Rumor Spreading Modeling: Profusion versus Scarcity

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***Abstract*—In this paper, we focus on the very specificity of rumors as pieces of information for modeling their process of propagation. We consider a population of pedestrians walking in a city and we assume that a rumor is transmitted by *word of mouth* from one to another. Although the diffusion of a rumor is of course a multi-dimensional process driven by sociological, economical and psychological elements, in this first step, we emphasize one main dimension of this complex phenomenon only. This dimension is the neighborhood of individuals likely to spread the information. With a confrontation of two antagonistic properties of the neighborhood that are *profusion* and *scarcity* of spreaders, we highlight specific characteristics of rumors. This study could lead to the psychological mechanism involved in the decision for a person to become or not a spreader himself/herself. In summary, we study if *scarcity* could be the silver bullet explaining how a rumor spreads.**

I. Introduction

Rumors have been studied for years and originally in economics, psychology and social sciences [10], [15] where the word to mouth phenomenon has been explored to understand why a rumor turns off rapidly or crosses social groups and to find solutions to stop it. Besides that much emphasis has been put on diffusion modelling issues with researches combining epidemiological mathematics and stochastic solutions [14], [6], [13]. As shown by most of these researches published before 1980, the rumor phenomenon was studied as a word of mouth story telling while there is also a recent and increasing interest in considering social networks as main media responsible of the rumor spreading [8], [5], [19], [2]. In this paper, we consider *word of mouth rumors* only as a first step that could allow enhancements to online rumors or *e-rumors* in further works.

The analogy between epidemics spreading and rumor propagation is a common assumption in most of these works that propose solutions inspired by compartment epidemiological models. Diffusion phenomena are generally modelled according to two complementary approaches: (i) mathematical representations in control theory or (ii) agent-based and data driven simulations. For instance, epidemiological compartment models like the SIR (*Susceptible-Infected-Recovered*) model defined by Kermack and McKendrick [9] and the DK (Daley-Kendall) model [6] for rumor modelling were originally represented by differential equations while more recent approaches [6], [12], [17], [8], [18], [5] take advantage of multi-agent systems (MAS) and social network graphs to simulate state transition rules.

But rumor propagation has a very high specificity compared to epidemics. The Oxford dictionnary defines a rumor as a *currently circulating story or report of uncertain or doubtful truth*. The diffusion of a rumor is a multi-dimensional process driven mainly by socio-psychological elements. As it is mentioned frequently [7], [3], [19], diffusion modelling is indeed very similar across different applications, such as the spreading of viruses, diseases, rumors or knowledge. Rumor transmission especially can obviously be regarded as a kind of contagion process.

The three individual states *Susceptible, Infected, Recovered* traditionally considered for infectious disease can be directly transposed in the rumor context as *Ignorant, Spreader and Stifler*. In the finite state automata, transition rules *Susceptible to Infected* and *Infected to Recovered* are frequently considered as similar as *Ignorant to Spreader* and *Spreader to Stifler*. An *Ignorant* (resp. *Suceptible*) may become a *Speader* (resp. Infected) when he meets a *Spreader* (resp. *Infected*). A *Spreader* (resp. *Infected*) may become a *Stiffler* (resp. *Recovered*) after a given time and he does not spread the disease or tell the story any longer.

For Daley and Kendall [6], the novelty of the story is a main criterion for an individual likely to tell it, there is a *"reluctance to tell stale news"*. Based on this consideration, the DK model is built on the principle of *novelty* according to which a *Spreader* stops telling the story when he knows it has lost its novelty. Like the SIR model, it is a compartment model that involves three states (Ignorant-Spreader-Stifler).

However, it models individual agent behaviour in reaction to their neighborhood since an active *Spreader* of the rumour switches to *Stifler* whenever he encounters somebody who has heard it before. Various modelling approaches have been proposed as slight variations of the DK model. With this new model, Daley and Kendall showed that the proportion of individuals who know the story at the end of the process is always between 0 and 80% whatever be the transmission ratio.

Let's remark that the SIR and DK models are based on simplistic assumptions:
(i) the population is fully mixed i.e individuals with whom a susceptible individual has contacts are chosen at random into the whole population;
(ii) all individuals have approximately the same number of contacts in the same period of time;
(iii) the transition from one state to another one relies on a probability. For instance, all *Infected* (resp. *Spreaders*) transmit the infection with the same probability.

Most extensions of the original DK model define spot refinements on individual behavior of Spreaders and Stiflers and on pairwise contacts. Kawachi et al [8] introduce the *lack of confidence* of a *Susceptible* in a *Spreader* that makes him switch directly to *Stifler*. Cheng et al [5] rather considered the quality of the link as the *trustiness* between two individuals as a main factor for spreading the story or not. Xia and Huang [17] focused on the evolution of *belief* of an agent about rumor and *anti-rumor*. The approach of Borge et al [2] is rather similar since they consider that a *Spreader* may become *inactive* at times.

In this sporadic set of propositions, one may however identify four characteristic properties of rumor spreading processes admitted as well on the global scale:

(a) **Longness** since it takes a relative long time for *Spreaders* to tell the story so that the rumor starts [19];

(b) **Slowness** since the propagation starts slowly and the information spreads in a short time [19]. According to Kawachi [8], a rumor even spreads "on a large scale in a short time";

(c) **Incompleteness** since the *infection* does not reach the whole population [6];

(d) **Sparseness** since individual neighborhoods are not densely populated by *Spreaders*. There is no dissemination wave since Spreaders are rather dispersed [8].

On the local scale of each individual the rumor spreading follows also specific rules: **(i)** the transition *Ignorant to Spreader* is an individual behavior of the *Ignorant* and not an individual behavior of the *Spreader* [8], [2];
(ii) state transitions and especially *Ignorant to Spreader* are complex individual decision-making processes. In this context, another way to translate and implement the novelty concept is rather to consider the decision-making process depending not only on the nature of the rumor but also on the neighborhood of each individual likely to tell the story and especially on the state of its neighbors according to the rumor. No novelty means a widely gossiped news thus no scarcity of the story in his neighborhood. On this matter, Rosnow and Fine [15] identified the feature of *scarcity* as a key dimension for rumor spreading. *"Rumours arise when information is scarce"* [11].

In this paper, we propose an innovative approach by investigating the *"profusion/scarcity*" property of the rumor. We bring this new perspective on the context of individuals likely to tell the story themselves once they know it. By defining a spatio-temporal model of rumor spreading, we propose to consider the following issue: what is the most realistic between the two antagonistic properties *profusion* and *scarcity* to disseminate a rumor, and why? The rest of the paper is organized in three sections. Section 2 is devoted to the *ODS* model of rumor spreading that we propose. In Section 3, we present experimental results obtained by simulation and we discuss them. We conclude in Section 4.

II. A SPATIAL MODEL OF RUMOR SPREADING

If a simple handshake allows a virus to be transmitted from an *Infected* individual to a *Susceptible*, a rumor is transmitted by *word of mouth* from individuals to individuals. In both cases, a physical contact is required. While rumor modeling should consider representation of these cornerstones that are spatiality, contact, social environment and psychological context, it is also valuable to focus on one of them and to study this sub-model Word of mouth rumors are indeed very difficult to follow, they are complex phenomena and do not generate data as online rumors that propagate on social media. To validate assumptions or rules, one can quantitatively observe trends and chatacteristics that are their signatures.

To this effect, we propose the *ODS* compartment model that integrates the spatial dimension. The propagation relies only on physical contact and mobility. We assume indeed that each individual has a location in a world represented by a grid composed of cells. For each individual, the neighborhood is composed by the others around him/her on the same cell. Individuals are mobile and they create new social contacts when they move. The diffusion is relying on the induced social network and on individual spreading behaviour. Mobility is a key element for the effective modelling of virus spreading. It is also well known that human mobility patterns affect the spatio temporal dynamics of an epidemics. With *spatiality*, *mobility*, *dynamicity* and *socio-psychological* aspect, our goal is to better fit the framework to reality. For a comparative study, we define two versions: ODS_p with *profusion* property and ODS_s with *scarcity* property. The *profusion* property characterizes situations in which an *Open-minded* individual transmits the rumor when there is a high proportion of his/her neighbours that are *Disseminators* thus he/she may hear the story very often. The *scarcity* property characterizes situations in which an *Open-minded* individual transmits the rumor when there is a low proportion of his/her neighbours that are *Disseminators* thus he/she may hear the story very rarely.

While unlikely in a real population, we went with this approach to identify relevant dynamical properties in a first simple model before increasing both complexity and realism in further works. With the agent based modeling approach we follow, the diversity of situations regarding the individual mobility of individuals can be considered.

A. The ODS compartment model

Starting from SIR and DK foundations, we have defined the three classical compartments or states as such *Open-minded* O, *Disseminator* D, and *Stifler* S:

- *Open-minded* agents are the individuals who have not yet heard the rumor, and, consequently, are susceptible to becoming informed;
- *Disseminators* are active individuals that are spreading the rumor;
- *Stiflers* are individuals that have got the rumor but are no longer spreading it.

Each of the three groups O, D and S individuals are equivalent with respect to the spreading process. The total population size N is equal to $O + D + S$.

Transitions from compartment O to compartment D and from compartment D to compartment S between times t and $t+1$ characterize the dynamics of the model. ODS is a *spatio-temporal* model of spreading since spatial location of agents allows the transmission due to a physical contact. Considering the complexity of the analysis caused by the introduction of mobility, mobility schemes in ODS are assumed to be as simple as possible: each individual moves with a constant speed and at each step his/her current direction is randomly chosen. Let us note that most of the mobility models are based on random walks [4].

B. Principles

ODS differs mainly from SIR and DK models on main principles since:

- the aim is to model the spreading of a rumor, thus with the spatial dimension;
- contacts between individuals are not chosen at random and they occur between neighbors only;
- agents move and so at each time step, the number of contacts for an individual is not a constant - it follows a Poisson law which mean is the density of individuals on the grid;
- the probability that a D-individual transmits the information to an O-individual upon contact depends on each individual and varies over time. Thus it is referred as $\beta_k^{OD}(t)$.

1) "O to D" transition: A first condition under which the transition "OtoD" may occur is that the two protagonists are physically in contact since this is necessary to allow a *word of mouth* transmission.

As far as a rumor is concerned, it is the potential receiver, and not the transmitter, who decides whether or not he will become itself a transmitter. This is a crucial difference with infectious disease spreading. Now, the question is how an O-individual comes to make the decision to become a disseminator? In the ODS generic model, we assume that the likelihood that an O-individual a_k becomes himself a D-individual is function of the rate r_k^D of D-individuals in his neighborhood. On this basis we define two alternative solutions to ODS: the first one, called ODS_p, is driven by the *profusion* of information, while the second, called ODS_s, depends on *scarcity*.

Algorithm 1 OtoD

1. **for** each $a_i \in D$ **do**
2.   **for** each $a_k \in O$ in the neighborhood of a_i **do**
3.   Compute r_k^D the proportion of D in the neighborhood of a_k $\{r_k^D > 0\}$
4. a_k will become D with probability $\beta^{OD} = F(r_k^D)$ $\{F$ is a monotonic function from $[0;1]$ to $[0;1]\}$
5.   **end for**
6. **end for**

Transition based on profusion: In the first instance ODS_p of the model, it is assumed that the higher the rate r_k^D, the higher the probability that the O-individual a_k becomes himself disseminator will be.

Let's define the function F (algo. 1 line 4) as $F_p(x) = \frac{1}{1+e^{-c(2x-1)}}$ where c is a constant[1]. Then the value $p_k^D(t) = F_p(r_k^D)$ can be interpreted as the *profusion* of disseminators around the O-individual a_k. Profusion follows an increasing sigmoid curve: the more the profusion, the more the number of D-individuals in the vicinity will be: if $p_k^D = 0$, there are no infected individuals in the vicinity, while if $p_k^D = 1$, all the neighbors are infected. So, the probability that a_k becomes a disseminator is $\beta^{OD} = p_k^D$ (algo. 1 line 4).

Transition based on scarcity: The alternative instance ODS_s, is based on the assumption that the higher the rate r_k^D, the lower the probability that the O-individual a_k becomes himself disseminator will be. Let's define the F function as $F_s(x) = 1 - \frac{1}{1+e^{-c(2x-1)}}$, where c is a constant[1]. Then the value $s_k^D(t) = F_s(r_k^D)$ can be interpreted as the *scarcity* of disseminators around the given open-minded individual a_k. Scarcity follows a decreasing s-curve: the higher the scarcity, the lower the number of disseminators will be: if $s_k^D = 0$, all the neighbors are disseminators, while if $s_k^D \approx 1$ there are very few disseminators in the neighborhood. So, the probability that a_k becomes itself disseminator is $\beta^{OD} = s_k^D$ (algo. 1 line 3).

2) "D to S" transition: The "D to S" transition is common for both instances ODS_p and ODS_s. It is explained in algorithm 2 and is shared with the SIR model. It is based on the fact that the mean period of time that a D-individual remains in his state is fixed to *Dperiod*. Let's note that $\gamma = \frac{1}{Dperiod}$ is the removal or recovery rate.

Algorithm 2 DtoS

1. **for** each $a_k \in D$ **do**
2. a_k becomes S according a *Poisson* law with mean $\gamma = \frac{1}{Dperiod}$
3. **end for**

C. Simulation

The pseudocode for simulating the ODS models is defined in algorithms 1, 2, 3 and 4. Algorithm 3 is the pseudo-code

[1] In the experiments the constant c will be fixed to 5

for the main procedure ; at the end of the run, there are no O-individuals which could become an D-individual. Algorithm 4 allows to simulate the flow of people throughout the "world".

Algorithm 3 Simulation of the generic *ODS* model

1. $t \leftarrow 0$
2. Initialize the parameter $DPeriod$ $\{\gamma \leftarrow \frac{1}{DPeriod}\}$
3. Initialize the population size to N
4. Create N agents
   {each agent have a $state$ variable in $\{O, D, S\}$}
5. Place at random the N agents on the grid
   {each agent have a $position$ in the 2-D space}
   {each agent have a $heading$ which indicates the direction he is facing}
6. Set all the agents O except one which is D
7. **while** $\exists$ one D agent **do**
8. Call OtoD
9. Call DtoS
10. Call walk {ask all agents to move}
11. $t \leftarrow t + 1$
12. **end while**

Ensure: $\nexists$ D agent

Algorithm 4 walk

1. **for** each individual **do**
2. randomly choose his $heading$
3. forward one step
   {one step is the distance between two adjacent nodes on the grid}
4. **end for**

For experiments we have used the *NetLogo* multi-agent programmable environment[2] [16]. Simulations are performed on a $L \times L$ toroidal lattice of cell-locations, with L set to 100 (so the world consists of 10^4 cells). All the qualitative results we present are at least averaged over 100 runs[3,4]. The density of agents in the world is one, that is there are $N = 10^4$ agents[5]. To simulate the *word of mouth* contacts, we fix the neighborhood of an agent (algo. 1 line 2) to a small area of size one step around him[6].

III. Results and Discussion

As the aim is to compare the two models ODS_p and ODS_s, we have defined indicators for useful comparison and characterization of a rumor spreading: *Transmissibility potential*, *Rumor curve*, *Number of individual in compartments*, and *Spatial distribution of compartments*.

A. Transmissibility potential

This indicator is intended to report if the invasion will succeed or not. In the SIR model of epidemic spreading, there is a threshold phenomenon such that the number of *Susceptibles* that become *Infected* initially must exceed a critical threshold for an infection to invade.

The *Transmissibility potential* can be defined as the reproductive ratio $R_0 = \frac{\beta \times N}{\gamma}$, that is the number of secondary infections that result from a single *Infected* individual in a fully *Susceptible* population. If everyone in the population is initially in state S, one-individual infection (i.e. $\exists! a \in I$) can invade only if $R_0 > 1$, thus $Dperiod > \frac{1}{\beta \times N}$ [1].

As, in the ODS model, the parameter β both depends on each individual and varies in time, there may still be a need to raise the question: will the rumor pervades the entire world or will the invasion fade?

Experimental results We have conducted experiments to find under what condition a rumor will pervade or will the invasion quickly fade? Initially, we assume a single D-individual in a fully O-population.

Figure 1 shows the occurrence rate (y-axis) for a rumor to pervade according to the mean duration $Dperiod$ (x-axis) during which a *Disseminator* remains in his state. Results have been averaged over 500 runs.

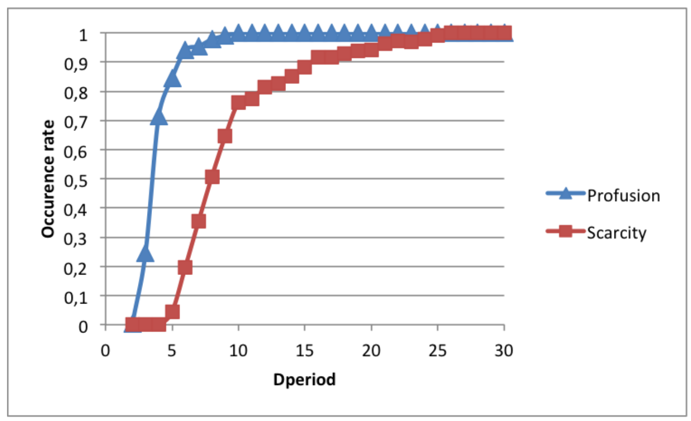


Fig. 1. Probability for a rumor to occur plotted against $Dperiod$

For a given value of $Dperiod$, we can observe a **threshold phenomenon**: for ODS_p (resp. ODS_s), the probability of invasion is 0.5 for $Dperiod = 4$ (resp. 8).

In case of scarcity, there is **no rumor invasion** until $Dperiod = 5$ while in case of profusion, the probability is quite high (equal to 0.7) for $Dperiod = 5$. In general, for a given $Dperiod$, the spreading of the story is less easy for scarcity than for profusion. In summary, in case of scarcity, the $Dperiod$ has to be much wider than in case of profusion to see the rumor spreading. This feature of ODS_s is consistent with the **longness** that is identified as one characteristic of a rumor as underlined in Section I.

B. Rumor curve

The *rumor curve* is similar to an *epidemic curve*: it shows the number of new occurrences of a disease (y-axis) *per* unit time (x-axis). By analogy, we consider the *rumor curve* that illustrates the rise and fall of new cases of a rumor over time.

The shape of such a curve provides clues that may be helpful in identifying a phenomenon. It is useful to help

[2] https://ccl.northwestern.edu/netlogo/

[3] A loop '`for each agent` a_i `do`' is implemented in *NetLogo* with the instruction: **`ask`** `agents [ commands ]`. This means that all the agents run the given commands; in addition, each time `ask` is used, the set of agents is iterated in a different (random) order. This helps preventing the model from treating any particular agent differently from the others.

[4] The order in which we examine the agents should not have a crucial influence on the nature of macroscopic results

[5] Many agents can stand on a same cell

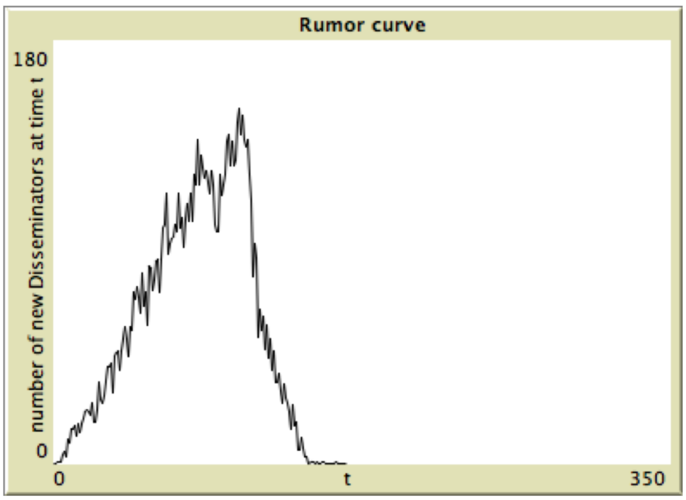
[6] One step corresponds to the size of a square cell

identifying the *speed of spreading* (or the number of ticks until no more O can switch to D) and observing when the rise is the greatest.

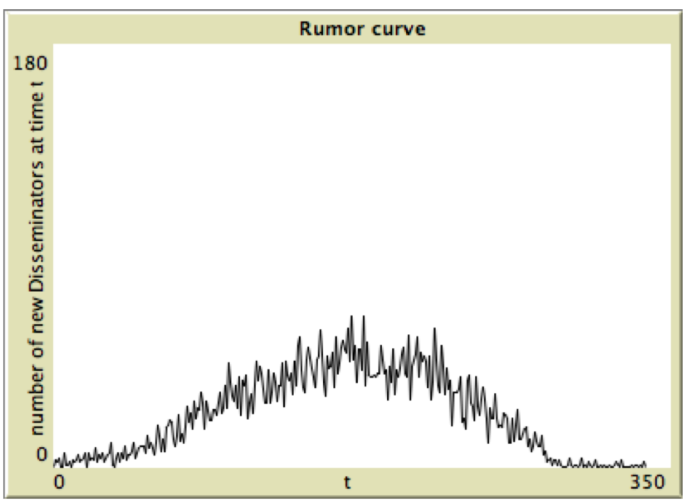
Experimental results In this experiment, we set $Dperiod = 10$ to ensure the rumor probability to be high enough.

Results are displayed in Figure 2: the shape of the curves are typical of *point source epidemic curve* and so it suggests a point common source of infections/exposure for the individuals.

However, while for epidemic spreading the curve is characterized by a uni-modal curve with a tight clustering of cases in time with a sharp up-slope and a trailing down slope, here the down slope front is steeper and even more for the ODS_p model.



(a)



(b)

Fig. 2. Rumor curve ($Dperiod = 10$), profusion (a) scarcity (b)

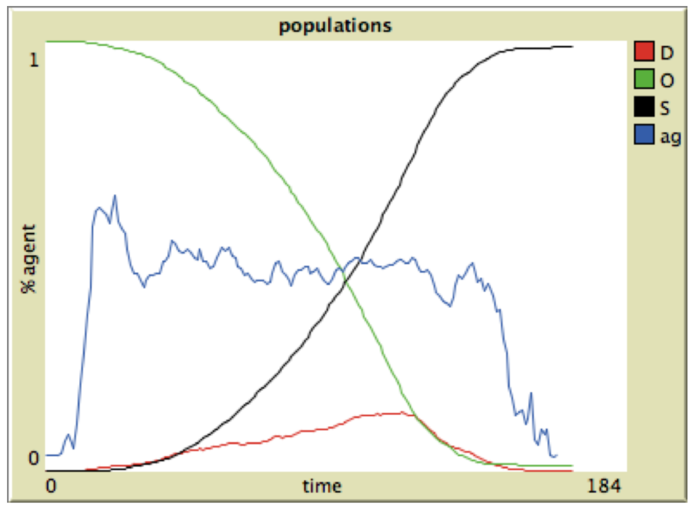
Regarding the speed of spreading, in case of scarcity, the curve shows that the process is starting much slower and has a smaller amplitude than in case of profusion. Figure 2(b) shows that the time of spreading is twice as high for ODS_s model than ODS_p.

This is consistent also with the **slowness** feature characterizing a rumor. Note that figure 2 is meaningful snapshots of curves obtained on one significant run.

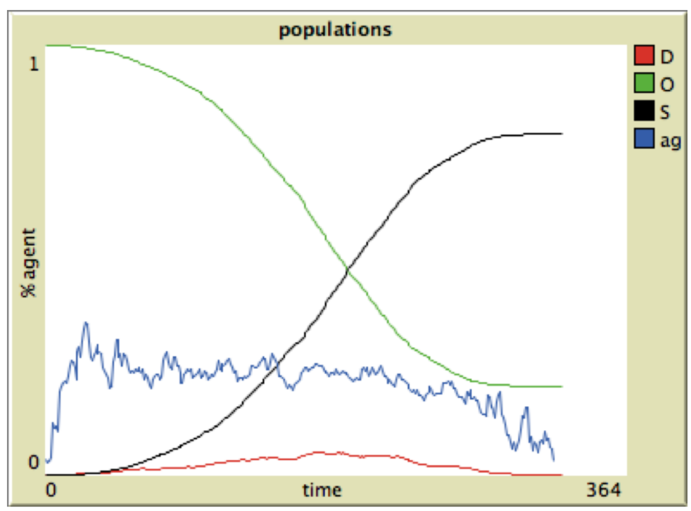
C. Number of individuals in each compartment

We have figured the evolution in time of the three indicators O, D and S that represent the proportion of individuals in each compartment respectively. The main interest is directed to the evaluation of the final proportion of individuals who were infected or ultimately hearing the rumor (i.e. S at convergence).

Experimental results Figure 3 is intended to present meaningful curves obtained on one run, it shows the portion of *Open-minded*, *Disseminator* and *Stifler* populations (y-axis) as a function of time (x-axis) when the parameter $Dperiod$ is set to 10.



(a)



(b)

Fig. 3. Proportion of individuals in each compartment as a function of time ($Dperiod = 10$), profusion (a), scarcity (b)

As for the classical SIR model, we can observe that the portion of O-individuals decreases monotonically as they are impacted by the rumor and the fraction of stiflers increases monotonically. The fraction of D-individuals goes up at first when individuals get the rumor, and then it goes down when they become S-individuals. The two models differ on some other aspects:

i) with ODS_p the time taken to reach the equilibrium state is around 160 ticks while it is twice as high, around 320 ticks for ODS_s;
ii) with ODS_p the peak in rumor is around tick 100 with about 12% of the population informed while it is around tick 190 with about 5% of the population informed;
iii) with ODS_p most people (98%) are aware of the rumor in the final population while there are still around 20% of O-individuals in the final population.

Ceteris paribus, with ODS_p the whole population finally gets the story and every individual becomes a Stiffler while the story does not reach the whole population with ODS_s.

So, at the end of the process, with ODS_s there remain individuals that are not Stiflers. This is consistent with the **incompleteness** feature that was identified as a characteristic of a rumor (Section I).

Figure 4 shows the influence of the $Dperiod$ parameter (x-axis) on the final proportion of individuals (y-axis) in each compartment and on the time taken to reach the equilibrium state.

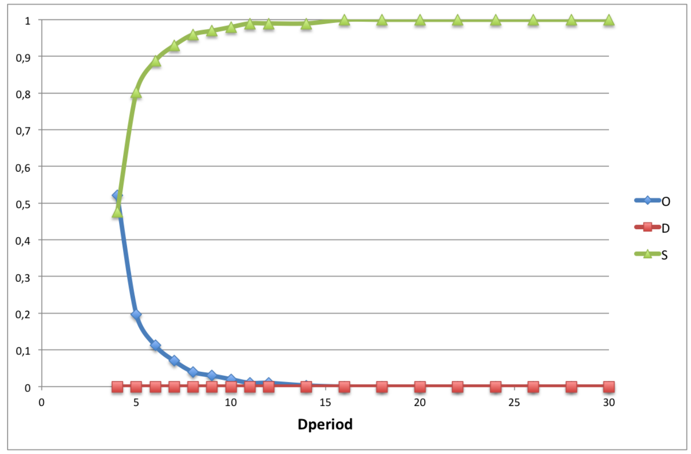
Note that in all cases the number of Disseminators is equal to zero as we look at the system when it converged:

i) with ODS_p as $Dperiod$ increases, the final proportion of O-individuals monotonically decreases from approx. 0.5 to 0, while with ODS_s the final proportion of O-individuals follows a decreasing s-curve from approx. 1 to 0. With ODS_p as $Dperiod$ increases, the final proportion of S-individuals monotonically increases from approx. 0.5 to 1, while with ODS_s the final proportion of S-individuals follows an increasing s-curve from approx. 0 to 1. Let's note that the two curves are actually crossing when the proportions are equal for $Dperiod = 8$.
ii) with ODS_p the time taken to reach the equilibrium state monotonically decreases as $Dperiod$ increases from 4 to 10, then it reaches a plateau of approx. 165 steps.
iii) with ODS_p starting with $Dperiod = 5$, the global time increases to reach a maximum of approximately 456 steps for $Dperiode = 8$, then it decreases until $Dperiod = 15$ and finally reaches a plateau of approximately 270 steps.

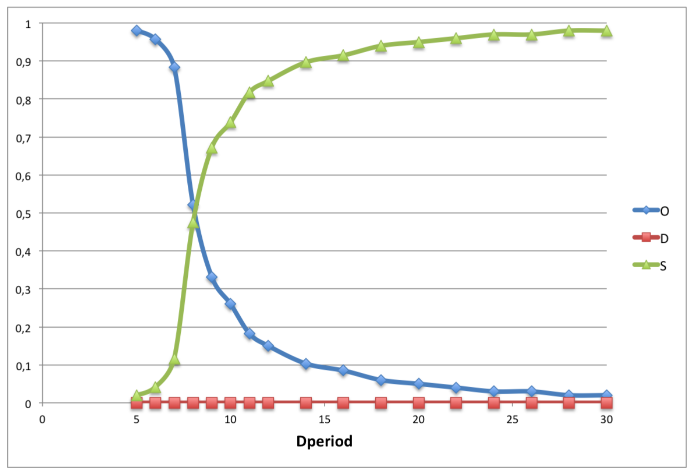
Note that Figure 4 highlights the **incompleteness** feature of the spreading for ODS_s.

D. Spatial distribution of compartments

The spatial distribution of compartments shows how individuals are distributed over time according to their compartment on the space when there is at the intial time a uniform distribution and an only disseminator placed at the center of space. To study the spatial distribution of compartments it is necessary to determine the emergence of some shapes. In a first step we visualize how the different shapes evolve, then we define a global measure of aggregation/dispersion for agents in the D-compartment.



(a)



(b)

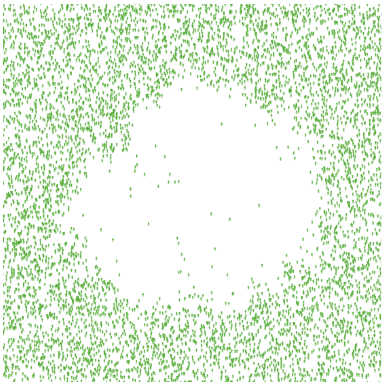
Fig. 4. Proportion of individuals in each compartment vs. Dperiod (at the end of the rumor spreading), profusion (a), scarcity (b)

Experimental results First, we can observe directly on the world-space the spatial distribution of individuals in each compartment.

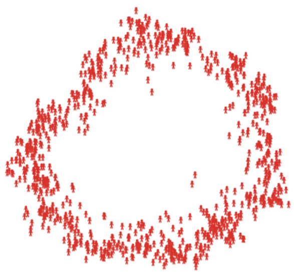
Note that initially the only disseminator is placed at the center of world. Figures 5 and 6 show the population when the rumor reaches approximately the "middle" of the space, thus at $t = 70$ (resp. $t = 120$) for ODS_p (resp. ODS_s):

i) with ODS_p, the O-individuals are removed from the center (5(a)), while with ODS_s some O-individuals remain non-impacted from the center (6(a));
ii) with ODS_p, the rumor spreads as a wave (as in the SIR model or a fire spreading model) (5(b)), while with ODS_s, disseminators tend to disperse slowly over the world (6(b));
iii) with ODS_p, O and S populations are separated by the disseminators that form a sort of frontier (5(a), 5(c)), while with ODS_s some O-individuals are integrated into the crowd of S-individuals (6(a), 6(c)).

Then we define a numerical criterion to evaluate the global aggregation level (or conversely the degree of dispersion) for



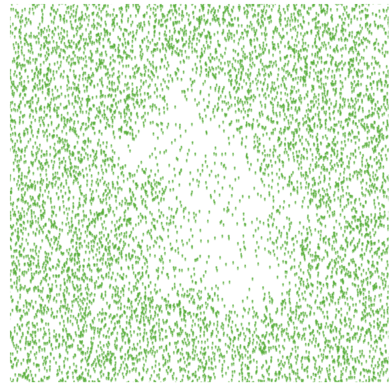
(a) $t = 70$



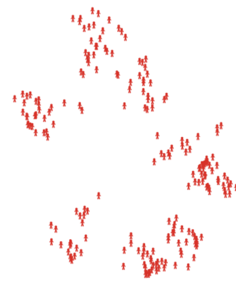
(b) $t = 70$

(c) $t = 70$

Fig. 5. Spatial distribution of compartments ($Dperiod = 10$) with profusion and O-persons (a), D-persons (b), S-persons (c)



(a) $t = 120$



(b) $t = 120$

(c) $t = 120$

Fig. 6. Spatial distribution of compartments ($Dperiod = 10$) with scarcity and O-persons (a), D-persons (b), S-persons (c)

disseminators with the *D-aggregation index* :

$$ag_D(t) = \frac{1}{|D|} \sum_{k \in D} p_k^D(t) \tag{1}$$

Low values for this index correspond to configurations where D-individuals will be spread over the world while high values correspond to configurations with more homogeneous patterns of D-individuals. The *D-aggregation index* evolution curves (see the irregular curves in Figure 3) give more quantitative results on the spatial distribution of disseminators. In both cases, profusion or scarcity, the aggregation index roughly follows a plateau with a height of 0.50 for ODS_p and 0.27 for ODS_s.

With ODS_p the rumor spreads on a *quasi* isotropic wave while with ODS_s, as D-individuals are sparsely located on the space, there are several seats of ”infection”.

This is consistent with the **sparseness** feature that was identified as a characteristics of a rumor (Section I). We can observe this feature spatially in Figures 5 and 6 and numerically as well in Figure 3 with the *D-aggregation index* distribution curve. The aggregation degree is high for ODS_p and low for ODS_s; thus this shows a high **sparseness** of individuals spreading the story in case of *scarcity*.

IV. Conclusion

In this paper, our objectives have been to propose a model of rumor diffusion that integrates the local context of individuals making the phenomenon.

The main novel property we have introduced is the *scarcity* of the story and we have checked if it might be a core dimension in the process of rumor buiding.

Agent-based simulations has shown that *scarcity* induces characteristic features of a rumor identified as longness, slowness, incompletness and sparceness.

Since simulations have been conducted in a simple framework in this first stage, we plan to extend this work. A first evolution will be to consider an explicit social network like a scale free network. Contacts allowing transmission will be then determined not only by the location of individuals but also by social constraints. Extensions of this work will be to investigate according to an incremental approach models that are more complex and more closed to real world situations regarding social environment and psychological context of people gossiping.

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