Advocate Influence on Politics Through the Media: A Multi-agent Simulation[1]

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1. Introduction

One of the key issues that political campaigners are faced with is how best they can use their resources in order to bring specific issues to the attention of the public; campaigners may be faced with a range of choices, from harnessing the power of the media to using more direct means of communication such as public debates or canvassing. Available resources are generally limited, and the issue often becomes one of how best to allocate scarce resources among a range of possible alternatives.

In our project, we seek to frame this question in a rigorous way by constructing a modelling environment that simulates the process of how media influences a population of agents' ranking of the importance of a set of issues. The model, we hope, should help us perform a range of "dry lab" experiments in order to test alternative resource allocation strategies, where the campaigner's goal is to obtain the greatest possible impact on the population. Although, for exemplification purposes, we describe this issue in terms of political advocacy, we must remark that similar questions are faced by other actors who are interested in bringing certain issues to the attention of the largest possible number of people, for instance advertisers who must decide which specific media outlet to target, and with what frequency. Modelling in this area might provide a useful instrument, both as a testbed for different theories of media influence and as a normative tool for testing actual strategies.

The paper is structured as follows. In the next section, we introduce some of the relevant literature dealing with the influence of media on the popular consciousness and with social influence and networks. In section 3, we describe our model, both in its simplest and more complicated versions. In section 4, we present some results that we have obtained from a first set of simulation runs. Finally, in section 5 we expand on the model's advantages and limitations, and we suggest possible avenues for future research.

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2. Media and Social Influence: A Brief Overview

2.1 The Influence of Media on the Popular Consciousness

The idea of a 'mass media' and its possible effects on public opinion first entered the academic discourse in the late 1950's and early 1960's as television broadcasts began reaching into almost every home in the United States, permanently changing the way Americans received and processed news, particularly about political and social issues. Since then, an enormous amount of literature has been published on the topic in the social sciences, particularly political science and psychology, with a handful of theories on media influence dominating the fields. The major approaches are summarized here.

The first dominant theory to emerge in this field asserted that the mass media had only "minimal consequences" on public opinion. This view, endorsed by Joseph Klapper in his 1960 work *The Effects of Mass Communication*, asserts that individuals will filter out information that they find discrepant with their pre-existing beliefs and process only the material in accordance with these beliefs. In this way, the media does little to change the opinions of individuals; rather it merely activates and reinforces *a priori* preferences. Some recent research claims a slightly more direct effect of media on public opinion. Joslyn and Ceccolli (1996) found that the positive or negative tone of media coverage during the latter part of the 1992 presidential election had some overall effects on the evaluation of candidates, although the authors admit that these effects were sometimes muted by pre-existing political dispositions.

In the early 1980's the direction of media research shifted emphasis from identifying the effect of media on opinions to the looking at the effect of media on shaping *what* the public thinks about, which psychologists call *priming*. This new theoretical framework, dubbed the *agenda-setting,* continues to influence and inform current media research today, including the model in this paper. Lawrence Jacobs and Robert Shapiro (1996) offer the following synopsis of the main findings of agenda-setting media research: "Much of the recent research pointing to significant influences of the media had emphasized the media's impact on what the public sees as high on the policy agenda, on how the public learns about issues, and on the standards or criteria that individuals use in making judgments and forming attitudes"(p.11). This approach has been of particular interest to political science researchers concerned with how certain issues become relevant during electoral campaigns. Iyengar and Kinder (1987) found that viewing television news made specific issues more 'salient' for individuals, giving them an easily accessible framework for evaluating candidates and their subsequent political performance. This framework was later extended to explain how by simply priming audiences, media can alter opinions. "The news media exert a powerful influence over what considerations are in fact salient to voters. Both frequent and recently disseminated is retrieved with greater ease; *hence political opinions reflect news coverage*" (Joslyn and Ceccolli 1996, our emphasis p.150). Other researchers haven taken a more nuanced view of media influence, positing an interdependent model of media effects, where "public opinion grows out of an interaction between media messages and what audiences will make of them" (p.349).

The model presented in this paper uses as its foundation the agenda-setting perspective, which is the most established theory in the media effects literature. Most researchers agree that the mass media play a (*the*) significant role in introducing and keeping issues in the public discourse merely by covering them regularly. There is much less consensus on the effects, direct and indirect, of media on the strength and direction political beliefs. These dynamics, which proved difficult to model cleanly, were removed from the model presented here.

2.2 Social Influence and Networks

Another dynamic critical to our model concerns the role of interpersonal influence in social networks. While the media affects how its audience rates the importance of certain issues, our research also attempts to describe how these rankings diffuse through the rest of the population to individuals who were perhaps not exposed to the same types of media as their peers. A 1993 literature review by sociologists Peter Marsden and Noah Friedkin evaluated a number of approaches, both mathematical and conceptual, to studying the dynamics of social influence through network analytic models. In their discussion of the substantive bases for the study of social influence, they highlight Bonnie Erickson's use of *social comparison theory* as a foundation for her social influence research. The authors summarize this theory writing that the "framework posits that, in a situation involving ambiguity, people obtain normative guidance by comparing their attitudes with those of a reference group of similar others. Attitudes are confirmed and reinforced when they are shared with the comparison group but altered when they are discrepant" (p.129). Erickson's work supports the evidence from earlier studies by the 'Wisconsin School' social stratification researchers, which demonstrated the isomorphic effects of peer influence on career aspirations in a wide sample of adolescents (Duncan, Haller, Portes 1971).

Another related theory comes from Serge Moscavici's 1985 book chapter "Social Influence and Conformity," which posits that alleviating interpersonal conflict (discrepancy really) results in increased similarity among actors in a number of spheres of attitude and behavior. Social network analysis studies have traditionally dealt with the issue of interpersonal influence on attitudes and behavior within closed, local networks, and have not dwelled specifically on what effects exogenous factors like media influence would have on social influence in community networks.

2.3 Modeling the Media: An Agent Based Approach

While agent-based modeling has grown in popularity among many social science fields, the use of this technique as a tool to model media influence has apparently been ignored. This review of literature, which included searches of the major journals of public opinion, political science, psychology and sociology found no basic, fundamental agent-based models of the media's influence on how the public ranks the importance of political and social issues. In the spirit of Robert Axelrod, the barebones agent-based model presented in this paper attempts to capture the simplest dynamics of media and social influence over time in a closed population. Based on the previous research in this area, we expect that over repeated iterations, individuals in the population will tend toward attitudinal isomorphism because of the power of the media's agenda setting function and the pressures to conform as predicted by social comparison theory.

3. Constructing a Model for Media Influence

3.1 The Model

The model presented in this paper is a first attempt at simulating a process of media influence on a population of agents, in order to test several strategies for resource allocation on an advocate's part. The model is a drastic simplification of reality, founded on a set of restrictive assumptions. While its purpose is to provide a simple framework in order to address this issue, we are aware that it should be improved and expanded with more realistic features, as we will argue in section 5.

The model's main simplifications include:

- our world is populated by only two kinds of entities, p agents (i.e. "citizens") and m media, connected in a network;
- we assume that each agent ranks a set of issues $X_1, X_2, \ldots X_n$ in terms of importance with weights $w_1, w_2, \ldots w_n$;
- each agent's ranking of issues is influenced by interactions both with (a) other agents and (b) with the media. While interactions with other agents are bi-directional (in principle, each agent can influence or be influenced by anyone else) interactions with the media may be uni-directional or bi-directional (i.e. media may or may not be influenced by certain agents'views).

Agents and media outlets have certain, similar properties. In particular each agent A_i is associated with:

- a vector $W_i = (w_{1i}, w_{2i}, \ldots w_{ni})$ denoted $Rankagent_i$ which describes the "importance" that A_i assigns to a set of issues, with W_{ni} in the interval [0;1]. The sum of the weights will always be equal to one;

- a parameter Inf_i representing the "influence" of A_i, that is, his or her ability to influence the views of the other agents with whom he or she interacts. Inf_i is a parameter that can be set in various ways. To begin with, we will set $Inf_i = K$ for every A_i. In a later version of the model, we will set different values of Inf_i for different agents, in particular, we will assign different values of Inf_i to different agents in order to capture their degree of "opinion leadership", according to a well known model first introduced by Rogers in the 1960s and now very popular in market research[2] whereby agents in a population can be divided into "innovators", "opinion leaders", "followers" and "laggards";
- a parameter Sus_i representing the "susceptibility" of A_i, that is, his or her likelihood to be influenced by the other agents with whom he or she interacts.

Each media outlet M_j is associated with:

- a vector $W_j = (w_{1j}, w_{2j}, \ldots w_{nj})$ denoted $Rankmedia_j$ which comprises the "importance" that M_j assigns to the (same) issues, with w_{nj} in the interval [0;1]. To start with, we assume that our process takes place on a sufficiently short time span so that the media's ranking of issues is fixed; this assumption will be relaxed in later versions of the model;
- a parameter N_j which is the number of agents that each media outlet influences. The "radius" of influence of media outlets tends to vary widely, so a distribution of values for N_j would better represent reality than a constant N across different outlets. The current version of the model assigns each media outlet a different probability p_c of connection to the agents in the model, in particular we assume the presence of a large media outlet with $p_c = .90$ and a small media outlet with $p_c = .30$.
- Media have influence and susceptibility too. In the first run of the simulation, we set $Inf_j=1$ and $Sus_j=0$ for all media; that is, all media have the same influence and they cannot be influenced by any individual agent's views (hence their rank matrixes $Rankmedia_j$ do not change); it is possible to relax this assumption and assume that media susceptibility is different from zero.

At each time step, each agent interacts with a number of other agents and media according to his or her network of connections[3]. The network topology is imposed at the start of the simulation; in different runs of the model, we will experiment with different kinds of network structure (random, scale free, small world networks). Initially, we envision that the network topology will

[2] See Rogers, E. (1962) Diffusion of Innovations, NY: Free Press. For a similar theory and application to marketing see G. Moore (1995) Inside the Tornado: Marketing Strategies from Silicon Valley's Cutting Edge, NY:Harper Business.

3 We can imagine that individual agents communicate though a variety of one-to-one media (telephone, email, direct communication) while mass media can broadcast their views through a range of one-to-many media (TV, radio, newspapers). In our model, we do not include modes of many-to-one or many-to-many communications among agents, such as public debates, blogs, forums etc.

remain fixed at each time step t. However, later versions of the model - which we have not yet developed - may include an evolving network.

At each time step, each agent A_i modifies its ranking of issues according to the following formula:

$$Rank_{agent=i,time=t+1} = Rank_{agent=i,time=t} + (Suceptibility_{agent=i}) \times \frac{1}{j} \times \sum_{j=agents} (Influence_{agent=j} \times Rank_{agent=j,time=t})$$

where j is the set of all agents connected to agent i.

The ranks must be renormalized each time this algorithm is executed. Renormalized simply means that the sum of the elements in the $n \cdot 1$ matrix must be 1. This is easily done by redefining every element as follows: $e_i = e_i / \Sigma_{j=1 \text{ to } n}\, e_j$.

3.2 Initializing the model

Connections in the model are determined by numbers arbitrarily entered by the user. Specifically, our model asks what would be the probability that a given agent would be connected to another agent. This creates some variance among agents but maintains a generally symmetric structure. Changing the probability of connection in the random network will provide us with a way to explore variability in results; we will also try to test the model by wiring the agents by methods other than random connections. Initialization of media outlets follows a similar process except (a) media outlets tend to be connected to a higher percentage of agents, and (b) each media outlet's connection probability is entered independently, allowing the user to create an arbitrary distribution of media outlet sizes for each run of the model.

Every agent and every media outlet are assigned, at the start of the simulation, a random $(3 \cdot 1)$ rank matrix, where the elements w_{1i}, w_{2i} and w_{3i} are such that: $(w_{1i} + w_{2i} + w_{3i} = 1)$ and $w_{3i}=0$.

Since the model is, in our intentions, a framework for testing available resource allocation strategies on the part of an advocate, at the start of the simulation we set the importance of one of the issues (namely, issue 3) to zero for all agents and media; at some time step t (we posit $t = 1$) we then change the ranking of the issue for one or both media outlets according to the strategy chosen by the advocate. For $t > 1$, the importance of issue 3 for the media reverts to zero, and we then follow the dynamic diffusion of the issue in the population[4]. Eventually, the importance of the issue in the population will fade altogether. The quantities that we should be able to measure with this model are the extent and speed of diffusion of the third issue's importance in the population according to different strategies and different types of underlying social network topologies.

4 This method of an advocate having an influence on the media for one time step is akin to inputting a delta function as a boundary condition for the heat equation. By this instantaneous but powerful change in the boundary conditions and by examining the evolution of the system over time, one can gain important information about the system.

The available strategies for the advocate are constrained by the total available resources; if C is the total amount of available resources, then the amount of "importance" that the advocate is able to "buy" for each issue in media 1 and 2 (α_1 and α_2 respectively) is given by the formula:

$$C = N_1\, \alpha_1/(1+ \alpha_1) + N_2\, \alpha_2/(1+ \alpha_2)$$

Therefore, we can think of α_1 and α_2 as the "coverage" that the advocate can obtain from media outlets 1 and 2 at time $t = 1$ by spreading his or her resources $C = C_1 + C_2$ such that $C_1 = N_1\, \alpha_1/(1+ \alpha_1)$ is spent in order to obtain coverage from media outlet 1 and $C_2 = N_2\, \alpha_2/(1+ \alpha_2)$ is spent in order to obtain coverage from media outlet 2[5]. The N in the $N\, \alpha/(1+ \alpha)$ term shows that the advocate has to pay more for more coverage. The $\alpha/(1+ \alpha)$ is the renormalized effect of buying α influence. Before the advocate influences a media, the media outlet has $W=[w_1,\ w_2,\ 0]$. The advocate, for one time step, is able to alter that and have $W=[w_1\, \alpha/(1+ \alpha),\ w_2\, \alpha/(1+ \alpha),\ \alpha/(1+ \alpha)]$. Note that the altered matrix sums to 1.

We initialize all runs of the simulation with the same number of agents (100), media (2) and issues (3). Each run of the simulation consists of 70 time steps and 10 trials.

We posit eleven possible resource allocation strategies for our advocate, as illustrated in the table below (strategies are numbered from 1 to 11, with an increasing amount of resources allocated to the large media outlet):

		Strategy 0	Strategy 1	Strategy 2	Strategy 3	Strategy 4	Strategy 5	Strategy 6	Strategy 7	Strategy 8	Strategy 9	Strategy 10
Media1 connects to about 30 agents	C_1	10	9	8	7	6	5	4	3	2	1	0
Media 2 connects to about 90 agents	C_2	0	1	2	3	4	5	6	7	8	9	10

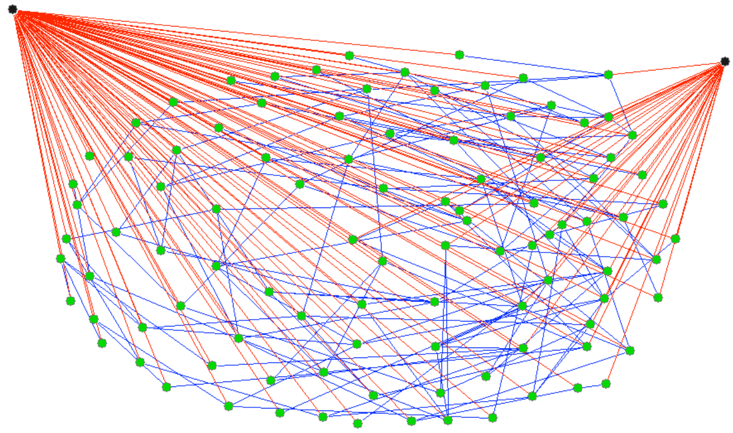
4. Results

The first runs of the model include a randomly assigned interaction network with probability of connection among agents equal to .40. Large and the small media outlets are connected with probability p_c =.90 and p_c =.30 respectively.

Figure 1 below illustrates one example of such random network with connection probability .40.

[5] This algorithm represents the diminishing returns associated with very high investments in media influence. That is, no matter how much an organization invests in influencing a media outlet, it will never be, for example, the subject of every single article in a newspaper. This algorithm is an imperfect representation of these dynamics and is worthy of further consideration and research.

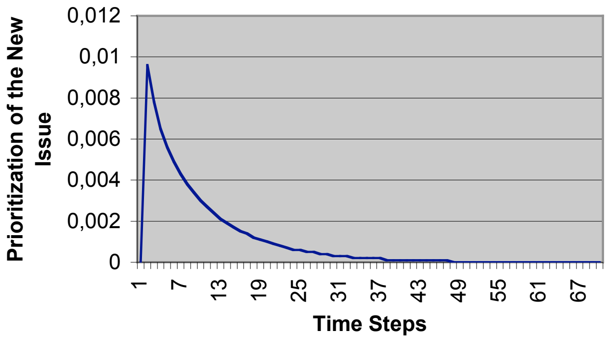
Fig. 1 – Random interaction network with probability of connection 0.40



The model is initialized with constant agent susceptibility ($Sus_i=1$ for each agent A_i), constant agent influence over other agents ($Inf_i=1$ for each agent A_i), constant media influence ($Inf_j=1$ for each media outlet) and non susceptible media. We run 10 trials of the model for each of the eleven possible strategies.

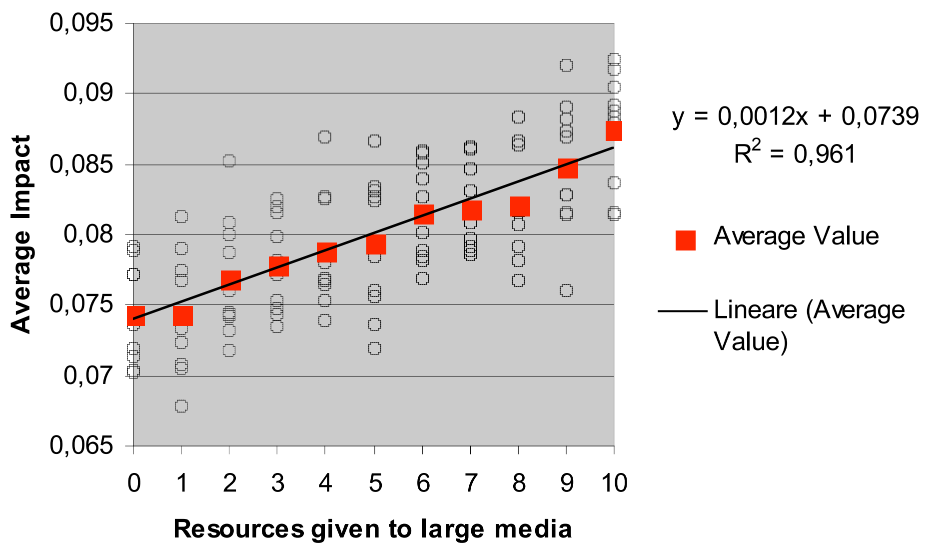
The diffusion of the issue is similar for all agents in the population: the new issue introduced at time $t=1$ peaks in the agents'individual ratings after a couple of time steps and then steadily loses importance. One way to illustrate this is to measure the average prioritization of the issue, defined, at each time step t, as the sum of the weights assigned to issue 3 by all agents in the population, divided by the number of agents. Figure 2 illustrates the the average prioritization of issue 3 in the population, over time, for one of the strategies; a similar trend is obtained whichever strategy is chosen, but the average value of the prioritization of the issue in the population may differ according to the chosen strategy.

Fig. 2 – An Average Agent's Prioritization of the New Issue



In order to show how different strategies may yield different results in terms of average value obtained by the issue in the population, we define the average impact of a resource allocation strategy as the sum of the average prioritization values over time (graphically, the average impact is the area under the function shown in fig.2). That different strategies yield different average impacts is illustrated by figure 3 below, which shows how, on average, the greater the resources invested in order to obtain coverage from the large media, the greater the average impact over the population. In fact, the greater initial outreach of the large media outlet creates a greater "momentum" for the issue, which is amplified in subsequent time steps thanks to the agents' interactions with other agents.

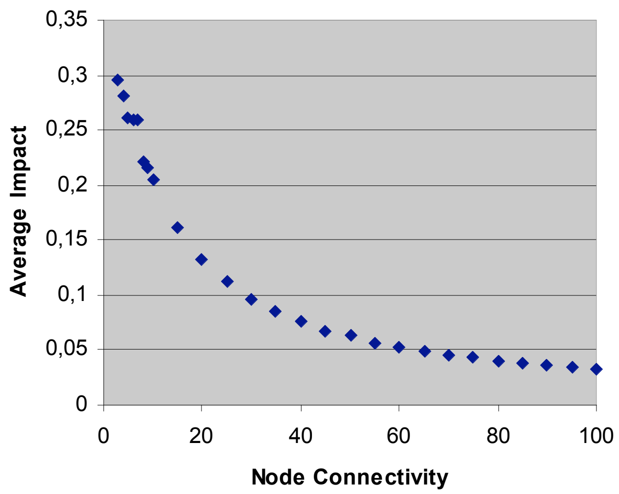
Fig. 3 – Average Impact of Different Resource Allocation Strategies



Tweaking the values of some of the model's parameters does not affect the average issue prioritization trend, nor the result that investing more resources in the large media outlet yields a consistently higher average impact. We proved this by running various trials of the model with different values for the agent influence parameters. In particular, we constructed a model where agent influence differs according to whether the agents are "innovators" (*Inf=1*), "opinion leaders" (*Inf=0.66*), "followers" (*Inf=0.33*) or "laggards" (*Inf=0*). The results of these trials are consistent with those obtained with the first version of the model.

Changing other aspects of the model leads to more interesting comparisons. First, we tweak the probability of connection among agents. We test this on a version of the model where there is only one media outlet, and all the advocate's resources are put into that media; for each trial, we change the connection probability among agents. As shown in figure 4 below, this yields the slightly counter-intuitive result that the average impact is higher the less connected the agents in the network. This, however, can be explained if we note that when agents are loosely connected to each other they rely mostly on the media in order to form their opinions, whereas when agents are densely connected their views are strongly affected by the opinions of the other agents they get in contact with. Hence, media targetting strategies are more effective in a loose social network.

Fig. 4 – Average Impact and Node Connectivity



The second aspect of the model that we may attempt to change is the topology of the interactions network. We run the model with three different kinds of network topologies, in particular:

- a scale free interaction network
- a small world interaction network
- a small world interaction network with a "local" media outlet

In order to make the networks comparable, we keep all other parameters unchanged, namely: probability of agents'connection equal to .40, constant agent influence and susceptibility ($Inf_i=Sus_i=1$ for each agent A_i) constant media influence ($Inf_j=1$), zero media susceptibility, a large media outlet with p_c=0.9 and a small one with p_c =0.3.

The scale free network is shown in figure 5a. Figure 5b shows the frequency distributions of the edges in the scale-free network that we have constructed for the model (the fit to a distribution with exponent –2, indicated in red, is quite good).

Fig. 5a – Scale free interaction network

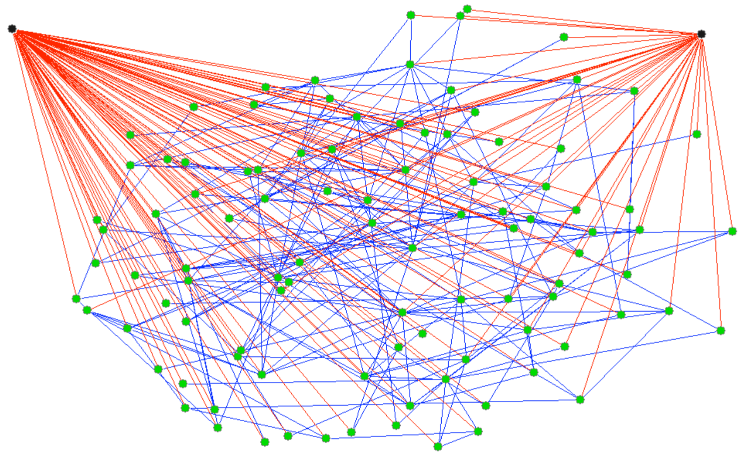
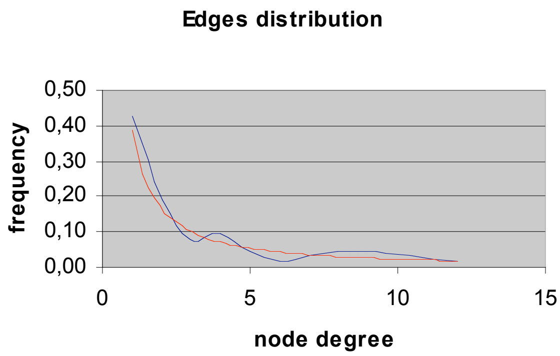


Fig.5b – Frequency distribution of edges in the scale-free network



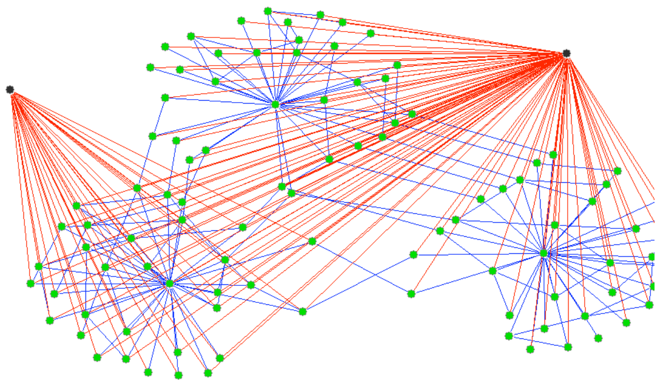
Our small world network contains subgroups of tightly connected nodes (clusters) linked to each other by few inter-cluster connections. It is characterized by short diameter (the longest shortest path in the network is 6) and short average path length (average distance among reachable pairs: 3.54707).

Note that we have chosen to construct scale free and small world networks "manually" (i.e. by imposing certain features on the networks and verifying *a posteriori* that they satisfy certain conditions for "small world-ness" and "scale free-ness"). A more rigorous approach would have been to start with a perfect, regular lattice,- where every node is connected to its four closest neighbors in a ring, and then to rewire the lattice giving each node random probabilities to be connected to other nodes[6].

[6] Random rewiring procedure for interpolating between a regular ring lattice and a random network, without altering the number of vertices or edges in the graph. We start with a ring of n vertices, each connected to its k nearest neighbours by undirected edges. (For clarity, n ¼ 20 and k ¼ 4 in the schematic examples shown here, but much larger n and k are used in the rest of this Letter.) We choose a vertex and the edge that connects it to its nearest neighbour in a clockwise sense. With probability p, we reconnect this edge to a vertex chosen uniformly at random over the entire ring, with duplicate edges forbidden; otherwise we leave the edge in place. We repeat this process by moving clockwise around the ring, considering each vertex in turn until one lap is completed. Next, we consider the edges that connect vertices to their second-nearest neighbours clockwise. As before, we randomly rewire each of these edges with probability p, and continue this process, circulating around the ring and proceeding outward to more distant neighbours after each lap, until each edge in the original lattice has been considered once. (Watts and Strogatz, 1998)

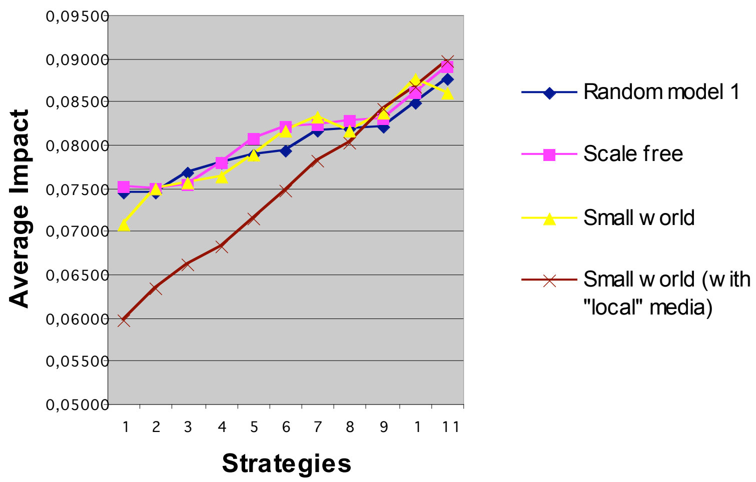
We run the small world network model with two different kinds of media connection topologies. One is the usual combination of large and small randomly connected media. The other is a combination of a large randomly connected media outlet and a small media outlet whose connections are not random but rather all directed to one of the clusters. This kind of topology intends to simulate a situation where a small "local" media competes against a large "national" media. Figure 6 below illustrates the network's topology in this latter case.

Fig.6 – "Small world" network with one "national" and one "local" media outlet



For each one of the three network topologies, we test the 11 possible resource allocation strategies, and we then compare the results. Figure 7 below shows how the average impact of each strategy differs according to the underlying network topology. The most interesting result here is that the increasing trend is more pronounced when agents'connections form a small world and the small media outlet is very "local": here, it pays even more to invest all available resources in the large, "national" media. In this kind of world, in fact, the impact of the smaller media is very localized, and it takes a much longer time for the issue to find its way out of the local cluster and reach the rest of the population.

Fig. 7 Average impact of various resource allocation strategies with different networks



Different types of network topologies have very different network features (such as network density and average distance among pairs of nodes) but despite this they all yield similar results in terms of average impact. As can be seen from figure 8a and figure 8b below, again, the only outlier is the small world network with a local media outlet, which yields a much smaller average impact than the others.

Fig. 8a - Network density vs. impact

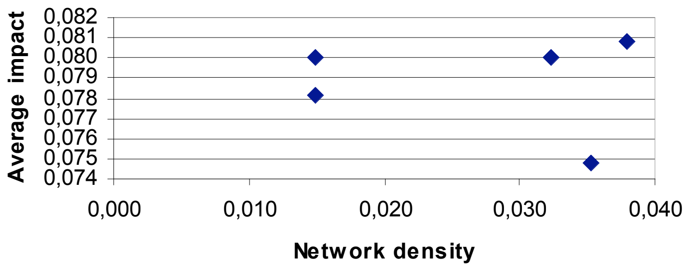
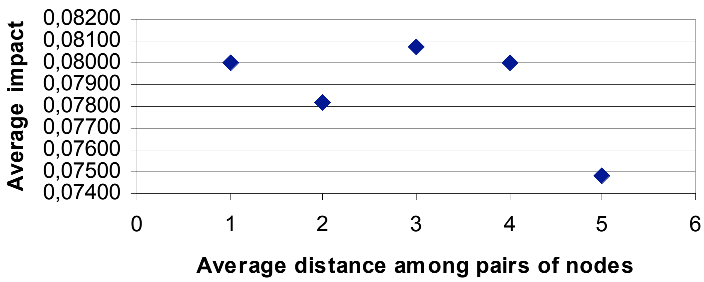


Fig 8b - Node distance vs.impact



5. Conclusions

The first simulations run on a very simple version of the model, leading us to highlight two preliminary results:

- advocates should focus resources on attracting the attention of large media outlets which will have a greater aggregate impact on agents than small media outlets, and
- putting resources in a less connected (less dense) network yields the largest impact.

The current version model lets us perform comparisons with respect to the average impact of issues according to different resource allocation strategies and network topologies. However, there is a problem with linearity of interactions: in fact, interesting spontaneous dynamics will not emerge until we introduce dynamic nonlinear interactions in the model. This can be done by introducing interaction dynamics that are either stochastic or endogenous to the model, or both. In order to introduce stochastic dynamics, we may wish to rewire the network at each time step, maybe at random with a certain probability (agent-media connections may also change this way). More realistically, we can think of introducing endogenous interaction dynamics by making the probability of interaction at each time step *t* dependent on the outcomes of interactions that have taken place in the previous time step *(t-1)*. One of the possibilities in this sense would be, for example, to assume that the media influence agents only when the latter are "reasonably close" to the media's views, thus rendering the probability of interaction at time *t* dependent on a measure of distance between "views" (here, ranking of issues) held by media and agents at time *t-1*.

Or: interactions could be modelled as repeated games: at each time step, an agent could play a "game" with the agents connected to it, and the outcome of the game could decide how an agent changes its views. These games could be designed in myriad ways – to incorporate the ranking of issues or to be independent of them – and can be seen as rational discussion among agents where persistent advocacy would, over time, build trust between an advocate and a media outlet.

Another feature of our model is that each issue evolves independently of other issues; however, in the real world, issues are often related to one another. It may be interesting to complicate the model by introducing correlations between the rankings of different issues. If, for example, one issue is a raise in taxes for a school district and a second issue is shutting down a high school, a change in the importance of one will probably change the importance of the other.

At the same time, the more complicated versions of the model would allow us to explore a range of other questions such as: what is the rate of diffusion of an advocate's actions across the network? What would happen if we include more media outlets? How can we include political beliefs about certain issues in the model, instead of focusing only on their priorization?

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