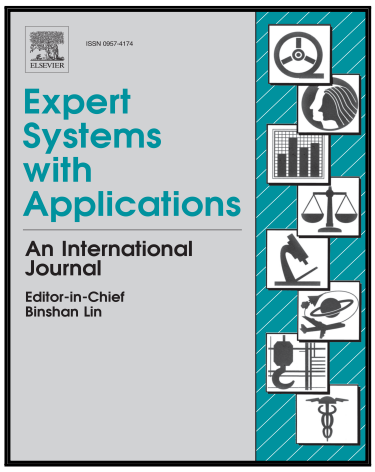

Validating viral marketing strategies in Twitter via Agent-based Social Simulation

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Highlights

- We present a method to validate viral marketing strategies in Twitter.
- The method is based on an Agent-based Social Simulation research methodology.
- A rumor spread model and control strategies are also presented as a case study.
- The model and the strategies are evaluated against others in the literature.
- An open-source simulator and the Twitter data employed are also given.

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Validating viral marketing strategies in Twitter via Agent-based Social Simulation

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Abstract

A number of *marketing* phenomena are too complex for conventional analytical or empirical approaches. This makes marketing a costly process of trial and error: proposing, imagining, trying in the real world, and seeing results. Alternatively, *Agent-based Social Simulation* (ABSS) is becoming the most popular approach to model and study these phenomena. This research paradigm allows modeling a virtual market to: design, understand, and evaluate marketing hypotheses before taking them to the real world. However, there are shortcomings in the specialized literature such as the lack of methods, data, and implemented tools to deploy a realistic virtual market with ABSS. To advance the state of the art in this complex and interesting problem, this paper is a seven-fold contribution based on a (1) method to design and validate viral marketing strategies in Twitter by ABSS. The method is illustrated with the widely studied problem of rumor diffusion in social networks. After (2) an extensive review of the related works for this problem, (3) an innovative spread model is proposed which rests on the exploratory data analysis of two different rumor datasets in Twitter. Besides, (4) new strategies are proposed to control malicious gossips. (5) The experimental results validate the realism of this new propagation model with the datasets and (6) the strategies performance is evaluated over this model. (7) Finally, the article is complemented by a free and open-source simulator.

Key words: Agent-based Social Simulation, Viral marketing, Social Network Analysis, Rumor Spreading Model, Twitter, Big Data

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1 Introduction

Marketing is building your brand, convincing people that your brand (meaning your product/service/company) is the best and protecting the relationships you build with your customers (Cohen, 2015). Marketing phenomena usually are too complex for conventional analytical or empirical approaches such as analytical modeling or consumer behavior experiments (Rand & Rust, 2011). Particularly, these approaches do not allow researchers to state "what-if" scenarios to test their hypotheses. This makes marketing a costly process of trial and error: proposing a theory, imagining its effects in the market, trying in the real world, and seeing results (Statell, 2015).

Agent-based Social Simulation (ABSS) combines computer simulation and social science by using a simple version of the agent metaphor to specify single components and interactions among them. ABSS [1] has become one of the most popular technologies to model and study complex adaptive systems such as: disaster management (Serrano et al., 2014), intelligent environments (Campuzano et al., 2014), economy (Farmer & Foley, 2009), and marketing (Rand & Rust, 2011). In the marketing case, these models do not rely on the assumption that the markets will move towards a predetermined equilibrium state, as other models do (Farmer & Foley, 2009). Agents, which can model from consumers to brands and institutions, act according to: its current situation, the state of the world around it, and the rules governing its behavior. Therefore, the straightforward application of ABSS in marketing is modeling a virtual but realistic market to test marketing strategies, i.e. what-if scenarios, before taking them to the real world. This allows: testing a great variety of possible strategies at negligible cost; predicting the effects of these strategies for their evaluation; and, more importantly, increasing the understanding of the market and enhancing the strategies design by continually asking and testing what-if scenarios.

To advance the state of the art in this complex and interesting problem, this paper presents a contribution based on a method to design and validate marketing strategies in Twitter by ABSS. The method is inspired by Gilbert and Troitzsch's methodology (Gilbert & Troitzsch, 2005) which, with over two thousand citations, is the most popular research method by ABSS. On the one hand, the method proposed is innovative because of its concrete coverage: ABSS for marketing in Twitter. On the other hand, thanks to the more specific scope, the method includes new tasks to deal with the shortcomings detected in the state of the art. In particular, guidelines are given for: data scraping; data preprocessing; exploratory data analysis; model implementation; and, the

[1] With some differences, ABSS can also be referred as agent-based models (ABM), multi agent based simulation (MABS), or social simulation (SocSim) (Li et al., 2008).

use of this data to validate the virtual market realism. Although there are extensive works in Twitter data analysis such as Russell's books (Russell, 2011a, 2011b), to the best of the authors' knowledge, this is the first research work where guidelines are given to use Twitter data in an ABSS research.

To illustrate both the method proposed and the use of Twitter artificial societies for marketing, the method is applied to an extensively studied problem: rumor propagation and control in social networks. This case of application enhances the explained main contribution, (1) a method to design and validate viral marketing strategies in Twitter, with: (2) an extensive review of related works of the problem chosen; (3) an innovative diffusion model based on the exploratory data analysis of two different gossip datasets in Twitter; (4) new strategies proposed to control hearsay; (5) experimental results to validate the realism of this new propagation model with the datasets; and, (6) the strategies validation over this model. Finally, the article is complemented by a (7) free and open-source tool called BigTweet. This implementation not only ensures the reproducibility of the experimental results presented, but also allows the interested reader to adapt the illustrative simulation to different virtual markets and social networks. Extended versions of the experiments and the validation Twitter datasets are also given on-line (Serrano & Iglesias, 2015b).

The paper outline is the following. Section 2 revises the related works. Section 3 gives and overview of the method proposed. Section 4 deals with the agent-based model design and the marketing strategies. Section 5 addresses the main issues in the data scraping, preprocess, and analysis. Section 6 copes with the model construction and gives free and open-source code. Section 7 details the experimental results. Finally, section 8 concludes and gives future works.

2 Related works

In the spirit of the systematic review methods (Nassirtoussi et al., 2014), several review questions were formulated before locating and selecting relevant studies. These questions are the following:

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

	Target system			Method				Reproducibility		
Ref.	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10
Valecha et al.	✓	✓	✓					UR		
Mendoza et al.	✓	✓	✓							
Starbird et al.	✓	✓	✓							
Cha et al.	✓	✓	✓							
Weng et al.		✓	✓	✓	✓					
Gupta et al.	✓	✓	✓							
Kwon et al.	✓	✓	✓					UR		
Qazvinian et al.	✓	✓	✓					UR		
Nekovee et al.	✓			✓						
Zhao et al.	✓			✓						
Shah and Zaman	✓			✓						
Domenico et al.	✓	✓	✓	✓						
Jin et al.	✓	✓	✓	✓						
Tripathy et al.	✓	✓	✓	✓	✓	✓				
Liu and Chen	✓	✓		✓	✓					
Seo et al.	✓	✓	✓	✓	✓	✓				
Yang et al.	✓	✓	✓	✓	✓	✓				
Gatti et al.		✓	✓	✓	✓	✓				

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

- 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); and, (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 revised and answers for these review questions.

Works such as (Valecha et al., 2013), (Mendoza et al., 2010), (Starbird et al., 2014), and (Cha et al., 2010); hint at the potential of understanding hearsay diffusion and having strategies to control them. Nevertheless, they do not cope with these strategies or their evaluation by simulation techniques. With a different goal; (Weng et al., 2013), (Gupta et al., 2013), (Kwon et al., 2013), and (Qazvinian et al., 2011); propose machine learning models after an exploratory data analysis of Twitter. In a sense, the research line presented in these works is complementary of the presented here. On the one hand, machine learning approaches may employ features taken from simulated models (Kwon et al., 2013). On the other hand, the strategies tested with simulation can be undertaken when detected gossips by these machine learning approaches.

The epidemiological modeling is popularly employed to model rumor diffusion. In this line, the population is divided into several classes such as susceptible (S), infected (I), and recovered (R) individuals. The standard model in this

line is the *SIR* model (Hethcote, 2000). Some works in this vein are: (Nekovee et al., 2007), (Zhao et al., 2013), (Shah & Zaman, 2011), (De Domenico et al., 2013), and (Jin et al., 2013). 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 (Rand & Rust, 2011). These works employ social simulation (a society is modeled), but they are not ABSS works (equations describe the society instead of agents). Furthermore, unlike ABSS, they do not allow the exploration of individual-level theories of behavior which can be used to examine larger scale phenomena (Rand & Rust, 2011).

Works studied above do not use ABSSs except for Weng et al. paper (Weng et al., 2013), i.e. question five has "no" as an answer in table 1. However, there are a few works in this line as (Tripathy et al., 2010), (Liu & Chen, 2011), (Seo et al., 2012), (Yang et al., 2003), and (Gatti et al., 2013). These present significant contributions in the use of ABSS to study information diffusion in Twitter and have been studied in depth for the current contribution. 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. Furthermore, the works also lack general methods to conduct ABSS researches in this scope.

3 Method

This section presents a method to design and validate marketing strategies in Twitter by ABSS. As explained in the introduction, it is founded on Gilbert and Troitzsch's (Gilbert & Troitzsch, 2005) methodology which involves: (1) studying the target system, (2) modeling it, (3) implementing a simulation, and (4) studying the results after executing the simulation. The main tasks involved in the methodological proposal given here are displayed in figure 1 and described as follow:

(1) *Target market definition.* In ABSS terminology, the target system is the "real world" phenomenon to research on using simulation (Gilbert & Troitzsch, 2005). Here, the target will be a market and, more specifically, a set of Twitter users (and/or tweets) who will be modeled to evaluate marketing strategies over them.
(2) *Related works revision.* Reviewing specialized literature about the chosen target market is the first information source for the next tasks. Systematic review principles (Kitchenham et al., 2009) are recommended here to

Fig. 1. Method for designing and evaluating marketing strategies by agent based social simulation.

state research questions about the possibility of getting assumptions and data about the target market. These assumptions should allow researchers to generate a first model of the target, the marketing strategies to be evaluated, and the data to enable validating the realism of the model.

(3) *Agent-based model design.* The model design associates the real system, the target, with a representation of this system (the model). Typical decisions in modeling the target are (Rand & Rust, 2011): scope of the model, agents definition, agents' properties, agent's behaviors, environment, time step, input and output. One of the most important requirements of an ABSS model is its simplicity because the whole ABSS research process is motivated by the necessity of obtaining simpler manners of studying the target market. Another important requirement, typically in opposition to simplicity, is to make the model descriptive and realistic.

(4) *Marketing strategies design.* Unlike other authors' works (Rand & Rust, 2011), this paper contemplates marketing strategies an extra task in the method; i.e. those what-if scenarios that agent-based social simulation allows to understand, evaluate, and predict. On the one hand, the coupling between the strategies and the agent-based model is very high, i.e. the degree to which each program module relies on each one of the other modules. On the other hand, a single model of the market should open the door to evaluate a number of strategies over it.

(5) *Data scraping and preprocessing.* Besides the related works revision, the second and main information source to model and validate marketing strategies in Twitter is to scrap and pre-process data from this social

network. More specificity, Twitter REST APIs (*Twitter REST API documentation website*, 2015) provides programmatic access to read and write Twitter data. Most of the works revised in section 2 use these APIs and detail more or less its use for a specific case.

(6) *Exploratory data analysis.* Exploratory data analysis about detecting and describing patterns, trends, and relations in data, motivated by certain purposes of investigation (Andrienko & Andrienko, 2005). In this method, the purpose of analyzing the data obtained from the tasks (2) and (5) is to improve the designs of tasks (3) and (4). Besides, this task also has to decide the data that will be used for validating the model realism in task (8).

(7) *Model construction.* This task consists of translating the model into something which can be used by a computer (i.e. programming the model). A general programming language or an ABSS framework can be used for the construction of the models. The second option is much more convenient because a number of the recurring problems in the construction of ABSS models have been solved in this kind of software packages. The use of simulation displays, typically provided in these frameworks, is very important in this task as a basic mechanism to verify the software, i.e. checking that it meets the model specification and requisites. Concerning these requisites, one of the most important and commonly forgotten is to offer repeatability and reproducibility by a single and parametrized random seed.

(8) *Validation experiments.* While the verification included in the model construction checks if the model has been built right; the validation evaluates if the right model has been built. This, in the ABSS research paradigm, means validating the realism of the model constructed using the data obtained from the target system. In this method, this data comes from the related works revision and the data scraping tasks. Moreover, the exploratory data analysis obtains a final view of the real system to be compared with the simulation executions.

(9) *Strategies experiments.* Once the market model has been validated, the effects of marketing strategies over that model can be conducted in this task. Again, the coupling between the strategies and the agent-based model is very high. Therefore, it is not feasible to obtain a realistic simulated market which is suitable to evaluate any strategy (or designing these strategies independently of the model). This makes the method as important as the results obtained for a specific research.

(10) *Publishing work.* The final output of an ABSS research is new knowledge of the target system (Gilbert & Troitzsch, 2005). In the method presented here, the authors want to emphasize the necessity of publishing not only the knowledge obtained (results), but also the data these results rest on and the source code generated during the research. Of course, results on the research may need to be private for the sake of companies interests. However, once the results are published in scientific forums, they should

always come with the data, methods, ideas, and code to reach them. Regarding the data distribution, there may have been legal limitations such as Twitter Terms of Service (*Twitter terms of use website*, 2015). Even so, there are always possible manners to share the data such as giving just Tweets IDs and the code used to recover the full Tweets information if they are still available.

It is important to note that, although the tasks in the figure are laid out in a circular pattern, the method is not a sequential process as the classic *waterfall model* in general software development. As explained, when performing any task of the method, a continuous revision of the previously undertaken tasks is expected. In this sense, the method offers an *iterative and incremental development*. Even the order of tasks is just a suggestion. For example, "validation experiments" could be implemented before the "model construction" in the spirit of the *Test-driven development* methodology where tests are written before the code to be tested. Another example would be to perform the "model construction" before "data scraping" and "exploratory data analysis". This would allow producing a first prototype as soon as possible in the spirit of the *Manifesto for Agile Software Development* (Beck et al., 2001), which states that "working software will be more useful and welcome than just presenting documents to clients in meetings".

While the introduction has already chosen and justified a target market to be studied in this work, misinformation spread and control in Twitter, and section 2 has dealt with the second task of the method, related works revision; next sections give more details of the remaining methods tasks and apply them to the rumor propagation and control case.

4 Baseline and proposed models for rumor spread and control

This section revises the explained decisions to reproduce Tripathy et al.'s approach (Tripathy et al., 2010) for modeling the gossip diffusion in Twitter, let us call it M_1, and the control strategy over this model, let us call it $M_{1.1}$. Then a new propagation model M_2 is detailed which can be combined with the baseline control approach $M_{2.1}$. Finally, a new misinformation control strategy over this model is defined $M_{2.2}$.

As explained, the method presented is iterative and incremental, but for the sake of clarity, the results are presented "unrolled". In other words, the authors did not figure up the new model without modeling the baseline approach, scraping and analyzing Twitter data, constructing this baseline, and validating it with the real data.

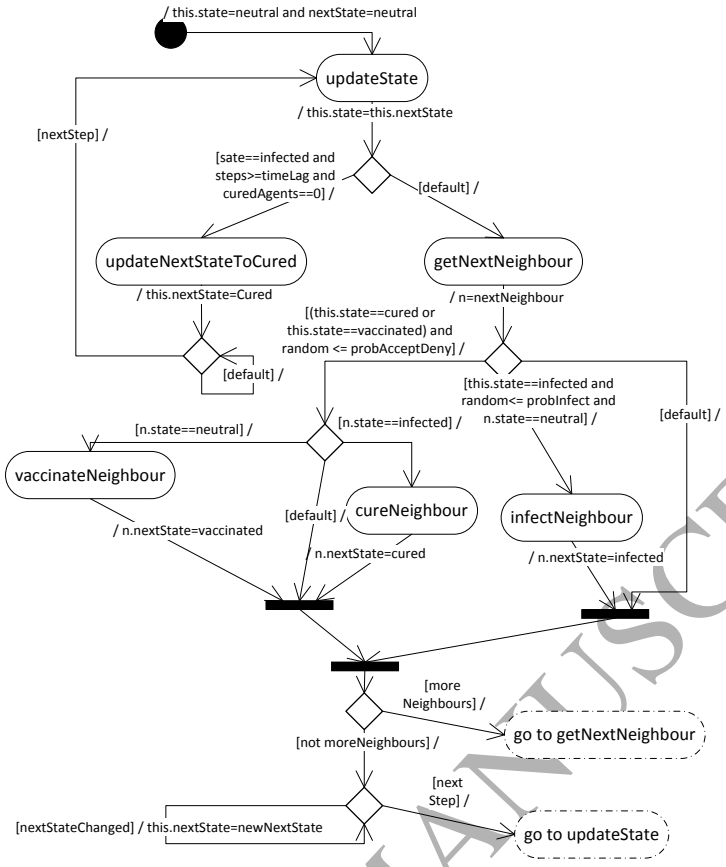


Fig. 2. UML activity diagram for rumor spread model M_1.

4.1 Baseline spread model M_1

The baseline approach is based on the cascade model (Weng et al., 2013). Agents are Twitter users with a state property which can be: *neutral* (initial state); *infected* (believe the misinformation); *vaccinated* (believe the anti-rumor before being infected); or, *cured* (believe the anti-rumor after being infected). The basic behavior, given in the UML activity diagram displayed in figure 2, involves: (1) initializing a number of infected users; (2) each infected user at time t tries to infect each of its uninfected neighbors with a given probability (*propInfect*); (3) after a given delay (*timeLag*), a random infected node starts an anti-rumor spread to its neighbors, trying to cure or vaccinate them with a probability (*probAcceptDeny*) each time step t; and, finally, (4) cured and vaccinated users also try to cure or vaccinate their neighbors with a probability (*probAcceptDeny*) each time step t. The model implementation is also available online (Serrano & Iglesias, 2015b).

The environment is a BA scale-free synthetic network because they are strong adversaries for gossip control strategies and provide researchers with a base-

line since it is assumed that the strategies performance is better than in real networks. To give more information to reproduce this environment, this paper experiments with 1K nodes and a maximum of 10 links initially added per new node. More specifically, the Barabási-Albert preferential attachment graph generator of the graph stream project has been employed [2]. The authors have experimented with BA networks where each node added comes with several links because this is not only more realistic (Twitter users are forced to follow a number of Twitter accounts at the beginning), but also makes information disseminate faster.

A time step of an hour is assumed, and the output is the number of users endorsing the misinformation (with infected as state) and the number of users denying it (with vaccinated or cured as states). With the details given, the input parameters in M_1 are the following: random seed, number of users, maximum links per node (for the BA network construction), initially infected users, probability of infect, probability of accept a denial, and time lag.

4.2 Baseline control model $M_{1.1}$

The baseline approach considers a control strategy based on including a number of special users called *beacons* representing an authority that detects the propagation of misinformation and combat it. Therefore, the agents' states are extended with: *beacon-off* (beacon before detecting a rumor in a neighbor) and *beacon-on* (beacon after detecting a rumor). When an infected node has an inactive beacon as neighbor, the latter is activated in the next time step. Active beacons, as cured and vaccinated users, start an anti-rumor spread to its neighbors, trying to cure or vaccinate them with a probability (*probAccept-Deny*) each time step t. Since anti-rumors start from the beacons, the time lag parameter explained for M_1 is not used in $M_{1.1}$.

A modification in the original control strategy design is that instead of selecting beacon nodes at random, a *centrality* parameter is included to try to make the beacon follow the most important nodes according to: the degree, betweeness, closeness, PageRank, or eigenvector centrality indicators (Abraham et al., 2010). As a result, the parameters for this explained control model are: *number of beacons*, and *centrality* function to include them in the environment.

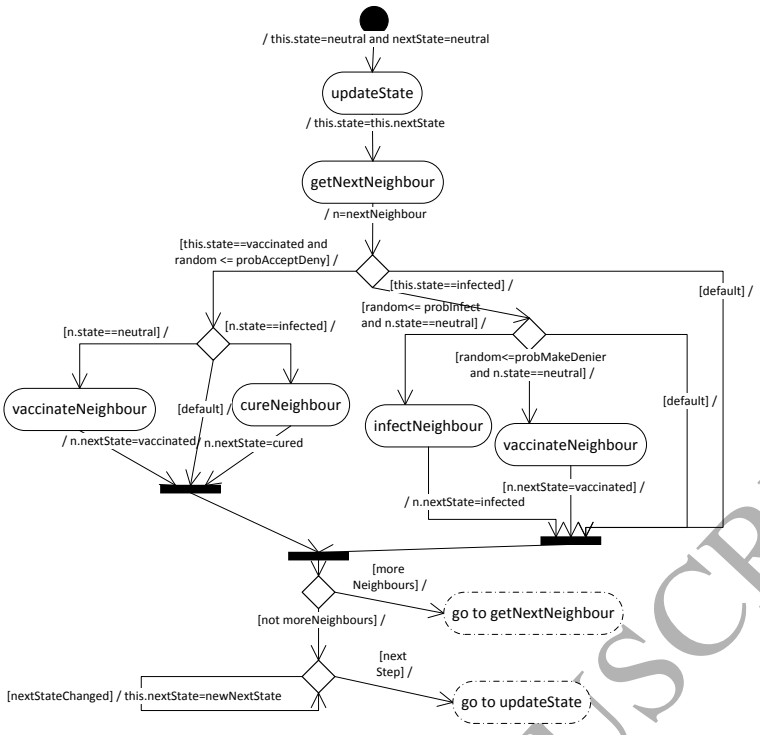


Fig. 3. UML activity diagram for a new rumor diffusion model, M_2.

4.3 New spread model M_2

After studying M_1 executions and real Twitter data, the authors found out that the "cured" concept is hardly validated in Twitter gossip spread. On the one hand, if retrieving tweets about hearsay (or anti-rumors) in a specific topic, all the information for most of the users comes from just one tweet which says if the user is endorsing or denying the misinformation. On the other hand, psychologically, the infected users who make a mistake, may not be as enthusiastic as M_1 assumes about spreading their faults with anti-rumors. M_2 modifies M_1 to include this idea by allowing only vaccinated users (the ones who have not been previously infected) to disseminate anti-rumors.

Another idea included in M_2 is that, independently of any *time lag*, a neutral node which has an infected neighbor, can become a vaccinated user if this node knew from any external information that the misinformation was false. With this in mind, M_2 modifies M_1 to include a *probability of making a denier*, i.e. turning a neutral user into a vaccinated user when spreading a rumor.

Thus, the M_2 behavior, which is detailed in the UML activity diagram displayed in figure 3, is: (1) initializing a number of infected users; (2) each infected user at time t tries to infect each of its uninfected neighbors with a

[2] GraphStream project website : `http://graphstream-project.org/`

given probability (*propInfect*); (3) instead of infecting them, these neighbors may become vaccinated if they were neutral with a probability (*propMake-Denier*); and, finally, (4) vaccinated users (but not cured users) attempt to cure or vaccinate their neighbors with a probability (*probAcceptDeny*) each time step t. Additionally, the model implementation is also available online (Serrano & Iglesias, 2015b).

With the details given, the input parameters in M_2 are the same as in M_1 except the time lag which is replaced with *propMakeDenier*: random seed, number of users, maximum links per node (for the BA network construction), initially infected users, probability of infect, probability of accept a denial, and probability of making a denier. Concerning the output, the cured agents are counted in M_2 as users endorsing the gossip along with the infected agents; and only vaccinated agents are counted as users denying the misinformation.

4.4 New control model $M_{2.2}$

As explained, M_2 can be combined with the control strategy detailed in section 4.2 giving $M_{2.1}$. However, this section proposes a new control model based on the original control strategy. More specifically, since there is no cost or restriction in following Twitter users, this model proposes that the beacon not only has to spread anti-rumors to its neighbors, but also follow these neighbors' contacts. In this manner, even if the beacon neighbors do not disseminate the anti rumor, the beacon can do it itself at the following time step. This strategy intends to minimize the observed effect in cured agents: they may not propagate anti-rumors because it would involve admitting a mistake in previous tweets.

5 Rumor datasets and analysis

The baseline model, reproduced and implemented in this paper, and the proposed diffusion model have been validated using two rumor datasets introduced by Qazvinian et al. (Qazvinian et al., 2011). The first dataset called "Obama" includes tweets which spread misinformation that president Obama is muslim. The second dataset called "Palin" deals with Sarah Palin divorce gossips. Although the cited work includes other rumors, these were the topics with more tweets retrieved: 4975 for the Obama dataset and 4423 for the Palin dataset. Hence, they were the most useful for simulation purposes.

Qazvinian et al. (Qazvinian et al., 2011) not only retrieved tweets based on regular expressions, `Obama & (muslim|islam)` for the Obama dataset and

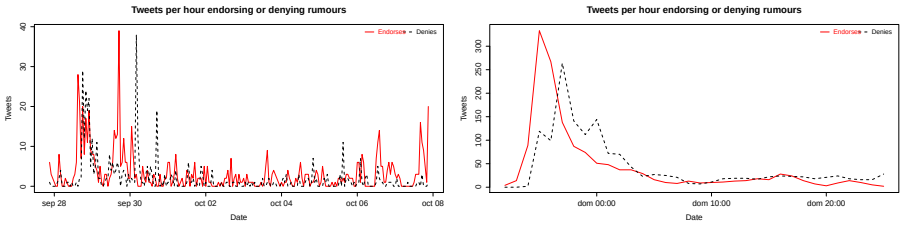


Fig. 4. Tweets endorsing or denying rumors per hour. Obama dataset on the left and Palin dataset on the right.

`Palin & divorce` for the Palin dataset, but also annotated manually these tweets. The possible labels for the dataset are: *endorsers* (it spreads the gossip), *denies* (the user refutes the rumor), *questions* (the user questions the gossip credibility), *neutral* (the tweet is about the misinformation without endorsing or denying it), *unrelated* (the tweet is not about the rumor), and *undetermined* (when the annotator is undetermined). The mere existence of the "undetermined" label, used when a human annotator cannot decide illustrates the challenging problem of automatically detecting if a tweet is a rumor or not which, although is out of the scope of this paper, is a hot research topic.

The explained datasets were provided in different formats. In this paper, their tweets have been: (1) retrieved again from the id when available by using the Twitter REST API (*Twitter REST API documentation website*, 2015) (Obama case); (2) extended by retrieving retweets of the original tweets (Obama case); (3) anonymized for their distribution obeying the Twitter terms of use (*Twitter terms of use website*, 2015) (Palin case); and, made available at this paper additional material website under a creative commons license (Serrano & Iglesias, 2015b). Figure 4 shows the tweets per hour denying and endorsing the gossip for the two datasets.

Twitter datasets are composed of tweets but, as seen in the number of works revised in section 2, the misinformation diffusion models typically present the agents' states as output. Therefore, a mapping from tweets to states such as "endorser" and "denier" is needed. In this work, the last user's tweet decides its current state.

After studying Twitter data of these and other datasets, the authors found out that the "recovery" concept, which most popular rumor diffusion model relies on, is complex of being validated. The main reason is that when retrieving tweets about rumors (or anti-rumors) in a specific topic, all the information for most of the users usually comes from just one tweet which says if the user is endorsing or denying the rumor. The bar charts of figure 5 show the number x of users who have sent a number y of tweets for the two explained datasets. Note that the figure does not represent histograms, where the quantitative data is grouped into intervals, but bar charts where the x axis indicates the

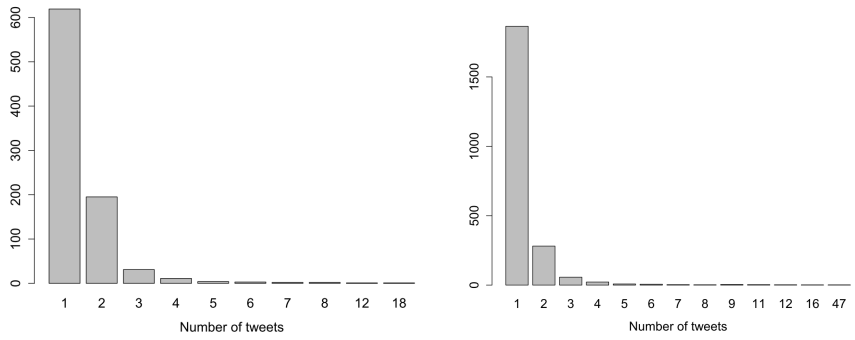


Fig. 5. Bar charts showing the number x of users who have sent a number y of tweets. Obama dataset on the left and Palin dataset on the right.

exact number of tweets sent by the user. This representation better illustrates the relevant data for the hypothesis stated here: the vast majority of users have sent just one tweet. Moreover, only 2 and 3 users have posted over 10 tweets for the Obama and Palin datasets, respectively. Therefore, even if the user has been "cured" of the rumor, there is not empirical evidence of it. This further supports the hypothesis the novel spreading model M_2 is based on: when a user is recovered, this user will not influence his or her neighbors in the social network to recover. Finally, this information has to been filtered even more when using a real topology instead of synthetic networks.

6 BigTweet simulator

For the problem of rumor diffusion, an implementation of the propagation models and control strategies presented in section 4 has been built. This simulator is called *BigTweet*. Figure 6 shows the simulator GUI including: the simulated network display; a chart with the number of agents per possible state (see section 4.1); and, the console frame. The console frame allows controlling an experiment execution (starting, pausing, stopping it); selecting parameters (random seed, spreading model, probability of infection, etcetera); and executing strategies (control model, number of beacons to include, position of them in the network, etcetera).

BigTweet employs the Mason social simulator (Luke et al., 2004) and a number of SNA frameworks (*Social network analysis software*, 2015): GraphStream for offering a dynamic network display, Gephi for further studying the social network by a powerful GUI, and iGraph for calculating centrality functions.

Besides the spread and control models, BigTweet includes the datasets studied in section 5 and implements the experiments detailed in the following section. With these, the authors want to emphasize the repeatability and re-

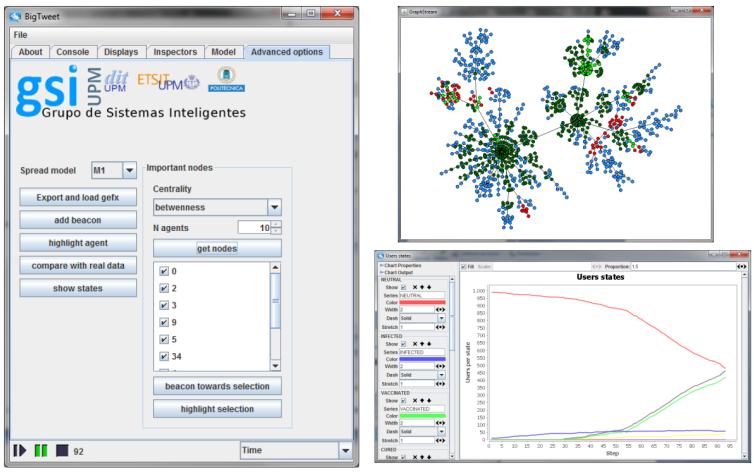


Fig. 6. BigTweet GUI.

producibility of their results. BigTweet is free and open source software and is available online under a GPL license (see additional material website (Serrano & Iglesias, 2015b) or BigTweet GitHub website (Serrano & Iglesias, 2015a)).

7 Experimental results

This section illustrates the eighth and ninth steps of the method presented in section 3, validation experiments and strategies experiments, in the context of the case study used throughout this paper: rumor diffusion in Twitter.

7.1 Validation experiments

As explained in section 3, the validation evaluates the realism of the model constructed using the data obtained from the target system. For that purpose, the gossip propagation model M_1 and the proposed model M_2 (see sections 4.1 and 4.3, respectively) are compared using the two Twitter datasets explained in section 5.

These experiments compare the number of users endorsing and denying a rumor in the simulation with the number of these users in the real data. Thus, the following *distance metric* is used to validate the realism of the simulations:

$$d(endorsers, simulation, dataset) + d(deniers, simulation, dataset) \quad (1)$$

Parameter	Min	Max	Inc
probInfect	0.01	0.1	0.005
probAcceptDeny	0.01	0.1	0.005
timeLag (M_1)	0	23	1
probMakeDenier (M_2)	0.01	0.1	0.005
random seed	1	20	1
Parameter	Fixde value		
Users	1000		
InitiallyInfected	2		
MaxLinkPerNode	10		

Table 2
Models parameters values for experimentation. M_1: only baseline, M_2: only proposed model.

, where d calculates the Euclidean distance [3] between the number of users (nu) of a specific *type* (endorser or denier) in the *simulation* and the *dataset* (Obama or Palin) for the days considered ($nDays$):

$$\left[\sum_{day=0}^{nDays}(nu(type, simulation, day) - nu(type, dataset, day))^2\right]^{\frac{1}{2}} \quad (2)$$

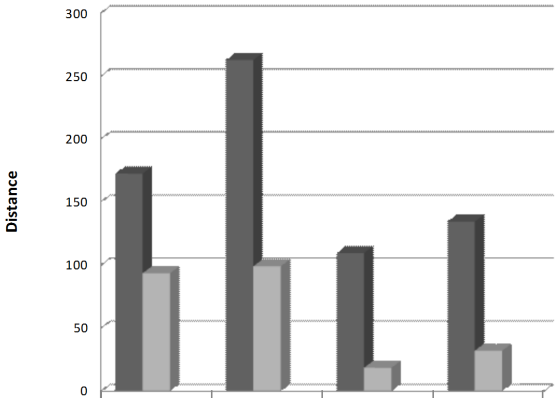
The number of endorsers and denier users is calculated differently for datasets, the baseline model, and the proposed model. In the datasets, a user is counted as endorser or denier if his or her last tweet was labeled as *endorsers* or *denies*, respectively. In the baseline approach, *infected* users count as endorsers and, *vaccinated* and *cured* ones as deniers. In the proposed model, cured agents are counted as users endorsing the rumor along with the infected agents; and only vaccinated agents are counted as users denying the rumor.

Table 2 shows the parameters employed for the two diffusion models explained in sections 4.1 and 4.3. Some parameters are specified with the minimum, maximum, and increment; while others have a fixed value. The parameters combinations give over 173K experiments for the baseline an over 170K experiments for the proposed model.

Figure 7 shows the main results. The figure shows the distances for the Obama and Palin datasets: (1) in the best case achieved by the models; (2) and, in the best mean of distances considering all random seeds for a set of parameter values [4]. These results show that the proposed model achieves reductions of

[3] Although comparing times series is a research topic per se, the Euclidean distance and the Root Mean Square Error (RMSE) are generally employed (Gatti et al., 2013).

[4] Standard deviations are also provided in the extended experiments (Serrano & Iglesias, 2015b).



	Obama		Palin	
M1	172.535	262.696	109.572	134.463
M2	93.51	99.022	18.546	32.095
Reduction	45.80%	62.31%	83.07%	76.13%

Fig. 7. Experimental results. Baseline model M_1 versus proposed model M_2 using Obama and Palin datasets.

distance between 45.80%, Obama best case, and 83.07%, Palin best case. These experimental results further supports the hypothesis that is more realistic to consider that users who have spread a rumor will not diffuse anti-rumors in Twitter as the new model introduced in this paper does. Experiments scripts and extended experiments results are available online in the additional material web (Serrano & Iglesias, 2015b).

7.2 Strategies experiments

As explained in section 3, the strategies experiments or "what if" scenarios allows evaluating marketing strategies over the market model validated previously. More specifically, the strategies $M_{2.1}$ and $M_{2.2}$, see sections 4.2 and 4.4, are assessed over the best case of M_2 obtained in the validation experiments.

The best case achieved with the Palin dataset is displayed in figure 8. These results can be reproduced with the following M_2 parameters: $probInfect = 0.02$; $probAcceptDeny = 0.01$; and, $probMakeDenier = 0.01$ (see table 2). As detailed in section 4.2, the control strategies are parametrized by the *number of beacons* and a *centrality* metric to select the nodes the beacons are linked with in the network: *degree*, *betweeness*, *closeness*, *PageRank*, or *eigenvector* centrality. A *random* selection of beacons is also included in the experiments as baseline. Finally, 100 different random seeds have been employed for each set of parameter values.

Figure 8 gives the mean of endorser users per number of beacons with the two

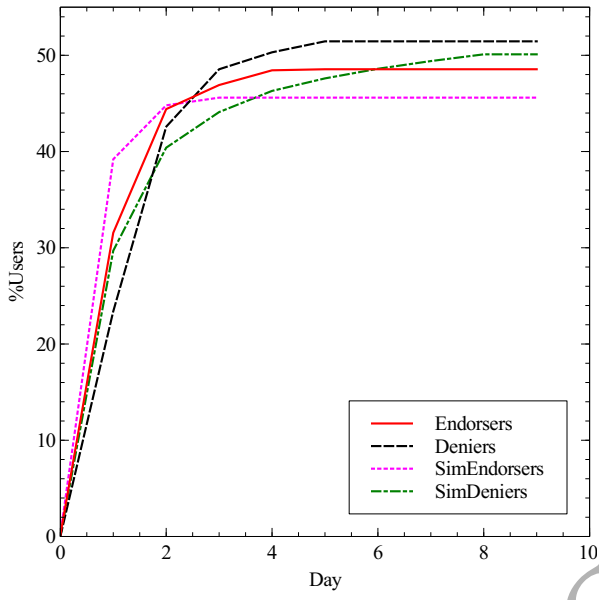


Fig. 8. Experimental results. M_2 model best case with Palin dataset.

control strategies and the different centrality metrics [5]. Surprisingly enough, the centrality measure has not a relevant impact. As a result, regardless of the centrality metric employed, the chart lines for $M_{2.1}$ are mostly overlapped when the beacons follow the users with the highest centrality. However, there are slight differences in the mean of endorser users when the number of beacons varies from 25 to 500. For example, the eigenvector centrality overcomes the other alternatives considering 25 beacons (91.9 with this centrality metric versus 96.15 with the second best option). This overlapping also happens with $M_{2.2}$ although the new control strategy gets a much more reduced number of endorser users with very little beacons. Concretely, $M_{2.2}$ only presents around 82 users infected with 5 beacons compared to the over 351 endorser users when using $M_{2.1}$ for any of the centrality metrics explored. Therefore, the proposed control model improves over 76% the endorsers compared to the baseline in this case. This supports the hypothesis of the new control strategy introduced in this paper: expanding the beacons contacts when hearsay are detected is a significant aspect in the misinformation control strategy.

The values for the two control strategies where the beacons are selected randomly also offer interesting results. Concretely, when the number of beacons is less than 25, $M_{2.2}$ with beacons selected randomly behaves better than $M_{2.1}$ with the centrality functions explored. Therefore, according to these results, if a company is willing (and has the resources) to address directly enough endorser users in the network when a rumor starts, it can overcomes the fact of having very little contacts or followers (*degree* centrality). These experiments

[5] Standard deviations are also provided in the extended experiments (Serrano & Iglesias, 2015b).

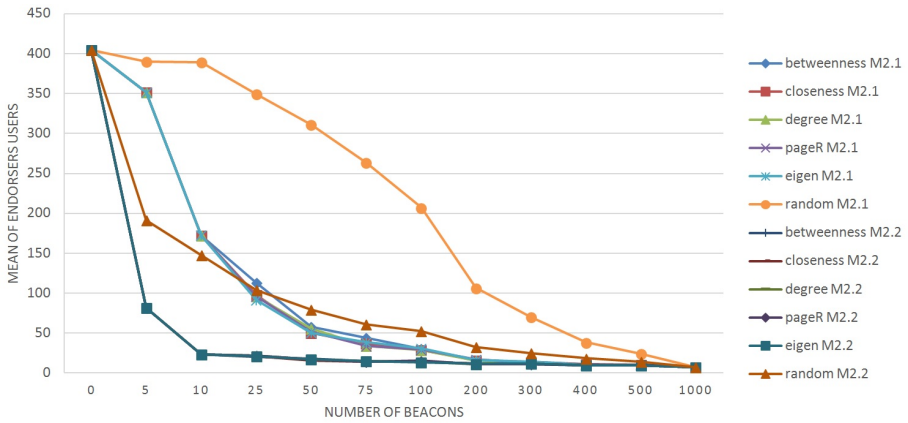


Fig. 9. Experimental results. Baseline control model $M_{2.1}$ model versus new control model $M_{2.2}$ using the case shown in figure 8 with several centrality metrics.

illustrate how the use of ABSS allows gaining insights into marketing strategies by modeling a realistic market and then experimenting with a number of strategies over that model. Experiments scripts and extended experiments results are available online in the additional material web (Serrano & Iglesias, 2015b).

8 Conclusion and future works

This paper advances the state of the art in the use of Agent-based social simulation (ABSS) to design and validate viral marketing strategies in Twitter. Although there are extensive works in Twitter data analysis such as Russell's books (Russell, 2011a, 2011b), to the best of the authors' knowledge, this is the first research work where guidelines are given to use Twitter data in an ABSS research. The method proposed contemplates among others: the agent-based model design, modeling the marketing strategies, the data scraping and preprocessing, the exploratory data analysis, the model construction, the validation experiments, and the strategies experiments. In addition to the method discussion, this work has followed a well studied problem of viral marketing to illustrate it, the rumor control and diffusion in social networks. An extensive review of related works reveals that the epidemiological modeling is the hegemonic approach to model misinformation spreading. This paper challenges that approach by assuming that users who realize that have spread a false rumor in Twitter typically: (1) will not spread anti-rumors, or (2) there will not be empirical evidence of the retraction. Therefore, the recovered users will not affect the recovery of their neighbors.

The main future work in this research line is the integration of the presented models with Big Data technologies. Another important future work is to consider the strength of ties in the study of viral marketing strategies. As proposed

by De Meo et al. (De Meo et al., 2014), interaction data can be used to predict the strength of ties: weak, intermediary, or strong. Moreover, events transmitting new information go preferentially through weak ties, i.e. links connecting different groups (Grabowicz et al., 2012). These links quickly spread messages and touch large segments of social networks users.

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