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Modeling Education and Advertising with Opinion Dynamics

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Abstract

We present a modified Deffuant-Weisbuch opinion dynamics model that integrates the influence of media campaigns on opinion. Media campaigns promote messages intended to inform and influence the opinions of the targeted audiences through factual and emotional appeals. Media campaigns take many forms: brand-specific advertisements, promotions, and sponsorships, political, religious, or social messages, and public health and educational communications. We illustrate model-based analysis of campaigns using tobacco advertising and public health education as examples. In this example, "opinion" is not just an individual's attitude towards smoking, but the integration of a wide range of factors that influence the likelihood that an individual will decide to smoke, such as knowledge, perceived risk, perceived utility and affective evaluations of smoking. This model captures the ability of a media campaign to cause a shift in network-level average opinion, and the inability of a media message to do so if it promotes too extreme a viewpoint for a given target audience. Multiple runs displayed strong heterogeneity in response to media campaigns as the difference between network average initial opinion and broadcasted media opinion increased, with some networks responding ideally and others being largely unaffected. In addition, we show that networks that display community structure can be made more susceptible to be influenced by a media campaign by a complementary campaign focused on increasing tolerance to other opinions in targeted nodes with high betweenness centrality. Similarly, networks can be "inoculated" against advertising campaigns by a media campaign that decreases tolerance.

Keywords:

Opinion Dynamics, Social Networks, Media, Advertising

Introduction

- 1.1 Opinion dynamics models are a computational realization of Cartwright and Harary's (1956) structural balance theory, under which individuals' opinions regarding other people or ideas are influenced by those with whom they share affective social ties. Imbalance in structure is resolved through changes in opinions: opinions of the individuals tend to move in a direction of increasing similarity, whether positive or negative. Opinion dynamics models also draw upon concepts underlying Asch's famous experiments on opinion formation and conformity under social pressure (Asch 1955), and French's (1956) work on social power in networks.
- 1.2 Several different approaches to modeling opinion dynamics have been proposed (see Castellano, Fortunato & Loreto 2009 for a comprehensive review). Initial approaches incorporated elements of statistical physics particle spin interaction models. Spin models calculate current state by polling the states of neighboring elements. Opinion dynamics models have extended these basic neighborhood interaction dynamics by introducing continuous-valued states, confidence bounds that constrain interactions, and network topologies that introduce additional social structure to the modeled community. In addition to analyses of the fundamental dynamics of the system, opinion dynamics models have been employed to investigate the diffusion of ecologically sound agricultural practices in farming communities (Weisbuch et al. 2002), the formation of extremist groups in larger communities (Deffuant 2006), and the effects of influence-based interventions on differential social structures, including gendered networks (Moore, Finley, Hammer & Glass 2012).
- 1.3 Opinions of individuals are influenced by the opinions of their peers, but they are also affected by elements exogenous to the immediate social networks in which individuals act and make decisions (Crosby, Salazar & DiClemente 2011). Education, entertainment, and advertising influence individuals and serve to introduce and propagate topics and related opinions. In some cases, the intent to influence opinion is overt, as is often the case with paid commercial advertising. At other times, the influence can be more subtle, including, product placement, smoking in films (Charlesworth & Glantz 2005; Dalton, Sargent, Beach, Titus-Ernstoff, Gibson, Ahrens, Tickle & Heatherton 2003), or product references in youth-targeted popular music (Graser 2005).
- 1.4 Effects of media campaigns propagate through social networks. When media campaigns successfully change the opinions of a target audience, the affected individuals may influence the opinions of their friends and neighbors, potentially amplifying the effective reach of the campaigns. Modern marketing studies incorporate social networks effects, both for product promotion and for corporate branding (Richardson & Domingos 2003; Ragas & Bueno 2002).
- 1.5 This model is similar to that proposed by Mckeown and Sheehy (2006) in that both models use mass media agents that broadcast opinion values on the continuous interval $[0, 1]$. The model presented here differs in that the approach uses a weighted averaging function for determining node opinions, such that mass media is integrated with peer opinions in a single function. Heterogeneity in the plasticity value (analogous to edge weight in this model, and represented by μ in the presented equations), not explored in this paper, can then express whether a media node has more or less influence than a peer. This model also differs in that the social networks presented are not the lattice structures presented in [1], but rather directed random graphs using Erdős-Rényi (i.e., Bernoulli) and Barabasi-Albert (i.e., scale-free) topologies. Although still highly abstract, these graph topologies are more representative of real world social networks.
- 1.6 Similarly, Carletti et al. (2006) built on the original Deffuant et al. approach to consider the effects of broadcast media. Their approach incorporates media influence via a media entity that periodically interacts with all individuals in the population simultaneously. That approach differs from the one presented here in that it incorporated a well-mixed population with undirected interactions. In addition, the media campaigns in this model interact with selected individuals, rather than the entire network.

- 1.7 In this paper, we extend an existing opinion dynamics model to include the effects of media influences. Media messages related to smoking are used as the motivating example, including both commercial advertising and anti-smoking public health education campaigns. Cigarette smoking is the leading cause of preventable death in the United States, causing over 440,000 deaths per year (Mokdad, Marks & Stroup 2004). Despite restrictions on the forms and content of cigarette advertisements, the largest US cigarette companies spend over \$8 billion per year on cigarette advertising and promotion (DiFranza 2006; Federal Trade Commission 2012). Advertising campaigns across all classes of consumer products are ubiquitous – marketing is a \$250 billion per year industry, and young people in the United States, see an average of 3,000 advertisements for various products per day (Committee on Communications 2006).
- 1.8 This paper presents a model that incorporates media influences into a standard opinion dynamics framework, expanding the concept of opinion spread to include opinion sources outside of traditionally realized social networks. Section 2 of this paper outlines the model and the introduced extensions. Section 3 illustrates the model's functionality and presents the results of employing the model to analyze several scenarios. Section 4 concludes with a summary of results.



Theory

Opinion Dynamics Model

- 2.1 In this opinion dynamics model, opinion formation for a given individual is a result of a series of discrete interactions taking place with one or more neighbors. The model incorporates bounded confidence, where these interactions are limited to neighbors whose opinions are similar. This model also incorporates explicit social network topologies with interactions limited to nearest neighbors on the network. We consider only media-induced changes to opinions in the network. We have previously addressed how opinion shifts can cause behavioral shifts (Moore et al., in review).
- 2.2 In the original Deffuant–Weisbuch model (Deffuant et al. 2000), agents interact in dyads with each interacting pair chosen at random from within a well-mixed population. These agents then interact and mutually update their respective opinions, subject to the constraints of bounded confidence. The confidence bound, often referred to as tolerance, constrains agents to interact with (and update their opinions from) only those other agents whose opinions are close to their own:

$$|x_i(t) - x_j| \leq \epsilon \quad (1)$$

where

$x_i(t)$ = The opinion of individual i at time t

$x_j(t)$ = The opinion of neighbor j at time t

ϵ = The confidence bound or tolerance

- 2.3 Tolerance represents the range of opinion to which an individual might be receptive. An individual with higher tolerance will be more open to influence from his or her neighbors, while an individual with lower tolerance will be less open to influence. If, for a given dyadic interaction, Equation (1) holds, the opinions of i and j are updated according to the functions:

$$\begin{aligned} x_i(t+1) &= x_i(t) + \mu[x_j(t) - x_i(t)] \\ x_j(t+1) &= x_j(t) + \mu[x_i(t) - x_j(t)] \end{aligned} \quad (2)$$

where

$x_i(t+1)$ = The opinion of individual i at the next time interval

$x_j(t+1)$ = The opinion of individual j at the next time interval

μ = The rate-controlling plasticity value that determines the rate of convergence of the network

- 2.4 We adapt the opinion dynamics model proposed by Deffuant et al. by introducing two modifications: directionality (replacing undirected networks and well-mixed populations) and averaging (replacing sampling on dyadic interactions, similar to the approach suggested by Hegselmann and Krause (2002)). Iterating successively through each node in the network, our model examines the difference in opinion between that node and each of that node's out-degree neighbors. Using the neighbors whose opinions fall within that node's tolerance bounds, we update the node's opinion via the equation:

$$x_i(t+1) = x_i(t) + \frac{1}{|S_i|} \sum_{j \in S_i} \mu_{ij} [x_j(t) - x_i(t)] \quad (3)$$

where $x_i(t)$, $x_j(t)$ and $x_i(t+1)$ are as defined above, and

S_i = The set of out-degree neighbors of i whose opinions fall within the tolerance bounds

$|S_i|$ = The cardinality of S_i

μ_{ij} = The rate-controlling plasticity value representing the edge weight between i and j

- 2.5 Thus, the general algorithm for running a scenario could be represented as:

Generate results for a single network

– Generate one network

- Generate 250 nodes with initial opinions drawn from a uniform distribution on [0, 1]
- Connect nodes at random using a Bernoulli trial with probability of connection $P(\text{connected}) = 0.023$ to create a fully connected sparse random graph with a Poisson degree distribution. For the scale-free scenarios, generate the network using a preferential attachment algorithm as presented in Barabasi and Albert (1999) and implemented in JUNG with 3 seed nodes and 2 edges per node creating a sparse graph with scale-free topology. JUNG is a Java-based network software framework (Madadhain et al. 2005).
- Add media nodes (opinion values and connections) as determined by scenario

– Update opinions

- For each node i (note that media nodes, with an out degree of 0, do not undergo opinion changes):
 - Assess i 's current opinion
 - For each out degree neighbor (including media nodes, if applicable):

- Assess neighbor's current opinion
- Determine if neighbor falls within λ s tolerance bounds; if so, add neighbor's opinion as factor to summation portion of

Equation (3), weighted by outbound edge weight

- Divide by total number of neighbors and add to i 's current opinion to determine new value
 - Set λ s next step opinion to new opinion value
- Update all nodes' opinions with next step value. Synchronous updating prevents order dependency arising from node updates.
- Advance to next time step. Continue to update opinions until a steady-state condition is reached
- End generate results for a single network

Media Model

- 2.6 Commercial advertising and other kinds of marketing messages form opinions through various methods. Some make a direct appeal regarding an objective quality of the product, while others emphasize affective (appealing to the emotions) characteristics associated with the product or with people who use it (Caples 1998). Advertising campaigns can reach people via any number of media sources: traditional sources like television, radio, and print media, new media sources such as the internet, and stealth sources, such as paid placement of products in films and television shows.
- 2.7 We model marketing effects on social networks by explicitly incorporating media nodes that relay messages to randomly selected individuals in the population. Media nodes differ from nodes that represent individuals in the social network in that media nodes influence others without themselves being influenced. Media nodes often also have a greater number of incoming edges and can therefore influence a larger number of individuals directly. Balancing this greater reach into the social network, edges from media nodes may have a lower edge weight, indicating that the relative impact of an advertisement on a recipient's opinion may be less than that of a peer. Media nodes can be configured to be continually active, or may be activated for particular time intervals to simulate different messaging strategies. Continuous media activity is useful for analyzing dynamic trends induced by marketing activity, while pulsed media activity is useful for modeling series of time-dependent, possibly overlapping campaigns.

Opinion-Based Versus Tolerance-Based Campaigns

- 2.8 In this model, media campaigns can influence opinion via two pathways: (Comte 1868) by directly promoting an opinion or (Slanina 2009) indirectly by increasing or decreasing tolerance levels. Direct promotion is the most common media pathway, whereby the marketer attempts to shift the opinions of people in the population to a favorable one regarding products, behaviors, or ideas. Examples of this type of influence include tobacco advertisements that, prior to modern advertising restrictions, directly advocated smoking, promoting cigarettes as healthy options for weight and stress control (National Cancer Institute 2008). In contrast, public health educational campaigns inform the public about the health effects of smoking, and in so doing attempt to lower individual favorable opinions toward smoking and dissuade the behavior.
- 2.9 In a somewhat more subtle fashion, other media campaigns influence opinion dynamics via a second route: by increasing or decreasing a sense of uncertainty among a targeted audience. For example, sponsorship of social causes, and other past tobacco industry public relations efforts, can be viewed as attempts to improve public perception of the industry and make the general public more resistant to industry criticism (National Cancer Institute 2008). Industry efforts have also attempted to counter public perception of consensus on well-researched issues such as the health consequence of smoking and secondhand smoke (Oreskes & Conway 2010; Ong & Glantz 2000). Campaigns to affect the public perception of scientific research validity and regulatory bodies' actions may not directly change opinions toward tobacco as a primary effect, but can make people more open to subsequent opinion-changing campaigns (McDaniel & Malone 2009). Conversely, campaigns can bring about a decrease in uncertainty or tolerance by emphasizing certainty of a given position or by creating distrust of the opposing messages or message sources. For instance, the truth® campaign, a public health educational campaign targeted at youth, emphasized the untrustworthiness of tobacco industry messaging, and by targeting trust and affective components important to youth, led to a successful campaign to reduce youth smoking initiation (Apollonio & Malone 2009; Holtgrave, Wunderink, Vallone & Heaton 2009; Farrelly, Nonnemaker, Davis & Hussin 2009). Such scenarios will be explored in Section 3.2.



Results

- 3.1 In this section, we illustrate the functionality of this approach to modeling media campaigns using several scenarios. Unless otherwise specified, these investigations demonstrate effects on networks of 250 nodes connected as Poisson random networks with a 0.023 probability of connection, tolerances are set to 0.230, and edge weights are 0.050 for inter-node links and 0.025 for media node links. Initial opinions were drawn from a uniform random distribution on the interval $[0, 1]$. The induced network topology creates a sparse, single component Erdős–Rényi graph just above the phase transition to a giant component identified in Erdős and Rényi (1959), with an average node degree of 5.7 and a density of 0.023. This topology was selected to reduce effects induced by extreme disparities in nodal characteristics induced by scale-free and similar topologies in order to highlight the underlying physics. This topology also does not introduce the potential complications of community structure, some of which are analyzed in the examination on the role of high betweenness nodes below, and others of which are presented by Hammer et al. (2013).

Tolerance and Strength of Messaging

- 3.2 Tolerance values assigned to network nodes influence patterns of opinion change in opinion dynamics models. Individuals are easily influenced when exposed to opinions relatively close to the one they currently hold. However, large differences in opinion make it more difficult for adjacent nodes to influence opinion (Defuant 2006). Media campaigns should therefore exhibit diminishing success as the message becomes more extreme relative to the opinions held by the targeted audience. Organizations creating campaigns to educate the public regarding health and safety issues strive to present factual information to the audience in a manner that is understandable and resonates with the general public. Utilizing messages and images that elicit emotional responses has been effectively used in communicating the toll disease and risky behaviors can have on families, as Mothers Against Drunk Driving (MADD) campaigns have done since the 1980's (Fell & Voas 2006). Too extreme of a message can backfire and prove ineffective, however, as was seen in fear-based public health campaigns used to combat AIDS in Australia (see Rigby, Anagnostou, Ross & Rosser (1989) for an example).
- 3.3 The ability of a media campaign to affect opinions in a network is dependent on the value of the opinion being broadcast, as well as the existing opinions and tolerances held by other nodes in the network. For example, for a homogenous individual tolerance value of 0.23, a media node with an opinion of 0.85 can directly influence individuals on the interval $[0.62, 1]$.
- 3.4 Figure 1 shows opinions of individual nodes in response to two media messages, such as public education campaigns on the consequences of tobacco use. Each media node is connected at random to 20 network nodes. The first media node (Media Node 1) has a broadcast opinion of 0.65 and is represented by the horizontal long-dashed line. The opinion broadcast by the second media node (Media Node 2) varies between 0.5 and 1.0, and is represented by the angled line. One hundred stochastically generated networks were used, and 100 runs were conducted on each network by varying the value assigned to Media Node 2.
- 3.5 For Media Node 2 broadcast opinions between 0.5 and 0.88, node opinions primarily fall between the two broadcast opinions. An attractor is created midway

between the opinions of the two media nodes. As Media Node 2 broadcasts become more extreme, a population of nodes develops with lower opinions, as shown by the lightly colored patched area at the lower part of the figure. This group's tolerances are out of range of the broadcast message. These nodes cannot respond to the opinion of the media node if the media node randomly connects to individuals outside their tolerance bounds, or to individuals influenced by the message but unable to influence their neighbors. Of note is the discontinuity in result space at a broadcast opinion of 0.88. As Media Node 2's broadcast opinion approaches 0.88, it exceeds the tolerance bound of the nodes with opinions near that of Media Node 1's message (the lower broadcast message opinion is 0.65 and the tolerance is 0.23). The more extreme, the more likely the upper media node is to be outside the tolerance range of individuals, ultimately becoming ineffectual. The majority node opinion at this high range is just below the Media Node 1 opinion.

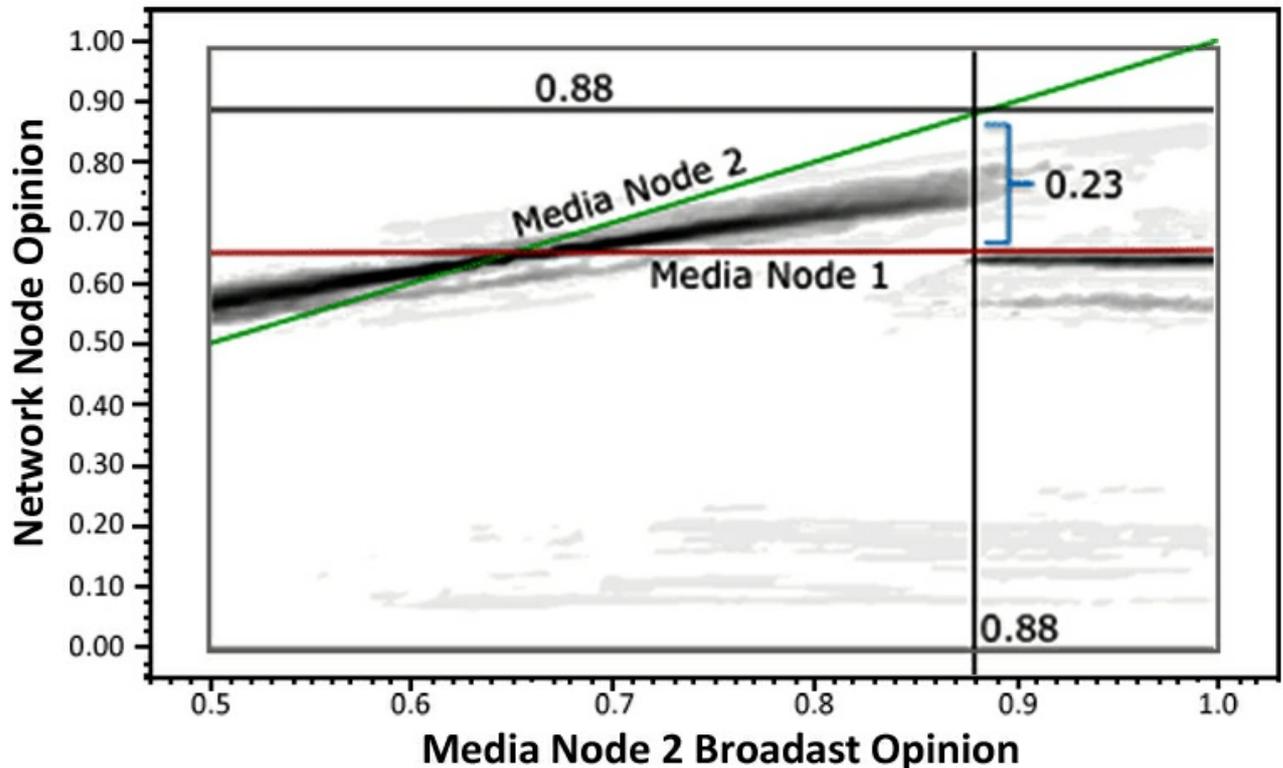
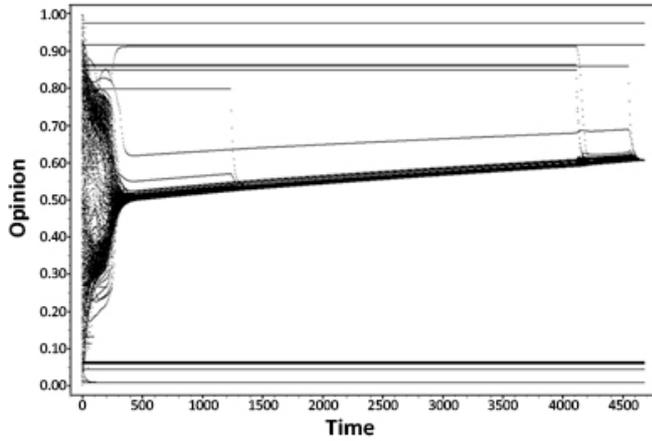


Figure 1. Opinion Sweep contour map displaying network opinion results for a campaign in which broadcast message opinion ranges from 0.5 to 1.0 (Media Node 2), with a complementary campaign (see Section 3.2, below) with an opinion of 0.65 (Media Node 1). Results are shown for opinion on each node after reaching equilibrium, for 10,000 runs. Greater intensity of color indicates higher node concentration.

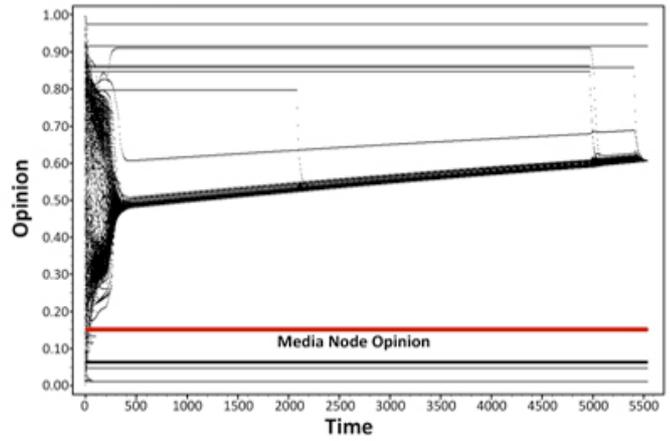
Complementary Campaigns

- 3.6 In these experiments, we show that media nodes can more effectively influence a network by acting in a complementary fashion. Although moderate messages can effectively reach and influence more people through both direct and neighbor-based effects, a moderate message alone may be insufficient for some purposes. For example, a more extreme message may be necessary to motivate behavior change. However, due to tolerance bounds, the extreme message, acting alone, may not reach enough individuals to effect the desired change, and will be especially ineffective in influencing individuals who already hold a strongly opposite opinion.
- 3.7 Messages that are intended for diverse audiences can work synergistically, or in a complementary fashion. A moderate media campaign can influence a broad array of opinions, bringing them closer to the desired value. A complementary strong campaign can then achieve greater effectiveness, because a greater fraction of the population has been brought within tolerance of the stronger opinion. If a media campaign can be thought of as imparting the activation energy necessary to change the state of a system, it can, at times, be necessary to first move the system closer to the transition point. The extent of the movement needed is dependent on the underlying opinion of the target audience.
- 3.8 Figure 2 shows sample time series plots of opinions on a random network under the four scenarios of (A) no media influence, (B) extreme opinion media influence, (C) moderate opinion media influence, and (D) complementary moderate and extreme media influences. In contrast to the example shown in Figure 1, this example shows the effects of media campaigns broadcasting an anti-behavioral message by trying to shift opinions to lower values, i.e., less favorable. In this example, a general upward trend in opinion for scenario A is present due to the random effects of initial opinion allocation and differential connectedness among individuals in the network. In this network, there is a modestly positive opinion about smoking, although some members of the network hold either strongly positive or strongly negative opinions and maintain them throughout the simulation. The addition of an extreme opinion media campaign in scenario B does not affect the network significantly, due to the effects of individual tolerances. The addition of a moderate campaign in scenario C is able to shift the network from a modestly positive average opinion to a modestly negative opinion. Complementary media campaigns in scenario D, however, are able to shift the network to a negative opinion. Note that even the complementary campaigns are unable to decrease the opinions of those individuals with strongly positive views in this scenario. They do, however, serve to somewhat moderate the extremity of some individuals with strongly negative opinions, pulling them up to the modal opinion cluster. In this way, the interaction between the broadcast opinions can significantly decrease the average opinion in the network by decreasing the opinions of otherwise modestly positively disposed individuals, but can also serve to increase the opinions of strongly negatively opinionated individuals by attracting them into the modal opinion cluster.

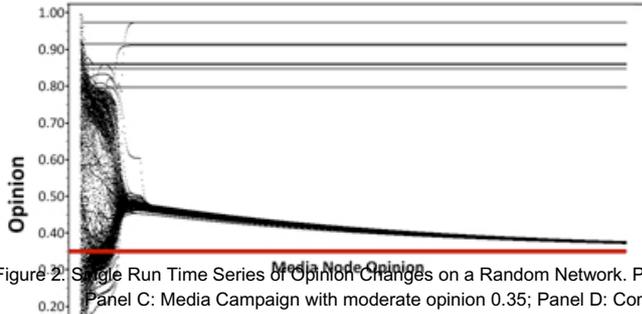
A - No Media Campaigns



B - Media Campaign Opinion 0.15



C - Media Campaign Opinion 0.35



D - Media Campaign Opinions 0.15, 0.35

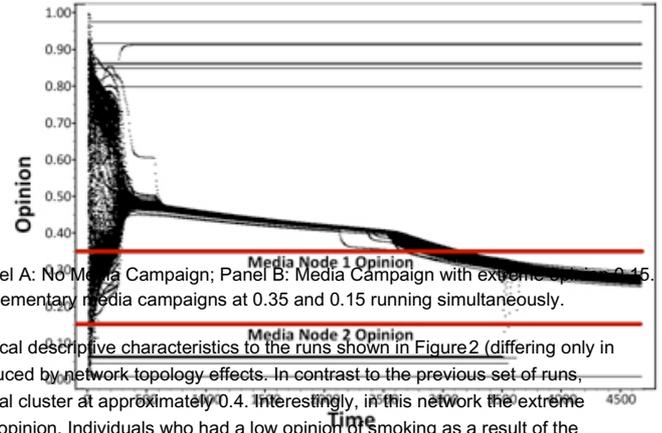


Figure 2: Single Run Time Series of Opinion Changes on a Random Network. Panel A: No Media Campaign; Panel B: Media Campaign with extreme opinion 0.15; Panel C: Media Campaign with moderate opinion 0.35; Panel D: Complementary media campaigns at 0.35 and 0.15 running simultaneously.

3.9 Figure 3 shows a time series plot from a second set of runs. These runs have identical descriptive characteristics to the runs shown in Figure 2 (differing only in the stochastic realization of network topologies), and illustrate the heterogeneity induced by network topology effects. In contrast to the previous set of runs, under the no media influence scenario A, this network has a modestly negative modal cluster at approximately 0.4. Interestingly, in this network the extreme media campaign in scenario B has a strong effect, inducing a bifurcation in network opinion. Individuals who had a low opinion of smoking as a result of the initial random allocation of opinions were radicalized by the extreme opinion media campaign. Because the radicalization occurred rapidly, individuals with a higher initial opinion were no longer open to being influenced by them, and thus approached another attractor – creating the single cluster with a strongly positive opinion around 0.85. In this network, the moderate campaign in scenario C does not induce this bifurcation, instead producing a slight decrease in modal opinion over the uninfluenced network. The complementary campaigns in scenario D also do not induce the bifurcation, but do decrease the modal network opinion over that of the moderate campaign.

A - No Media Campaigns

B - Media Campaign Opinion 0.15

Figure 3: Single Run Time Series of Opinion Changes on a Random Network. Panel A: No Media Campaign; Panel B: Media Campaign with extreme opinion 0.15. Panel C: Media Campaign with moderate opinion 0.35; Panel D: Complementary media campaigns at 0.15 and 0.35.

Effects of Betweenness Centrality and Tolerance

- 3.10 As previously discussed, some media campaigns seek to influence tolerance rather than directly targeting opinion. Declarations such as "scientific opinion differs" or "the jury is still out" have been made in regard to several issues, including smoking as a cause of cancer, the effects of second-hand smoke, and climate change (Oreskes & Conway 2010). This model shows how introducing doubt and thus increasing the tolerance of affected individuals makes them more open to and potentially accepting of alternative opinions.
- 3.11 Without external influences on opinion, increasing the tolerance of the network only increases consensus. In networks with relatively egalitarian social structures, without a large disparity in each individual's amount of influence, consensus opinion approaches the average of the initial opinion distribution (Weisbuch et al. 2002). With external influence, however, increasing tolerance increases the susceptibility of the network to the effects of media campaigns. Importantly, in some structured networks, the increase in tolerance doesn't need to be felt across all individuals; a small number of individuals can determine the susceptibility of the network.

C - Media Campaign Opinion 0.35

D - Media Campaign Opinions 0.15, 0.35

- 3.12 Many real world social networks exhibit community structure, in which individuals are more likely to be attached to members of their cluster than members of other clusters. The individuals who act as bridges between communities in a social network, having ties to two or more communities, are characterized by a higher betweenness centrality. The betweenness centrality of a given node is a measure of how many paths through the network pass through that node (Wasserman & Faust 1994). The ability for information to flow between communities and through the larger network structure is dependent on these high-betweenness individuals, who effectively act as bridges or gatekeepers. Note that this scenario is subtly distinct from models that analyze the power of influence on the part of high betweenness nodes. In this scenario, the media node is not targeting the high betweenness nodes with a direct attempt to influence opinions. Rather, it is considering the effects of altering the influenceability of those nodes to highlight their role as gatekeepers of opinion propagation.
- 3.13 Figure 4 summarizes the results of a tolerance-based scenario investigation. The networks here are constructed as scale-free networks, which exhibit heavy skewness in betweenness rankings as well as in degree centrality.
- 3.14 Results indicate that adjusting the tolerance threshold for the six nodes with the highest betweenness ranking (2.4% of the network) dramatically affects the ability of an exogenous media campaign to share the opinions and behaviors in the network. In this scenario, a scale-free network of 250 nodes with a base tolerance of 0.23 is subjected to two exogenous influences. A media campaign broadcasting an opinion of 0.75 is connected to the ten nodes with highest page rank centrality, while the six nodes with highest betweenness centrality have their tolerances values adjusted to a value of 0.0, 0.15, 0.30, 0.45 and 0.60. The increasing ability of the media campaign to influence the network is reflected in the increasing median opinion and in the decreasing variability in opinion. Variability decreases more rapidly above the median than below because the maximum value (1.0) lies closer to the broadcast opinion (0.75) than does the minimum value (0.0).

Tolerance Injection

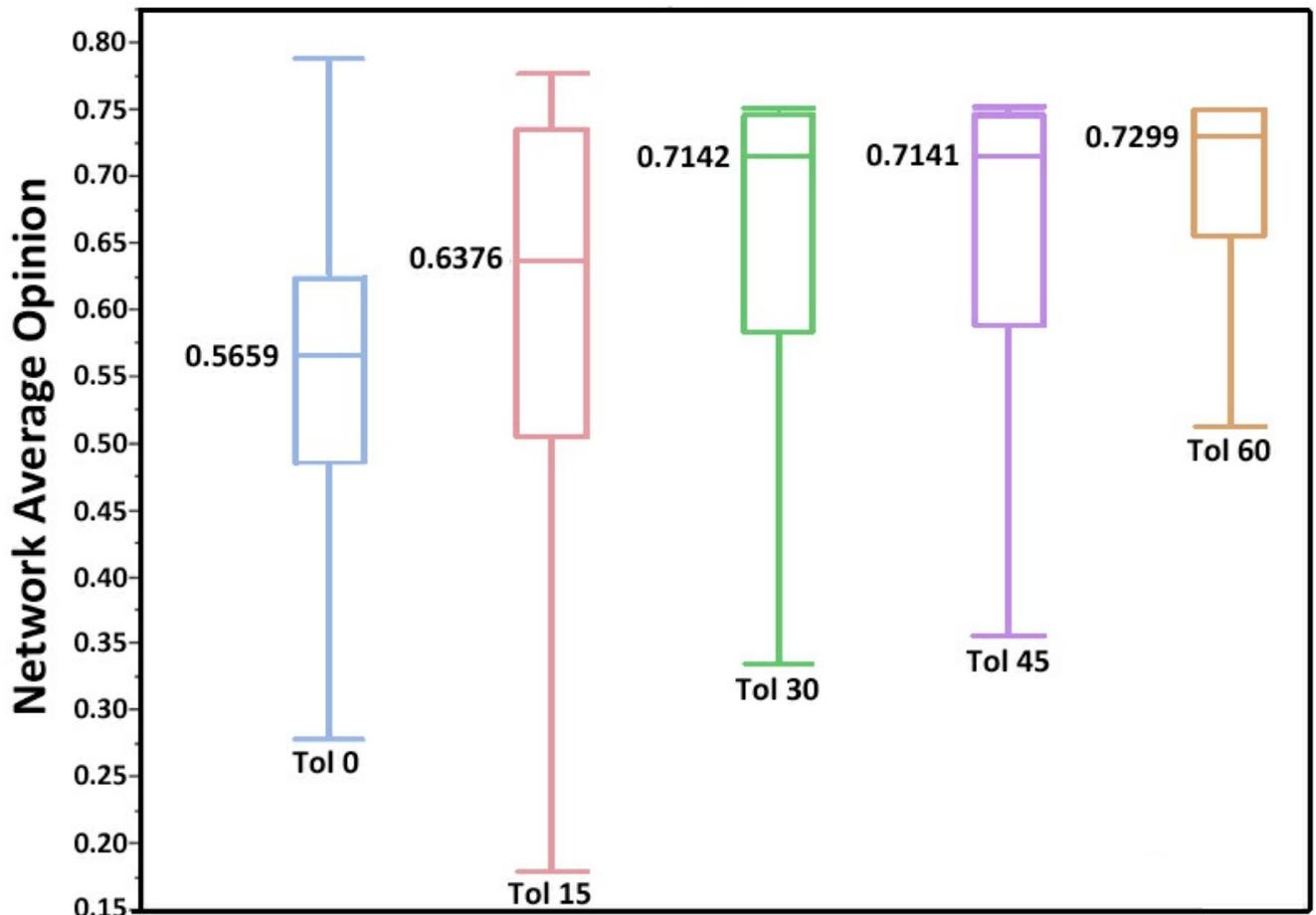


Figure 4. Box and whisker plots showing results from simulations in which a scale-free network of 250 nodes with a base tolerance of 0.23 is subjected to two exogenous influences: a media campaign broadcasting an opinion of 0.75 is connected to the ten nodes with highest page rank centrality, while the six nodes with highest betweenness centrality have their tolerance values raised. Bar label indicates the value to which tolerance was raised, midline value indicates network median opinion.



Conclusions

- 4.1 Media can influence the opinions of individuals, both through direct effects and through indirect social network effects. The ability of a single media campaign to affect network opinion is determined by the tolerance of individuals in the network and the perceived extremity of the campaign. Our simulations have indicated that campaigns which attempt to shift opinion to a value relatively close to the prevailing opinion in the network have a greater chance of success. Campaigns targeting opinions that differ sharply from existing opinion may have little success due to the number of individuals alienated by the extreme messages. This may even result in a boomerang effect which causes otherwise moderate individuals to move into the opposing camp (Hoyland, Harvey & Sherif 1957). The perceived extremity of the campaign can be broken down into components of the message itself, including its tone, focus, the source to which it is attributed as well as characteristics of the target of the campaign including their opinion tolerance and the perceived salience of the message. Thus, extreme messages to one segment of the network that are not viewed as relevant or from a low-credibility source may be discredited and avoid the unintended boomerang effect.
- 4.2 The model we present also suggests that the effect can be overcome by the use of complementary campaigns. Messages that are moderate (when compared to the mean population opinion) have a greater chance of influencing a wider range of individuals, which subsequently allows for them to be open to influence by more extreme campaigns. Properly designed complementary campaigns have a greater chance of achieving the intended effect, such as effectively informing the population about the harms of smoking, ultimately leading to behavior change.
- 4.3 Message extremity in this model should be considered as a subjective evaluation by an individual regarding the distance of the message from the individual's current position and the tolerance range of that individual. As such, it does not include such modifying characteristics as the tone of the campaign and source credibility as distinct components. In addition, these scenarios employ homogeneous values for tolerance and plasticity to simplify the presentation and analysis. Heterogeneity introduces complexity to the model, and to be of higher fidelity would need to include other, meso-level network factors such as assortativity on tolerance and plasticity variation to differentiate between friend, best friend, and family relationships.
- 4.4 The scenarios presented here consider the effects of simultaneous, constitutively active campaigns of a complementary nature. Sequential campaigns and campaigns of a competitive nature can behave differently. We examine some of the effects of simultaneous and sequential competitive campaigns in another paper (Moore et al., in review).
- 4.5 The ability to effectively change opinions throughout a network is strongly dependent on network structure as well as on individual characteristics such as tolerance. In networks with community structure, the tolerance values of individuals can determine the degree to which a shift in opinion can occur throughout the network. The ability for information to flow between communities and through the larger network structure is dependent on high-betweenness individuals. In some structured networks, the increase in tolerance doesn't need to be felt across all individuals to be effective; the tolerance of a few selected individuals can determine the susceptibility of the entire network.
- 4.6 In addition to directly targeting the opinion of the general public, media campaigns can also influence the opinion dynamics of a network by influencing tolerance levels of the campaign's intended audience. Our simulations have shown that by running a preliminary tolerance-based campaign to increase acceptability of a subsequent message, media campaigns can achieve a greater degree of success. Conversely, campaigns focused on decreasing tolerance within a social network can effectively block the acceptability and success of future media campaigns.



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