Proceedings of the 2015 Winter Simulation Conference
L. Yilmaz, W. K. V. Chan, I. Moon, T. M. K. Roeder, C. Macal, and M. D. Rossetti, eds.

AN AGENT BASED MODEL OF SPREAD OF COMPETING RUMORS THROUGH ONLINE INTERACTIONS ON SOCIAL MEDIA

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ABSTRACT

The continued popularity of social media in the dissemination of ideas and the unique features of that channel create important research opportunities in the study of rumor contagion. Using an agent-based modeling framework, we study agent behavior in the spread of competing rumors through an endogenous costly exercise of measured networked interactions whereby agents update their position, opinion or belief with respect to a rumor, and attempt to influence peers through interactions, uniquely shaping group behavior in the spread of rumors. It should be pointed out that this research is still in its nascent stages and much needs to be further investigated. Our initial findings, however, suggest that (i) rumors can survive under competition even with low adopting populations, (ii) latent positions in rumors seem to dominate extreme positions, and (iii) the timing of the effort expended by an agent affects the level of competition between rumors.

1 INTRODUCTION

Online interactions, especially on social media, differ fundamentally from traditional offline human interactions and represent a new paradigm for the spread of information, ideas, and rumors. Even though there is a rich theoretical understanding of the spread of rumors (Daley and Kendall 1965, Maki and Thompson 1973, Gani 2000, Dickinson and Pearce 2003, Hayes 1993), we are yet to fully study or understand the effects of modern communication channels (like social news media discussion sites), which are marked by unique agent behavior and online interaction dynamics, on the spread of rumors.

This research is motivated by Kaligotla and Galunic (2015), which examines the spread of rumors during the "Watertown Manhunt", the event involving the manhunt of the suspects of the Boston Marathon Bombings in April 2013. Live online discussions surrounding the event resulted in several names being publicly touted as being the perpetrators, before the real culprits were identified. This caused substantial anguish to the named individuals and/or their families and complicated investigations by law enforcement agencies. The event suggested that online social media can get things wrong for extended periods of time. That false rumors spread wildly, even in competition and are not easily stopped short of authoritative events, strongly motivates our work.

The term "social media" is commonly understood as virtual or electronic platforms which allow users (individual agents) to form online communities and interact by sharing information, ideas, personal messages, and other forms of communication. There is a marked difference between social news and information sites and social network sites, and between online and normal interactions. Social news and information web sites like *Reddit*, involve interactions among distant anonymous individuals (with little or no historical

978-1-4673-9743-8/15/$31.00 ©2015 IEEE

contacts), whereas social networking forums, like *Facebook*, blend everyday, face-to-face friends or closed peer networks with online interactions. Online interactions are also fundamentally different from common face-to-face interactions in their sheer volume and pace.

The concurrent diffusion of rumors/ideas and network evolution also results in multiple competing rumors. As is commonly seen, rumors rarely exist singularly. Studies of rumor contagion, however, traditionally tend to involve a single rumor (much like disease contagion models of a single disease) rather than a competition between alternative ideas/rumors attempting to gain uptake in an evolving network. The continued popularity of social media in the dissemination of ideas and the unique features of that channel create important research opportunities in the study of rumor contagion. This paper aims to understand agent behavior in the spread of competing rumors, through an endogenous costly exercise of measured networked interactions through which agents update their position, opinion or belief with respect to a rumor, and attempt to influence peers through interactions, thereby uniquely shaping group behavior in the spread of rumors. We would like to note that this research is still in its nascent stages and much needs to be further investigated and codified.

In section 2, we introduce relevant literature and present our research questions. Section 3 describes our conceptual model on which we develop an agent-based model. A *NetLogo* implementation is summarized in section 4. Simulation results are discussed in section 5. Section 6 summarizes the paper.

2 BACKGROUND

There exists a vast amount of literature across different fields related to diffusion of rumors, infection epidemics, opinions and ideas, on which we build our research. The classic rumor literature, based on epidemic modeling, began with Daley and Kendall (1965) and Maki and Thompson (1973). They introduced two types of stochastic models for rumors, which were later shown to be similar (Gani 2000, Dickinson and Pearce 2003, Hayes 1993). Bartholomew (1973) and Dietz (1967) offer a comprehensive overview of classical rumor literature.

Most papers in rumor literature use stochastic models, which typically make simplifying assumptions to have tractable analytical results. For instance, most epidemic models assume homogeneous agents with random or directed mixing. We are however interested in studying the setting where agents are heterogeneous and their choices are behaviorally motivated. The use of Agent-Based Simulation (ABS) to study this kind of problem is practical as it allows us to relax some assumptions to build intuition (Macal and North 2010). In a comparative study, Rahmandad and Sterman (2008) compare stochastic models and agent-based models for studying diffusion and highlight the strengths of each methodological approach.

In our study of the spread of competing rumors on modern (and future) social media channels, we extend existing theory by considering the following assumptions / constructs, with support from the literature:

A1. Rumors Exist in Competition. As mentioned in the previous section, rumors are rarely singular. Group sense making often leads to multiple competing explanations, which leads to multiple rumors. Osei and Thompson (1977) make a similar observation and consider a stochastic model with two rumors spreading in a closed population. They specifically consider a case where one rumor suppresses the other and determine the distribution of the maximum proportion of spreaders of the weaker rumor. Karameshu and Pathira (1960) consider a situation in which two social groups compete with each other, again calculating the distribution for the maximum size attained by the weaker group. Hu, Barnes, and Golden (2014) approach competing contagion through agent-based modeling to capture disease contagion patterns from different causes, one for a bio-terrorism attack and the other from an epidemic outbreak.

A2. Rumors Have Depth and Directionality. Rumors in reality are more like ideology that agents can adopt or believe in, with a continuum of exclusive and exhaustive positions, rather than a binary choice like an infection; while an agent either has an infection or not, there are multiple positions he/she can adopt in a rumor (support, neutral or contrarian). Moreover, not believing in rumor A is not the same as believing in rumor B. Schramm (2006), in his unpublished thesis, classifies rumors according to a continuum of positions and introduces the NSRCL model, which consists of five classes of agents: neutral agents

(N), extreme supportive agents (S), latent supportive agents (R), extreme contrarian agents (C), and latent contrarian agents (L). The agents interact randomly and change positions based on a matrix of interaction rules similar to those in Daley and Kendall (1965). He models the flow of ideology considering the case where both the supporters and contrarians openly vie for a greater share of support from the public. We adopt the NSCRL model in this paper.

A3. Rumors Spread by Agent Influence through Interactions. Agents interact with each other whereby they exchange information and expend effort in trying to influence their counterpart with their own belief or position. They do this using their online reputation and effort. We also assume that agents update their positions with respect to a rumor, much like the transition rules given by Daley and Kendall (1965) and Hayes (1993). There is also reason to believe that types of news sources can affect contagion. Onggo, Busby, and Liu (2014) make a distinction that individuals use information from different sources (which they refer to as broadcast news and narrowcast personal social networks) to form a perception on some social issue. They study the effect of broadcasting and narrowcasting on the dynamics of public risk perception and report that extreme narrowcast and average risk broadcasts are undesirable.

A4. Rumors and Networks Evolve in Parallel. Diffusion or spread of rumors happen concurrently with network evolution. Weng (2014) studies the co-evolution of diffusion and network topologies while considering heterogeneous agent types with respect to tie formation and strategies for network evolution. Golub and Jackson (2012) question whether large societies whose agents are naive individually can be smart in the aggregate when there is naive updating. Further work from these authors also include instances of Bayesian updating and network evolution.

None of these constructs is new by itself; indeed different papers have looked at these points individually. We believe we are the first in putting these constructs together given our research goals. This paper therefore aims at understanding the diffusion of rumors, taking into account agent characteristics (such as reputation and effort) and interaction dynamics while considering competing rumors. The research questions we seek to address specifically are:

i. How does competition between two rumor streams affect the diffusion of rumors?
ii. Does the initial distribution of agent population affect the evolution of rumors?
iii. How does time-dependent effort affect the diffusion of rumors?

3 CONCEPTUAL MODEL OF RUMORS ON NETWORKS

In this section, we describe a conceptual model of competing rumor diffusion on social media networks, which we then implement through ABS on *NetLogo*. We adopt the NSRCL setup of Schramm (2006), where there are five agent population classes for each rumor $x \in \{\mathbf{A}, \mathbf{B}\}$: N_x for Neutrals, S_x for Active Supporters, R_x for Latent Supporters, C_x for Active Contrarians, and L_x for Latent Contrarians. Each of these five subclasses are considered to represent a belief position within that rumor.

The two competing rumors, **A** and **B**, together offer mutually exclusive and collectively exhaustive explanations for some specific question or event. We assume that either of them is equally likely to be true, since the true explanation is ex-ante unknown.

These rumors compete for spread or adoption by agents who interact with each other in a community. Adoption here is defined as an agent who believes in one of the positions within one of the rumors and expresses his/her belief through measurable interaction like a comment or a tweet, trying to influence other agents in the network towards adopting his/her belief position. Note that over time, the agent in question is also subjected to influence by other agents, potentially changing his/her own belief position.

In this setup that there is no null state in the system, i.e., there exists no agent who does not adopt at least one of the belief positions across the two rumors, as an agent not believing in either rumor will not take part in the rumor space in the first place. We also differentiate between being Neutral in rumor **A** and being Neutral in rumor **B**. (The equivalent scenario in an epidemic setting is whether an agent is at risk of epidemic 1 or epidemic 2. For an agent who is equally at risk of both contagions, we assume a random assignment into one of the two neutral classes.)

Agents then interact with others randomly where they expend effort in trying to influence their counterpart. Hence, exchanging beliefs sometimes results in agents updating their positions regarding the competing rumors. Competition of rumors is thus simply measured by the total population of agents within each rumor, across all subclasses at time t. We aim to study the macro level outcomes of the adoptive positions of agents in competing rumor spaces under a simple set of interaction rules and network topology.

We assume a discrete time setup. Let $N_x(t)$ denote the total number of agents in class N for rumor x at time t. We define $S_x(t)$, $R_x(t)$, $C_x(t)$, $L_x(t)$ in an analogous fashion such that $N_x(t), S_x(t), R_x(t), C_x(t), L_x(t) \geq 0$ for all t. Let $S_{\mathbf{A}}(t)$ denote the total number of active supporters for rumor **A**, and $S_{\mathbf{B}}(t)$ denote the total number of active supporters for rumor **B**, at time t.

Let $S(t)$ be a 2×5 matrix which denotes the system population summary statistic at time t,

$$S(t) = \begin{bmatrix} N_{\mathbf{A}}(t) & S_{\mathbf{A}}(t) & R_{\mathbf{A}}(t) & C_{\mathbf{A}}(t) & L_{\mathbf{A}}(t) \\ N_{\mathbf{B}}(t) & S_{\mathbf{B}}(t) & R_{\mathbf{B}}(t) & C_{\mathbf{B}}(t) & L_{\mathbf{B}}(t) \end{bmatrix}.$$

Let $\mathbf{A}(t)$ and $\mathbf{B}(t)$ denote the total number of adopters for rumors **A** and **B,** respectively, at time t,

$$\begin{aligned} \mathbf{A}(t) &= N_{\mathbf{A}}(t) + S_{\mathbf{A}}(t) + R_{\mathbf{A}}(t) + C_{\mathbf{A}}(t) + L_{\mathbf{A}}(t) \\ \mathbf{B}(t) &= N_{\mathbf{B}}(t) + S_{\mathbf{B}}(t) + R_{\mathbf{B}}(t) + C_{\mathbf{B}}(t) + L_{\mathbf{B}}(t). \end{aligned}$$

We are most interested in measuring $\mathbf{A}(t)$ compared to $\mathbf{B}(t)$ given exogenous characteristics, relative to the total agent population in the system at time t, $P(t) = \mathbf{A}(t) + \mathbf{B}(t)$.

3.1 Modeling Individual Agent Dynamics

Each agent i, who is typically represented by a node in the network, is endowed with some inherent property called reputation (denoted by λ_i) and effort (denoted by ε_i^t). Assume that the nature of the competing rumors in question has a property called threshold, denoted by τ, which is constant for all agents and represents the minimum amount of influence necessary to trigger a change in an agent's belief position.

Reputation is used as a proxy for historical experience or publicly acknowledged expertise such that an agent with a higher reputation is more easily able to influence a peer, compared to an agent with low reputation. We assume that the reputation of an agent is constant through time.

Effort is viewed as a finite amount of energy an agent has at time t to expend in an interaction in an attempt to influence a peer to change his/her belief position. Effort can be characterized by a function given by $\varepsilon_{t+1} = \varepsilon_t - z_t$, where $z_t \leq \varepsilon_t$ is the energy expenditure for an interaction at time t.

Threshold is defined as the minimum influence required by some agent j in interaction with agent i, to be able to convince agent i to change his/her belief position in a rumor.

Let X_n^t denote the state of agent n at time t. We consider X_n^t to be a stochastic process on the state space defined by

$$\mathbb{S} = \left\{ \lambda, \varepsilon, \tau, \{N_x, S_x, R_x, C_x, L_x\}_{x \in \{\mathbf{A},\mathbf{B}\}} \right\}.$$

Interactions occur when two agents meet; as a result, a change of state can occur, governed by a function $f(x,i,j)$. We define influence as the process of a change of state of an agent from time t to $t+1$, after an interaction with another agent. Mathematically,

$$X_n^t \overset{f(x,i,j)}{\rightarrow} X_n^{t+1},$$

where $f(x,i,j)$ depends on the dynamics of the network and interactions specified in sections 3.2 and 3.3.

3.2 Modeling Network Structure and Evolution

Future work in this project aims to explore network evolution relating to spread of competing rumors. We currently model network evolution through the formation of a "giant component" on a random network.

Motivated by findings in Kaligotla and Galunic (2015), an important distinction to note between social media and traditional social networks is in terms of anonymity and the random mixing of distant individuals (among whom there has been little or no prior off-line contact). While traditionally interactions, even on social networks are typically with known peers (friends or followers), modern social media interactions are mainly characterized by random interactions between anonymous strangers. This impacts the evolution and topology of networks, where it has been observed that historical reputation of nodes affects neither the diffusion of rumors nor the centrality of the interaction networks.

In our setup, a node in the network is an individual agent. We model network evolution using a random graph model (Erdös and Renyi 1959) in which every possible edge occurs independently with some probability $0 < p < 1$. A property of this network structure is that, in a random graph of N nodes, each pair of nodes has an equal probability p of being connected. See also Watts (2002), Janson et al. (1993).

We consider a measured interaction (comments or tweets) between two agents at some specific time t to constitute a (directional) edge. Thus, when an individual agent j makes a comment or a tweet in response to agent i's comment or tweet, we form an edge directed from $i \rightarrow j$. We model these measured interactions as described in section 3.3.

At this stage of our research, we assume a closed population. We model evolution on the random network through the formation of new edges at each time step, forming increasingly connected components, eventually leading to a giant connected component. Thus, at each time step, two previously unconnected nodes are picked at random and an edge is formed between them. Multiple components eventually merge into a single giant component. This structure captures the discussion or interaction dynamics observed on social media like *Reddit* or *Twitter*, where people interact (or post tweets or reply comments) with each other, eventually forming a giant discussion thread (in the case of *Reddit*) or a giant hashtag group (in case of *Twitter*), where every individual measured interaction can be traced to every other interaction, either through the discussion thread or the hashtag group.

3.3 Modeling Influence and Transition Dynamics

We set the interaction dynamics defined by the function $f(x,i,j)$ with two components: first the influence dynamic (i.e., which agent manages to convince her peer) and second, the state transition rules governing the change of position adopted by an agent within competing rumors.

Consider an interaction between agents i and j at time t. Agent j (with state $X_j^t(\lambda_j, \varepsilon_j^t, \tau_j)$) manages to influence agent i (with state $X_i^t(\lambda_i, \varepsilon_i^t, \tau_i)$) if and only if

$$\left(\lambda_j \times \varepsilon_j^t\right) > \tau_i. \tag{1}$$

If the inequality in (1) is true, then agent i changes his/her state on account of being influenced using the allowable state transitions as summarized in Table 1 for within-rumor transitions (this is essentially a modified version of Schramm (2006)) and, in Table 2, for transitions across competing rumors.

For example, it may be that an agent who is Neutral in rumor **A** moves to a new position of Support in rumor **A**, e.g.,

$$\begin{aligned} f(x,i,j) \mid \left(\lambda_j \times \varepsilon_j^t\right) > \tau_i \quad &\Longrightarrow \quad X_i^t \rightarrow X_i^{t+1} \\ &\Longrightarrow \quad S_{\mathbf{A}}(t+1) = S_{\mathbf{A}}(t) + 1, \quad N_{\mathbf{A}}(t+1) = N_{\mathbf{A}}(t) - 1 \end{aligned}$$

Transition rules for different states have been a hallmark of rumor and contagion literature. For instance, as described in Hayes (1993), the DK and MT models have transitions similar to the epidemic SIR models, where interaction and transition rules define a state change from S (Susceptible) to I (Infected) and then from I (Infected) to R (Recovered).

Table 1: Proposed Transitions Within a Rumor.

j across / i down	N_A	S_A	R_A	C_A	L_A
N_A	-	$N_A \rightarrow S_A$	-	$N_A \rightarrow C_A$	-
S_A	$N_A \rightarrow S_A$	$S_A \rightarrow R_A$,$S_A \rightarrow R_A$	-	-	$L_A \rightarrow N_A$
R_A	-	-	-	$R_A \rightarrow N_A$	-
C_A	$N_A \rightarrow C_A$	-	$R_A \rightarrow N_A$	$C_A \rightarrow L_A$,$C_A \rightarrow L_A$	-
L_A	-	$L_A \rightarrow N_A$	-	-	-

Table 2: Proposed Transitions across Competing Rumors.

j across / i down	N_A	S_A	R_A	C_A	L_A
N_B	–	$N_B \rightarrow R_A$	–	$N_B \rightarrow L_A$	–
S_B	$N_A \rightarrow R_B$	–	$R_A \rightarrow S_A$*	–	–
R_B	–	$R_B \rightarrow S_B$*	–	–	–
C_B	$N_A \rightarrow L_B$	–	–	–	$L_A \rightarrow C_A$*
L_B	–	–	–	$L_B \rightarrow C_B$*	

Consider, for instance, Schramm (2006)'s depiction of an interaction between an agent who is an Active Supporter (S_A) and another agent who is an Active Contrarian (C_A). His transition rules prescribe that the Active Supporter becomes and Active Contrarian and vice versa, which might be a remarkably rare occurrence in social media conversations. Similarly, another transition rule in Osei and Thompson (1977) who consider a competition between two rumors in a closed population, assume that a *"Rumor A-spreader always becomes a rumor B-spreader."* While this assumption makes sense in their setting, it is unsuitable for us given our aim to model social media interactions where transitions across rumors occur in both directions. It is worth noting that most transition rules such as these are assumptions, and may heavily influence the results. While these assumptions are standard, logical, and even necessary, we argue that some of them render the current rumor contagion models unsuitable for capturing the observed interactions in social media. Our choice is motivated by social media, and will be evaluated for appropriateness as work progresses.

4 SIMULATION MODEL

We implement an ABS model on *NetLogo* (Wilensky 1999), based on our conceptual model presented in the previous section, which enables us to incorporate some of the key conditions observed in practice (e.g., heterogeneity of agents). More specifically, we develop two distinct *NetLogo* simulation models, one for simulating rumor competition between two rumors, and another built on top of our rumor competition model to simulate the spread of rumors through influence, by the interplay of reputation, effort, and threshold values. We model the network evolution using a preferential attachment model. The primary inputs to the model are the initial population subclasses across both rumors.

Our second simulation model considers agent effort. Our input parameters also include the mean and standard deviation of starting energy levels as well as the mean values for reputation and threshold. Output measures from our simulation include the system states and population of subclasses in each time step, and for the second model, the number of interactions and the mean effort at time t.

We verified and validated our *NetLogo* simulation model by first replicating Schramm (2006) using his interaction rules and finding results as predicted in his dissertation. We then incorporated the interaction rules described in Tables 1 and 2. It is important to note the fundamental assumption that all states are reachable. Future extensions of this research would include varying transition probabilities.

We relied on social news media data from Kaligotla and Galunic (2015) to set the parameter values in our simulation experiments. In this paper, we set the threshold value to be constant for all agents. We use an exponential distribution for reputation scores across agents, motivated by the empirical observations and use a normal distribution to assign energy to individual agents (we also use a heavy tailed Cauchy distribution for agent energy as a robustness check).

We simulate the difference in timing of effort in the second model by introducing a parameter called "Effort Decay Start." This parameter represents the time step (called ticks in *NetLogo*) at which every agent's energy parameter value starts decaying according to $\varepsilon_{t+1} = \varepsilon_t - 1 \mid t >$ Effort Decay Start. For all interactions over the ticks prior to the "Effort Decay Start" setting, there is no effort decay, i.e., $\varepsilon_{t+1} = \varepsilon_t \mid t \leq$ Effort Decay Start.

In both models, network evolution is simulated through a giant network component on a random graph. A network simulation for this type of network can be seen in Wilensky (1999) and Wilensky (2005), and is available on the *NetLogo* Model library. In order to simulate and consider real world social psychological processes like the confirmation bias, we intend to, in future work, explore different evolving network structures, including those based on some homophily.

In our simulation, we begin with a given number of nodes with no connected edges set in a circular layout. At each tick, two previously unconnected nodes are picked at random and an edge is formed between them. This is executed at every tick resulting in chains or groups called components, where each node is connected to every other node in that component. Eventually, multiple components merge into a single giant component. The simulation is forced to stop if and when all nodes are connected. The identification of connected components is done recursively through depth-first search, i.e., for a given node picked at random, all its neighboring nodes are explored at depth, before a new node is picked. As a result, all reachable nodes from a particular starting node will eventually be explored.

5 RESULTS

We run our simulation as described in the previous section to answer the questions set out in section 2.

5.1 Competition Effects : Rumor Survival in Competition

We seek to test our conjecture that the presence of even a small proportion of adopters of a rumor with respect to a competing one will ensure the survival of that rumor. To this end, we vary the initial total population of adopters of each rumor, $\mathbf{A}(0)$ and $\mathbf{B}(0)$. We simulate 30 runs of 200 time steps for each setting, and compare the values of $\mathbf{B}(t)/P(t)$ while keeping the total population of agents $P(t) = \mathbf{A}(t) + \mathbf{B}(t)$ constant. Given that no new agents enter the system, we find 200 time steps enough to achieve stability. We should note, however, that this is heavily dependent on our initial conditions of total agent population. We find that running longer simulations in our current setup does not change our conclusions and provides no further intuition or dynamics of interest. In future versions of our work, we intend to increase the agent population in our initialization, which will necessitate an increased run time.

Figure 1 shows the initial values and final results for each setting. Note that, for each setting, we keep the distribution of population subclasses within each rumor to be constant, except in setting 5, where we randomly choose a non neutral subclass for rumor B.

Variable(s)	Note	Setting 1	Setting 2	Setting 3	Setting 4	Setting 5*
A (t=0)	Initial Setting	50	75	90	95	98
B (t=0)	Initial Setting	50	25	10	5	2
P(t) = A(t) + B(t)	Initial Measure	100	100	100	100	100
A(t=0) / P(t=0)	Initial Measure	50.00%	75.00%	90.00%	95.00%	98.00%
B(t=0) / P(t=0)	Initial Measure	50.00%	25.00%	10.00%	5.00%	2.00%
A (t=200)	(Mean of 30 runs)	50.329	73.17396	88.99585	94.15191	98.13648
B (t=200)	(Mean of 30 runs)	49.671	26.82604	11.00415	5.848093	1.863516
A(t=200) / P(t=200)	(Mean of 30 runs)	50.33%	73.17%	89.00%	94.15%	98.14%
B(t=200) / P(t=200)	(Mean of 30 runs)	49.67%	26.83%	11.00%	5.85%	1.86%

Figure 1: Simulation Settings and Results : Rumor Survival in Competition.

We find that $\mathbf{B}(200)/P(200)) > 0$ across all ranges of set values, implying that even a small population proportion of adopters of a rumor in competition will ensure the survival of that rumor. While this is pretty intuitive given our setting, it highlights an important point - that of the significance of the transition matrix, especially regarding its symmetry and the presence of non-absorbing states. Note also however, that while the proportion remains stable, the population of the subclasses *within* each rumor does vary (see Figure 2), implying changing influence within that proportion (explaining observations in practice such as a small group of extreme views subsisting in the presence of an overwhelming majority of opposing views).

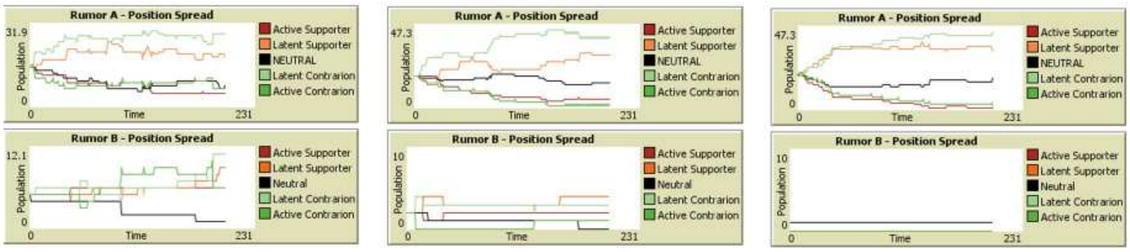

Figure 2: Simulation Settings and Results : Rumor Survival in Competition.

Our results indicate that, given a motive for mis-information or dis-information, any agent or group of agents, however small in proportion, can use their influence to ensure the survival of the rumor, however small the adoption percentage might be. The essence that all transition states are reachable seems to play a role in ensuring the survival of the rumor. This potentially could explain observations on social media where outlandish rumors continue to exist.

5.2 Population Effects in Rumor Competition

We also seek to test our conjecture that the distribution of states (or population subclasses) within a rumor affects the competition dynamics of the rumors . This would imply that, in a transition matrix where all states are reachable, the initial population of rumor subclasses impacts the final population of the rumor subclasses, meaning that initial population distribution within rumors affects the spread of influence and diffusion of rumors.

We investigate this conjecture by varying the population of the subclasses of the rumor, e.g. $S_x(0)$, while keeping all else equal. We initialize the distribution of population subclasses in four distinct settings: i) uniform, ii) extreme support skew, iii) extreme contrarian skew, and iv) convex as described in Figure 3.

	Uniform	Support Skew	Contrarian Skew	Convex Skew
S_A (t=0)	10	15	5	15
R_A (t=0)	10	15	5	8
N_A (t=0)	10	10	10	4
L_A (t=0)	10	5	15	8
C_A (t=0)	10	5	15	15
S_B (t=0)	10	15	5	15
R_B (t=0)	10	15	5	8
N_B (t=0)	10	10	10	4
L_B (t=0)	10	5	15	8
C_B (t=0)	10	5	15	15
P(t)	100	100	100	100

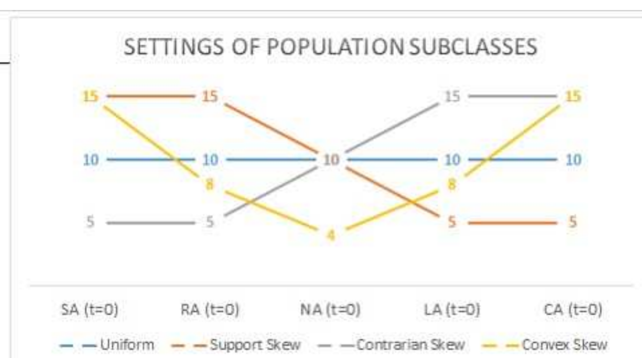

Figure 3: Simulation Settings : Population Effects in Rumor Competition.

We monitor $S(200)$ for 30 runs of 200 time steps. We can thus compare the final distribution at $t = 200$ with that at $t = 0$ and test whether there is a pattern by which the starting distribution of states within a rumor affects the competition after some time. Results are seen in Figure 4.

Output : Mean values of 30 runs	Uniform	Support Skew	Contrarian Skew	Convex Skew
S_A (t=200)	7.607	14.441	2.908	11.699
R_A (t=200)	12.439	19.392	5.332	9.816
N_A (t=200)	5.861	4.984	5.461	2.727
L_A (t=200)	14.346	6.786	20.070	12.791
C_A (t=200)	9.471	3.913	16.394	13.412
S_B (t=200)	8.339	15.667	3.029	11.415
R_B (t=200)	11.357	18.140	4.845	8.664
N_B (t=200)	5.806	5.539	5.612	2.787
L_B (t=200)	14.592	6.880	18.252	12.245
C_B (t=200)	10.182	4.259	18.098	14.444
P(t=200)	100	100	100	100

Figure 4: Simulation Output.

In Figure 5, we graphically represent the initial and final values across the population subclasses for each of our settings. As we can observe in the output in Figures 4 and 5, the latent states (for both support and contrarian positions) seem to consistently show an increased proportion, while extreme values seem to consistently decrease or remain the same. This indicates that, in a transition matrix where all states are reachable, extreme positions are less likely to dominate latent positions, irrespective of the initial distribution of rumor population subclasses.

Figure 5: Simulation Output : Population Effects in Rumor Competition.

5.3 Agent Effort

Finally, we seek to test whether the timing of the decay of limited effort expended in agents influencing each other significantly impacts outcomes (question iii. at the end of section 2) by investigating if greater effort expended at a later stage of network formation leads to either divergence or convergence of rumor populations. We modify the simulation to account for the spread of influence through the interplay of reputation, effort, and threshold values, as described in section 3. The initial settings for the population subclasses, and other variables is described in Figure 6.

Initial Settings					
S_A (t=0)	10	S_B (t=0)	10	Mean of Energy	10
R_A (t=0)	10	R_B (t=0)	10	S.D of Energy	2
N_A (t=0)	10	N_B (t=0)	10	Mean of Reputation	6
L_A (t=0)	10	L_B (t=0)	10	Threshold Constant	12
C_A (t=0)	10	C_B (t=0)	10	Effort decay starting at T	Case 1: t=0
					Case 2: t=45
					Case 3: t=90
A(t=0)	50	B(t=0)	50		

Figure 6: Simulation Initial Settings: Agent Effort.

To test our conjecture, we introduce "Effort Decay Start", a point in time at which an agent's effort starts decaying when influence is spread. To illustrate, suppose we set the effort decay to start at $t = 0$; then as soon as agent i influences agent j, agent i's effort available at $t = 1$ is decreased by 1. This decay continues every time agent i spreads his/her influence, until the effort score becomes so low, that influence is no longer transmitted. When we set effort decay to start at $t = 90$, then agent i has constant energy to influence his/her peers until $t = 90$, at which time effort decay starts occurring.

This enables us to see whether the timing of the effort expended at the beginning of a rumor spread (when effort decay start is lower) affects the outcome of a rumor, compared to the effort expended until much later in the spread of the rumor (effort decay start is higher). Note that, as time steps increase, the network grows and evolves into a bigger network component.

We run the simulation to time step $t = 150$ for 30 runs for each setting of the effort decay start (we find that stability is achieved by this point and running longer simulations in our current setup does not change our conclusions, nor provides additional insight), keeping all else constant. We then measure the average population of each rumor, $\mathbf{A}(150)$ and $\mathbf{B}(150)$, across the average of 30 runs for each time step.

Figure 7 illustrates the resulting measures across the timing of effort decay. The results indicate that effort expended much later in the spread of the rumor (and evolution of the network) results in greater average divergence between the competing rumor populations. This implies that competing rumors tend to converge quicker when effort is spent early in the process of network evolution. Another interpretation is that the longer the effort is expended in spreading influence for a rumor, the greater is the divergence of competing rumor populations and hence greater the amount of competition between rumors.

To address some known results in literature that human activity is heavy tailed, we run a quick test for robustness by repeating the simulation experiment using a Cauchy distribution, a heavy-tailed distribution, for agent energy and comparing it with our original assumption of normally distributed agent energy. While more robustness checks and further experiments are needed, it appears that our initial observation seems to hold. We see in each paradigm (heavy tail and normal tail) that effort expended much later in the spread of the rumor (and evolution of the network) results in greater average divergence between the competing rumor populations.

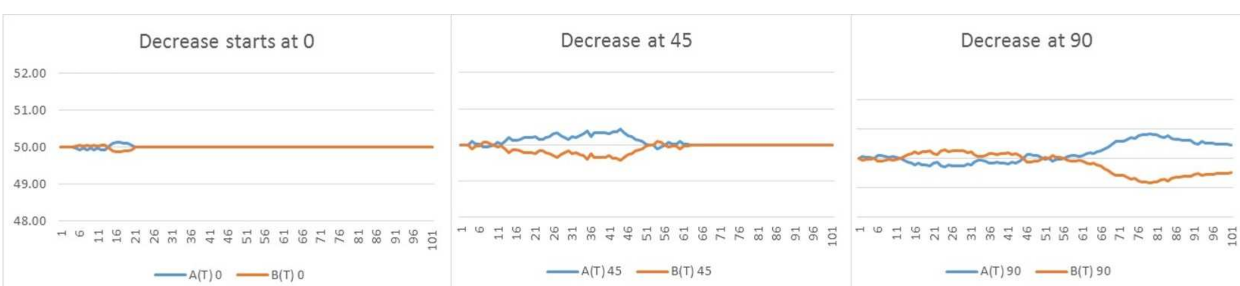

Figure 7: Effect of Effort decay starting at different times.

6 CONCLUSION

In this paper, we first developed a conceptual model of the spread of competing rumors on social media, motivated by seeking to understand the spread and survival of false ideas on new social media channels. We then develop an Agent Based Simulation model on *NetLogo* and implement a special case to confirm and validate the ABS model, by replicating results from Schramm (2006). We then generalize our implementation for a boarder class of question and applications of interest and report some initial results.

Our initial findings suggest that (i) rumors can survive under competition even with low adopting populations, (ii) latent positions in rumors seem to dominate extreme positions, and (iii) timing of effort expended by an agent affects the level of competition between rumors (measured as the divergence of rumor populations).

ACKNOWLEDGMENTS

The authors would like to thank Professor Roberto Szechtman of Naval Postgraduate School for introducing them to some of the key work in this domain and two anonymous reviewers for their insightful comments.

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