Rumors with Personality:
A Differential and Agent-Based Model of Information Spread through Networks

Devavrat V. Dabke* Eva E. Arroyo†

Duke University, Durham, NC

Supervised by:

Prof. Anita T. Layton
Depts. of Mathematics and Biomedical Engineering
Duke University, Durham, NC
alayton@math.duke.edu

Abstract

We constructed the "ISTK" model to approximate the spread of viral information—a *rumor*—through a given (social) network. Initially, we used a set of ordinary differential equations to assess the spread of a rumor in face-to-face interactions in a homogenous population. Our second model translated this system into an equivalent stochastic agent-based model. We then incorporated a network based off of a representative Facebook dataset. Our results showed that incorporating the structure of a network alters the behavior of the rumor as it spreads across the population, while preserving steady states. Our third model considered *features*: demographic information that characterized individuals in our representative population. We also generated a feature vector for the rumor in order to simulate its "personality." An increase in the average similarity of the rumor to the population resulted in increased propagation through the network. However, the addition of feature vectors prevents the rumor from saturating the network. Our agent-based, feature-equipped ISTK model provides a more realistic mechanism to account for social behaviors, thus allowing for a more precise model of the dynamics of rumor spread through networks.

1 Introduction

1.1 Background

A rumor is defined as a "proposition for belief of topical reference disseminated without official verification," [14] a notion that lends itself quite well to the imagination of applied mathematicians. The mathematics of rumor spread is somewhat explored, beginning with the epidemic model applied to information spread in a population by Daley and Kendall in 1965 [5]. This model's assumptions of homogeneous interactions and its lack of well-defined parameters likely caused "the superficial similarity between rumors and epidemics to break down on closer scrutiny" [5]. Nonetheless, the similarities of knowing and spreading a rumor, and having and spreading a disease, share parallels that only deviate in some of the intricacies of their mechanism. In both, an "infected" individual in a network desires to (or inadvertently spreads) their "condition." With disease, one of the mechanisms of suppressing spread is vaccination; with rumors it is an individual's eventual boredom and desire for novel information.

*Email: d.d@duke.edu
†Email: eva.arroyo@duke.edu

More recent models of rumor spread in a population examined the dynamics through randomized networks[13], examining the rumor transmission in exponentially distributed networks[17], and the time of rumor spread given contacts of the initial spreader in a regular network[9]. There is increasing emphasis on the structure of networks themselves and how this affects model dynamics[2,19,20,26,29]. Many of these models derive their structure and dynamics from complex yet internally homogeneous simulations of how individuals interact with rumors. However, with the advent of massive social media networks that allow sharing of information on a large scale, more analyses are focusing on behaviors (such as rumors) that are frequent in social media networks. Simulations of rumor spread through social media are becoming increasingly realistic by including "forgetting" mechanisms typical of social media[27], comparing time of rumor spread in random networks as compared to structured networks[15], methods for combatting rumor spread in social networks[24], and examining rumor spread on gaming networks[11].

1.2 The ISTK Model

In this paper we consider a stochastic rumor spread model with four categories of individuals: the "ignorant" individuals, those who have never heard the rumor; the "spreaders," those that have heard the rumor and are actively spreading it; the "stiflers," those who have heard the rumor and actively suppress further transmission (either because they now consider the rumor old news, or they never believed the rumor in the first place); and finally the "knowledgeable" population, those who have heard, but have subsequently forgotten the rumor. The rumor initializes in only a small fraction of the population, and spreads as the individuals interact. The "ignorant," "spreader," and "stifler" populations were presented in the Daley-Kendall model[5], but we have added a "knowledgeable" population, which has been postulated before as necessarily distinct from the ignorant population[27,28]. Assuming otherwise presumes that the attitude of an individual who has forgotten a rumor is identical to the behavior of an individual who had not yet heard the rumor. We account for this distinction with the addition of the knowledgeable population to the Daley-Kendall model. This model is henceforth referred to as the Ignorant, Spreader, Stifler, and Knowledgeable (ISTK) model. We use three variations of this model: one differential, and two agent-based. The differential ISTK model simulates a homogenous group of people, and has no awareness of the concept of individuals; it simply "moves" proportions of the group of people from one population to another over time. The first agent-based model, the "Simple model," simulates individuals through several iterations (rounds) over time. The model incorporates a network that represents the connections between individuals, which in this case is based off of Facebook friends. The second agent-based model, the "Feature-vector model," incorporates demographic data of these Facebook users.

In the "Feature vector model," we further consider 1. how a rumor might be targeted towards a certain demographic, and 2. how the "similarity" between a rumor and an individual affect a user's behavior. The original social network dataset included many different types of "features:" education level, gender, and language. Instead of assuming that every individual is equally likely to spread any rumor, we assumed that the rumor's targeted characteristics and the demographic information of each individual affected the likelihood of the rumor to spread. In this way, we equipped the rumor with a *personality*. If the individual from whom they heard the rumor was more similar to them, they were more likely to believe the rumor, and if the rumor's characteristics was more similar to theirs they were more likely to spread the rumor. There is evidence to suggest that people are more likely to believe information that comes from others with similar values[10]. The similarity of the rumor's personality to that of the individual's influenced the individual's probability to spread the rumor. The theory of confirmation bias suggests this behavior, insofar as we are more likely to accept information that confirms our previous beliefs[25]. The characteristics of the rumor itself contribute to how the rumor is spread between individuals in the Feature vector model, Section 3.2.

1.3 ISTK Model Equations

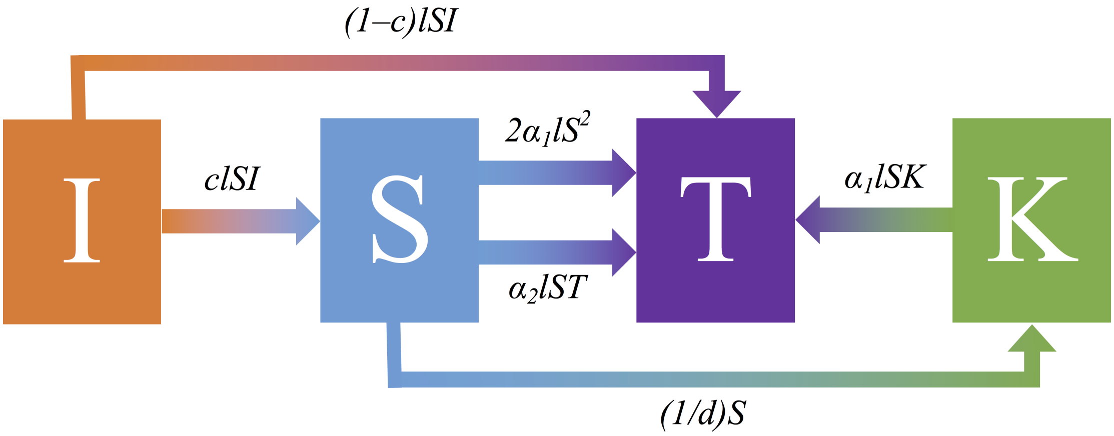

Figure 1: ISTK Model

I, S, T, and K, represent the total Ignorant, Spreader, Stifler, and Knowledgeable populations respectively. We also designate N to represent the total size of the population, in that $N = I + S + T + K$ (n.b. we assume no one dies or is born, so N stays constant, i.e. $\frac{dN}{dt} = 0$).

There are several common parameters to all four differential equations, as follows:

We represent the "credibility" of the rumor, expressed as a probability that the Ignorant believes the Spreader, as c. Therefore $(1 - c)$ the complement of c is equivalent to being incredulous of the rumor.

To represent the chance per day of interaction, l, we take the complement of the overall probability that an individual does not talk with a single Spreader. It is computed by a set of Bernoulli trials with success probability ρ where $\rho = 1 - \frac{S}{N}$ and number of trials to be τ (i.e. $l = 1 - \rho^{\tau}$).

d represents the number of days after which a population spontaneously forgets a rumor. α_1 that describes the loss of novelty of the rumor. α_2 describes the chance that the Spreader becomes a Stifler upon interacting with a Stifler.

The equations for each population follow:

$$\frac{dI}{dt} = -clSI - (1 - c)lSI \tag{1}$$

In Equation 1, the first term describes the interaction between an Ignorant and a Spreader. It is dependent on both the size of the Ignorant and Spreader classes, and is proportional to parameters c and l. The second term of Equation 1 accounts for the complement of "believing the rumor" (being "incredulous" of the rumor) and is proportionate to $(1 - c)$. Both terms remove some of the population from the Ignorant class and lead to the Spreader class and Stifler class respectively. Although we can simplify this equation to $(-lSI)$, we want to distinguish the credulous (c) and incredulous $(1 - c)$ group of people.

$$\frac{dS}{dt} = clSI - \frac{1}{d}S - 2\alpha_1 lS^2 - \alpha_2 lST \tag{2}$$

The first term of Equation 2 is the addition of members from the Ignorant class who believed the rumor. The second term characterizes the population which spontaneously forgets the rumor, and hence is inversely proportionate to the Spreader population and d. The third term of Equation 2 accounts for two Spreaders who interact with each other and foster disinterest in the rumor (since the rumor has lost its novelty). When these two Spreaders interact (S^2), we account for the chance that **each** Spreader could become a Stifler by multiplying the term by 2. The final term represents the disillusionment power of a Stifler when interacting with a Spreader.

$$\frac{dT}{dt} = 2\alpha_1 lS^2 + \alpha_1 lSK + \alpha_2 lST + (1-c)lSI \tag{3}$$

In equation 3, the first of which describes the removal of members from the Spreader class into the Stifler as defined above. The second term describes the population of Knowledgeable individuals who become a Stifler, as described in Equation 2. The third and fourth terms of Equation 3 describe the addition of members to the Stifler population from the Spreader and Ignorant populations, respectively.

$$\frac{dK}{dt} = \frac{1}{d}S - \alpha_1 lSK \tag{4}$$

Finally, Equation 4 describes the individuals in the Spreader class who forget the rumor and become Knowledgeable; and the population which loses the novelty of the rumor and become Stiflers.

In our model, we do not consider the interaction between a Stifler and an Ignorant because neither one has a reason to broach the subject of a rumor (the Ignorant because they do not know and the Stifler because they no longer care). Moreover, by a similar logic, when a Knowledgeable and Stifler interact, there is no change in populations.

Our equation differs from the Daley-Kendall model [5] primarily through addition of the Knowledgeable class, individuals in this category would have been in the Ignorant of Stifler classes in the original model. In addition, the Daley-Kendall model assumes all individuals who hear a rumor will believe it. In our case, this is not so, through addition of the parameter c. In the Daley-Kendall model it is possible to become ignorant after hearing the rumor, and in this case that is not possible.

2 Differential Model

2.1 Modeling Applications

Initially, we solved the differential model in order to compare a continuous model to a stochastic agent-based model. We examined how parameters based on face-to-face interaction had an impact on rumor spread versus interaction over a network (described by an adjacency matrix). Specifically, we used parameters for a model on consumer goods, in order to examine how long it took the rumor to reach a significant proportion (90%) of the population and the effect on the amount of time until steady states were reached with perturbations in initial parameters.

2.2 Estimating Parameters

The parameters necessary to estimate were *credibility*, the *loss of novelty*, and the *number of* ***close*** *interactions* for an individual. Using consumer statistics on perceptions of reliability of information from different sources, we initially estimated the credibility $c = 2.8/7$ [12]. Estimations in number of close contacts varied from 12–26 people per day, varying based on age [3,8,18]. We took the average number of close contacts to be 22 (i.e. $\tau = 22$, which determines our parameter of interaction l). Although the differential model itself does not change with the medium of Facebook, the meaning of τ changes. Instead of 22 close interactions per day, we selected an appropriate analog, in that we assumed the average individual reads approximately 22 posts per day. We estimated the value representing loss of novelty at $\alpha_1 = .01$, and $\alpha_2 = .02$, since the spreaders will have a stronger effect on the stiflers. In all cases, these were the "baseline" parameters, and were only modified for the Feature vector model, in which case parameters c and α_1 were based on the features vectors of agents, and rumors. Sensitivity analyses for c, and δ were run on the interquartile ranges of the studies on which they were based. α_1 was an approximated variable, so we simply run as small of an α_1 variable that the differential model was capable of processing, up to an α_1 value of .25.

3 Agent-Based Models

3.1 Simple Model Method

In order to incorporate a network into our model, we constructed an agent-based model (a useful stochastic technique for modeling dynamics with graphs) [23]. We discretized the data we used for the differential model, in essence using our parameterized proportions as the probabilities that certain individuals would move between populations. Using data from the Facebook network, we allowed individuals to communicate only with those to whom they are connected. Since agent-based models are based on probabilities, and are inherently non-deterministic, we essentially have to perform many "trials" of the model. Each trial consists of initializing a set of "agents" into one of the four populations: Ignorant, Spreader, Stifler, or Knowledgeable. In each trial, there are several time-steps, at which point each agent has a "turn." At each turn, an agent can interact with other agents, and move from one population to another. The rules the define what an agent can or cannot do on a turn are described by the ISTK model. For example, in the differential ISTK model, an Ignorant becomes a Spreader by the term $clSI$. Translating this term to the agent-based model: lSI represents the chance that an Ignorant and Spreader interact (as characterized by the network), and c represents the credibility of the rumor, as expressed as a probability. We performed 400 distinct trials, where each trial constituted 22 days.

Each person began as ignorant, except for a randomly selected subset of the population, who became spreaders. The chance of becoming a spreader was set at 5% distributed randomly (i.e. without considering the network). Because it is a large population (4 039 individuals), each trial would have had around 202 spreaders, but the actual number of spreaders varies from trial to trial. Additionally, it was possible for all of the spreaders to be concentrated in a subnetwork or a "pocket of friends."

To begin each day, every user was assigned an amount of time logged in by picking randomly from a normal distribution with a mean of 23 minutes and a standard deviation of 4 minutes, bounded above 0. We made the assumption that the majority of people will probably be logged on during an 8 hour period of the day; therefore, we only modeled 480 minutes per day, within which the users select their logon time (n.b. users also could not log on in the last 23 minutes of the day, as 23 minutes a day was set as the mean browsing time). Each user had a probability of 14/365 to "post" in a given day. Then, based on the time that they are "logged on," users were assigned a "time" which they made their post form a uniform random distribution. This occurred on each of the 22 days that constituted a trial.

Reader State \ Poster State	I	S	T	K
I	—	$\mathbb{P}(S) = c = 0.8$ $\mathbb{P}(T) = 1 - c = 0.2$	—	—
S	—	$\mathbb{P}(T) = \alpha_1 = 0.01$	$\mathbb{P}(T) = \alpha_2 = 0.02$	—
T	—	—	—	—
K	—	$\mathbb{P}(T) = \alpha_1 = 0.01$	—	—

Table 1: Next reader state for possible interactions between reader and poster. $\mathbb{P}(X)$ denotes probability that reader changes to class X

Each "day," after determining the logon time, posting order, and post time, the simulation of rumor spread began. Every minute, each user could "view" posts written at that minute from people to whom they were **directly** connected. Users were also capped at reading 10 posts a minute. If a poster was a spreader, they had chance $\delta = \frac{1}{d} = \frac{1}{22*480}$ of forgetting the rumor. Then, based off of the probabilities in Table 1, the state of each person was immediately recalculated. Therefore, if a person changed state at a particular minute within a day, then that person would interact as that state with other users in every minute after that. Finally, after 22 days, the trial ended.

3.2 Feature Vector Model Method

This model followed a similar logic as the preceding agent-based model. However, the different interactions accounted for the similarity between two agents or the similarity between an agent and the rumor. First, a baseline feature space of dimension $D = 195$ was taken as a subsample from the Facebook dataset[16]. Each feature corresponds to some data from the original Facebook profiles, like language, identified gender, etc. Although we fortunately can access realistic demographic data, the individual features are not particularly important. We are simply finding a metric for personality similarity to demonstrate that we can model how targeted rumors spread in the context of a (social) network. It is a reasonable assumption that a piece of viral information can be in fact targeted with demographic information. We then examine how assuming personality similarity influences credibility of rumors impacts rumor spread in a population. Each feature is boolean, taking either "true," "false," or "N/A" if the value is unknown. Any "N/As" for a given feature were filled in randomly with some probability p, where $p = \frac{x_t}{x_f + x_t}$, x_t is the number of *true* values there were for a particular feature across the population, and x_f is the corresponding number of *false* values. The rumor itself was also initialized with a particular feature vector, each term generated randomly. A "most similar" rumor vector was generated, which was created by rounding every p to 0 or 1 for each feature. The "most dissimilar" rumor vector was the logical complement of the "most similar" rumor vector.

Next, pairwise angular similarity $S_{p,r}$ was taken between the two interacting agents, poster and reader, where

$$S_{p,r} = \cos(\theta) = \frac{\vec{\mathbf{v_r}} \cdot \vec{\mathbf{v_p}}}{||\vec{\mathbf{v_r}}||||\vec{\mathbf{v_p}}||}$$

where the poster has feature vector $\vec{\mathbf{v_p}}$ and the reader has feature vector $\vec{\mathbf{v_r}}$. Angular similarity between the feature and the reader was also determined, where

$$F_r = \cos(\theta) = \frac{\vec{\mathbf{v_r}} \cdot \vec{\mathbf{f}}}{||\vec{\mathbf{v_r}}||||\vec{\mathbf{f}}||}$$

$\vec{\mathbf{f}}$ is the feature vector of the particular rumor.

We also determined a "baseline" $b = 0.5$, which is the "influence" of an original parameter, and where $1 - b = 0.5$ represents the influence of the interaction of feature vectors. This baseline determined how much each parameter was affected by the similarity scores of feature vectors, and guaranteed the values would be at least half of the original model values. The simple agent-based model was run again, with $bc + (1 - (bc))F_k$ substituted for c and $b\alpha + (1 - (b\alpha))S_{p,r}$ substituted for the respective α values and agents i and j.

We tested 86 different feature vectors, with 100 trials each. In addition for our simulated "most similar" rumor and the "most dissimilar" rumor, we ran 300 repetitions with each rumor, of the stochastic agent based model, with the same population.

4 Results

4.1 Differential Model and Simple Agent-Based Model

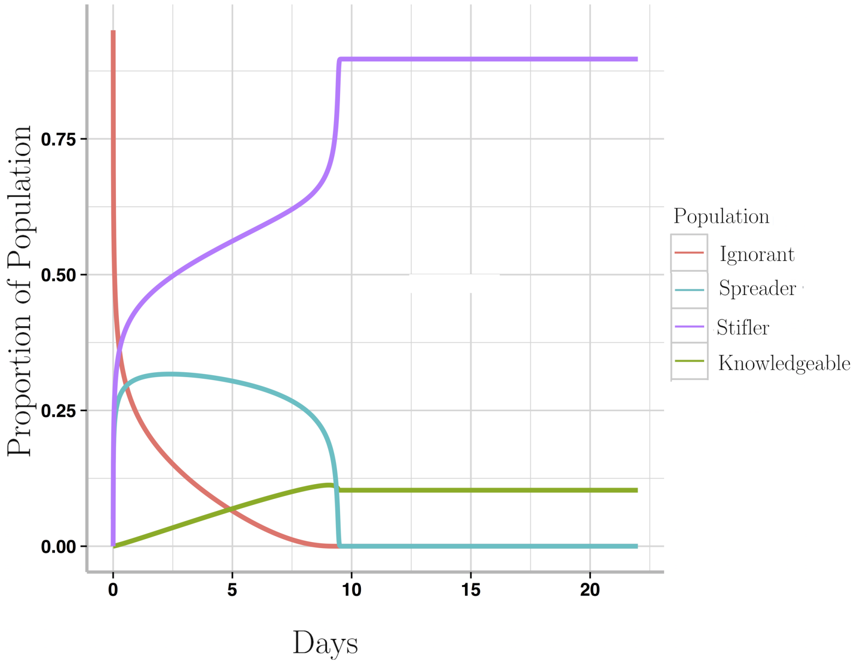

Figure 2: Differential model proportions of the population in each class over 22 days.

For the differential model, as is demonstrated in Figure 2, the spreader and ignorant populations become negligible by the end of the 22 days, and the knowledgeable and stifler populations stabilize above 0. The ignorant population declines, as the spreader population initially grows, and then declines as the stifler population grows. In the differential model, essentially all individuals learn about the rumor. Varying the parameters impacts how quickly the population hears of the rumor, but not the ignorant and spreader populations.

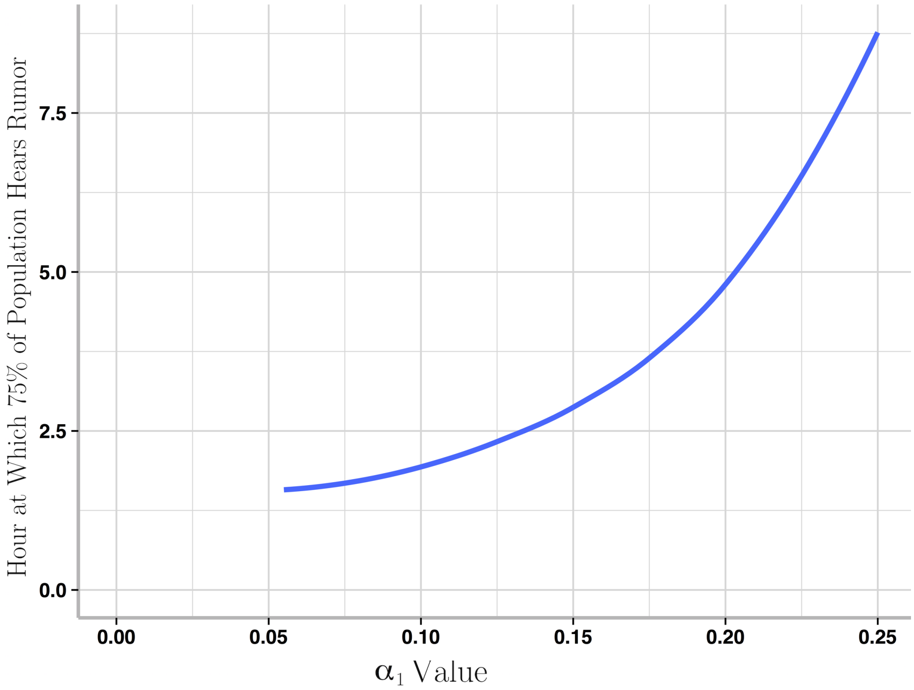

Figure 3: Results of the sensitivity analysis of parameter α_1 in the differential model. For each value of α_1 the time at which 75% of the population had been exposed to the rumor is recorded.

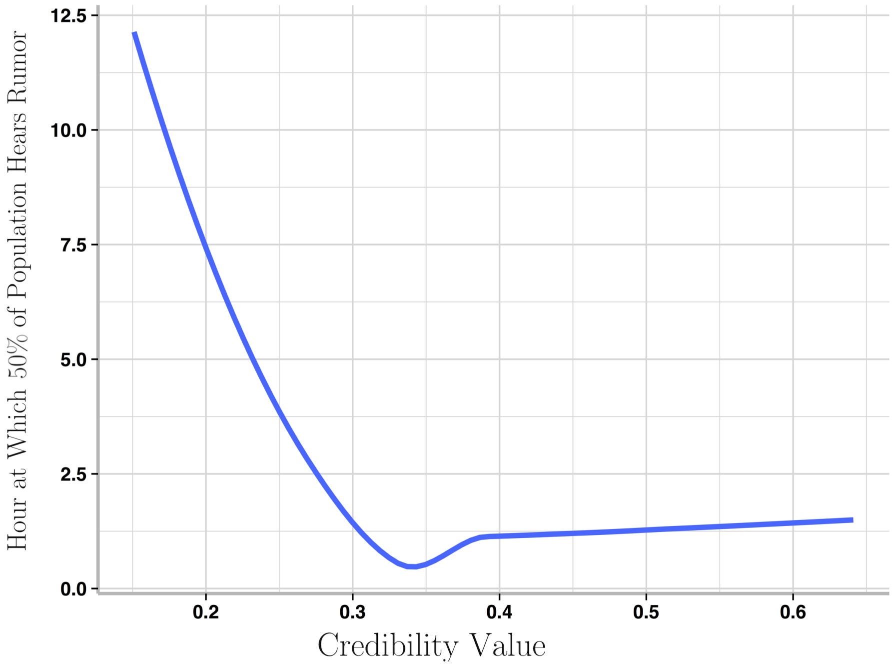

Figure 4: Sensitivity analysis of parameter c in the differential model. For each credibility value the time at which 50% of the population heard the rumor

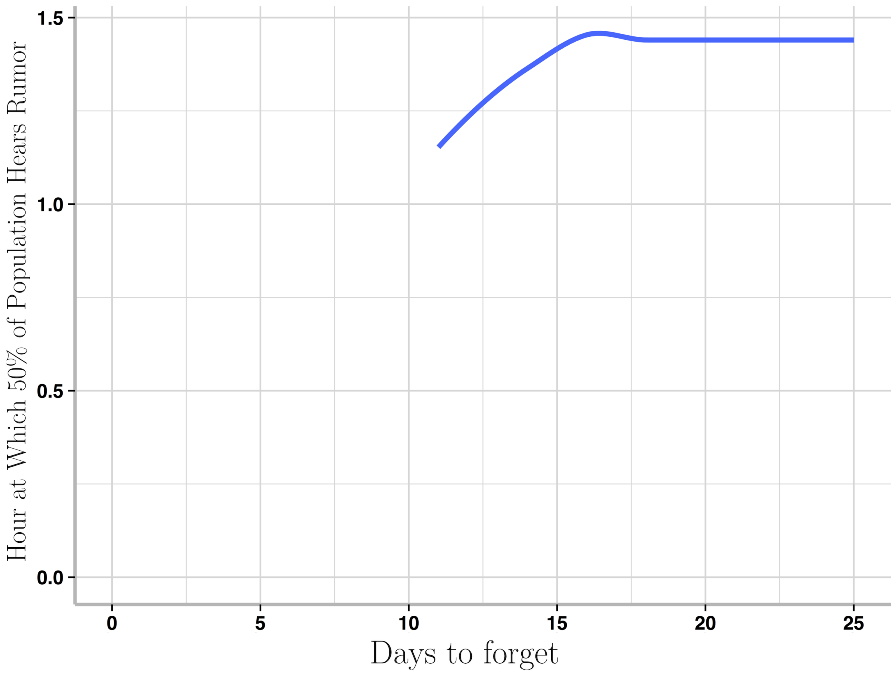

Figure 5: Results of the sensitivity analysis of parameter d (average days to forget) in the differential model. The hour that 50% of the population heard the rumor is recorded for each value of d.

Looking at Figures 3, 4, and 5, increases in credibility decrease the amount of time until the rumor spreads to the majority of the population. The increase in average days to forget increases the time by which half of the population has been exposed to the rumor. The sensitivity analysis indicated that the time to reach the steady state depends most heavily on the α values. As α increases, the time at which 75 percent of the population hear the rumor increases. When varying parameters, the α_2 value was a constant double of the α_1 value.

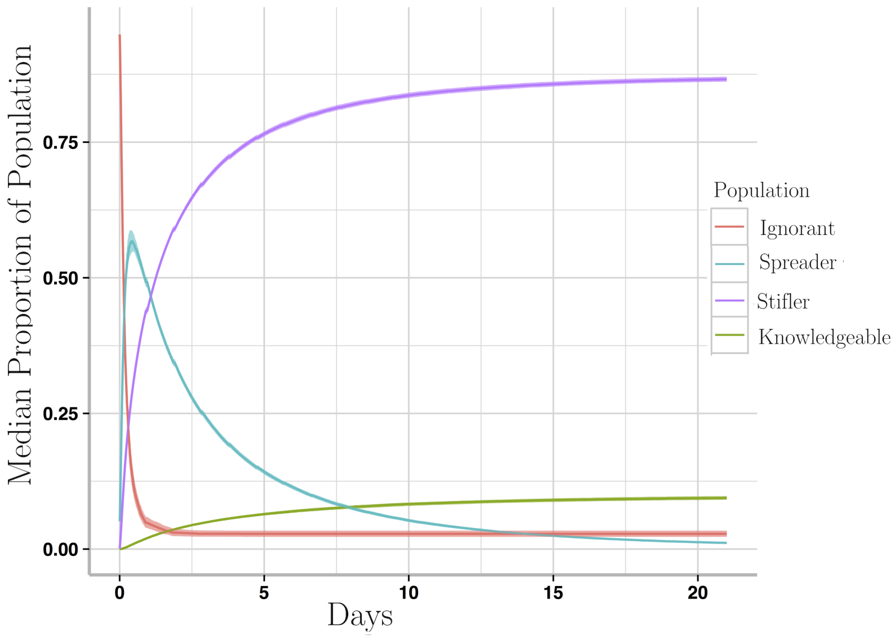

Figure 6: Results of the agent-based model. Solid line indicates median proportion of population across the 400 trials; shadow indicates IQR.

By comparison, in the analogous agent-based model (Figure 6) there are some individuals who do not hear the rumor at all by the end of the simulation.

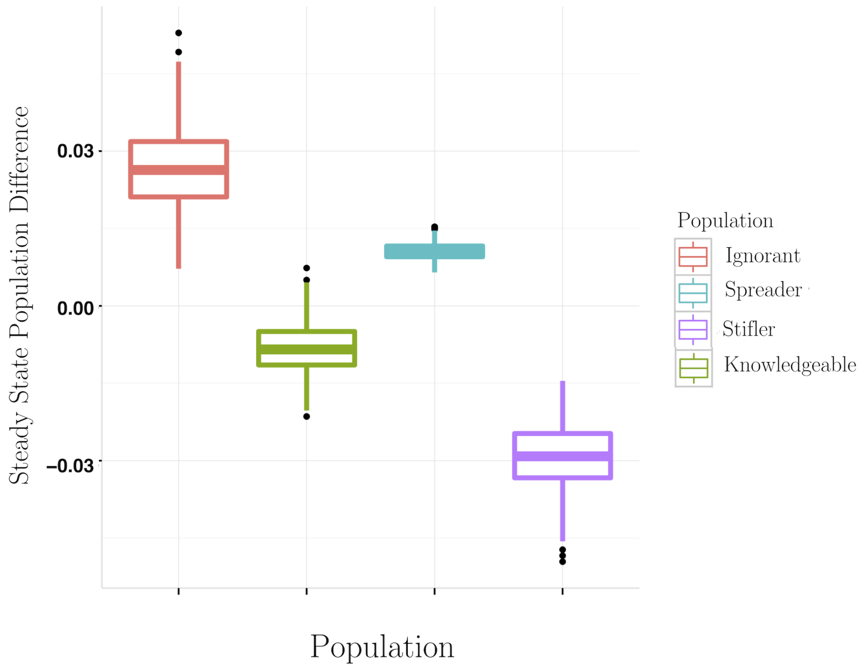

Figure 7: Box-and-whisker plot comparing the steady states in Figure 2 (differential model) and the end states in Figure 6 (Agent-based model).

In this agent-based model, as expected in a stochastic model, there are pockets of "ignorance" that remain. Additionally, the slope of the population graphs are more gradual, rather than moving sharply, as in the differential model. While the dynamics of how the differential model and the simple agent-based model reached their steady-states is different, the end states are generally similar, as seen in Figure 7. This shows a direct comparison of the steady states from the differential model shown in Figure 2 and the stochastic end states from the agent-based model in Figure 6 Though the differential model has no network, and is deterministic, we find that the agent-based model ends with essentially the same steady states. Both models seem to confirm that with the baseline α values we chose, most people end up as rumor stiflers and, most people will be exposed to the rumor. Very few people end up forgetting the rumor entirely.

4.2 Agent-Based Model with Feature Vectors

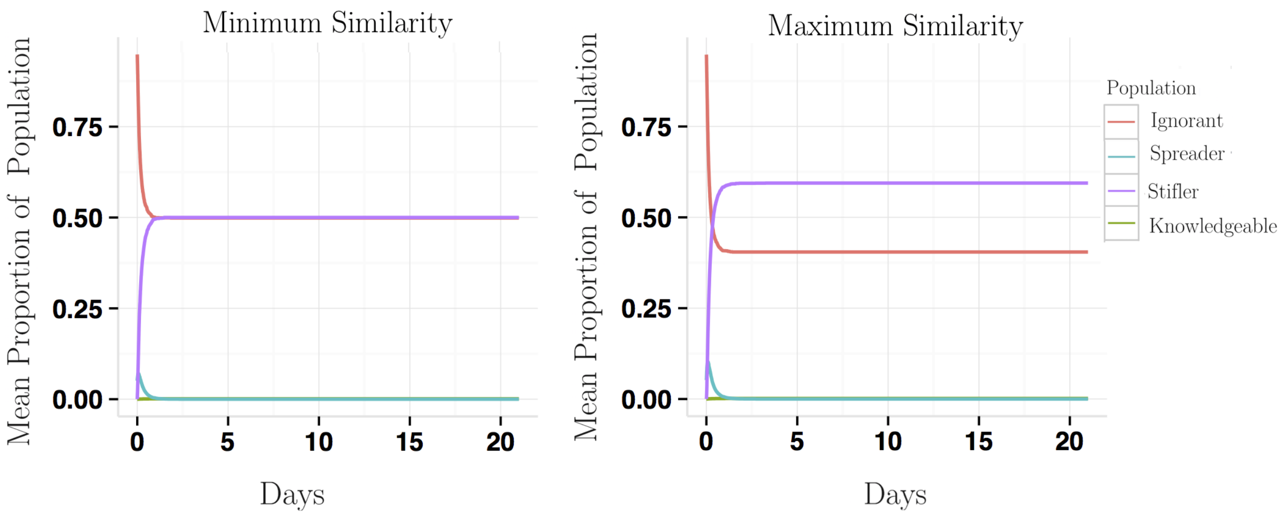

Figure 8: Results of the most and least similar feature vectors to the population in the agent-based model (average across 300 trials).

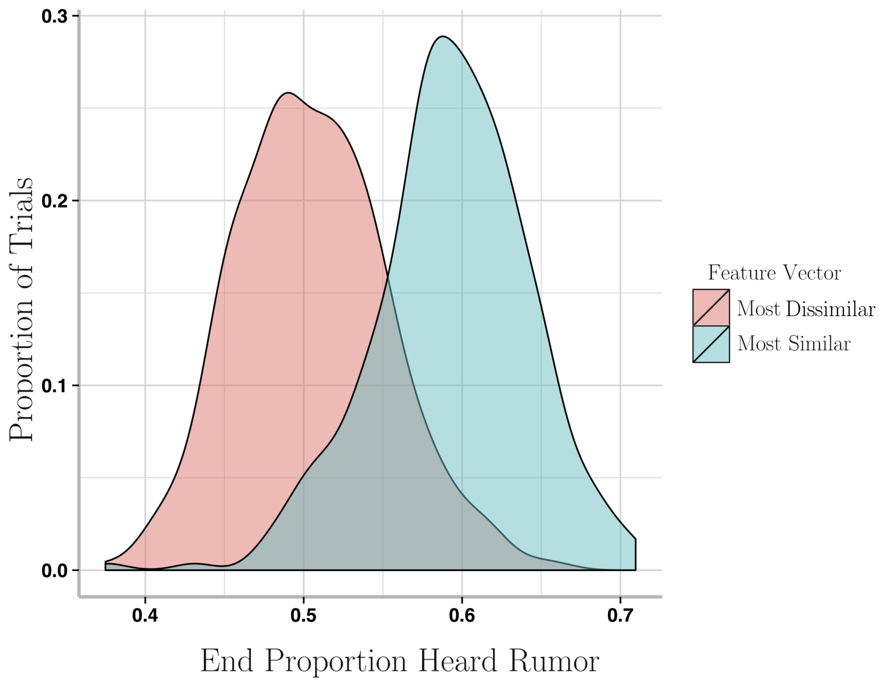

Figure 9: Density of the proportion of the population who heard the rumor after 22 days with the most and least similar rumors (300 trials).

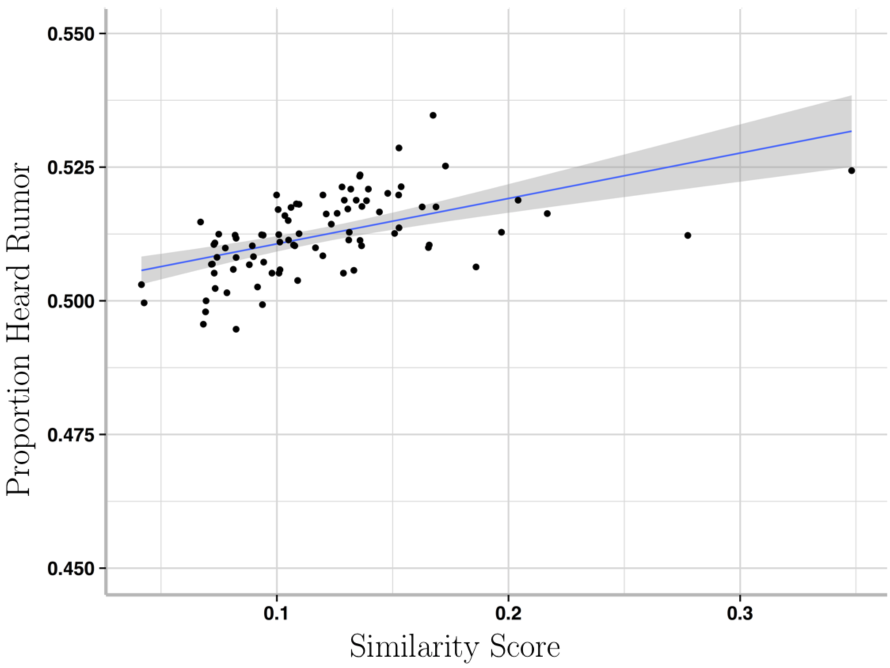

Figure 10: Linear model of the relationship between the final percentage of the population heard rumor and average similarity score of the feature vector ($r = 0.538$). Shading designates the 95% confidence interval.

When the similarity score is added, even the most similar rumor dies out, as seen in Figure 8. This plot is identical to Figure 2 and Figure 6, but is the stochastic agent-based case. However, the average similarity score of a rumor with the population does affect the spread (Figure 9). The most similar rumor to the population spreads to more of the population than does the least similar. The trend from the other feature vectors supports this claim, as demonstrated by Figure 10. The predictive power of the similarity in predicting the number of individuals who heard the rumor is decent where the bulk of the data lies. (n.b. the way that we generated most and least similar feature vectors did not guarantee that they were the absolute most or least similar to the population. To make the most similar vector, we rounded the total proportion of each feature in the entire population to either 1 or 0 to make it binary. The least similar vector is the logical complement of the most similar one. Therefore, in randomly generating feature vectors, we ended up with a few that were less similar than the "least similar" feature vector.)

5 Discussion

There was relatively little difference between the end states of the differential and simple agent-based models, despite the fact that the former aggregates the population and the latter provides more granularity. As previously noted by Chierchetti et al.[4], in a fully-connected network with push-pull interactions, a rumor will spread to the majority of the population with high probability. Though our model has a significantly different setup, we came to similar conclusions as this previous study's findings, though our model had a fully-connected network and assumed different interactions: individuals only had the opportunity to interact with the same individuals at every time step, as opposed to choosing new "partners" each time[4]. In the agent-based model, not every individual learned about the rumor, and the addition of some structured social network causes a delay in rumor spread. That is to say, the effects on one cluster are not immediately transferred to another cluster, as effects upon individuals must travel through the other individuals in a complex network in order to have large-scale effects on the population. Thus, the curves are less dramatic, change more gradually, and there is no guarantee every individual will hear the rumor: by the end of the 22 days essentially none of the population remains ignorant in the differential model, whereas in the agent-based model 2.8% of the population remains ignorant. However, the trajectories of the two models are qualitatively similar, suggesting that the agent-based model tends to a vanishing of an ignorant population, save for a small connected subnetwork. Just like the claim so well supported in push models, eventually there is a high probability all individuals will hear the rumor[1,21].

The incorporation of Feature vectors in the agent-based model changes the overall spread of the rumor. Even in the case in which most people hear the rumor (the most similar feature vector) there remains a significant population that never hears the rumor, a factor of the similarity between individuals and the rumor. Facebook friendships are a relationship that we take here to model real-world social networks. However, Facebook friends are likely to be more superficial. In fact, the average number of Facebook friends is 338[22], yet Dunbar's number suggests that humans cannot maintain more than 150 relationships due to neocortex size[7]. The social network we use shows the spread of a rumor in people who are not necessarily close, but do interact. Perhaps the feature-vector-based spread in a Facebook network is less effective in spreading the rumor due to this superficiality of relationships. Perhaps if individuals in a Facebook network cluster based on features, it would explain how a rumor could die out trying to navigate a dissimilar subnetwork. As indicated by our results, even where the rumor spreads, individuals become stiflers so quickly that the rumor dies out before reaching a large proportion of the population. This behavior is familiar to anyone who has been on social media, and had friends who relentlessly post stories that bear no significance to their personal beliefs or preferences.

Perhaps networks with clusters of similar people (by their feature vectors) would aid in the rapid transmission of a rumor across a network. In the Feature vector model, spread of the rumor is a factor of both the similarity of individuals to each other, and similarity of the rumor to each individual. We speculate that in a community with many highly similar individuals one could much more easily engineer a rumor to spread through the whole network. However, an individual hearing the rumor has less to do with their individual traits, than the similarity of individuals to each other in the population. We show that there is nothing in the topology of the network that prevents rumor spread in the simple agent based model, so inoculation against hearing the rumor is a factor of the general dissimilarity of individuals to each other in the population. We suspect that the inevitable "death" of our rumors may be due to a population of individuals with a great variety of different feature vectors. Future models should investigate how the similarity of individuals' feature vectors impacts the spread of any rumor.

6 Conclusions

Since the rumor tends to spread rapidly at the start of the simulation (resulting in a corresponding boost in the stifler population), these results inspire the consideration of different network configurations. A rumor spreads rather more quickly in preferentially connected real-world graphs than in common theoretical mathematical graphs[6], however, In our case, even the "best-performing" rumor—one that maximized spread—still died out. However, it may be possible to engineer a rumor that saturates the network. In all, it would seem as though our model—in part thanks to the advent of increased computing power for simulations—can begin to unravel the nuances and intricacies of information spread through a social network. By arriving at a model that uses feature vectors and graphs, we have greater control and specificity in looking at the spread of viral information, possibly leading us to mathematically "perfect" viral information.

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