Investigation of spreading phenomena on social networks

Gergely Kocsis and Imre Varga

***Abstract* — In this paper the results of our investigations related to social spreading are summed up and concluded. In our work we studied information spreading on different network topologies. Based on a novel complex network generating method we managed to generate several test cases for social simulations focusing mainly on the case of declining social networks. We ran simulations using a previously presented model of information spreading. As a result we showed how the effectiveness of the spreading depends on the way and the intensity of declining. Later, using a modified version of the model we examined the effect of dynamically active agents in the system. As the most important result of this study we showed that increasing the activity of central nodes of a social network alone does not make the spreading significantly more effective.**

***Index Terms* — information spreading, declining social networks, complex networks, cellular automata simulation**

I. Introduction

THE investigation of social spreading phenomena has been in the focus of research for a couple of decades. However in the last 15 years with the appearance of online communities its importance has become much greater as it turned out that the models used to model classical societies based on personal contacts are also applicable for these social structures [1-3]. While the classical topics of the field were in most of the cases related to disease spreading, rumor spreading, opinion spreading, etc. [1,2], today – reflecting to the questions of the informational society – one of the most important questions is information spreading. In our work we study the spreading on the most widely known group of online societies, on social networks. In this very work we focus on to major topics: *(i.)* declining social networks and *(ii.)* networks of dynamically active agents. In the first part we try to understand how the dynamics of information spreading change on social networks that have passed their golden age, and start to decline. Based on this result we give a hint, where is the point when it does not worth anymore to spread information (e.g. advertise) on these networks. In the second part of our work we examine the change of the spreading when we assume that agents may not be always active and ready to spread or receive information. More practically our goal is to find out that in such a network what can one do to speed up the spreading only by manipulating the activity of agents. The results of our work may be used later in planning advertising campaign strategies, or anti-spam actions.

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II. Spreading on declining social networks

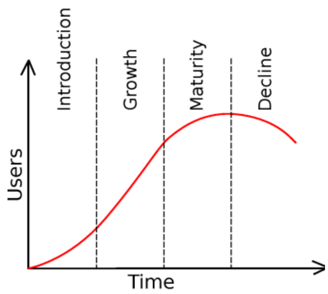

Fig. 1. Life cycle of a social network. First, when the network is introduced more and more users come and it keeps growing till the maturity. The last phase however is always declining.

As history shows, online social networks follow the universal rules of diffusion of new technologies [1] during their life cycle and go through four different stages [4] (see Fig. 1.). At the very beginning, when they are just introduced, the number of users starts to increase slowly. Later more and more users join and the network grows much faster. After a while however the system reaches its possible maximal size, and enters to its maturity phase. The aim of the owners of all social networks is of course to stay as long as possible in these latter two stages. Several examples show however (MySpace, Orkut, iwiw, etc.) that after a while social networks start to get out of fashion. This means that users leave them, they arrive to their fourth stage and the declining starts. In our work presented in [5] we focus on information spreading on social networks of this fourth kind. As one possible result we wanted to get an idea if it is worth to advertise such networks or not.

In the next three sections the two steps of this work is presented. First we model the network structure and then we model the behavior of the nodes of the network.

A. Reproducing the topology of declining social networks

To be able to run our simulations the first step was to find a way to generate topologies similar to the ones that online social networks have. Finally we worked out a two step method for this [6,7]. First we generate a network that is topologically more or less similar to a real social network in its mature phase. And then we attack it to catch the declining.

As it is widely known from the literature real social networks have a so called scale-free topology meaning that there are a huge number of actors with a low number of connections and only some that have a high number of neighbors [8-10]. More precisely this means that the degree distributions of these networks follow a power law form

($P_k \sim k^{-\gamma}$), where k is the number of neighbors and the exponent γ can be used to identify different types of networks. By comparing a the properties of a real social network sample [11] (with the degree distribution in the first place) it can be seen that unfortunately the most widely used Barabási-Albert (BA) model [12] does not provide us a similar network [13]. Namely there is a clear difference between the exponent of the degree distribution of the sample ($\gamma \approx 2.5$) and of the BA generated network ($\gamma = 3$). We found a mixed model of generating scale-free networks to be functional for our needs. Namely we used the model of Lee et. al. [14] which is a mixture of the simplest Barabási-Albert (BA) model and the model of Bianconi et. al. [15]. In both models the generation of the network starts the same way: we start from a fully connected network of m_0 nodes and then we add new nodes one-by-one to the network. Each new node is connected to the network by m edges. The difference between the classical BA model and the model of Bianconi et. al. is the way how we choose the other endpoints of these new edges. The BA model is often referred as a so called popularity driven model, since the endpoints of the new edges are selected based on the existing number of links of the nodes, i.e. a node with a bigger number of edges has a bigger probability to be the end of the new edge as well. On the other hand the model of Bianconi et. al. uses a so called fitness driven algorithm i.e. we define a random real fitness value between 0 and 1 for all nodes, and the probability to connect the new edge to a node is proportional to the product of its fitness and the number of their existing connections.

In our case the two models above were mixed in the following way [5]. We also started from the fully connected core of m_0 nodes and we also added $m = m_0 - 2$ new edges with each new node. However when we selected the endpoints of the new edges we used the classical BA algorithm with probability p, and the fitness driven algorithm with probability $1 - p$. We iterated this process till the total number of nodes in the system N_0 reached a desired value. Using this mixed model we were able to generate networks that are fairly similar to a sample network that we had containing data of almost 60 million Facebook users. Or more precisely the exponent of the degree distribution matched to the respective exponent of the sample [6].

After we became able to generate a topology that is similar to a real social network, we tried to find a way to model the declining itself. However unfortunately we have not found any published results in the literature how this declining goes. One obvious solution would have been for this problem to sample a social network through its whole life cycle (or at least at the end). However with respect to the time cost of this process we found that this is out of the scope of our current work. Instead we worked out different node-removing processes for three different possible declining scenarios. Following the terminology of the literature [16], hereafter we refer to this node-removing as *attack*. Namely we used central, peripheral and general attack to model the situations where the most popular, the least popular or random actors leave the network more likely respectively. From the algorithmic point of view this means that in all three cases we started from the above generated network of N_0 nodes and $\sim N_0 m$ edges. After this we removed $N_0 \eta$ nodes with their edges (where η is the strength of the attack). The difference between these options is that in the central case the probability of a node to be removed is linearly proportional to its degree. In the case of peripheral attack the probability of removing a node is inverse linearly proportional to the degree, while in the case of general attack all nodes are removed with the same probability.

Not surprisingly the topological examination of these attacked networks showed that the most dramatic changes appear in the case of central attack [16]. The general attack has only a minor effect on the topology, while the peripheral attack almost leads back to a previous state of the same network. (Since removing the lowest degree nodes means removing the nodes that were added at the end of the generation.)

With the use of this two step grow-and-destroy model we became able to produce networks with the same properties as declining social graphs (assuming that the declining of real social networks follows one of the three scenarios presented above). As a next step of our research we focused on the spreading of information on these topologies.

B. Information spreading

To model the spreading of information in social systems we used a simplified version of a previous model introduced by Kun et. al. [17]. In this cellular automata model the actors of the system get information from two different channels: *(i.)* there is an external source that provides a constant amount of information for all actors and (ii.) actors can also get information from each other. As an example if we look at the case of online advertising the external information channel may model public advertisements placed on web pages, while the inner channel represents discussions of users about the advertised items. In the model the actors are represented by interacting agents sitting on the nodes of an underlying topology. The agents can be in two different states: uninformed σ_0 and informed σ_1. We use the variable S_i to denote whether an agent i is in an informed state or not. If agent i is in state σ_0, $S_i = 1$, and if it is in state σ_1, $S_i = 0$. We introduce two parameters of the system to describe the sensitivity of agents to the information channels. The parameter α tells how sensitive are the agents for the inner information channel, while β describes the sensitivity for the external information channel. Originally α and β were both random real numbers for each agents, however based on the results of the original study of the model we set both of them to be the same for all agents.

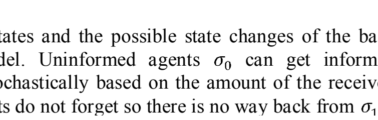

Fig. 2. The states and the possible state changes of the basic information spreading model. Uninformed agents σ_0 can get informed σ_1 or stay uninformed stochastically based on the amount of the received information. Informed agents do not forget so there is no way back from σ_1 to σ_0.

The model evolves in discrete time-steps using synchronous update rules. i.e. the state of agent i at time t depends on the states of itself and its neighbors at time $t-1$. In each time-step agents get stochastically informed based on the amount of the received information at the given time-step (see Fig. 2.). The probability of changing to informed is

$$A(\alpha,\beta) = 1 - \exp\left(-\left(\alpha S_i \sum_{j=1}^{n_i} (1 - S_j) + \beta S_i\right)\right), \quad (1)$$

where in the *exp()* function the amount of information received by agent i is caught. Namely in the sum we add all the information coming from the informed interacting partners and multiply the result with the sensitivity to the inner channel. Then we add the amount of information from the outside multiplied by the respective sensitivity. Note that for simplicity both the amount of information coming from the external source in one time-step and the amount of information coming from an informed neighbor are set to 1 "unit".

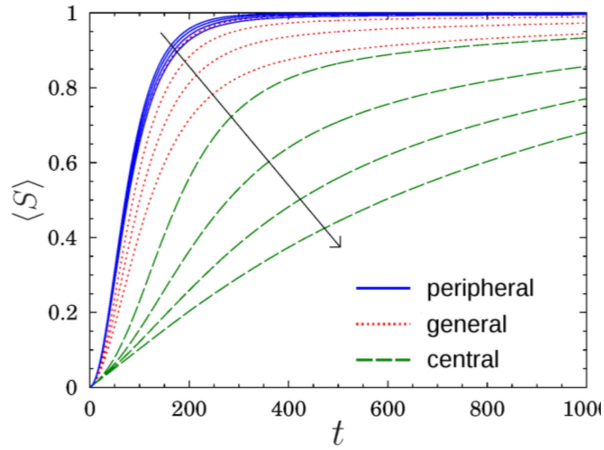

Fig. 3. The effect of the attack on the spreading. On the figure the ratio of informed agents in the system $\langle S \rangle$ is presented as a function of time t Different colors and styles are for different ways of attack. Note that with the increase of the amount of removed nodes (marked by the arrow) the spreading slows down in all cases but in the central attack case especially.

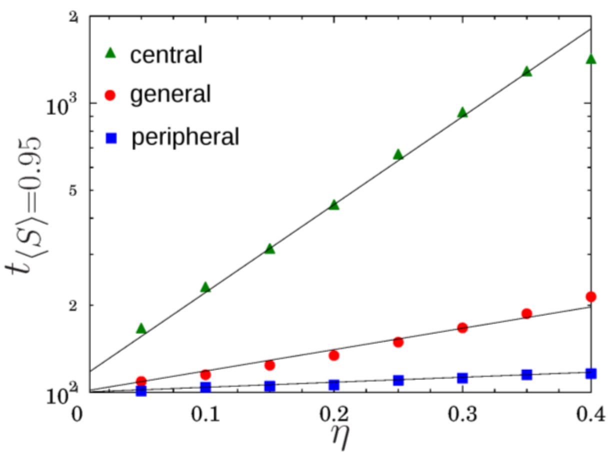

Fig. 4. The time needed to reach an almost homogeneous informed state in the system depends on the attack strength exponentially. Note that this exponential form is independent of the exact type of the attack, however different attack types result in different levels of dependence.

Since our main goal here was to study the effect of the declining of the network on the spreading, and not the spreading model itself, in all our simulations we used the same parameter set that proven to be quite good in representing real life scenarios [17]. Namely we set the sensitivity parameters to α=0.01 and β=0.001.

C. *The effect of declining*

To study the effect of declining on the spreading of information, we ran computer simulations on various network topologies attacked in different ways. As a key property of the spreading, we focused on the ratio of informed agents in the system $\langle S \rangle$ as a function of time t. Our results showed that the spreading process is qualitatively independent of the system size, but it highly depends both on the way how we attack the system, and the strength of the attack. It can be seen in Fig. 3. that while peripheral attack hardly affects the spreading even in the case of removing 40% of the agents, general attack makes the spreading increasingly slower as more and more nodes are removed from the network. In the third case, when we applied central attack the spreading dramatically changed. Even for a small number of removed agents the spreading gets much slower than in the case without attack. Of course this effect again increases with the increase of the amount of removed nodes.

Another interesting result of our work was found when we plotted the needed time for the system to reach an almost homogeneous informed state $t_{\langle S \rangle = 0.95}$ (i.e. where 95% of the agents are informed) as a function of the strength of the attack η. We had to use this almost homogeneous state instead of totally homogeneous one because close to saturation the evolution of the system slows down dramatically implying that the respective simulation time increases in this sense as well. However this almost homogeneous informed state also fits our needs to describe consensus. The results showed that the needed time to reach this state depends exponentially on the strength of the attack (see Fig. 4.). In a practical sense this result means e.g. that if a social network is losing its users linearly the effectiveness of information spreading (e.g. advertising) is decreasing much faster.

III. THE EFFECT OF THE INACTIVITY OF AGENTS

In the first part of our research we focused on systems, where the agents of network were handled to be always active. Most social networks however do not share this property [18,19] so we found it reasonable to examine how the activity of agents affects the spreading. Even though the topic is marginally present in some related works [20,21], we found that the exact question have not been answered yet. What we did to get a better insight, is that we modified the previous model and examined the behavior of it in networks from simple square lattices to complex topologies [22]. Note that in this case instead of reactions for the underlying topologies we focused on the spreading itself.

A. The modified model

To make our model able to describe activity of the agents we added a new parameter of the agents $\gamma_i \in [0;1] \in \mathbb{R}$ to describe how often an agent goes inactive. This means that for a value of γ_i close to 1 the agent is almost always inactive while in the opposite case when γ_i is close to 0 it is active in most of the time. Note that in contrast to α and β, γ_i is not a system wide parameter but it can be different for different agents. However at the beginning of our investigations to make our results more clear we set $\gamma_i = \gamma_j$ for all $i, j \leq N$ where N is the number of nodes. The property that agent i is active or not is caught by the variable R_i, where $R_i = 0$ if the agent is inactive, and $R_i = 1$ if it is active. By introducing these new parameters of the agents of course the number of possible states is increased and the state-change rules themselves have changed as well.

First of all, based on the informed/uninformed property S_i and the activity R_i now agent i can be in four different states $\{\sigma_0, \sigma_1, \sigma_2, \sigma_3\}$. These possible states are presented on Table 1. The basic state change rule related to the activity of agents is the following: In each time-step agent i stays or changes to inactive with probability γ_i and stays or changes to active with probability $(1-\gamma_i)$. The most crucial state-change of course in this case again is the change from the active uninformed state σ_0 to active informed state σ_1 (Inactive agents can not get informed or spread information, and informed agents do not go uninformed regardless of their activity). This state-change rule again depends on the received information, however to catch the effect of our new parameters we had to alter eq. (1) a little bit. In this modified model the probability of agent i to get informed is:

$$A'(\alpha,\beta) = 1 - \exp\left(-\left(\alpha S_i R_i \sum_{j=1}^{n_i}\left((1-S_j)R_j\right) + \beta S_i R_i\right)\right). \quad (2)$$

Note that eq. (2) differs from eq. (1) only through the parameters R_i and R_j, where these parameters describe that inactive agents can not receive or spread information. Based on this modified equation and the parameter γ_i. The state-change rules are presented on Fig. 5.

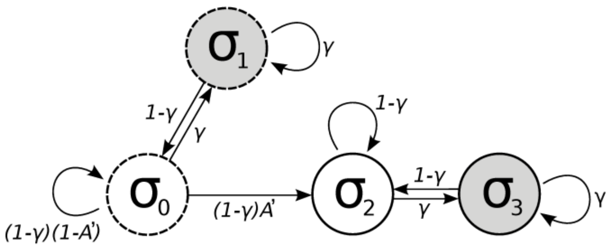

Fig. 5. The states and the possible state changes of the modified information spreading model. Agents can stay or change to inactive (*grey filled*) with probability γ and stay change to active with probability $(1-\gamma)$. The state-change from uninformed to informed is led by the modified probability A'.

In order to study the evolution of our modified model we ran simulations on different network topologies. As a first try to get a qualitative insight of the evolution we used a small regular square lattice. This simple topology made it very easy to visualize what is happening, and compare the original and the modified model. Snapshots of a system containing $N = 100x100$ agents at different time-steps are presented on Fig. 6. In the first row the pictures are from the original model while the second row is for the modified model ($\gamma_i = \gamma = 0.5$). Our results show that the evolution of the system does not change qualitatively however it takes noticeably more time for the modified model to reach an almost similar state as the original model. This means that the way of the spreading is

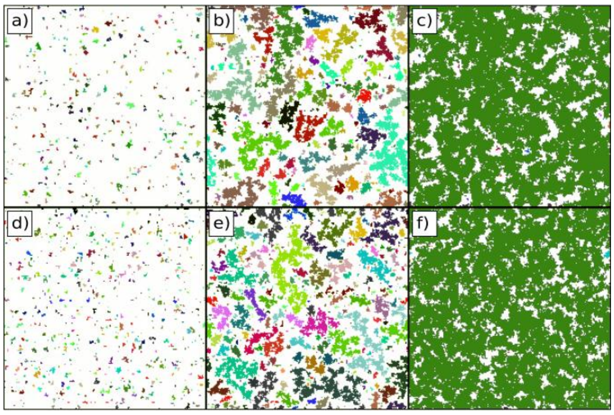

Fig. 6. Snapshots of the evolution of the model on a square lattice of $N = 100x100$ agents. *a, b* and *c* are for the original model while *e, f* and *g* are for the modified model including dynamic activity. Note that the respective pictures in the two rows show the same structure, however in the second row a longer interval of time is covered. (The snapshots were made respectively for *a, b, c, d, e, f* and *g* at $t = 100, 250, 375$ and $t = 350, 800, 1250$. Colors identify separate clusters of informed agents.)

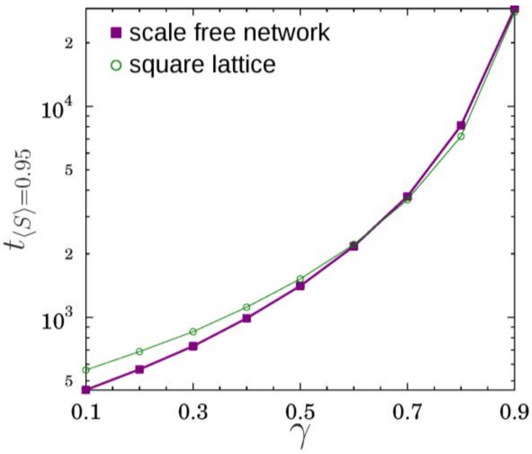

Fig. 7. The time needed for the system to reach an almost heterogeneous informed state in the case of square lattice $N = 10^6$, and on a scale free network similar to real social network topologies. The dependence in both cases are faster than exponential.

TABLE I
POSSIBLE STATES OF AGENTS

	$S = 1$	$S = 0$
$R = 1$	σ_0: active, uninformed	σ_2: active, informed
$R = 0$	σ_1: inactive, uninformed	σ_3: inactive, informed

Depending on the values of S and R agents can be in four different states. S describes whether an agent is informed (0) or not (1), while R tells whether the agent is active (1) or not (0). The values of S and R have been chosen so that the form of the later state-change rules stay reasonably easy.

not changed, but it is much slower. Of course this slowing is not similar for different values of the probability of being inactive γ. In order to find out how the spreading depends on the probability of being inactive we plotted the time needed to reach an almost homogeneous state as a function of the parameter γ. The results are presented on Fig. 7. Note that we again used the 95% informed state of the system ($\langle S \rangle = 0.95$) because of the same reason as in the case of the examination of declining social networks. On the plot we used a semi-log scale in order to show that the dependence of $t_{\langle S \rangle = 0.95}$ is faster than exponential.

Our observations on the square lattice gave us a first insight of the effect of the inactivity of agents, however since we wanted to get results that are closer to real social systems we had to apply complex network topologies again. So as a next step we ran the modified model on a scale-free network. Based on a Facebook data sample we also used previously [11], this network was generated so that it has similar topological properties as online social networks, however to make our simulations faster we used a smaller number of nodes. What we have found in this case was very similar to the square lattice case despite of the obvious differences in the topology. On Fig. 7. we also plotted the time to reach the almost homogeneous state as a function of time in the case of our scale-free generated network. Note that not surprisingly, especially at small values of γ, spreading on the scale-free network is a bit faster. However by observing the whole picture the same sentence becomes true again: As the probability of being inactive increases linearly, the time needed to reach the almost homogeneous state $t_{\langle S \rangle = 0.95}$ increases faster than exponentially.

B. Heterogeneous activity

In the previous cases we always assumed that all agents of the system have the same probability of being inactive i.e. $\gamma_i = \gamma$ for all $i \leq N$. However this is not a realistic assumption in the case of social networks. Thus the next step of our research was to examine the effect of heterogeneous activity in the system.

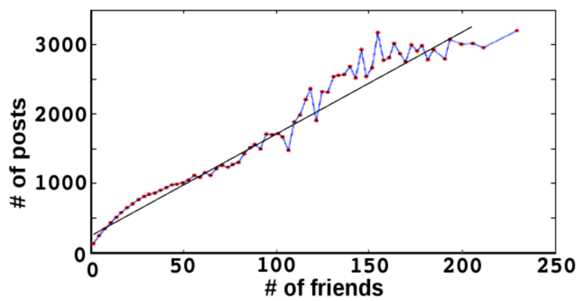

Fig. 8. The activity of users in a social network is linearly dependent on their number of friends. Here we defined activity as the number of posts a user posts in his/her timeline. Figure based on [23].

In order to get realistic results we studied the work of Huberman et. al. [23] and found that in real social networks the activity of users is in linear connection with the amount of friends (see Fig. 8.). In our case this means that if we would like to make our model more realistic, we have to make γ_i a function of the degree of agent i. To do this we chose the following form:

$$\gamma_i = \gamma \left(1 - \frac{n_i}{n_{max}}\right), \tag{3}$$

where n_i is the number of connections of agent i and n_{max} is the highest degree in the system. Eq. (3) means that the lowest degree nodes keep their level of activity, while agents with a lot of connections become more active. In the case of scale-free networks this simply means that we make the central nodes more active.

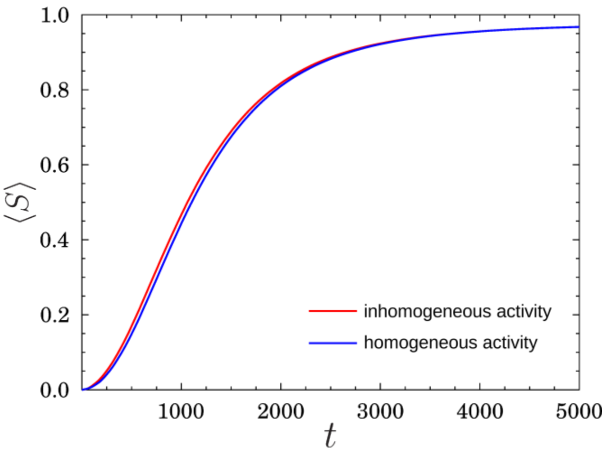

Fig. 9. The average amount of informed agents in the system as a function of time t in the case of homogeneous and inhomogeneous activity. Note that the increased activity of high degree nodes does have as much impact on the spreading as one would expect.

As a result of our simulations surprisingly we found that despite of the inhomogeneous probability of being inactive the spreading process shows hardly any noticeable changes. On Fig. 9. we plotted the average amount of informed agents in the system $\langle S \rangle$ as a function of time t for both homogeneous and inhomogeneous inactivity. It can be clearly seen that making the central nodes of the network more active does not have a major effect on the spreading. In a practical sense this would result for example that in the case when one wants to improve the efficiency of an online advertising campaign, making the most active user more active alone does not have the required effect. The reason of this is that however these central nodes became more active and ready to spread information more likely, since the contacts of them are still inactive with the same probability there is no one to interact with. A possible solution would be of course to focus instead on the increase of the activity of all the agents of the system (i.e. decrease the value of γ, see Fig. 7.).

IV. DISCUSSION

In this paper the results of our investigations related to spreading phenomena on social networks have been presented. Our work built up from three major parts. At first, starting from a network sample we developed a way to generate network topologies with similar key properties as real social networks. To do this we examined the topological properties of the real and the generated networks. With the use of an information spreading model we also studied how spreading behaves on these networks. As a second part of our research we investigated spreading on declining social networks.

Namely we studied the effect of different types of attack on the spreading, using the same information spreading model as above. We showed that independently of the type of the attack the time to reach an almost fully informed state of the system depends exponentially on the strength of the attack (from 0% to 40% nodes removed). In the third part of the work we examined how the presence of dynamically active/inactive agents effects the spreading. For this we altered the original model a bit, and introduced some new states, and state-change rules. We found here that even though the dynamic activity does not change the spreading qualitatively, it slows it down. Namely the needed time for the domination of informed agents shows faster than exponential dependence on the probability of being inactive. Finally we studied the effect of inhomogeneous activity and found that increasing only the activity of high degree nodes in social networks does not have the expected result. The activation of low degree nodes is also needed to make the spreading significantly faster.

It is clear that additional investigations are required to make our findings more precise. However these results may be found useful in the future when planning online advertisement campaigns or anti-spam actions. As a further step we would like to examine spreading phenomena on spatially and temporally dynamic networks in order to take one more step to bring our results closer to reality. It is also known from the literature that beside the degree distribution the structure of the community also plays an important role in spreading phenomena [24]. Based on this idea it would be also promising to examine the spreading on networks with different community structures.

V. ACKNOWLEDGEMENT

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