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THE IMPACT OF BROADCASTING ON THE SPREAD OF OPINIONS IN SOCIAL MEDIA CONVERSATIONS

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ABSTRACT

We extend our earlier work by focusing on broadcasting opinions (one-to-many interactions) alongside narrowcasts (one-to-one interactions) in social media conversations taking explicitly into consideration the behavioral characteristics of agents and the properties of the underlying network. In particular, we construct a generalized model for the spread of influence through broadcast and narrowcast interactions on social media discussion sites, and implement an agent-based model to develop insights regarding the effects of broadcasting. Our preliminary experiments show that increased broadcasting (in terms of frequency, depth, and number of broadcasters) increases homogeneity in an evolving scale-free network.

1 INTRODUCTION

In our previous work (Kaligotla et al. 2015), we noted that interactions on social media differ fundamentally from traditional offline human interactions, representing a new paradigm for the spread of information, ideas, and opinions. We developed a conceptual model of the spread of competing rumors on social media using agent based modeling methods. In this paper, we extend that work by focusing on a key aspect of social media conversations – that of broadcasting opinions (one-to-many conversations) occurring alongside one-to-one conversations (also called narrowcasting in Onggo et al. 2014). We also consider the effects of behavioral characteristics of the agents and the properties of the network on the diffusion of opinions (or rumors / ideas, which we use interchangeably).

The specific context of this work is in the realm of online discussion forums. Social media interactions commonly occur in the format of a discussion thread (Welser et al. 2007), as is regularly seen in product/service discussion forums, usenet groups, wikis, blogs, and sites like reddit.com, imgur.com, and even nhl.com. However, we are yet to fully understand the dynamics of modern communication channels and their impact on the spread of opinions, partly due to their unique features, in spite of the extensive literature on the spread of rumors (e.g., Daley and Kendall 1965, Maki and Thompson 1973, Gani 2000, Dickinson and Pearce 2003, Hayes 2005). Our general understanding is lacking on the topic of diffusion of opinions via agent influence through networked interactions, particularly on social media discussion threads. Our aim is thus to develop a better understanding of the dynamics of micro level agent interactions to understand macro scale outcomes related to social media discussions.

To this end, this paper constructs a generalized model for the spread of influence through broadcast (one-to-many) and narrowcast (one-to-one) interactions on social media discussion sites, and implements an agent-based model to develop insights regarding the effects of broadcasting. The paper also reports our preliminary findings. In section 2, we introduce the relevant literature and present our research questions.

Section 3 describes our conceptual model, which is instantiated as 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 LITERATURE REVIEW

Bartholomew (1973) and Dietz (1967) offer a comprehensive overview of classical rumor literature, which is based on epidemic modeling. See also Daley and Kendall (1965), Maki and Thompson (1973), Gani (2000), Dickinson and Pearce (2003) and Hayes (2005) for different models and their analysis.

Given our motivation to study heterogeneous agent behavior across intertwining systems, the use of Agent-Based Simulation (ABS) (Macal and North 2010) is practical as it allows us to build intuition while avoiding making restrictive assumptions for mathematical tractability. We also refer to Rahmandad and Sterman (2008) regarding the advantages of using agent-based models for studying diffusion.

Like in our previous work, we make some primitive assumptions with support from literature:

Opinions Exist in Competition, with Depth and Directionality. Group sense making often leads to multiple competing explanations, which leads to multiple opinions. Osei and Thompson (1977) consider a case where one rumor suppresses the other and determine the distribution of the maximum proportion of spreaders of the weaker rumor. A similar paper regarding competition between two social groups is Karameshu and Pathira (1960). 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.

Like in our previous work (Kaligotla et al. 2015), we adopt the NSCRL model in this paper (Schramm 2006), where opinions are represented by a continuum of exclusive and exhaustive positions rather than a binary choice. In this setup, there are five types or positions of opinions which agents can adopt: neutral agents (N), extreme supportive agents (S), latent supportive agents (R), extreme contrarian agents (C), and latent contrarian agents (L). Agents interact with each other through some network rules and change opinion positions based on a transition matrix, similar in idea to the SIR tables in Daley and Kendall (1965). Competition in this context is one where each opinion position vies for a greater share of support from agents.

Opinions Spread by Influence on Social Media through Agent Interactions. We also know that influence does occur through social media. Epstein and Robertson (2015) talk about the influence of the Internet in changing attitudes and beliefs via search engine manipulation, through five double-blind randomized experiments. In this research, we consider individual agent interactions whereby influence is the main driver for the spread of opinions.

In this paper, we use the term *broadcast* to refer to one-to-many interactions and disseminations of opinion or information, and the term *narrowcast* to mean one-to-one interactions. This definition is consistent with Goel et al. (2015) who compare the two modes of diffusion through a large data set. We also assume that agents update their opinions much like the transition rules given by Daley and Kendall (1965) and Hayes (2005). It is, however, different from Onggo et al. (2014) who 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.

Opinions and Networks Evolve in Parallel. Another starting primitive that enables us to capture some of the features observed in practice is that the diffusion of opinions happen concurrently with network evolution. In our context, a discussion thread grows just as new people come in, interact, and update their opinions. 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.

Scale-free network models mimic the format of social media discussions. It has been noted in the literature that scale-free networks are commonly observed in social media (Barabási, Albert, and Jeong 2000, Albert and Barabási 2002). Here, we model social media discussion threads by this network model where new agents enter into a discussion thread and reply to another particular comment. Comments and replies generate a tree-branch structure with a power law distribution of comments with low and high number of branches.

In this paper, we introduce a generalized model of broadcasting influence alongside traditional diffusion of opinions/rumors via narrowcasting. As an extension of our previous work, we (a) introduce an open network with a maximum network size, thereby maintaining a scale-free model growth; (b) consider some specific behavioral characteristics of agents: in particular, higher threshold levels (defined in the next section) for extremists, lower threshold levels for non extremists, and (c) introduce the concept of influence through broadcasting and narrowcasting, the mechanisms with which opinions are spread and shared on social media platforms. While none of these constructs is new by itself, we believe we are the first in putting these constructs together given our research goals.

The research questions we seek to address specifically are:

Q1. Effect of broadcasting on the spread of opinions:
  1a. How does a larger number of broadcasters affect diffusion outcomes?
  1b. How does the depth and frequency of broadcast influence affect the diffusion of opinions?
  1c. How does the type or characteristics of broadcasters affect the diffusion of opinions?

Q2. Effect of the behavioral characteristics of the agents on the spread of opinions:
Does a difference in threshold levels (influence required to trigger change) affect the spreading of rumors?

Q3. Effect of network characteristics on the spread of opinions:
How does an increase in probability of a new agent joining the discussion thread (depicted by a new vertex entering the graph) rather than further interaction among the existing agents (depicted by a new edge between already existing vertices) affect the diffusion of opinions?

3 THE MODEL

We present a general model for the spread of influence on social media discussion threads. To this end, we introduce a system of interacting constructs: a number of agents (represented by nodes on a network) interact with each other via replies or comments (denoted by directed edges) through some network evolution structure. Through each reply or comment, an agent states his opinion while trying to influence other agents via narrowcasting or broadcasting. The change of agent opinions is governed by a transition matrix.

In particular, we track two *competing* opinions (or rumors) in question, **A** and **B**, which are assumed to be mutually exclusive and collectively exhaustive. Every agent adopts (or believes in) only one of these two opinions at any point of time, with some degree of strength. In this setting, the spread of competing opinions is simply measured by the number of agents adopting one of the opinions – and not competition in a game-theoretic sense.

We model the agents and their interactions through time as a graph $G^t = (V^t, A^t)$ whose set of nodes V^t represents the agents and whose directed arcs $(m,n) \in A^t$ represent replies or comments in a discussion thread, for $t = 0, 1, \ldots, T$, where T is the stopping time of a sample path. Sample paths will stop when the graph reaches a size of N nodes, and we let $\mathbb{T} \triangleq \{0, 1, \ldots, T\}$ be the set of times up to the stopping time.

A directed arc (m,n) represents the direction of influence from node m to node n. Node m represents the communicating node and node n is the receiving node. This representation illustrates a basic social media discussion thread dynamic where node m first makes a comment, that is then replied to by node n. This implies that node m's comment influenced node n enough to spark a measured interaction.

We adopt the NSRCL framework of Schramm (2006) and Kaligotla et al. (2015) for agents and their opinions to reflect depth and directionality. Let $N_x(t) \geq 0$ denote the total number of agents in class N (neutral) for rumor $x \in \{\mathbf{A}, \mathbf{B}\}$ at time t. We define $S_x(t)$, $R_x(t)$, $C_x(t)$, $L_x(t)$ in an analogous fashion. Let $P(t)$ be a 2×5 matrix, which reflects the adoption of the two opinions at time t,

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

Let $\mathbf{A}(t)$ be the sum of the elements in the first row of the matrix $P(t)$, so that it denotes the total number of adopters of opinion $\mathbf{A}$. Let $\mathbf{B}(t)$ be the sum of the elements in the second row of the matrix $P(t)$.

3.1 Agents

Let node $n \in V^t$ represent an individual agent with the following characteristics:

(i) Agent reputation, ρ_n, a positive random variable drawn from some distribution F_ρ, represents the proxy for experience or publicly acknowledged expertise.
(ii) Agent energy, ε_n^t, where ε_n^0 is a positive random variable drawn from some distribution F_ε, represents the finite amount of energy an agent has at time t to expend in an interaction for influencing a peer to change his/her opinion position. We assume all agents are inherently behaviorally motivated to expend energy (through a comment, a reply or broadcasting a tweet) to convince their peers to adopt their opinions.
(iii) Agent threshold, τ_n, is some constant that denotes the minimum influence required to change an agent's opinion.
(iv) Each agent possesses an adopted opinion $E_n^t \in \{\mathbf{A},\ \mathbf{B}\}$.
(v) An agent's opinion strength, η_n^t, denotes the degree of belief strength for an agent's adopted opinion at t, where $\eta_n^t \in \{N, S, R, C, L\}$.

We then denote by X_n^t the state of agent n at time t, represented by the following:

$$X_n^t = \left(\rho_n, \varepsilon_n^t, \tau_n, E_n^t, \eta_n^t\right) \qquad \forall n \in V^t, \forall t \in \mathbb{T}. \tag{1}$$

3.2 Network Evolution

Each node represents an individual agent with the above properties. Each directed edge represents a comment between a pair of agents. We use a scale-free network with degree-based preferential attachment for new and existing edges, following Albert and Barabási (2002) and Barabási, Albert, and Jeong (2000). At each time step $t = 0, 1, \ldots, T-1$, one of the following occurs:

(i) With probability P_{new}, one new agent, labeled n_t, is added to the network as a recipient of communication and state variables in Section 3.1 are assigned. A node $m_t \in V^t$ is selected as a communicator via a preferential attachment mechanism;
(ii) With probability $1 - P_{\text{new}}$, one node $m_t \in V^t$ is selected as a communicator with uniform distribution over nodes in V^t and a node $n_t \in V^t$ is selected as the recipient of the communication via a preferential attachment mechanism.

Once the random pair (m_t, n_t) is selected, the network is updated as follows:

$$\begin{aligned} V^{t+1} &= V^t \cup \{n_t\} \\ A^{t+1} &= A^t \cup \{(m_t, n_t)\} \end{aligned} \tag{2}$$

With every new edge formed, the communicator node and the receiver nodes undergo state transitions as described in Section 3.4.

3.3 Broadcast and Narrowcast Influence

We begin by first noting that broadcast influence is different from a one-to-one dyadic (narrowcast) influence and then observing that broadcast influence is different from traditional broadcasting. While traditional broadcasting involves a simpler one-to-many dynamic, broadcasting influence in the context of social media conversations implies direct and indirect influence on network peers simultaneously through public broadcasts like comments/tweets (Figure 1).

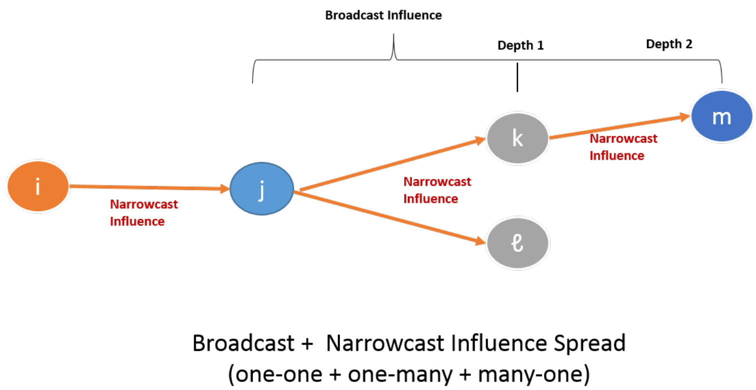

Figure 1: Concept of broadcast and narrowcast influence.

Direct influence occurs through a directed one-to-many interaction. Indirect influence, on the other hand, propagates through the network along a directed path with nodes receiving the broadcast. Figure 1 shows this dynamic, where node j broadcasts to nodes k and ℓ simultaneously. Node k then interacts with node m. Indirect influence in the context of social media discussions is the fact that node m is publicly aware of the broadcast from node j to node k, and hence is indirectly influenced by node j in addition to being directly influenced by node k. (This is relevant in the context of a social media discussion thread where a reply to a comment happens in a tree-branch structure of comments.) In contrast, observe that node i narrowcasts to node j.

We formalize the broadcast influence through a number of key constructs:

Depth of a broadcast: This refers to the length of the longest path between a communicator node and a recipient node. In Figure 1, the path length between node j and node m is $d_{ij} = 2$, which represents a broadcast of depth two. (A broadcast of depth 1 is therefore analogous to a narrowcast.) In this paper, we consider only broadcasts of depths of less than or equal to three. This is consistent with the depths observed in practice by Goel et al. (2012).

Broadcast influence discount: At each hop of a broadcast, the influence carried by the broadcast is assumed to dissipate relative to the influence of a narrowcast by some factor γ because a one-on-one interaction arguably has a higher degree of influence owing to personalized interaction. Therefore, we discount the influence carried between any two nodes on a path by γ^{depth}.

Number and Frequency of broadcast: We assume that only some nodes broadcast, either due to some inherent or some contextual property (e.g., a PR or news agency's tweets or comments compared to those of a random individual). Similarly, we assume that broadcasts are timed and occur at some defined intervals of time, relative to narrowcasts. Finally, we also make the assumption that broadcasts only take place within existing vertices.

3.4 Influence and Transition Dynamics

We formally define influence as a function that governs the change of state for some agent n_t from time t to $t+1$ following an interaction from another agent m_t in a narrowcast or in a broadcast. We drop the subscript t for the agents in order to clarify notation.

The state transition of agent n in such an interaction is described as follows

$$X_n^{t+1} = f(X_n^t, X_m^t, G^t). \tag{3}$$

For agents $\ell \in V^t$, $(\ell \neq n)$, $X_\ell^{t+1} = X_\ell^t$. The function $f(X_n^t, X_m^t, G^t)$ has the following characteristics:

Change of opinion: In an interaction from agent m to agent n, agent n updates his or her opinion and opinion strength (E_n^t, η_n^t) as a function of agent m's opinion and opinion strength (E_m^t, η_m^t) if and only if agent m's reputation times energy expended is greater than agent n's own threshold. In a broadcast, agent m's influence dissipates by the discount factor γ and the depth of the broadcast. We introduce the function g to compute a recipient agent's change of opinion and opinion strength; this is implemented using transition tables (see Table 1 and Table 2 when agent n had adopted rumor $E_n^t = \mathbf{A}$). Formally, for $n \neq m$,

$$Narrowcast: \left(E_n^{t+1}, \eta_n^{t+1}\right) = g\left((E_n^t, \eta_n^t), (E_m^t, \eta_m^t)\right) \text{ iff } \left(\rho_m \times \varepsilon_m^t\right) > \tau_n \tag{4}$$

$$Broadcast: \left(E_n^{t+1}, \eta_n^{t+1}\right) = g\left((E_n^t, \eta_n^t), (E_m^t, \eta_m^t)\right) \text{ iff } \left(\rho_m \times \varepsilon_m^t\right) \times \gamma^{depth} > \tau_n \tag{5}$$

$$(E_n^{t+1}, \eta_n^{t+1}) = (E_n^t, \eta_n^t) \text{ otherwise.} \tag{6}$$

Change of energy: The depletion of the agent energy reflects the amount of energy spent per interaction, which, in turn, contributes to the influence strength. Energy depletion is denoted by κ_B for broadcasting and by κ_N for narrowcasting. Thus,

$$Narrowcast: \varepsilon_n^{t+1} = \left(\varepsilon_n^t - \kappa_N\right)^+ \tag{7}$$

$$Broadcast: \varepsilon_n^{t+1} = \left(\varepsilon_n^t - \kappa_B\right)^+ \tag{8}$$

In this paper, we take $\kappa_N = \kappa_B = 1$ for simplification.

At each step, as agents update their states, $P(t)$ is updated. As an example of a change of agent state, an agent who is Neutral in opinion **A** may move to a new position of Support in opinion **A**, i.e.,

$$X_i^t \to X_i^{t+1}: S_{\mathbf{A}}(t+1) = S_{\mathbf{A}}(t) + 1, \quad N_{\mathbf{A}}(t+1) = N_{\mathbf{A}}(t) - 1.$$

Table 1: Transitions within an Opinion: node m communicating to (and influencing) node n.

m down ; n across	$N_{\mathbf{A}}$	$S_{\mathbf{A}}$	$R_{\mathbf{A}}$	$C_{\mathbf{A}}$	$L_{\mathbf{A}}$
$N_{\mathbf{A}}$	-	-	-	-	-
$S_{\mathbf{A}}$	$N_{\mathbf{A}} \to S_{\mathbf{A}}$	$S_{\mathbf{A}} \to R_{\mathbf{A}}$	-	-	$L_{\mathbf{A}} \to N_{\mathbf{A}}$
$R_{\mathbf{A}}$	-	-	-	-	-
$C_{\mathbf{A}}$	$N_{\mathbf{A}} \to C_{\mathbf{A}}$	-	$R_{\mathbf{A}} \to N_{\mathbf{A}}$	$C_{\mathbf{A}} \to L_{\mathbf{A}}$	-
$L_{\mathbf{A}}$	-	-	-	-	-

4 IMPLEMENTATION AND ANALYSIS

We implement an Agent Based Simulation model in *Netlogo* (Wilensky 1999), which enables us to incorporate some of the key conditions observed in practice, most notably agent heterogeneity and influence spreading as a result of broadcast and narrowcast networked interactions. We also describe our input measures, experimental settings, and the response measures of interest.

Table 2: Transitions across Competing Opinions: Node m communicating to (and influencing) node n.

m down ; n across	$N_{\mathbf{A}}$	$S_{\mathbf{A}}$	$R_{\mathbf{A}}$	$C_{\mathbf{A}}$	$L_{\mathbf{A}}$
$N_{\mathbf{B}}$	-	-	-	-	-
$S_{\mathbf{B}}$	$N_{\mathbf{A}} \rightarrow R_{\mathbf{B}}$	-	$R_{\mathbf{A}} \rightarrow S_{\mathbf{A}}$	-	-
$R_{\mathbf{B}}$	-	-	-	-	-
$C_{\mathbf{B}}$	$N_{\mathbf{A}} \rightarrow L_{\mathbf{B}}$	-	-	-	$L_{\mathbf{A}} \rightarrow C_{\mathbf{A}}$
$L_{\mathbf{B}}$	-	-	-	-	-

We implement the broadcast influence with a frequency factor such that a selected number of nodes broadcast through a specified depth with the specified frequency. We introduce a broadcaster selection option whereby either the broadcasting nodes are selected at random or preselected from specific opinion positions. We develop three experimental conditions for studying each of our research questions. We capture network evolution through a scale-free network. Figure 2 shows the experimental factor settings. Total Population represents the maximum size of the network. Note that the two numbers for Total Population and Neutrals represent the high and low settings for the input factors. Every experiment is run for 30 replications for each setting. The size of the network at time 0 is always two.

SIMULATION SETTINGS		Exp 1.A	Exp 1.B	Exp 2	Exp 3
Population Factors	S_A	50	50	50	50
	S_B	50	50	50	50
	R_A	50	50	50	50
	R_B	50	50	50	50
	C_A	50	50	50	50
	C_B	50	50	50	50
	L_A	50	50	50	50
	L_B	50	50	50	50
	Neutrals	600 / 1100	600 / 1100	600 / 1100	600 / 1100
	TOTAL POPULATION	1000/1500	1000/1500	1000/1500	1000/1500
Agent Factors	Mean of Max Energy	10	10	10	10
	Std-Dev of Max Energy	2	2	2	2
	Mean-reputation	10	10	10	10
	threshold-extremists	10	10	30 / 10	10
	threshold-nonextremists	10	10	10	10
Broadcast Factor	Broadcaster Selection	Random	Random	Random	Random
	Number of Broadcasters	0 / 1 / 5 / 10 / 20	1	1	1
	Broadcast Frequency	150	30 / 90 / 150	150	150
	Broadcast Influence Discount Factor	0.5 / 0.8	0.75	0.75	0.75
	Broadcast Depth	2	1 / 2 / 3	2	2
Network Factors	Prob. New Node Entry	0.5	0.5	0.33 / 0.5 / 0.8	0.33 / 0.5 / 0.8

Figure 2: Simulation settings.

We track three response measures: Δ_1 reflects the difference between the proportions of the population adopting the two rumors at the end of the time horizon of interest, T. Δ_2 reflects the difference in extreme positions (namely, supporters and contrarians) across the two rumors at time T as a proportion of total population. Δ_6 reflects the emergence of extreme support for rumor **A** as a proportion of the total population.

In our first experiment where we study the impact of broadcast factors, we need to control for the number of broadcasts. To this end, we introduce three additional measures, Δ'_1, Δ'_2 and Δ'_6, which normalize the previous measures for the total number of broadcasts to filter out the size effects. Formally,

$$
\begin{aligned}
E[\Delta_1] &= \sqrt{(N^{-1}(\mathbf{A}(T)-\mathbf{B}(T)))^2} \\
\Delta'_1 &= E[\Delta_1]/\#\ of\ broadcast\ links \\
E[\Delta_2] &= \sqrt{(N^{-1}(S_{\mathbf{A}}-S_{\mathbf{B}}))^2+(N^{-1}(C_{\mathbf{A}}-C_{\mathbf{B}}))^2} \\
\Delta'_2 &= E[\Delta_2]/\#\ of\ broadcast\ links \\
E[\Delta_6] &= \sqrt{(N^{-1}(S^T_{\mathbf{A}}-S^0_{\mathbf{A}}))^2} \\
\Delta'_6 &= E[\Delta_6]/\#\ of\ broadcast\ links
\end{aligned}
\tag{9}
$$

In addition to $E[\Delta_i]$, we monitor $Var(\Delta_i)$ for which a small value indicates homogeneity of opinions.

5 DISCUSSION

5.1 Effect of Broadcasting Influence

This experiment explores how broadcast influence interacts with and differs from narrowcast influence. We split this experiment into two sub-experiments, the first to study the effects of the number of broadcasters and the second to study the effects of the depth and the frequency of broadcasts. Note that for all experiments in this subsection, we use Δ'_1, Δ'_2 and Δ'_6 as our response measures.

5.1.1 Number of Broadcasters

We vary the number of broadcasters (broadcast nodes) at a particular broadcast frequency (in this case, every 150 time units), where broadcasters are selected at random from existing nodes. The results are presented in Figure 3, where the number of broadcasters is shown on the x-axis. We observe that a higher number of broadcasters (in addition to narrowcasting) leads to more homogeneous outcomes, i.e., to a state where none of the two opinions dominates.

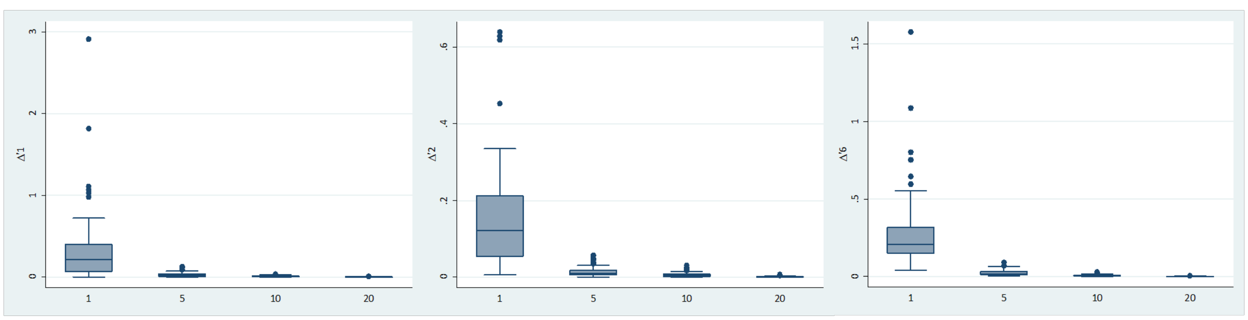

Figure 3: Effect of number of broadcasters.

Our response measures show a marked decrease in both mean and variance as the number of broadcasters is increased, implying that a higher number of broadcasters in a social media conversation results in an environment where opposing influences are negated, thereby achieving more homogenous outcomes. The fact that this pattern appears already at the instance of the first broadcaster compared to no broadcasters implies that the broadcast effect is significant.

To identify the drivers behind this observation, Figure 4 shows a scatter plot of successful opinion changes versus the number of agent interactions (edges representing broadcasts and narrowcasts) in settings with different numbers of broadcasting nodes. The plot shows that, even though the number of interactions increases with an increase in the number of broadcasting nodes, contrary to expectations, the total number

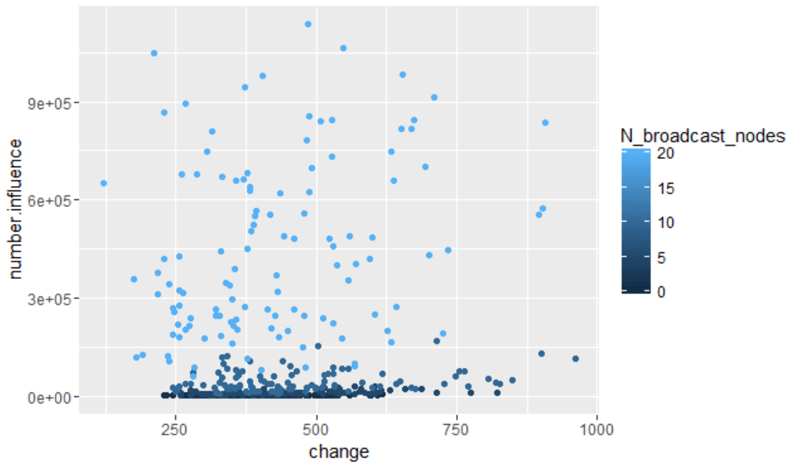

Figure 4: Scatterplot of opinion changes and influence interactions by the number of broadcasters.

of changes does not increase proportionally, denoting that agent characteristics (reputation, energy, and threshold) are playing a significant mitigating role.

5.1.2 Broadcast Depth And Frequency

The second inquiry into the micro-dynamics of broadcast influence is the effect of depth (path length) and frequency (broadcasts per time steps). Using the settings shown in Figure 2, we vary the depth of broadcasts from of 1 to 3 while varying frequency of broadcasts from 1 every 30 time steps to 1 every 150 time steps with a fixed number of broadcasters. Figure 5 shows the results.

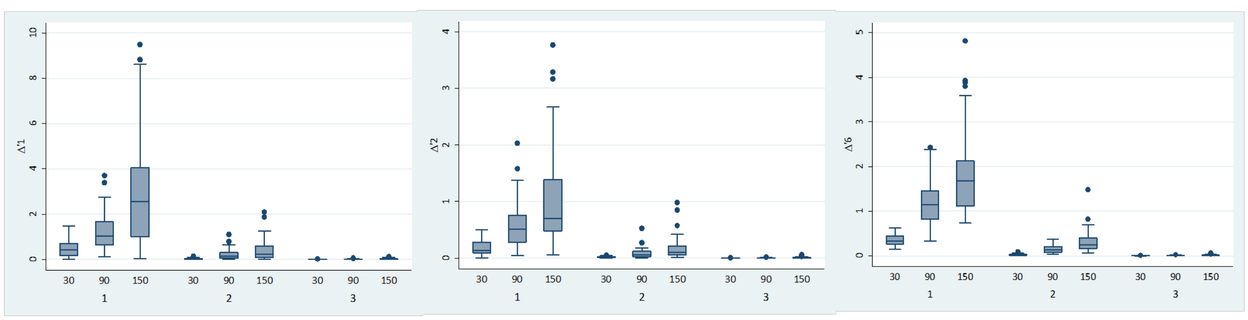

Figure 5: Effect of frequency and depth of broadcast.

We again find evidence for the argument that increased broadcasting leads to more homogeneous outcomes. On the x-axis of the figure, corresponding to frequency (30-90-150), a lower number of time steps implies broadcasting with higher frequency. Similarly, an increase in depth (1 - 2 - 3) implies more broadcasts with further but dissipating influence. We observe a strong pattern across all our response measures: higher frequency and greater depth of broadcasting results in higher homogeneity of outcomes. This observation implies that one way to counter the spread of extreme opinions is to conduct more frequent broadcasts with greater depth.

To recap, we learn from sections 5.1.1 and 5.1.2 that *a more intensive broadcasting activity (in terms of number, frequency, and depth) may dilute the influence of the comments and therefore reduce their heterogeneity on social media discussion threads.* This has the important implication that a possible way to combat and counter the spread of extreme opinion online is to increase the number, the frequency and the depth of diverse broadcasts.

5.2 Effect of Behavioral Characteristics of the Agents

We now turn to our second question related to the effect of behavioral characteristics of the agents on rumor diffusion. More specifically, we ask whether there is a difference in rumor outcomes when extreme opinion holders have higher threshold levels (more influence required to trigger change) compared to non-extremes having lower threshold levels and whether the interaction between maximum agent size and different threshold levels affects rumor outcomes.

To this end, we compare rumor outcomes for our response measures across two settings. A setting of 0 indicates that extremes have higher thresholds while a setting of 1 indicates that extremes and non-extremes have similar thresholds. We compare the outcomes for Δ_1, Δ_2 and Δ_6 over two levels of total network size (to see whether network size has an interaction effect). Figure 6 shows our results.

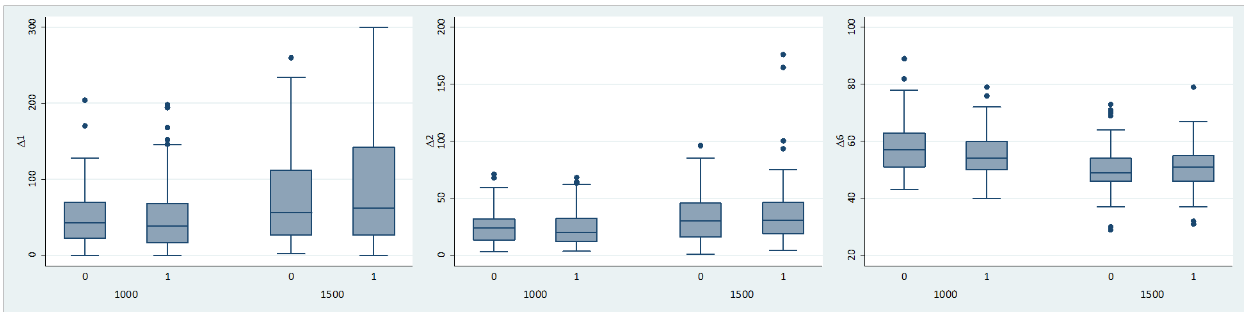

Figure 6: Effect of behavioral characteristics of agents (0 - higher extreme threshold value; 1 - constant thresholds value) and network size N.

The results suggest that, in most cases, having different thresholds (condition 0) increases homogeneity (reduces variance), while the effect is tempered by increasing the network size. This is a little counterintuitive at first. Given that higher threshold values for extremes implies fewer changes of opinion among them, this setting should preserve the heterogeneity of rumor outcomes. However, we see the opposite; i.e., having different thresholds decreases heterogeneity. On the other hand, increasing the number of agents in the system increases heterogeneity markedly.

This indicates that, in setting 0, extremes (supporters and contrarians) are not likely to change their opinions; only the neutrals and the latents do, resulting in more homogeneous outcomes. When the population increases, outcomes become more heterogeneous as there are simply more agents interacting. Further analysis is required to better understand this interaction. We conclude that *while a higher threshold for extremes increases the homogeneity of opinions, this is mitigated by the total network size.*

5.3 Effect of Network Characteristics

We finally study the effect of an increase in probability of a new agent (node) entering the graph (rather than the creation of a new edge between already existing vertices) on the diffusion of rumors. In practice, this is akin to asking how new people entering a conversation affect the outcome compared to existing people commenting with each other.

Ceteris Paribus, we change the probability of new node entry and the total network size, and study the effects on our response measures. Figure 7 shows results.

We observe similar patterns as before. Increased network size increases heterogeneity. Similarly, increasing the probability of new node entry slightly increases the variances of outcomes. There are fewer instances of new edges between existing nodes and therefore less dense graphs.

It is important to note, however, that Δ_6 shows a different pattern as it compares the changes in extreme positions on opinion **A** alone, whereas Δ_1 and Δ_2 compare outcomes across both rumors **A** and **B**; i.e, Δ_6 does not measure heterogeneity across rumor outcomes, only within that particular extreme rumor position.

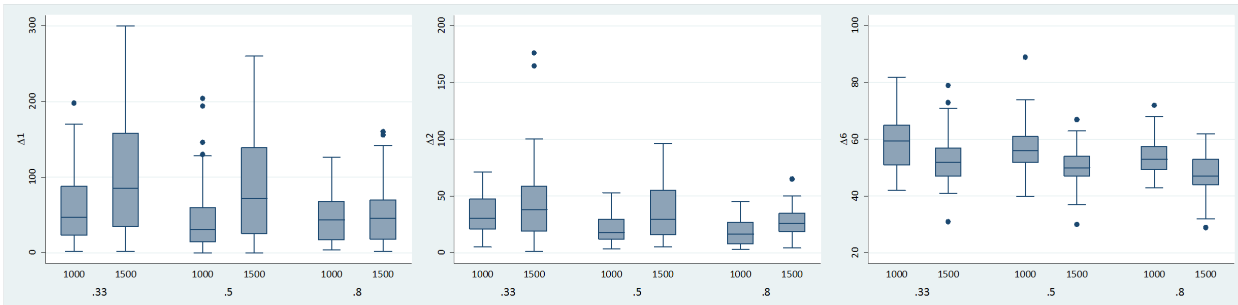

Figure 7: Effect of network characteristics: network size N and probability of new node P_{new}.

We conclude that *increased probability of new node entry interacts with increasing network size to increase heterogeneity of opinions.*

6 CONCLUSIONS

We extended our earlier work by focusing on broadcasting opinions (one-to-many interactions) alongside narrowcasts (one-to-one interactions) in social media conversations taking explicitly into consideration the behavioral characteristics of agents and the properties of the underlying network. Our main observations can be summarized as follows: (i) Increased broadcasting (in terms of number, frequency, depth, and opinion types) increases homogeneity in an evolving scale-free network; (ii) A higher threshold for extremes increases homogeneous opinions; this is mediated by total network size; and (iii) Increased probability of entry of a new node interacts with increasing network size to increase heterogeneity of opinions.

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