A survey of Twitter Rumor Spreading Simulations

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Abstract. Viral marketing, marketing techniques that use pre-existing social networks, has experienced a significant encouragement in the last years. In this scope, Twitter is the most studied social network in viral marketing and the rumor spread is a widely researched problem. This paper contributes with a survey of research works which study rumor diffusion in Twitter. Moreover, the most useful aspects of these works to build new multi-agent based simulations dealing with this interesting and complex problem are discussed. The main four research lines in rumor dissemination found and discussed in this paper are: exploratory data analysis, rumor detection, epidemiological modeling, and multi-agent based social simulation. The survey shows that the reproducibility in the specialized literature has to be considerably improved. Finally, a free and open-source simulation tool implementing several of the models considered in this survey is presented.

Keywords: Agent-based Social Simulation, Agent Theory and Application, Rumor Spreading Model, Data Mining for Social Networks, Information Diffusion Model, Social Networks, Twitter, Review.

1 Introduction

Viral marketing, marketing techniques that use pre-existing social networking services, has experienced a significant encouragement over the past few years because a number of reasons. Among others: the low cost of these campaigns; traditional marketing techniques do no longer cause the desired effect; and, people influence each other's decisions considerably [12]. Rumors are the basis for viral marketing [18] and, therefore, rumors diffusion is a topic widely studied. Besides, Twitter is the most studied social network in viral marketing. Twitter allows researchers to study global phenomena from a quantitative point of view for the first time in humanity's history [3]. The main reason for this is that, unlike the leading social network Facebook[1], users' messages in Twitter are public by default.

Multi Agent Based Simulation (MABS) combines computer simulation and agent theory by using a simple version of the agent metaphor to specify single

[1] Leading social networks: `http://goo.gl/bjFfWC`

components and interactions among them [23][2]. MABS has become one of the most popular technologies to model and study complex adaptive systems such as: emergency management [24], intelligent environments [6], e-commerce [25], economy [4], trust and reputation [26], and marketing [20]. In the rumor case, MABS allows researchers to understand how a piece of information spreads on a network and evaluate strategies to control its diffusion; maximizing it in the case of advertisement or minimizing in the case of malicious rumors.

This paper contributes with a survey of research works which study rumor diffusion in Twitter. Moreover, the most useful aspects of these works to build new MABS dealing with this interesting and complex problem are discussed. After revising the review questions in section 2, the main research lines found in the specialized literature are discussed. Section 3 covers works which address an exploratory data analysis of gossips. Section 4 details works which attempt to detect Twitter rumors by several techniques. Section 5 introduces the epidemiological models for rumors dissemination. Section 6 details research works which study Twitter hearsay under the multi-agent based simulation paradigm. Finally, section 6 concludes and gives future works.

2 Review questions

In the spirit of the systematic review methods [28], several review questions were formulated before locating and selecting relevant studies. These questions are the following:

- Q1. Does the work deals with rumors dissemination?
- Q2. Does it include the Twitter case?
- Q3. Real data is employed in the study?
- Q4. Does the paper simulate the information spread?
- Q5. Is there multi-agent based simulation?
- Q6. Are there what-if scenarios?
- Q7. A general methodology is presented to evaluate and use simulations?
- Q8. Is the data provided?
- Q9. Is the implementation given?
- Q10. Is it free and open source software?

Note that these questions fall in three main categories: (1) type of target studied (Q1-Q3); (2) method employed (Q4-Q7); (3) reproducibility of the research (Q8-Q10). Moreover, the questions are not disjoint, e.g. if no real data is employed (Q3), data cannot be provided (Q8).

Table 1 summarizes the works reviewed and answers for these review questions. A quick glance at the reproducibility fields show that there is great room for improvement in this matter.

[2] With some significant differences, MABS can also be referred as agent-based models (ABM), agent-based social simulations (ABSS), or social simulation (SocSim) [15].

	Target system			Method				Reproducibility		
Ref.	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10
Valecha et al. [32]	✓	✓	✓					UR		
Mendoza et al. [17]	✓	✓	✓							
Starbird et al. [29]	✓	✓	✓							
Cha et al. [2]	✓	✓	✓							
Weng et al. [33]		✓	✓	✓	✓					
Gupta et al. [8, 9]	✓	✓	✓							
Kwon et al. [14, 13]	✓	✓	✓					UR		
Qazvinian et al. [19]	✓	✓	✓					UR		
Nekovee et al. [18]	✓			✓						
Zhao et al. [35]	✓			✓						
Shah and Zaman [27]	✓			✓						
Domenico et al. [3]	✓	✓	✓	✓						
Jin et al. [11]	✓	✓	✓	✓						
Tripathy et al. [31]	✓	✓	✓	✓	✓	✓				
Liu and Chen [16]	✓	✓		✓	✓					
Seo et al. [22]	✓	✓	✓	✓	✓	✓				
Yang et al. [34]	✓	✓	✓	✓	✓	✓				
Gatti et al. [7]		✓	✓	✓	✓	✓				

Table 1. Review questions for survey. Check mark: yes, empty space: No, UR: under request.

3 Exploratory data analysis studies

This section deals with works which, without simulating the rumor propagation, conduct a exploratory data analysis of rumor data to gain insights into this problem.

Valecha et al. [32] analyze Twitter data of the Haiti earthquake in 2010[3]. The authors categorize seven different communication modes for four time stages at this occurrence. The paper concludes that information with credible sources contributes to suppress the level of anxiety in Twitter community, which leads to rumor controlling and high information quality.

In this vein, Mendoza et al. [17] explore the behavior of Twitter users in the 2010 earthquake in Chile. The authors classify the tweets manually in affirms, denies, or unknown. They also conclude that rumors tend to be questioned more than news by the Twitter community.

Starbird et al. [29] present another exploratory work which deals with the 2013 Boston Marathon Bombing[4] and conclude that corrections to the misinfor-

[3] On January 12, 2010, a devastating earthquake with a magnitude of 7.3 struck Haiti. More than 220,000 people were killed and over 300,000 injured.

[4] The Boston Marathon bombings were a series of attacks and incidents which began on April 15, 2013, when two pressure cooker bombs exploded during the Boston Marathon, killing 3 people and injuring an estimated 264 others.

mation emerge but are muted compared with the propagation of the misinformation.

Cha et al. [2] use Twitter data to gain insights into viral marketing and, more specifically, to compare three measures of influence: indegree, retweets, and mentions. These authors conclude that popular users who have high indegree are not necessarily influential in terms of retweets or mentions, while influence is gained limiting tweets to a single and specialized topic.

These works hint at the potential of understanding rumors spread and having strategies to control them. Nevertheless, they do not cope with these strategies or their evaluation by simulation techniques.

4 Rumor detection studies

Another important research line in rumor diffusion is the rumor detection, specially with machine learning techniques but also with social network analysis methods.

Weng et al. [33], without dealing with rumors specifically, address meme propagation in Twitter. Memes are parts of cultural tradition, e.g. thoughts, cultural techniques, behaviors, etcetera [5]. In Weng et al.'s work, memes are identified with a Twitter hashtag, i.e. a metadata tag used in Twitter and which consists of a word or an unspaced phrase prefixed with '#'. The authors, based on real data, compare memes spread with four simple simulated models: random, cascade, social reinforcement, and homophily. Finally, the authors present a method to detect if a meme will go viral depending on the meme first 50 tweets and machine learning techniques. Although this is a very significant work which gives sound results to support the hypothesis presented, it does not intend to give realistic simulated models or use them for designing and testing any what-if scenario. Moreover, as displayed in table 1, data and implementations are not given.

Other works also propose machine learning models after an exploratory data analysis of Twitter. Gupta et al. [8, 9] study tweets of the Boston marathon blasts and propose a regression prediction model. This model allows calculating the number of nodes which will be infected in a network assuming that fake content is published by a specific user.

In this vein, Kwon et al. [14] identify a large number of characteristics in rumors under three main categories: temporal, structural, and linguistic. Then these features are used in several machine learning algorithms to classify a Tweet as rumor or non-rumor.

Qazvinian et al. [19] also deal with rumor detection and explore the effectiveness of three categories of features: content-based, network-based, and specific memes.

These machine learning models are important contributions for viral marketing, but they do not allow researchers to test marketing strategies with them. Moreover, as pointed out in some works [19], identifying new emergent rumors directly from the Twitter data is more challenging than the classification of a dataset previously retrieved.

In a sense, the research line presented in these works is complementary of the use of rumor spreading MABSs. On the one hand, machine learning approaches may employ features taken from simulated models [14]. On the other hand, the strategies tested with simulation can be undertaken when detected rumors by these machine learning approaches.

5 Epidemiological modeling

The epidemiological modeling is the hegemonic research line to model rumor spread. In this line, the population is divided into several classes such as susceptible (S), infected (I), and recovered (R) individuals. These analytical models are usually formulated using differential equations since the transition rates from one class to another are mathematically expressed as derivatives. The standard model in this line is the *SIR* model [10] (susceptible, infected, recovered). Moreover, the *SI* (susceptible, infected) and *SIS* (susceptible, infected, susceptible) models are also very used.

Nekovee et al. study the SIR model applied to rumor spread in complex social network [18]. In this vein, Zhao et al. [35] extends the SIR model with forgetting mechanisms. Shah and Zaman [27] use a SI model to study algorithms to find a rumor source in a network. Domenico et al. [3] study Twitter rumors about the Higgs boson discovery and reproduce the global behavior using the SI model and extending it. Jin et al. [11] employees the *SEIZ* model (which considers exposed individuals, E, and sceptics, Z) for capturing diffusion of rumors and news in Twitter.

The main appealing of these works is the accuracy they achieve by adjusting automatically the model parameters, e.g. population size, with fourth generation programming languages such as MATLAB. On the other hand, comparing these model to real-world data is difficult and they often require overly simplistic assumptions [20].

These works employ social simulation (a society is modeled), but they are not MABS works (equations describe the society instead of agents). Furthermore, unlike MABS, they do not allow the exploration of individual-level theories of behavior which can be used to examine larger scale phenomenon [20]. For example, if a single Twitter user gives extensive information for an event while the remaining users post just one tweet (as in Mendoza et al.'s [17] work); MABS allows this special user to be modeled.

6 Multi-agent based simulations

Works studied above do not use MABSs except for Weng et al. paper [33], i.e. question five has "no" as an answer in table 1. However, there are a few works in this line.

Tripathy et al. [31] present a study and an evaluation of rumor-like methods for combating the spread of rumors on social networks. They use variants of the independent cascade model [33] for rumor spread. Besides, the authors criticise epidemic spread models such as SIS and SIR because, among others, anti-rumors can be spread from person to person unlike vaccines for viruses which can only be administered to individuals. Tripathy et al. also propose an anti-rumor strategy which consists of embedding agents called *beacons* in the network which detect rumors and spread anti-rumors.

Liu and Chen [16] build an agent-based rumor spread model using SIR as baseline and implemented in NetLogo [30], a popular MABS framework. Although the authors find out interesting conclusions with regard to the Twitter case using the simulation model, this model is not founded on real data.

Seo et al. [22] present a simple MABS based on gathering retweets (not necessarily rumors), getting the largest connected component in the network, and calculating the retweet probability of each edge $x \to y$ with the number of retweets given in that edge. More than the simulation, the contribution rests on the use of this model to evaluate a method to identify rumors and their sources by injecting special nodes called *monitors*.

Yang et al. [34] employ MABS to analyze the 2013 Associated Press hoax incident[5]. The authors give three profiles for twitter users (broadcaster, acquaintances, and odd users); probability density functions for each profile; and a study of the effects of removing relevant nodes of the network in the information spread. The authors conclude that removing the node of the highest *betweenness centrality* [21] has the optimal effect in reducing the spread of the malicious messages.

Gatti et al. [7] address the general information diffusion modeling instead of the rumor spread. These authors explore President Obama's Twitter network as an egocentric network and present an MABS approach where each agent behavior is determined by the Markov Chain Monte Carlo simulation method. As in other works revised [34], simulation is employed to find users with more impact on the information flow.

The last works revised present significant contributions in the use of MABS to study information dissemination in Twitter. Nonetheless, as shown in table 1, the efforts in reproducibility are quite questionable. None of them give: the data the results are based on, the simulation implementation, or the source code (three last questions in the table). This hinders researchers from verifying the results or reusing these works in their research or developments.

Conclusion and future works

Although creating virtual populations to test viral marketing strategies is considered an effective and useful approach [1, 4, 20], there are a number of shortcomings in the specialized literature which hinder researchers from learning

[5] On April 23 2013, the Associated Press Twitter account was hacked and a malicious message was sent stating that the White house had been attacked and President Obama was injured.

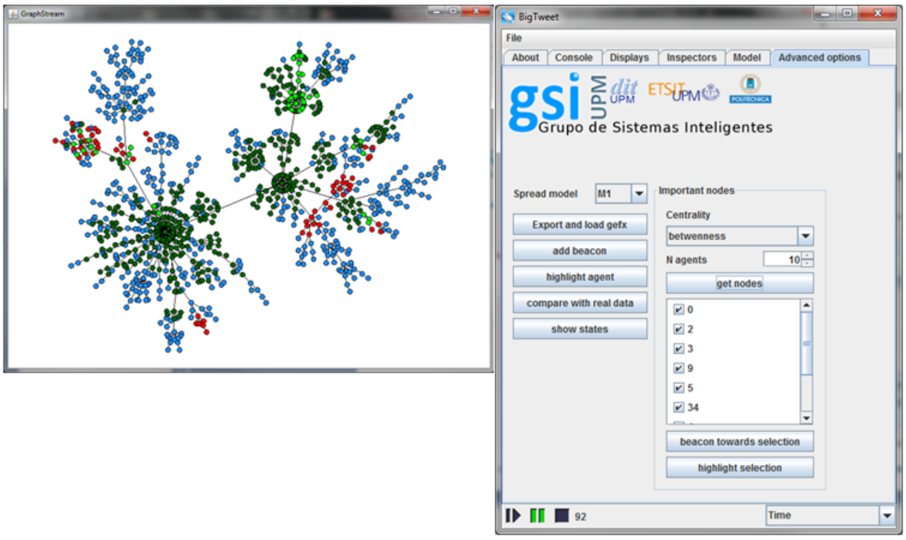

Fig. 1. BigTweet, a rumor spread simulator for evaluating viral marketing strategies.

and reusing these works for new cases. More specifically, for the Twitter rumor spreading case, the authors have found a lack of: (1) general methods to conduct such research, (2) data to validate the realism of the proposed models, and (3) tools (specially free and open-source code) to deploy these simulations. As in many other problems in computer sciences, without these three elements researchers are condemned to reinvent the wheel for each case. Besides, the Big Data technologies, which provide researchers with a great deal of information about prolific users, make the transition from analytical models to multi-agent based simulation models a must because the latter modeling paradigm allow the exploration of individual-level theories.

Under the Big Market research project ("Big Data platform to simulate and evaluate marketing techniques in realistic environments"), the authors have developed free and open-source simulation tool whose interface is shown in figure 1. This simulator called "Big Tweet"[6] implements several of the models considered in this survey to evaluate viral marketing strategies.

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[6] GitHub repository `https://github.com/gsi-upm/BigTweet`, presentation video `https://www.youtube.com/watch?v=rGROCQ1lNxo`

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