Simulating Components of the Reinforcing Spirals Model and Spiral of Silence:

An Agent-Based Modeling Approach

Abstract

Communication processes occur in complex dynamic systems impacted by person attitudes and beliefs, environmental affordances, interpersonal interactions and other variables that all change over time. Many of the current approaches utilized by Communication researchers are unable to consider the full complexity of communication systems or the over time nature of our data. We apply agent-based modeling to the Reinforcing Spirals Model and the Spiral of Silence to better elucidate the complex and dynamic nature of this process. Our preliminary results illustrate how environmental affordances (i.e. social media), closeness of the system and probability of outspokenness may impact how attitudes change over time. Additional analyses are also proposed.

Introduction/Background

Communication processes that give rise to socially significant phenomena such as public opinion, social identities, lifestyle communities, and ideological polarization have been theorized to be complex dynamic processes in Spiral of Silence theory (SoS, Noelle-Neumann, 1979; Noelle-Neumann & Peterson, 2004) and in the Reinforcing Spirals Model (RSM; Slater, 2007; Slater, 2015). Such dynamic models are challenging to study methodologically (see Slater, 2007). Classic longitudinal approaches may not have appropriate time intervals, a long enough timeframe for effects to evolve, address contexts in which the processes are expected to unfold in ways that might be readily measurable or be able to cope with modeling relevant contingent variables as well as core processes. We utilize agent-based modeling (Namatane & Chen, 2016) to model and simulate the effects of RSM and SoS willingness to engage in and ability to reach consensus as an alternative approach. In time we will explore implications of these simulations for topics such as political polarization and growth of extremist ideologies.

Complex agent-based social network models are developed incrementally and require researchers to elucidate underlying assumptions of important communication theories and models and also the impact particular mental states or choices would have on individuals distributed throughout a population. Therefore, ABM also provides an important exercise in theory development by forcing consideration of each implicit and explicit assumption and allows us to visualize the impact of that assumption on a complex dynamic system. We begin by simulating dynamics that are important in SoS and RSM using Netlogo (Wilenski 1999).
Our model focuses on underlying processes that may work in political and other contexts. Our model is premised on the following assumptions:

1) Communication processes are dynamic and longitudinal in nature.
2) Individuals are impacted both by internal states and interactions with the environment.

3) It is possible for a network experiencing RSM and SoS processes to reach an equilibrium state.
4) RSM and SoS can be modeled using in face-to-face networks using small-world networks. We assume this because interpersonal networks often have small world properties.
5) Individuals are able to recognize true opinion position of communication partners when these partners speak out their opinion.
6) Individuals listen only to speaking partners with opinions not too far from theirs, i.e. inside a tolerance interval.
7) Individuals update their opinions to the average value of listened opinions.

ABM allows researchers to organically develop and test, additively, the impact of different processing and interaction patterns on a larger social network. In this phase of our work, we are simulating how opinion spaces may evolve into being relatively cohesive or fractured. SoS predicts cohesiveness of opinions (relative few and uniform groups of shared opinions); RSM predicts that opinion groups will tend to fractionalize (with some proportion tending to become relatively extreme). One factor, according to the RSM, are the effects of closed communication norms among more polarized or extreme identity groups. Another factor is diversity of opinions/beliefs in the opinion space: In a highly connected, social media driven world, the range of assertions, beliefs, and opinions is likely to be much wider than in the news environment of another generation (though agenda setting still occurs Feezell, 2018), in which gatekeeping and agenda setting limited the margin and diversity of individual agendas (McCombs & Shaw, 1979). A third factor is reduced dependence on physical proximity given the affordances of social media in the contemporary environment. We also look at extent of the agents' own opinion expression, given the importance of this concept in SoS and the greater facility for such expression offered in the social media environment. See Appendix 1 for a technical description of how we approached our modeling efforts, and Table 1 for a summary of model parameters.

Results

The major results of our simulation experiments are summarized in Figure 1. The key finding regards the principal drivers of fragmentation in the opinion space. There are noticeable differences in fragmentation, or in models not reaching equilibrium, associated with each of our four factors. However, the model is dominated by one unmistakable finding: that fragmentation was universal across the simulations when communication norms were closed (little tolerance for divergent opinion) and when there was a wide range of opinions available in the opinion space. Effects of proximity and ability to express one's own opinion were modest by comparison.

Discussion

Though this model is incomplete, our result suggest that we can effectively use ABM to model l the complex dynamics of the RSM. Diversity of information impacts the simulation absent the influence of media gatekeepers. The importance of closed communication norms, an unwillingness to consider other viewpoints also has a significant effect, which has been less well discussed in the literature. Conversely, willingness to consider such viewpoints can have dramatic effects in reducing fragmentation. The impact of proximity and the ability to express one's own opinions were considerably less powerful though not without impact. Overall, this is an important first step in describing the dynamics of RSM and Spiral of Silence.

Next, we will model effects of mass media, of Twitter-type influencers, of selectivity in media use, of the impact of emergent social identity threats and of distinguishing social media networks from more proximal interpersonal networks. Further, we will be completing analyses of network structure and comparing model fit statistics, provide a more complete understanding of how adding variables to the model impacts overall fit.

References

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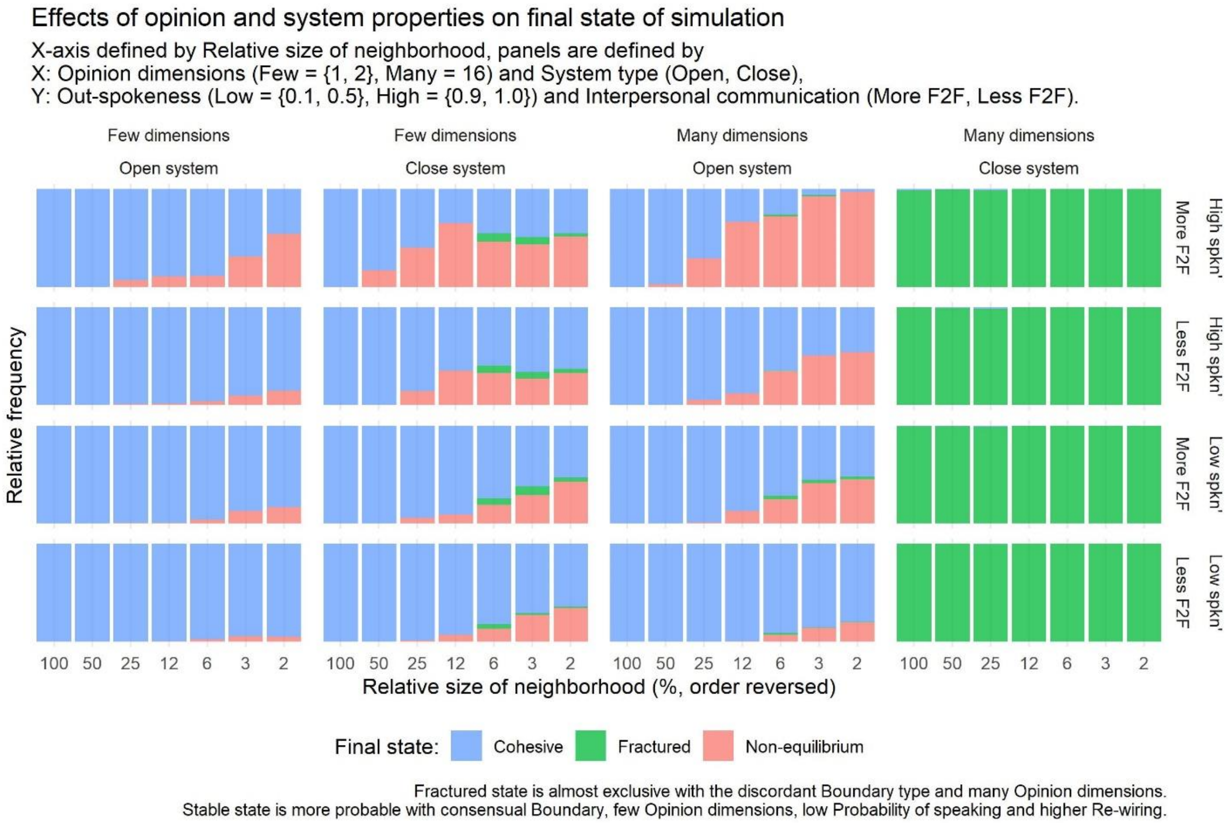
Table 1. Parameters used in the simulation experiment:

Prameter name (description)	**Used values**
N (number of agent in simulation)	129, 257, 513
Neis (number of neighbor connected via close links)	8, 32, 128
Rewiring (probability that the link with close neighbor is substituted by the link with random agent regardless its proximity)	0.05, 0.25
Opinions (number of opinions defining dimensions of the opinion space)	1, 2, 16
Updating (number of opinion dimensions updated at given step)	1, 8, 16
Boundary (relative fraction of theoretically maximal distance in given opinion space defining whether the communication partners are in opinion space close enough and respective agent will use their opinions for updating its own)	0.1, 0.2, 0.3
Boundary-drawn (method how is individual value of boundary drawn for respective agent – Constant is default for HK, i.e. all agents have same value given by value of parameter ε, Uniform means that the overall average of values is equal to parameter ε, but individual values are drawn from uniformly random distribution)	Constant, Uniform
P (probability that respective agent will speak its opinion out in given step)	0.1, 0.5, 0.9, 1

Note: For the final graph we compute variable 'Relative neighborhood size' according formula Neis / (N – 1) * 100. We also constructed variable 'System type' from variables 'Boundary' and 'Boundary-drawn' followingly: conditions with 'Constant' method and 'Boundary' parameter 0.1 and 0.2 and 'Uniform' method with 'Boundary' 0.1 we coin as a 'Close system', the resting three combinations we coin as 'Open system'.

Figure 1. Summary of simulation results.



Appendix 1: Technical description of modeling approach

We started our effort with the classical version of Hegselmann-Krause bounded confidence model of opinion dynamics (HK, 2002) and advance it in several ways. HK captures dynamics of reaching group consensus and supposes that: (1) all agents have one opinion on the continuous scale, (2) all agents always share their opinion with all other agents, (3) all agents have boundary given by their own opinion and +/- parameter ε, (4) parameter ε is same for all agents in simulation, (5) in each step of simulation all agents take into account opinions of all agents inside their boundary, then compute average of these inside-boundary opinions and take this average as their new opinion. this average as their new opinion. We use HK model since it captures opinion dynamics very smoothly, step-by-step, in high detail. It is also able trace gradual small individual changes smoothly over long course of time. Therefore we can explore SoS and RSM in a dynamic fashion. By manipulating margin of boundary the HK model allows us to explore the role of opened and closed system norms. Finally, as described bellow, HK model allows us easily add features and sub-processes that allows us explore RSM and SoS further.

We propose four advancements regarding boundary universality, number of opinions, properties of network connecting agents and universality of speaking out the opinion. (1) We propose not to let agents interact in full network, i.e. each agent with all other agents, but we introduced small-world network (Watts-Strogatz algorithm) and let agents interact only with their neighbors in this network. (2) We propose not one opinion as HK, but several opinions as dimensions of opinion space, where the boundary is Euclidean distance in this n-dimensional space. For comparability of results from simulations with different number of opinion dimensions we understand parameter ε as fraction of theoretically maximal distance in given n-dimensional space given by ‘n’ opinions. (3) We propose a diversity of parameter ε. In some simulations we sharply follow

HK model, but in some simulations we assign each agent its own value from randomly uniform distribution, but with same population average (i.e. when ε parameter for simulation is 0.3, then we draw for each agent its own value from interval <0, 0.6>). (4) We allow agents to not speak at every step of the simulation. We introduced parameter ‘p’ what is probability that the agent will speak its opinion at given step, then only agents that succeed in probability check speak their opinion at given step, but all agents update their opinions every step regardless their outspokenness.

All these advancements demonstrate their value and effect in the experiment where we varied classical parameter (margin of boundary) and all new parameters (see Table 1). The results we measure at the level of whole simulation. We record whether the simulation reaches stable state in 5000 steps or not and in case of reaching a stable state we record whether in resulting state there is at least one group of 6+ agents with completely same position in opinion space or whether there are only many groups of size at maximum 5. We also test the impact of willingness to consider the attitude of others. We allow a uniform distribution (or a set value) of 0.1, 0.2 and 0.3 around willingness to consider the opinion of others. This allows us to understand how different levels of openness to change impact closeness in an opinion space. Finally, we test the impact of a large or a small number of opinions mattering. This allows us to understand how the number of key issues (1 or 2 versus 16) in an opinion space impacts convergence in that space.