only interact with their direct neighbours - opinion dynamics are thus localized. Agents have an initial opinion on a scale from 0 to 1 about an abstract subject. They also have a reputation, an opinion acceptance rate, and a reputation acceptance rate. It is furthermore probable that reputation dynamics - the change in ranking of agents - in turn depends on opinion dynamics. Agents who share opinions will often also hold each other in high regard, while agents who strongly disagree will often also dislike each other. Opinion dynamics and reputation dynamics thus are connected in feedback mechanisms. Finally, the update in opinion and reputation in time occurs according to functions that are based on social distance (difference in opinion) and difference in reputation in a smooth fashion (i.e., without 'if-then-else' constructs).

A. Model description

The whole model is implemented as a cellular automaton with field size $N_x \times N_y$ where each 'cell' represents an agent with a fixed location. There is 'diffusion' of the quantities 'opinion' $X^t_{x,y}$ and 'reputation' $Y^t_{x,y}$, both bounded between 0 and 1, where x and y indicate spatial location.

1) Main spatial equations: The field rules are

$$X^{t+1}_{x,y} = X^t_{x,y} + A_{x,y} \sum Y'^t_{x,y} \left(f(X'^t_{x,y} - X^t_{x,y}) \right) \ , \quad \text{(1a)}$$

$$Y^{t+1}_{x,y} = Y^t_{x,y} + B_{x,y} \sum X'^t_{x,y} \left(g(Y'^t_{x,y} - Y^t_{x,y}) \right) \ , \quad \text{(1b)}$$

where $'$ denotes the Von Neumann neighbours (i.e., the 4 neighbouring agents influence the agent simultaneously, while at the boundaries we use boundary conditions to close the field), and f and g are functions described below. The agent opinion adoption rate $A_{x,y}$ and the agent reputation acceptance $B_{x,y}$ are individual agent properties and hence have a spatial location that remain fixed in time. Unlike well-known opinion dynamics models agents undergo simultaneous and biased updating, i.e., some agents adapt their opinion (and reputation) more than others in an interaction. For notational convenience the explicit time and space dependence of variables and parameters are now droppped.

2) Opinion update function: The function f for agent opinion updating is given as

$$f(X' - X) = sgn(X' - X)\left(-(X' - X)^2 + 1\right)e^{-r(X'-X)^2}\ , \qquad (2)$$

where *sgn* (signum) conserves the sign of the difference in opinion (because of the square the sign would be otherwise lost). This function is evaluated separately for each neighbour before the agent opinion is updated. Maximum opinion exchange occurs in the limit $|X' - X| \rightarrow 0$ (i.e. two agents practically share an opinion, although no convergence will then occur anymore). If the opinions diverge maximally (namely 1 or -1) there is no exchange of opinion. The function is generic, i.e., only basic aspects of agent interactions are considered. Parameter r is a measure of social distance. For $r \rightarrow 0$ the function becomes a parabola (crossing the x-axis at 1 and -1), while for increasing r there is a decrease in social distance (see Fig. 1).

3) reputation update function: The reputation of an agent is updated according to function g, which is given as

$$g(Y' - Y) = (u(-(Y' - Y)^2 + 1)e^{-w(Y'-Y)^2}) - v\ , \qquad (3)$$

which is again a generic function, depicted in Fig. 2. The parameters u, v and w have arbitrary values. It is assumed that neighbours with similar reputation will 'flock together', while agents of dissimilar social status do not hold each other in high regard. As status in principle is unbounded it is required to re-scale variable S at every iteration to keep both status and opinion bounded between 0 and 1.

II. Model results

A. Model behaviour

An example of how opinions change dynamically is depicted in Fig. 3. Each agent is indicated by a distinct colour. The dynamics of reputation for the exact same simulation is given in Fig. 4. In this example after 1000 iterations there are still 3 distinct opinions. Although opinions still change after some time, reputation seems to converge to some steady state very fast. Interesting switches in reputation occur between agents who quickly come to a shared opinion with each other. For instance, the black, green, and pink agents quickly share an opinion. Interestly, while the black agent starts with having by far the lowest reputation of the three, he rises quickly to being the most dominant agent within the village! As the shared opinion of these three agents still changes after their opinion merger, it stands to reason that the black agent must be dominant in this opinion change. Further scrutiny reveals that black is in fact the agent in the middle of the village and has both a relatively high agent opinion change adoption rate A and agent reputation acceptance rate B, thus fulfilling a key role in the (local) opinion dynamics.

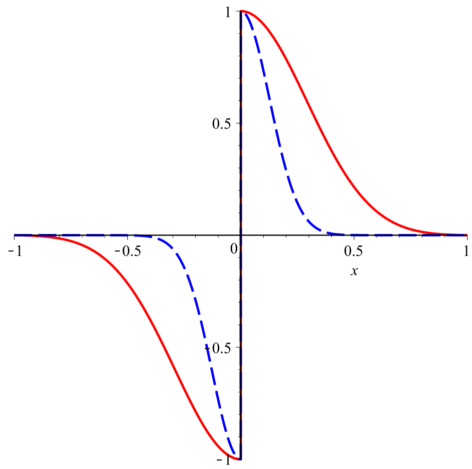

Fig. 1: Function f to translate the difference in opinion X between two agents to opinion convergence. The x-axis gives the difference in opinion between two agents. Note that the function is "squeezed" more as the value of r is larger, i.e., the social distance is smaller then. In solid red $r = 5$, in dashed blue $r = 30$.

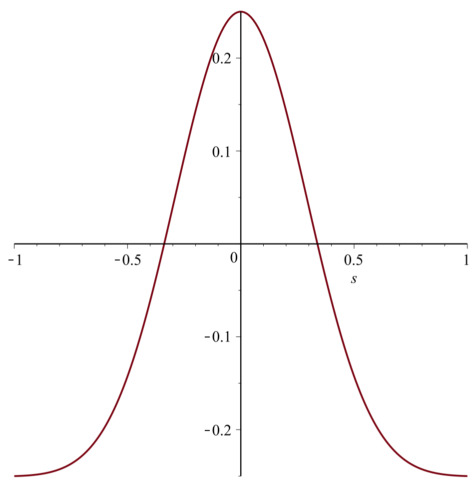

Fig. 2: Function g to translate the difference in reputation Y to reputation convergence or divergence. The x-axis gives the difference in reputation between two agents. When agents are 'equal' they tend to listen to each other - birds of a feather flock together - while very 'unequal' agents show strong disdain for each other.

B. Model analysis

A significant number of runs were extended far beyond 1000 iterations, and their results suggest that eventually under all conditions the system converges to one shared opinion in a small village. Indeed, although function f visually seems to be zero very quickly for large values of r, there is still an incremental convergence for any difference in opinion smaller than the maximum difference of 1. As the model is purely deterministic, given enough iterations opinions will eventually merge. It is therefore relevant to look at the influence that various factors have on the rate of convergence.

Sensitivity analysis [5] has been used to quantitatively analyze how model behaviour is affected by changes in different factors. The output of interest is n, the number of distinct opinions at time t divided by the total size of the village (i.e., this is a discrete output variable). Obviously, n has a minimal value of $(N_i \times N_j)^{-1}$, i.e., there is always one distinct opinion. Fig. 5 shows a one-at-a-time analysis of n within a small "village" of 3×3 after a 1000 iterations, in which r is the varied factor - all other parameters are fixed, as are the bounds on the initial distributions - for 25 runs per value of r. Depicted in red is the mean of these runs, open diamonds indicate the most common value, and blue crosses indicate the minimum and the maximum value from the sets of 25 runs.

There is a clear increase in the mean for increasing r, which is to be expected. There is a 'step-up' value where the minimum number of distinct opinions goes from one to two, i.e., the end-time of 1000 iterations is not sufficient even for such a small village to converge to one opinion. Also, the number of distinct opinions clearly increases for increasing r. However, no strong nonlinearities or tipping points seem to occur within the considered parameter range.

We also consider global sensitivities by performing a variance-based sensitivity analysis [5], [6]. The assumed distributions for initial conditions are uniform $\mathcal{U}(m \mp d)$, where m is the average value and d the variance around this average value. For $X[0]$ and $Y[0]$ draws were made from $\mathcal{U}(0, 1)$, while for A and B draws were a bit arbitrary from $\mathcal{U}(0, 2)$. The factors varied in the sensitivity analysis are social distance r, and $d_{X[0],Y[0],A,B}$ (i.e., respectively variance in the opinions $X[0]$, reputation $Y[0]$, opinion adoption rates A, and acceptance rates B). Sampling has been done from a hyperdimensional 'chessboard', i.e., parameters are taken from a limited set of combinations from p with equi-distant steps. For each set of fixed values 10 simulations have been run.

The global variance-based sensitivity is given as

$$S_p = \frac{E(Var(n|p))}{Var(n)} \ , \tag{4}$$

where p is the input under consideration, E is the expected value, and the other parameters are considered to be 'unknown'. Marginals can be ignored as only uniform distributions have been used. Observe that the time point is fixed in this analysis, i.e., one has to do the same type of analysis for each different selected time point. The results of the global variance-based sensitivity analysis are given in Fig. 6, in which the sensitivity of n is given in time. Not surprisingly, the sensitivity of n to the initial distribution of opinions $X[0]$ (grey) is high, however, it is significantly smaller than 100 %. In other words, a significant portion of the variance in n is explained by interactions between inputs. The sensitivity to $X[0]$ decreases in time, while the influence of the opinion acceptance rate A (black) and later the social distance r (red) increases. Observe, that an increasing portion of the total variance has to be explained from higher-order interactions.

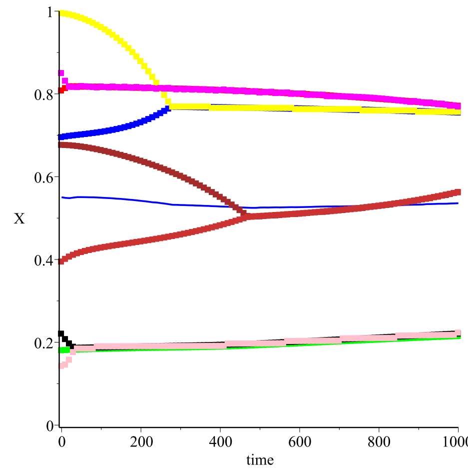

Fig. 3: A simulation of changes in opinions X up to 1000 iterations for $r = 15$ in a "village" of 3×3. Different colours indicate different agents. In this example there are still three clearly distinct opinions at the end-time.

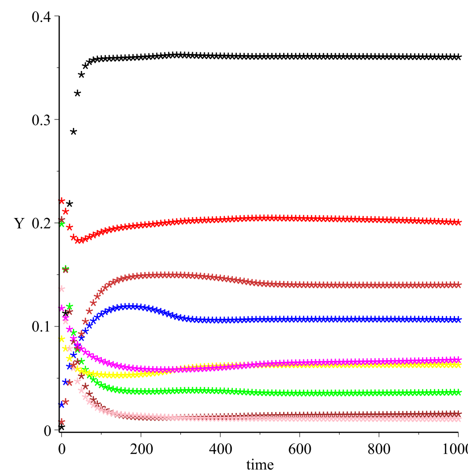

Fig. 4: The dynamics of Y (reputation) for the same simulation as X (Fig. 3).

III. Discussion

Although agents in the model always seem to converge to one opinion eventually, the number of iterations before convergence occurs can vary strongly, depending on different factors. For practical purposes it may be intractable to allow for a large number of iterations, e.g., in real spatial planning it may be realistic to have a certain end-point, and thus more than one distinct opinion to be considered.

Of the considered factors that may influence opinion dynamics (reputation, peer pressure, empathy, and spatial isolation effects) not all have been investigated properly. Of the considered parameters not surprisingly the most influential is the initial opinion distribution, but it is not at all a 100 %, and furthermore this sensitivity decreases in time. Instead, the importance of the social distance (r) and opinion acceptance rate (A) increase. Furthermore, a significant portion of the variance in opinions is not explained by single-order effects. Two parameters that remain to be explored in more depth are the size of the village and the radius of communication with neighbours. For large enough village sizes opinions may in practice never really converge because of local isolated patches. Such patches then would have no real opinion exchange anymore with their neighbours outside the patches, resembling the behaviour of models that show segregation of agents, such as the well-known Schelling model. Effects of spatial segregation should be confirmed by a more extensive sensitivity analysis that includes the village size as variable factor.

The above in turn also raises another relevant point, namely how to perform a spatially explicit sensitivity analysis. The method applied here considers only an aggregate output (the number of distinct opinions), but it may be obvious that because of the local interactions there are spatiotemporal correlations which need to be considered. Currently the development and application of methodologies for spatial sensitivity analysis is limited because of the conceptual and numerical difficulty of dealing with spatial structure in model analysis, which in turn results in a common absence of spatial sensitivity analyses [7].

Our model currently considers agents with a spatially explicit fixed position but with a non-spatial opinion. However, in spatial planning agents typically differ in their opinions about different locations, for instance, two agents may agree on one location but disagree on another. Future model extensions will incorporate this spatially explicit opinion difference. Also, the current version of the model is fully deterministic - barring the randomly drawn initial conditions - but it is plausible that internal noise - such as misconception about each other's opinions - as well as outside interference will prevent convergence towards one shared opinion. The addition of noise may result in a 'natural' social distance which in many other models is imposed explicitly as an 'if-then-else'-construct. The functions for opinion and reputation change are now very generic and not grounded in any social theory other than very basic assumptions about opinion and reputation dynamics. However, as the exchange of opinion and reputation is 'decoupled' from the update other exchange functions can be 'inserted' which are based on social theory or experiments. Future model extensions may also include different descriptions of the exchange of opinion and reputation.

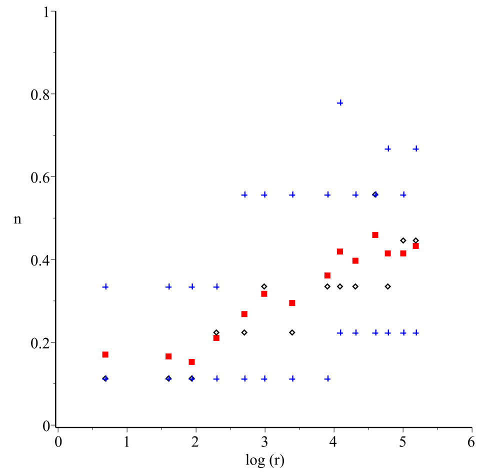

Fig. 5: A plot of n as function of $ln(r)$ for a village of 3×3 after 1000 iterations. Red solid box is mean, open diamond is mode, and blue crosses are minimum and maximum values out of 10 runs. There is a 'step-up' point around $ln(4)$ where the minimum number of distinct opinions is two instead of one.

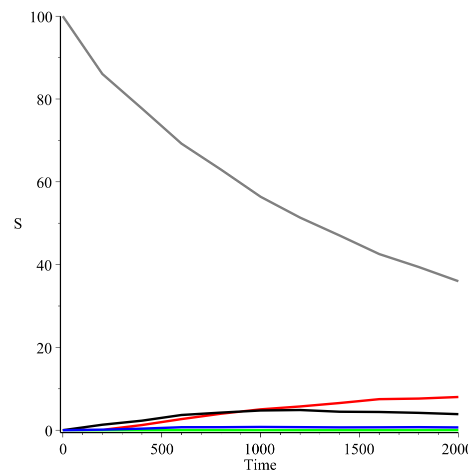

Fig. 6: A plot containing the global time-dependent variance-based sensitivity of n for several inputs, namely r (red), $d_{X[0]}$ (grey), $d_{Y[0]}$ (green), d_A (black), d_B (blue). A significant portion of the variance in n is not explained by single-order effects, i.e., higher-order (interaction) effects have to be investigated.

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