FUZZY SOCIAL NORMS AND INDIVIDUAL COMPUTATION

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ABSTRACT

How important are social norms in our daily lives? Would it be intolerable to have to think about every decision that we make? For example, when we wake up in the morning, we usually don't think about whether or not to get dressed, but automatically do so.
On the other hand, do social norms limit our ability to think for ourselves and force us into a type of 'herd' mentality?
Epstein (2001) introduced a simple, agent-based model to compare the strength of a social norm with that of individual thought, using a binary value to represent the norm of an agent. In the present paper this model is extended to include a real value representing the degree of intensity of the agent with respect to the social norm. Runs of the model are given, comparing the results obtained with the proposed model to those of Epstein.

Keywords: fuzzy social norms, individual thought, agent-based modeling.

INTRODUCTION

Conventions govern much of our daily behavior. As we consider a normal business day, we see that we usually get dressed when we go outside, we drive on the same side of the road as the rest of the motorists in the country we are living in, we greet other people perhaps by shaking their hand, in a restaurant we probably eat our steak with a knife and fork, and also leave a tip, even though the service may not have been up to standard. These, and other illuminating examples, can be found in the literature on social norms (c.f. Young (1993,1996), Azar, (2004)), although the reader can obviously think of his or her own examples. While one might differentiate between a convention and social norm in terms of the possible sanctions imposed, here the distinction is not considered. Generally, following Young (1993), we can describe a convention as a "Pattern of behavior that is customary, expected, and self-enforcing. Everyone conforms, everyone expects others to conform, and everyone wants to conform given that everyone else conforms". Further, Kandori, Mailath, and Rob (1993) and Young (1996) show that, from a formal point of view, conventions may be represented as equilibria of suitably defined games.

The idea of self-enforcing behavior regularity is the one usually dealt with in the field, however Epstein (2001) also considers another important aspect, namely, that once the social norm is established, we then tend to conform without thinking about it. This can be beneficial in our daily behavior, as the idea of having to consider every decision that we make could be intolerable. However, social norms can also involve prejudice, which when enforced by society in general can lead to equally intolerable conditions for some sectors of that society. To consider this aspect, Epstein developed a simple, agent-based model with two attributes for each agent corresponding to "how the agent behaves" and "how much the agent thinks about how to behave". Epstein showed, through simulations, that the model captures the feature that *individual thought is inversely related to the strength of a social norm*.

However, social norms are not always clear-cut in terms of how the individuals behave. An individual can exhibit what appears to be "fuzzy behavior"; for example, the degree to which we conform to leaving a tip varies from individual to individual. There are different ways in which fuzzy behavior can be introduced into Epstein's model; here, we take a straightforward approach and use the idea of "degree of intensity", a notion prevalent in fuzzy preference theory (c.f. Ross (1995)). We then repeat some of Epstein's experiments with this model in order to see what aspects of "strength of social norm vs. individual thought" the new model captures.

The paper is organized as follows: in the next section the Epstein's model and the one proposed here are described. This is followed by results obtained using the proposed model, and finally a discussion and some conclusions are given.

MODELS

First, Epstein's model is described in the next subsection, and then the one proposed is given.

Epstein's model

Epstein (2001) introduced a simple, agent-based model to capture the feature that individual thought – or computing – is inversely related to the strength of a social norm. In this model, Epstein arranged the agents into a fixed ring and assigned two attributes to each of them. One attribute is a binary value representing the behavior of the agent, for example, whether or not to dress. The other attribute is a positive integer value, called the radius, representing the number of agents to the left and to the right of the agent under consideration that will be sampled when updating the agents' norm. The radius is adaptive and can vary from agent to agent. An agent is considered to have "stopped thinking" when its radius has the value 1, for in this case, the agent does not consider the behavior of any other.

To update an agents' radius, whose current value is r, the relative frequency, F(r), of the norms of the r agents to the left and the r agents to the right is calculated. Similarly, F(r+1) is calculated. If

$$|F(r)- F(r+1)| > tol \qquad (1)$$

then the radius is increased to r+1, where tol is a fixed real parameter allowing a measure of "tolerance" in the decision process. Otherwise, F(r-1) is calculated. If F(r-1) does approximately equal F(r), then the radius is reduced to r-1 (providing r>1). If neither condition obtains, the radius is left unchanged at r. The logic behind this updating is that if a larger sample doesn't yield a different value, then try a smaller radius to see if it changes, else we assume that the sample size is appropriate. Epstein refers to this as the 'lazy statisticians rule'.

To update an agents' norm, the value of the majority of agents within the radius is assigned. This may be considered as 'When in Rome, do as the Romans do'.

Once the constants for the tolerance (tol), maximum radius (maxrad), number of generations (maxgen), and the number of agents (maxpop) are initially fixed, pseudo-code for the basic algorithm can be expressed as:

```
assign initial values to the norm and radius of each agent
for i = 1 to maxgen
        for j = 1 to maxpop
                choose an agent randomly
                update agent's radius
                update agent's norm
        end-for
end-for
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The choice of an agent within the second for-loop is essentially sampling with replacement; that is, the second for-loop essentially represents choosing maxpop agents, with the possibility that the same agent is chosen repeatedly whilst others may not be chosen at all, and updating the radius and norm of the agent. If an agent is not chosen its' radius and norm remain unchanged. This is referred to as one cycle, or generation.

Using this model, Epstein conducted a series of interesting simulations in which he tried to compare the strength of social norms with individual thought, finding an inverse relationship between them.

A fuzzy model

Social norms can appear quite fuzzy at times, when an individual behavior is not always clear cut. We can find, for example, motorists not always stopping at red lights, not always using indicators when overtaking another car or turning at a corner, diners responding differently in their tipping habits, and so forth. There are different ways of introducing fuzziness into Epstein's model; here we take an uncomplicated approach and use the idea of "degree of intensity", a notion common in fuzzy preference theory. In this case, a real valued number in the interval [0,1] is assigned to the agents' attribute of behavior. This attribute is then updated in the following way:

a. If the majority of the agents within the radius have their norms greater than 0.5, then calculate the mean value of their norms and assign it to the norm of the agent.
b. If the majority of the agents within the radius have their norms less than 0.5, then calculate the mean value of their norms and assign it to the norm of the agent.
c. Otherwise, leave the agents' norm unchanged.

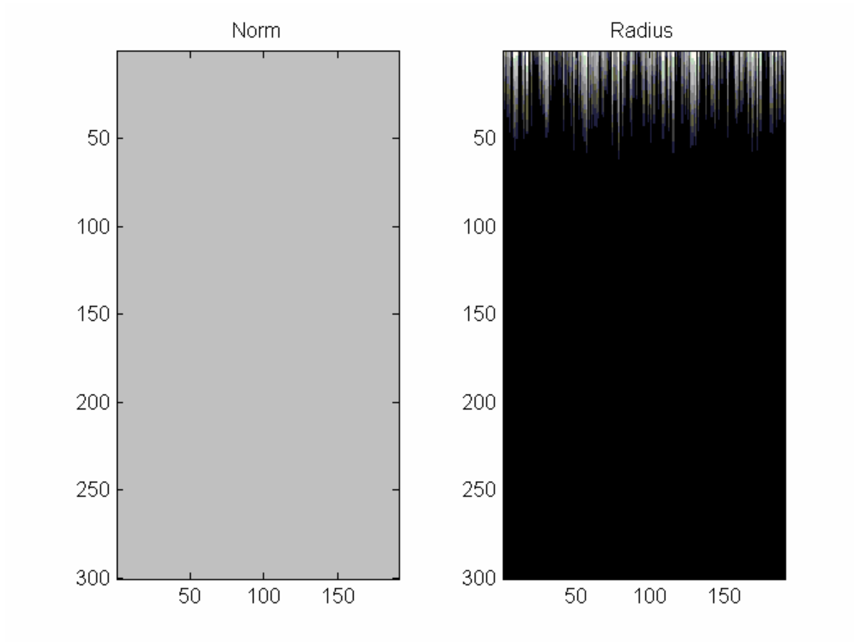
The reason for the above norm updating is also related to the activity of the majority of the agents within the agents' radius, with the actual value calculated according to the mean of the majority.
The rest of the model is the same as Epstein's.

SIMULATIONS WITH THE MODEL

We shall present several simulations of the proposed model, similar to those given in Epstein (2001), which illustrate the evolution of the norms. In all of the simulations that follow, the tolerance parameter, tol, is set to 0.05, the number of generations, maxgen is 300, and the number of agents maxpop is 191.

The simulations are shown in two panels which represent the evolution of the norms and radii for each of the agents. The ring of agents is arranged across the panel, while the generations evolve down each panel. A new row is thus drawn after each generation. The values of the norms and radii are represented in gray scales, with darker colors showing smaller values within the context of the corresponding panel.

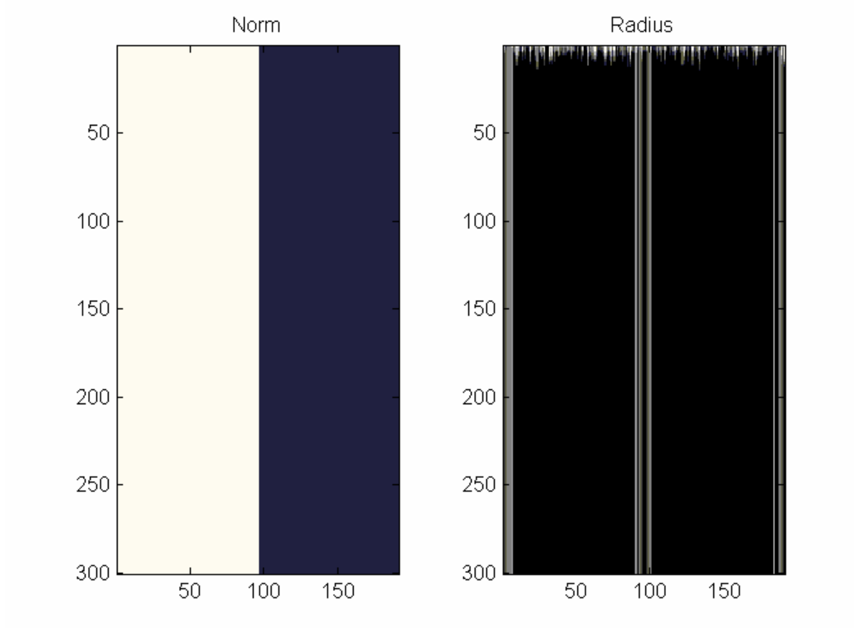
The first simulation assigns the initial value of 0.8 to the norm of each agent and randomly assigns a radius with a maximum value of 60 (in order to allow a relatively wide influence initially). Hence all agents have the same "degree of intensity", and when we apply the update radius rule, the same thing happens as in Epstein's simulation; namely, for each agent $F(r+1)=F(r)$ and $F(r-1)=F(r)$ so according to the radius update rule, the agent reduces its norm from r to r-1. When we apply our norm update the value remains at 0.8. This procedure would, in fact, apply if the same fixed value were initially assigned to all of the agents norms. The left panel of Simulation 1 has the same color for the entire evolution (signifying that the agents remain with their initial norm value, close to 1.0), whereas in the right panel at the start of the run there are different shades reflecting the random values initially assigned to the radii. As the



Simulation 1: All agents initially given norm value of 0.8 and maxrad is 60

simulation continues, all of the radii have the minimum permitted value of 1, giving rise to only the black color. As with Epstein, the right panel can be interpreted as the elimination of individual "thinking".

In the second simulation, the maximum radius is reduced to 10 and we divide the agents into two groups: the first 95 agents (as appearing in the left panel) are given the norm value 0.9, and the rest of the agents



Simulation 2: Two groups of agents, each with fixed norm values

the norm value of 0.1. Random values are assigned to the radius of each agent. It can be seen, from the left panel, that the assigned norm values do not change with the evolution; however the radii, in the right panel, become fixed in the 'interior' of each group and only continue varying on the boundaries between the groups. Here, we can interpret this as individual thinking being eliminated inside each group, whilst agents on the boundary continue to be influenced by their surrounding neighbors. This is clearly seen in Figure 1, where, at the end of the 300th generation, the norm and radius values of each agent are shown.

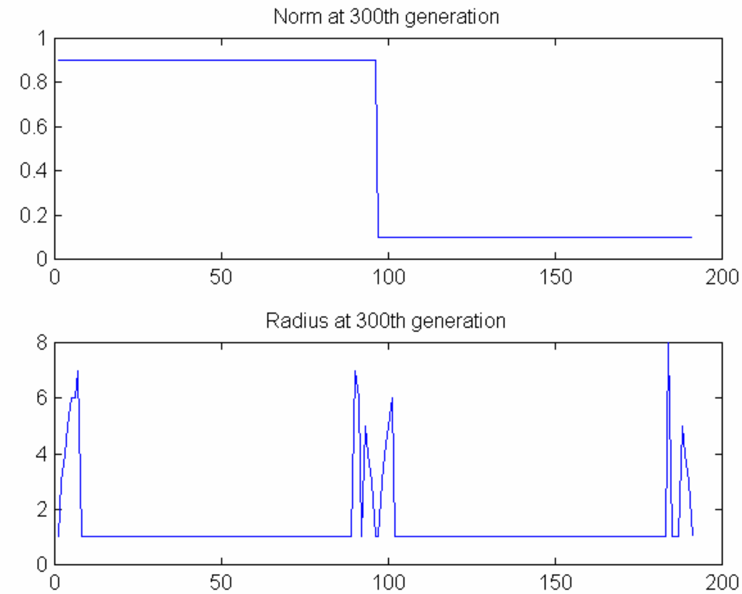
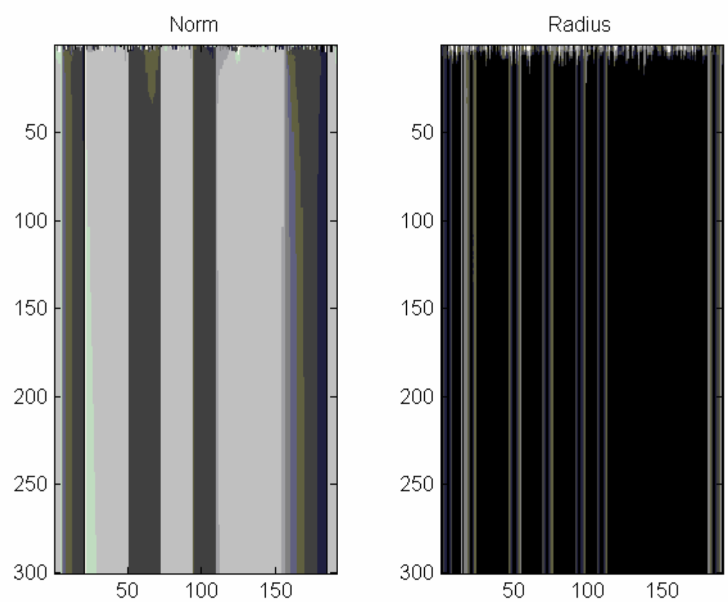


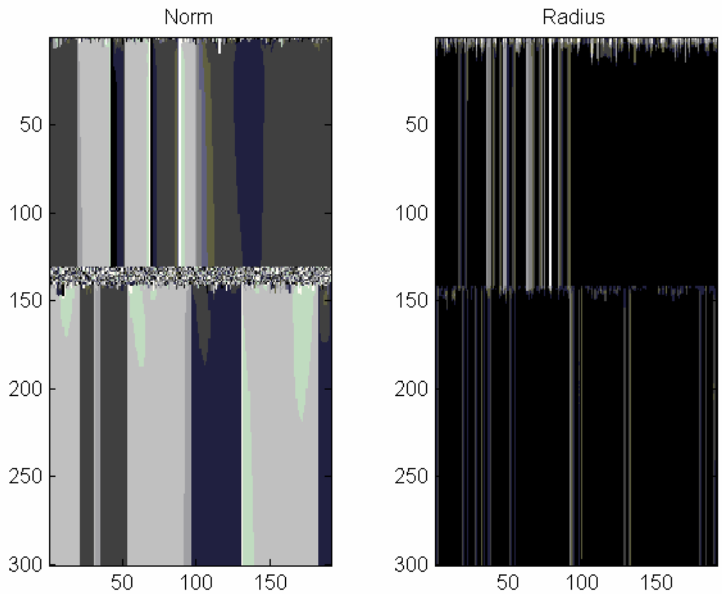
Figure 1: Norm and radius values of all the agents at the end of the second simulation



Simulation 3: All agents initially given random norm and radius values

In the third simulation, the maximum radius is maintained at 10 and random values are assigned to both the norm and radius of each agent. In this case, there is a activity similar to that obtained by Epstein, namely there are alternating local norms in the right panel, and that within each of these groups the right panel shows that thinking has been eliminated. One difference with Epstein's simulation of the same experiment is that the norm values can vary from group to group, reflecting an auto-organized clustering of behaviors.

For simulation 4, the values are the same as simulation 3, but between the generations 130 and 140 the norm of each agent is randomly reset. We see that, before the generation 130 and after generation 140, the evolution is similar to that of simulation 3 but with the "shock" producing a readjustment of the groups



Simulation 4: As simulation 3, but with a "shock" between generations 130 and 140

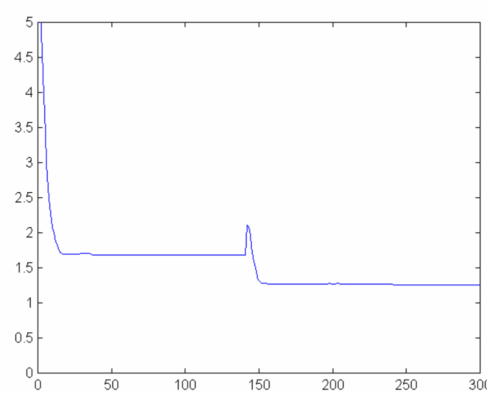
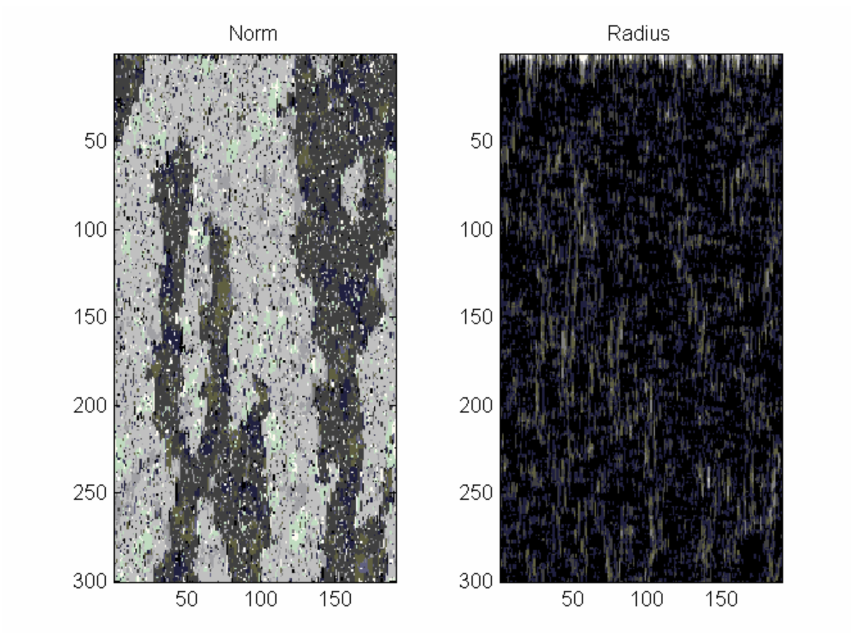


Figure 2: Evolution of the average radius for simulation 4

which think alike. Figure 2 shows the evolution of the average radius. The value is initially stable until the shock, when there is a sharp increase in value. The average then becomes stable again with another value. This is also similar to the Epstein's results.

Finally, in simulation 5, a noise level of 0.15 is fixed for the entire run. This means that approximately 15% of the agents have their norms reset at each generation. Epstein was interested to see if any type of norm patterns emerged. We also obtain the emergence and disappearance of norms, with "thought" most intense at the norm borders.



Simulation 5: Simulation with noise added

Figure 3 shows the evolution of the average radius.

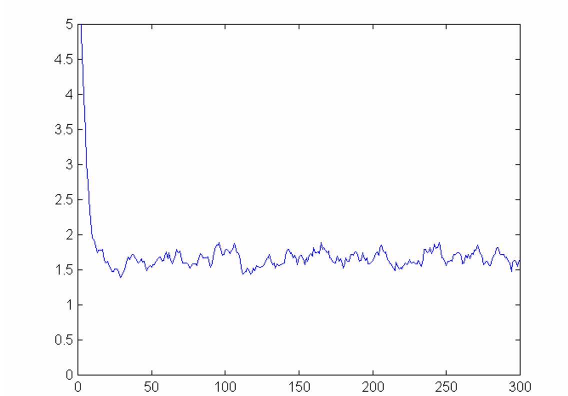


Figure 3: Evolution of the average radius for simulation 5

DISCUSION AND CONCLUSIONS

In the present work, an extension has been given to a model of Epstein to include the idea of the degree of intensity of an agent with respect to a social norm. In this simplified fuzzy model, it is assumed that the agents influence their neighbors by the way in which they behave, and that this behavior is related to their degree of intensity of acceptance of the social norm. This difference with Epstein's model allows the possibility of representing more complex situations in which there are no clear cut behaviors, even within groups that accept the same norm. In fact, in our simulations one can observe groups which contain subgroups with diverse degrees of acceptance, or rejection, of a norm inside each group.

The model proposed in the present paper can be considered as a first step towards a model where the relationship between agents is completely fuzzy. In this case, the model can be extended to use general fuzzy sets for each agent, with the corresponding influence calculated using a fuzzy operation between the neighboring sets.

Further extensions to the model, in other directions, are also possible; for example, norm updating could include some dynamic knowledge of an agents past behavior, perhaps to include a period of unwillingness to change, thereby avoiding automatic changes of behavior.

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