The Mechanism for Spreading Online Reputation

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Abstract

Acquiring a good reputation and being able to convey to an audience the good image of a company or a destination is a vital issue in today's virtual world. The quality of what is transmitted and the influence of social networks through which the promotional or marketing messages are spread are the major elements at play. This work examines the second issue: how messages are spread over a social network. Through a series of numerical simulations this paper highlights the main factors affecting the diffusion of information in a social networked group and clarifies the role played by different actors with respect to the influence and importance of their position in the network.

Keywords: online reputation, social networks, information diffusion

Introduction and background

Since the dawn of the Internet and over the course of the history of the Web, one of the major issues for all those wishing to *play the game* has been one of visibility accompanied by the wish (or need) to satisfy users in order to increase awareness of one's own online presence and convert this awareness into higher returns (usually measured in terms of image, revenue, number of visitors).

In the first phase (which can be identified by what is known as Web 1.0) the focus of researchers and practitioners was on the intrinsic attributes of the online presence (the website) and on its position on the part of the tools provided to search and access the Network (search engines). It was an era characterized by a wealth of publications, scholarly and otherwise, dealing with the evaluation of the different aspects of a website such as structure, content, usability, usefulness (see for example Ilfeld & Winer, 2002; Law et al., 2010; Mich et al., 2003; Morrison et al., 2004; Park & Gretzel, 2007) and with the importance and the requirements for a good level of popularity and ranking on the result pages of the most widely used search engines (see for example Bifet et al., 2005; Green, 2003; Sen, 2005).

Today the visibility issue has assumed a different meaning. In a cyberspace strongly characterized and influenced by all those technologies and functionalities collectively known as Web 2.0, the problem is how to exploit the growing trend of online socialization. Probably it is too early to try to find sound methods to derive monetary advantages, but the current virtual environment is more than suitable for use as a means to propagate the image and the reputation (good or bad) of all companies, organizations or individuals which, in a way or another, make use of electronic media.

In trying to understand the basic mechanisms that rule this phenomenon, one can find instruction from the most recent studies on complex networked systems. In fact, the spreading of ideas, opinions and news has been extensively examined and found to be highly dependent upon the structural features of the networks which serve as a medium (Barrat et al., 2008; da Fontoura Costa et al., 2011; Newman, 2010). It is thus possible to find a broad set of work popularizing the network analysis concepts in an attempt to find the best possible ways for increasing the speed and extent of the spread of information which is the final objective. One point that is made by many is the role and the importance the most *influential* elements in the networks considered (blogs, online social networking sites, file sharing sites etc.). These, as network science has shown, are the better connected members in a social network and play a significant role in all diffusion processes (Galeotti & Goyal, 2009; Watts & Dodds, 2007; Ziegler & Lausen, 2005).

Two issues are important here. The first one concerns the determinants that make a network element (normally an individual) *influential*. There is good literature available on this very topic. Both scientific works and popular articles discuss in detail the main factors that assign this status. The most cited elements are type and frequency of activity on the online social networks (OSNs), quality and diversification of the contributions (Huffaker, 2010; Pulizzi, 2011; Trusov et al., 2010; van Eck et al., 2011) and even the time of day or the day of week (Zarrella, 2011). Obviously, a number of tools have been made available online based on these elements which have the objective of identifying the opinion leaders (Stratmann, 2010).

The second issue concerns the role of the network position of the influentials, the quantity and the quality of their connections to other members of the network. The idea, as expressed by Hinz et al. (2011: 30) is that: "*marketers should pick highly connected persons as initial seeds if they hope to generate awareness or encourage transactions through their viral marketing campaigns since these hubs promise a wider spread of the viral message*". The social graph is thus examined and possible measures which could give such hints are calculated. In network science these measures are well known as centrality metrics (Newman, 2010). A number of them exist and a number of studies have pointed out characteristics, roles and importance in the different possible topological structures which can be exhibited by a network.

The aim of this contribution is to examine this latter issue and assess the characteristics of a dynamic diffusion process when initiated from influential nodes in a complex network as opposed to what happens when randomly chosen nodes are the starting points (seeds) for the process. A series of simulations highlights these characteristics and show the differences found in terms of efficiency and effectiveness.

The paper is organized as follows. The following section presents a short discussion of the diffusion mechanisms, and then the methods and the materials used are described. A further section contains and discusses the results, and the last one reports on concluding remarks and indications for future research.

Diffusion mechanisms

The most commonly used way for modeling the flow of information or ideas through a network are based on an analogy with the diffusion of a disease (Bailey, 1975; Hethcote, 2000). The analogy is clear: a sick individual infects some other individual with whom a connection (contact) exists, in the same way that a knowledgeable individual is able to transfer information or communicate ideas to some other member of the network.

A long tradition of epidemiology studies has dealt with the issue of describing the spread of a disease in a population of living organisms. From Daniel Bernoulli's analysis of smallpox at the end of 18th century, mathematical modeling and numerical simulations have helped in the study of the effects of bacterial, parasitic and viral pathogens infections and the possible countermeasures.

The mathematical models used are based on the cycle of infection in an individual. The 'host' is first considered susceptible (S) to the disease. Then, if exposed to the infection it becomes infected (I) and is considered infectious for a certain period of time. Finally, the individual can recover (R) by acquiring some immunity or by being 'removed' from the population. These basic elements (along with some possible variations) are used to characterize the different models which are identified by the initials of the types of infection considered. Therefore, we have SI models, in which hosts can be only susceptible or infected; SIS models in which they go through a complete cycle: susceptible, infected, then susceptible again; and SIR models which consider susceptible individuals that are infected and end their process by being removed (i.e.: immunized or eliminated from the initial population). Again the analogy with knowledge flow though a destination network is clear - stakeholders may be susceptible to receiving new knowledge, but until they are 'infected' knowledge transfer does not take place.

The SIS model, among these, looks quite suitable to describe the diffusion of information in a social network. In this, actors are ready (susceptible) to acquire the information transmitted; when they come into contact with an *infected* individual they accept the information with a certain probability which may represent the attitude or the willingness the actor has to accept the information; at the same time, an infected element, with a certain probability, *forgets* what has been accepted in a previous exchange and becomes susceptible again.

The mathematical treatment has much in common with the one used to describe the percolation phenomenon (the diffusion of a fluid through a porous medium). The curves describing the results of the infection are mostly s-shaped curves belonging to the family of logistic curves, and are in many cases similar to those representing the growth of a population. Traditionally, all epidemic models have assumed homogeneous mixing: i.e. all individuals are equally able to infect all others, and have taken into account a random distribution of the contacts between individuals that are responsible for the infection (diseases spread through some kind of contact between the population elements). In some cases the models are refined by making assumptions about the population affected: e.g. the way the hosts react to the infection, recover from the disease or are removed from the population. Normally the process is ruled by a critical parameter

representing the combined probability of infection and recovery. This is the so-called basic reproduction number (or coefficient, ratio) R_0 = [probability to be infected / probability to recover guides the process]. When R_0<1 no disease is spread and the infection dies out, when R_0=0 the infection is endemic and when R_0>1 we have an epidemic diffusion which can span across the whole population.
Individuals in a population can be represented as nodes of a network in which the contacts between them constitute the links. Recent advances in the study of complex networks have allowed a reconsideration of epidemic diffusion models in order to take into account the effects of non-homogeneous topologies exhibited by many network (Grönlund & Holme, 2005; Kuperman & Abramson, 2001; Pastor-Satorras & Vespignani, 2001). These effects are quite important. For example, it has been known for a long time that epidemiological models show clearly defined threshold conditions for the spread of an infection. This threshold depends on the density of the connections between the different elements of the network. However, this condition is valid only if the link distribution is of a random nature, while in some of the structured, non-homogeneous networks that make up the majority of real systems, this threshold has been shown to be non-existent; in other words, once initiated, the diffusion process unfolds over the whole network (López-Pintado, 2008; Pastor-Satorras & Vespignani, 2001).
The formulation of an epidemiological model leads to the layout of a system of differential equations which can be, at times, difficult to deal with. In the last few years however, the availability of accessible computational tools, (both hardware and software) has fostered the development and the usage of numeric simulation models.

Data and methods

The best way to test our question would be to perform a series of experiments by initiating the diffusion of a piece of information on an OSN both by a randomly chosen individual and by an influential member of the community and compare the results in terms of speed and extent of diffusion. Rather obviously such experiments are quite difficult, if not impossible, to be performed (at least from a practical point of view). Fortunately, a numerical simulation, when conducted according to the most rigorous methodologies (Axelrod, 2006; Garson, 2009; Mollona, 2008), can provide results with a comparable reliability.
In the study of complex networks, the *importance* of a node (an actor in a social network) is traditionally assessed by measuring its centrality. Several metrics have been proposed for this assessment, they take into account different structural characteristics and therefore have different interpretations in a social setting; they are all based on the analysis of the patterns with which connections between nodes are distributed. The most known and widely used are (for formal definitions and formulas see (da Fontoura Costa et al., 2007; Newman, 2010):

- *degree*: the number of direct connections to the immediate neighbors of the node;
- *closeness*: the average distance to all other nodes in the network;
- *betweenness*: the frequency with which a node falls between all unordered pairs of other nodes on the shortest paths connecting them;

- *eigenvector*: calculated by using the matrix representation of a network and based on the idea that a relationship to a more interconnected node contributes to the own centrality to a greater extent than a relationship to a less well interconnected node;
- *PageRank*: similar to the eigenvector, is based on the idea that the centrality of a node is a function of the centralities of all nodes connected to it. In this case, following Gneiser et al. (2011) a symmetrized version of the metric was used in order to take into account the symmetric nature of the links in a social network ;
- *Katz score*: the affinity between nodes measured as a weighted sum of the number of paths between them.

These metrics can represent different meanings of importance. An actor can be important if she has many connections (friends) or can quickly reach all other actors in the network (closeness) or is a bridge or information broker between different parts of the network (betweenness). Moreover the actor’s importance can be greater if the connections are set, even indirectly, towards the other most important elements of the network (eigenvector, PageRank or Katz score).

In order to have a realistic environment for the simulations, Facebook was chosen as testbed. Since the privacy settings of the platform do not allow indiscriminate extractions, ten users volunteered to provide the data of their friendship networks. These were extracted with the help of NameGenWeb, a Facebook application for downloading social network data (Hogan, 2008). The program queries the Facebook API (Application Program Interface) for the list of the friends of an individual along with their ties to each other. Data are then saved in a format usable by other network analysis programs.

The number of nodes of the networks collected range from 372 to 2220. The analysis of their structures show a good similarity with those reported in the literature by wider studies conducted on Facebook and other similar platforms (Kumar et al., 2010; Pallis et al., 2011). As an example, Figure 1 shows the cumulative degree distributions of the smallest and the largest networks examined. The curves are compatible with a long-tail distribution and their main part follows well a power-law behavior typical of many complex networks. The initial curved portion (at low degrees) is again typical of networks with finite limited size (Newman, 2010).

The networks are relatively well connected, the average size of their largest component is of about 95% (for the simulations these largest components were used). The centrality metrics described above were calculated for all networks, and the results were normalized (values were divided by the number of nodes – 1). Given the different meanings of importance expressed by the different metrics, no single parameter can give a full representation of the importance of an actor in a social network. In order to overcome this issue a synthetic general measure was calculated, for each node, as the geometric mean of the centrality metrics. An aggregate measure has shown (see for example (Cooper et al., 2009) to be a good indicator in cases such as the one examined here and can be used as a good indicator for our purposes.

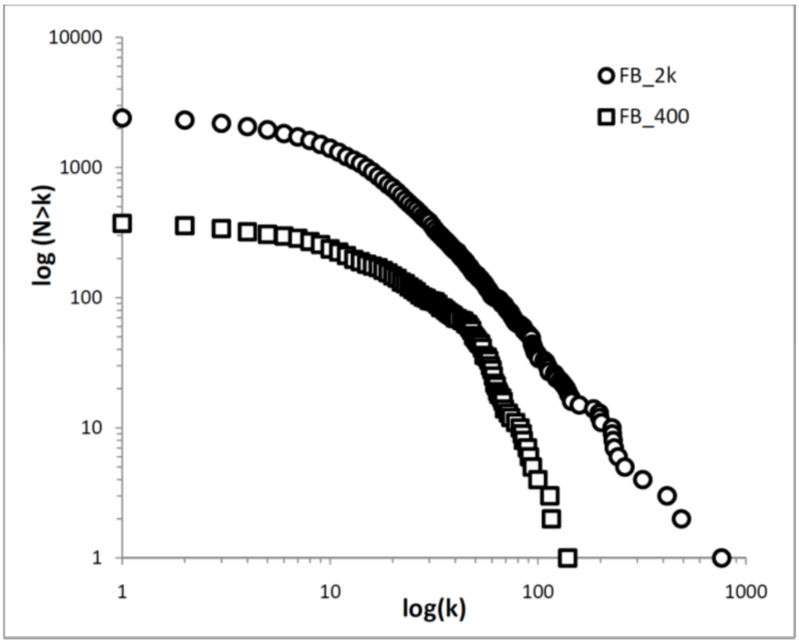

Figure 1. Cumulative degree distributions (log-log plot) of the smallest (FB_400) and the largest (FB_2k) networks examined. The networks have 372 and 2220 nodes.

The overall simulation was performed according to the following scheme:

- one or more nodes (the initial seeds) are selected as initiators of the *infective* diffusion;
- at each time step the nearest neighbors of an *sick* node are infected with probability p_i;
- at the same time, a sick node recovers and becomes susceptible again with probability p_s.

The probabilities used in the simulations are $p_i = 0.035$, $p_s = 0.03$, therefore we have $R_0 > 1$ and the diffusion is epidemic, i.e. it will reach the whole population.

Three types of simulations were run. In the first one a single starting node is selected randomly, in the second three nodes were selected randomly, in the third the three nodes with the highest importance (calculated as described above) were chosen as initial points for the diffusion process.

The output is the number of nodes infected at each time step. The simulations were run ten times for each network and all results were averaged.

Results and discussion

The results of the simulation runs are shown in Figure 2 and 3. The first one reports the cumulative number (averaged) of individuals who have accepted the information transmitted. The difference between the three simulations is clear and the curves unmistakably show that choosing more seeds among the best connected elements of the network increases the speed and the overall efficiency of the diffusion process.

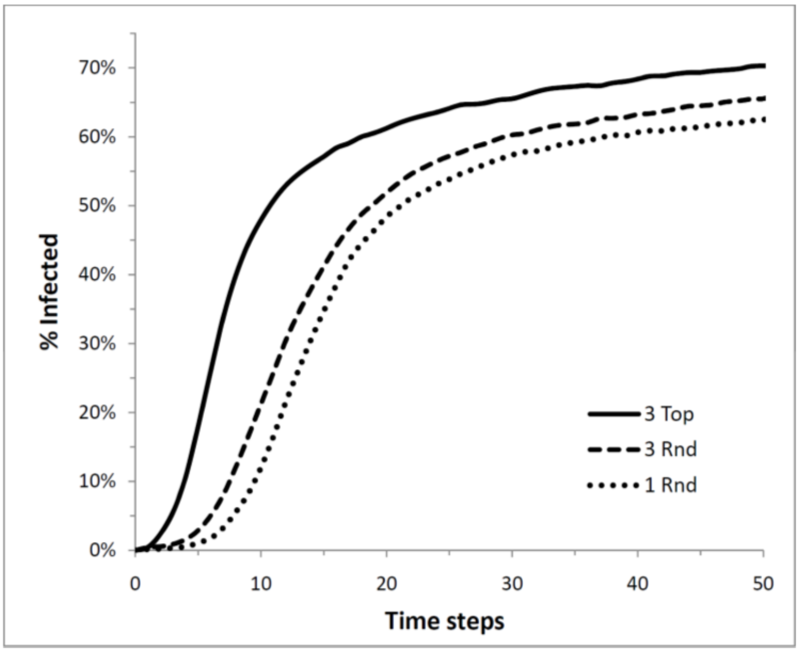

Figure 2 Cumulative number of informed individuals averaged over all networks and all simulation runs as function of time for the different seeding choices: 1 Rnd = one random, 3 Rnd = three random, 3 Top = three most important nodes.

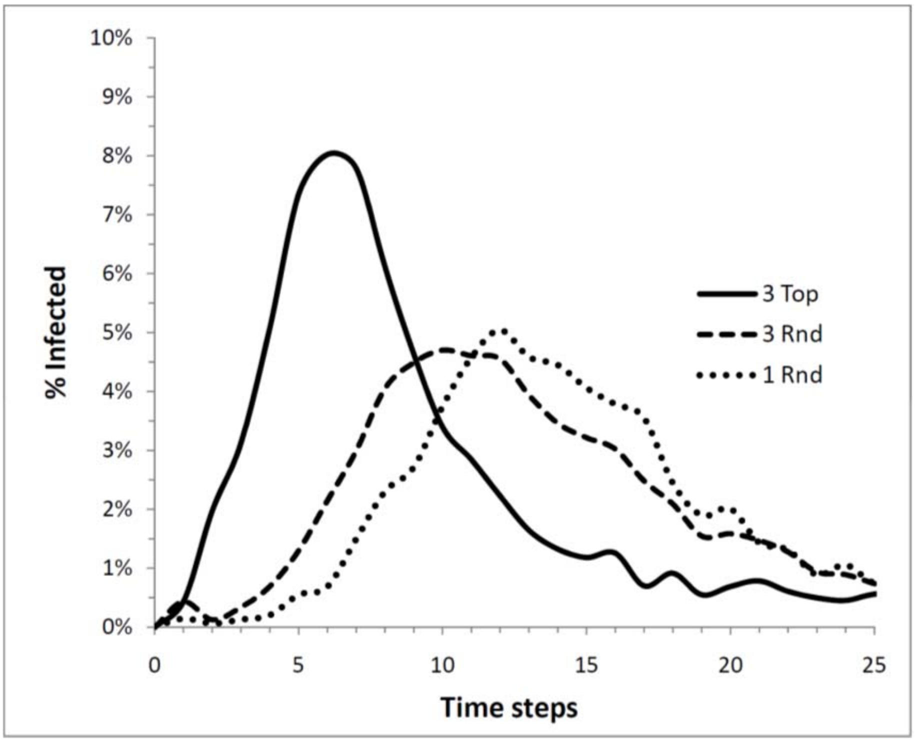

Figure 3 Number of informed individuals averaged over all networks and all simulation runs as function of time for the different seeding choices: 1 Rnd = one random, 3 Rnd = three random, 3 Top = three most important nodes.

Examining Figure 3, which shows the differential diffusion curves, it is possible to measure the difference in time (speed of diffusion) and the height (extent of diffusion) of the peaks. The difference in timing between 3 using a single random seed (1 Rnd) and three random initial points (3 Rnd) is of about 20% and that between the start from the three most important nodes (3 Top) and three random (3 Rnd) reaches 67%. While the heights of the curves are relatively equal for the random choice (difference is of about 7%), the curve representing the three top nodes is almost 70% higher. A Kolmogorov-Smirnov test confirms that the difference between the 3 Top curve and the 3 Rnd is significant with a p-value $<< 10^{-4}$ while the difference between the two random simulations is significant only at the 0.1 level. This result is somehow expected given the full connectedness of the networks examined. In this case, in fact, given the absence of disconnected components, the difference between choosing one or three starting points is small. These results fully confirm our initial hypothesis.

Concluding remarks

In a Web 2.0 world, the issues of image, reputation and trust play a crucial role for the people and the commercial organizations which actively use these technologies. Two factors determine the success in this regard. One concerns the quality of the online activity, and the capability of the entity involved to present itself as competent and reliable together with the ability to produce materials which are deemed interesting and attractive by the public. This is an issue that marketing and management experts, sociologists and psychologists have addressed and continue to study with a wealth of investigations that may guide the different actors in better understanding (and then exploiting) the current preferences, attitudes, needs and behaviors of the general online audience (see for example Fombrun & Shanley, 1990; Gotsi & Wilson, 2001; Hoffman et al., 1999; Keh & Xie, 2009; Minkiewicz et al., 2011; Walsh et al., 2009).

The second important factor concerns the role played by the structural characteristics of the network of relationships that connect the users of the various Web 2.0 environments. Recent literature in many diverse disciplines has shown that the topology of a network, the way in which the links connecting the different elements are shaped, has a decisive effect on the diffusion of information on the network. More than that, the *choice* of the starting points for the diffusion heavily affects the whole process in terms of speed, extent and efficiency (Barrat et al., 2008; da Fontoura Costa et al., 2011; Newman, 2010).

By using a series of numerical simulations, this work has highlighted these phenomena and has shown that when initiating the process from multiple well chosen elements, the diffusion is much faster and reaches a higher number of targets. The identification of the most influential nodes was been done by using purely topological considerations, i.e. the quality and the quantity of the links each network element has. These, as demonstrated in the scholarly and popular literature, are a good predictor of the perceived importance of the actors involved (Cooper et al., 2009; Ilyas & Radha, 2011; Kotowski & Boster, 2007; Watts & Dodds, 2007). Obviously, when adding to these considerations, those of more qualitative nature (examples can be found in Pulizzi, 2011; Stratmann, 2010; Zarrella, 2011), and possibly connected with a specific platform of interest, the final outcome can be tailored to the needs and wishes of the researcher or the practitioner dealing with these issues.

The results of the work presented here, even with the limitations highlighted above about the disregarding of more qualitative elements, have a general validity, mainly when it comes to the methods used. With a relatively simple model and a reasonable data collection effort it is thus possible to build a number of scenarios that can then be analyzed and valued with economic, organizational and financial considerations in order to provide the bases for a more efficient and effective promotional plan.

There is a final point to consider. The resources, the skills and the time needed to define an effective communication strategy and to control a situation with good continuity are of a magnitude that can prevent many small and medium organizations from using these techniques efficiently and effectively. A common effort in this direction is required. This can be done well by grouping a reasonable number of organizations which can, in this way, reach the *critical mass* of resources needed to assemble a common infrastructure able to provide good basis for individual decisions in these matters. The way in which this can be accomplished by balancing the necessity for cooperation and the natural (even if sometimes too heavy) competition existing in the tourism market is a topic which needs to be carefully addressed and may constitute an interesting and challenging line of research.

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