The emergence of shared social representations in complex networks

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Abstract. We introduce a model based on an assimilation algorithm to study the emerging of a shared social representation in a virtual community structured on a scale-free network. Individual representations are modelled as randomly extracted bit strings and evaluated in terms of fitness, coherence with respect to underlying culture. Simulation dynamic is based on this fitness value and on most represented opinions in the agent's immediate social environment. In a short time the virtual population converges towards a shared representation and the average fitness remains stable around middle values.

1 INTRODUCTION

The theorization by the social psychologist Serge Moscovici about *social representations* origins from a study about diffusion of psychoanalytic theory beyond the bounds of official circles and towards a much more vast audience [12]. The author highlights how, in this transition from a scientific context to a *naïve* one, the theory undergoes changes that reflect the differences between the two fundamental ways of approaching reality that deeply characterize western thought and the different constraints they pose. In the shift from a *reified universe* to a *consensual* one, to use the author's terminology, the original strength of internal logical coherence gets lost but what is created through informal interactions between individuals is a much more understandable view, an almost tangible experience: a shared social representation. These constructions have the function to cope with the unfamiliar, be it an object, an event, a theory or whatever, bringing it back to the soothing dimension of familiar reality [13].

In this work we try to simulate the emerging of a shared social representation in an agent-based model built upon the structure of a complex network. Agents will be driven by the need of giving sense to an hypothetical sudden event to get to a satisfactory representation of it through social interactions and opinions exchange.

2 RELATED WORKS

The themes of cultural assimilation and opinion spreading through social interactions in artificial societies have been addressed in many other studies before. Moscovici himself relied on computer simulation in the study of group polarization [8, 7]. Opinion shifting has been modeled by Nowak, Szamrej and Latané [14], Hegselmann and Krause [9] and Deffuant et al. [6] and cultural assimilation by Axelrod [3], Kennedy [10] and Parisi, Cecconi and Natale [15]. All these works are based on some kind of assimilation dynamic between individuals or groups interacting with their neighbors and influencing each other through an algorithm that relies on similarity, Latané's theory of *social impact* [11], or rather Boyd and Richerson's [5] *frequency bias*.

In our model a virtual society has to cope with the need of representing an event of growing importance in the life of the community. We imagine that each individual of this community will have a tendency to reach a more structured and coherent representation (i.e. one that better fits in the underlying shared culture) and that will try to satisfy this need adopting the most represented opinions in his neighborhood. What characterizes our algorithm from a plain frequency bias one though, is the introduction of relative impact of individuals, that will be proportional to their own fitness, and variable need for change of individuals, that will be inversely proportional to fitness. As a matter of fact we could imagine that an individual with a more coherent representation could exert a stronger social influence than others and feel more satisfied with his representation, thus less willing to change it. We chose to model the structure of individuals relationships network upon a *scale-free* graph as it seems to be the topology that better represents real social networks [4]. This class of networks shares the two fundamental properties of the so called *small-world* networks, namely high clustering coefficients (i.e. the neighbors of two linked nodes form two largely overlapping groups) and low diameter value (i.e. the average shortest distance between two nodes increases logarithmically with the number of nodes). But the main property of scale-free networks — the one to which their name is due — is that their degree distribution follows a power-law so that a few nodes, the *hubs*, will have many links while the vast majority will be poorly connected. In our simulation we chose not to consider the additional factors that may intervene in real social networks formation thus influencing their resulting topology, such as *aging* or *linking costs* [2], because we felt they were not relevant to the study of the specific topic of social representations emergence.

3 THE MODEL

The nodes of our scale-free network represent individuals. To each one of them is assigned a binary string composed by 450 randomly extracted values that stands for the representation of event X of the individual j. Each string is interpreted in blocks of 15 elements through *gray code* in a vector of real values. This coding is built so that two consecutive real numbers are represented by strings that differ from one another for just one bit. In our case this means that the changing of a string element will produce little incremental changes in the position of that string in the fitness hyperspace.

The 30 real values will then be transposed in the interval $[-600, +600]$ and used as coefficients of the *Griewank* function:

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$$C = \sum_{i=1}^{n} \frac{x_i^2}{4000} - \prod_{i=1}^{n} \cos\left(\frac{x_i}{\sqrt{i}}\right) + 1$$

The resulting fitness index C will be interpreted as the coherence of the representation in its cultural context (that we suppose as static during the time of the simulation). The Griewank function is a widely used benchmark tool in the context of global optimization but two of its properties that we found particularly fit to our simulation were determinant in our decision to rely on it:

- a subtle change in a string may cause an even strong fitness variation;
- two (or more) different strings may have the same fitness score.

In setting up the network we relied on the algorithm proposed by Albert and Barabási [1, p. 71] based on *growth* and *preferential attachment*: we started with a small number of nodes m_0 and step by step we added a new node with $m \leq m0$ connections linking it to m different nodes with a probability Π to be linked to the node i proportional to its degree k_i so that:

$$\Pi(k_i) = \frac{k_i}{\sum_j k_j}$$

We repeated the procedure until we obtained a 100 nodes network and then we checked that the nodes degree distribution followed a power-law curve. Then we computed for each node the initial string fitness value C and started the dynamic of the simulation that went on for 100 cycles.

3.1 Simulation Dynamic

At each time step for each node we will select a number of binary elements of its string, based on its fitness value, to submit to the revision process. This number will be inversely proportional to C_{MAX}, that for a 30 values vector like ours will be about 2701. Which elements will be revised is randomly decided so that the probability remains constant for each element (i.e. an element may be selected more than once).

The revision process of a node string element consists of three different phases (Figure 1): first of all the values (0 or 1) of respective elements in directly linked nodes strings are read; then the category (0 or 1) each of them represents is given a score between 0 and 1 proportionally to the fitness of the string it belongs; finally the element is accorded to the category with the higher score. Should categories end up with the same score the element value will be randomly extracted.

It's worth noting that in any case this procedure does not assure the extracted element value will change. Any change however is stored in a temporary buffer and the strings are actually updated only after all nodes have been processed.

At the end of each cycle we collect three parameters:

- average strings fitness
- maximum strings fitness
- dispersion (average hamming distance between strings)

To test the network topology impact we decided to run the same simulation on a random graph with a connection probability p_c = 0,1 between each possible pair of nodes. As graph construction is based on different arbitrary parameters (m and m_0 for the scale-free graph and p_c for the random graph) no guarantee is given that resulting architectures will be comparable. To maximize validity we chose to build the random graph before the scale-free one so that we could try to get the same number of total connections for the two graphs by choosing appropriate values for m and m_0.

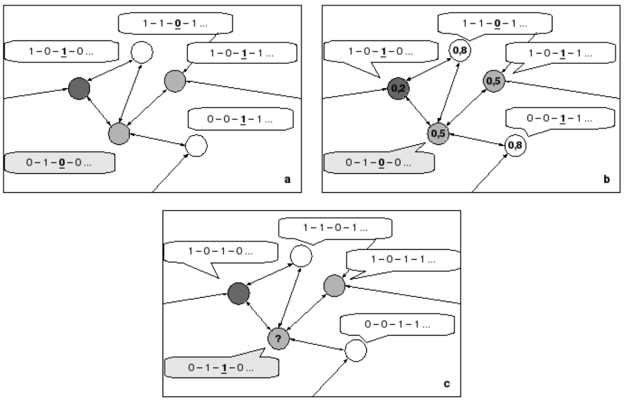

Figure 1. Revision process phases: a) an element from processed node string (in grey) is extracted and respective elements in directly linked nodes strings are read; b) the category each element represents (0 or 1) is added a value between 0 and 1 proportionally to the fitness of the string it belongs (showed as the tone of grey of the node); c) the extracted element is accorded to the most represented category.

Simulations have been run for different values of p_c and with the introduction of different percentages of mutations to test the impact of these factors on the assimilation dynamic. Mutations consist of value re-extraction of up to the chosen percentage of randomly selected binary values for each string at each time step. They could account for changes in individuals representations not specifically due to social interactions. Each experimental setup has been tested 50 times with different randomly generated starting conditions.

4 RESULTS

In the base setup, with no mutations and p_c = 0,1, dispersion decreases quickly, yet not reaching zero, in both topologies as can be seen in Figure 2.

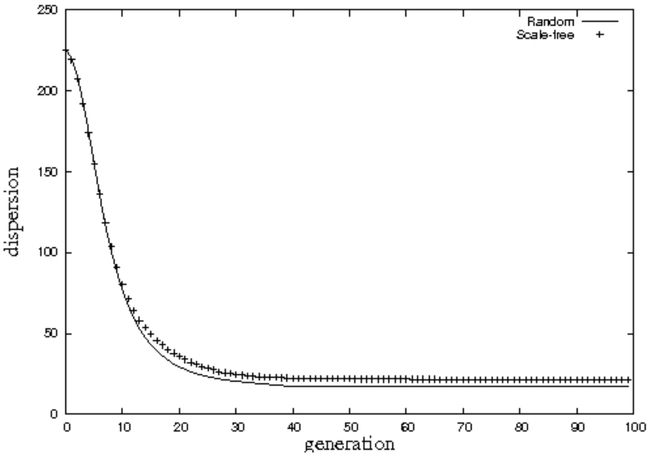

Figure 2. Dispersion through time in the two considered topologies: random graph (line) and scale-free graph ("+" points), with p_c = 0,1

We applied the Student's *t-test* to dispersion values of last simulation cycle for the two different graphs and the result was a significant difference for p $<$ 0,05. More in detail for the scale-free graph we had an average value of about 15,7804 and a standard deviation of about 7,7786, while for the random graph we had an average value of about 13,1765 and a standard deviation of about 3,7111. The t value was consequently of about 2,1363.

Increasing the number of connections though, we noted that this difference started decreasing so that with p_c = 0,2 we found no more a significant result.

Adding a little percentage of mutations (1%) to the base setup we had an even stronger decreasing of dispersion and a more significant difference (Figure 3): average value for last cycle dispersion in the scale-free graph over 50 replications was about 10,7980 with a standard deviation of 4,6018, while in the random graph it was about 8,0026 with a standard deviation of 2,5320. The t value was about 3,7635 and so the probability that the difference between topologies could depend on chance was less than 0,01 percent.

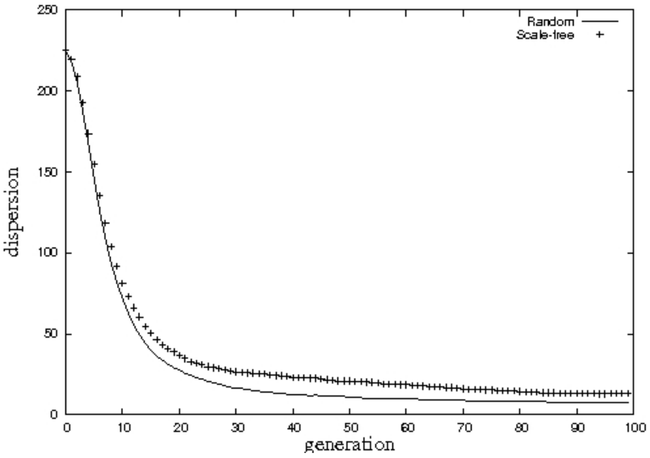

Figure 3. Dispersion through time in the two considered topologies: random graph (line) and scale-free graph ("+" points), with p_c = 0,1 and mutations at 1%

Even in this case the increasing of p_c had the effect of hiding the effect of topology in the assimilation dynamic. The same result was given by the introduction of an higher percentage of mutations (5%).

A result that remains constant through conditions is the fitness trend that in a few generations reaches an intermediate value and tends to stay stable throughout time (an example is reported in Figure 4).

5 DISCUSSION AND FUTURE WORK

We formalized the social construction of a representation of an element of novelty as a process that requires finding a satisfactory solution to a complex equation. The less coherent, with respect to the individual's view of reality, this solution will be the more he will feel the urge to come to a different solution and integrate the new element in a more stable structure. Moreover we imposed that the only way to reduce this angst would have been social exchange of opinions.

In all experimental conditions, based on these premises, we assisted to the emerging of a shared representation. We were surprised that the assimilation dynamic, though being subjected to the pressure towards high coherence, did not succeed in taking the fitness up. We would have expected it to behave like a genetic algorithm, instead it showed a peculiar course that deserves further in-depth studies.

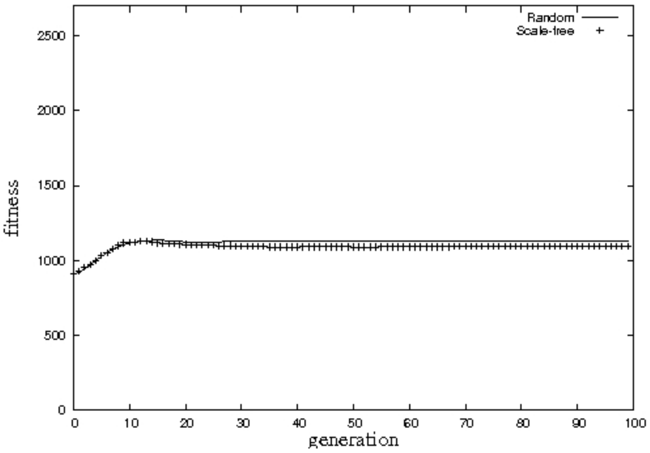

Figure 4. Average fitness through time in the population for the random graph (line) and the scale-free graph ("+" points)

However this result is perfectly in line with Moscovici's theorization which postulates, in the process of construction of a social representation, the sacrifice of a certain amount of internal coherence in favour of the probably more essential dimension of sharing.

ACKNOWLEDGEMENTS

We would like to thank the ESF-EUROCORES-programme TECT (The Evolution of Cooperation and Trading) for supporting our work.

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