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 (RSM) and the Spiral of Silence (SoS) to better elucidate the complex and dynamic nature of this process. Our results illustrate how individual differences, and probability of outspokenness may impact polarization and how attitudes change over time. Further, we find that closedness to other perspectives and group identification contributes substantially to polarization, consistent with RSM assumptions . Finally, we test the impact of number of simulations on outcome and find only minor differences in results comparing 365 simulations versus 3650 simulations.

**Introduction**

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-Nuemann, 1979; Noelle-Nuemann & Peterson, 2004) and in the Reinforcing Spirals Model (RSM) (Slater, 2007, 2015). Such dynamic models are challenging to study methodologically (see (Slater, 2007)).

There are a number of reasons these dynamic models are difficult to study empirically. 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. Further, studying complex social phenomenon poses both financial and personnel challenges (e.g. how do you fund and maintain a research team over a multiyear process in the current economic environment).

One way to address these issues is by using simulation studies to understand underlying processes and then use these models to decide what to test empirically. There are a number of different simulation approaches that could be utilized including dynamic systems and agent-based modeling. Other work has called for the incorporation of more complex agent-based models into communication research (Waldherr et al., 2021), particularly in the context of SoS and political communication (Alvarez-Galvez, 2018). In this paper we describe a process whereby we utilize agent-based modeling (Namatame & Chen, 2016) to model and simulate the effects of RSM and SoS. This paper, therefore, has three primary goals 1) to describe the utility of process for the application of ABM to this context 2) to describe the process whereby we apply ABM and 3) thoughts on how ABM can be applied more broadly the Communication-related studies.

Utility of ABM

Here we elucidate specific benefits of utilizing agent-based modeling for communication research. Agent-based models 1) force researchers to consider assumptions underlying models and theories in order to appropriate implement models in software 2) allow us to identify the boundary conditions of our models, that is, to understand how and when variables might contribute 3) is a fully transparent process that can easily be augmented and replicated by other scholars (as long as the model is made available through a forum like GitHub) and 4) can help us identify key points conceptually so that we can better spend time and financial resources doing research in areas that are likely to yield interesting results. This last point is particularly important in a world of an increasingly competitive funding environment.

Background

ABM has been applied in another of social scientific and communication contexts (Mass citations here). Germane to this study, there has been a body of research that considers how agent assumptions of the other impact agent behavior in modeling contexts. An early study, for example, considered the impact of different power structures on how agent-based communication systems develop (Marsella et al., 2004). Another study focused on the application of ABM to understanding communication in multi-layer networks (Ge et al., 2013) and yet another study focused on ABM and within-team interactions (Crowder et al., 2012).

Other work has focused on applying agent-based modeling to understanding transmission (Ge et al., 2013), either of disease processes (Parker & Epstein, 2011), emotional responses (Schweitzer & Garcia, 2010), social contagion or of communication constructs in important contexts {Alvarez-Galvez, 2016 #13; Barbrook-Johnson, 2017 #14}. Other work has focused on risk communication strategy {Haar, 2016 #15}, communication of monetary policy {Salle, 2015 #16} or diffusion of innovation in markets {Bohlmann, 2010 #17}. Though these are projects that utilize ABM across contexts, these agent-based models can be used as a starting point for larger conversations about social decision making and also served to clearly elucidate the impact of particular decision making strategies.

ABM, SoS and polarization

Indeed, scholars have already begun to utilize ABM to understand the processes of polarization and those put forth by the Spiral of Silence Theory {Song, 2017 #18}. In a recent simulation study of SoS, researchers that utilized a network-based model, found that a central node with a strong opinion significantly impacted the overall willingness to communicate in a network {Ross, 2019 #19}, this may be exacerbated by a significant number of neutral individuals within the opinion space {Cabrera, 2021 #20}. Further, very small changes in the communication network could significantly impact polarization {Ross, 2019 #19}, as can individual difference variables {Cabrera, 2021 #20}, particularly willingness to voice a minority opinion {Ma, 2021 #21}. Other work on SoS suggests that consensus can be reached within localized networks {Cabrera, 2021 #20}, but to obtain consensus more broadly, homogenous mass media matters {Sohn, 2022 #23}. Further, polarization is a greater risk when there are too few individuals in a network with intermediate opinions {Sohn, 2022 #23} or when agents experience high levels of valence or arousal {Schwietzer, 2020 #25}, perhaps leading to a limited capacity to process complex opinions. Polarization is also more likely when there is a focus on minimizing conflict {Coscia, 2022 #26}, and a greater emphasis on group conformity {Zhang, 2020 #27}.

Our process

Most of the work in the field of communication focusing on utilization of ABM to understand polarization or SoS has included only a small number of variables to describe the SoS or polarization processes. Though this provides a good description of a smaller set of variables, it does not take advantage of the ability of this technique to consider environmental complexity in an emergent system. Our work is unique because it includes different metrics for polarization and numerous variables related to individual agent decision making in an additive fashion, allowing us to consider what is most important in final models for polarization or SoS.

Creating an underlying model

Our first step is similar to other work that has been completed related to Communication to understand polarization of SoS. We begin by simulating dynamics that are important in SoS and RSM using Netlogo {Tisue, 2004 #28}. Our model focuses on underlying processes that may work in political and other contexts. We then test to see whether this model can impact polarization/cohesion. 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. Some key elements of 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. (In later iterations, media influences can be simulated within such networks, but the current work is focused on modeling underlying network dynamics).
5. Individuals are able to recognize true opinion position of communication all other network members when these partners speak their opinion.
6. Individuals communicate with 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.

The model that we present here is initially based on Hegselmann-Krause {Hegselmann, 2002 #29}. We started our effort with classical version of Hegselmann-Krause bounded confidence model of opinion dynamics (hereinafter HK). HK captures dynamics of reaching group consensus and supposes that: (1) all agents have one opinion on the continuous scale from -1 to +1, (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) all agents take each step of simulation all opinions inside their boundary, then compute average of these inside-boundary opinions and take this average as their new opinion. We modified this model to come up with a basic set of parameters. We describe these basic parameters below:

1. **Opinion assimilation:** Agents that have n-dimensional continuous opinion positions that areupdated according to the true opinions of other influencing agents. The updating rule is adapted from the HK model; although instead of all agents adopting the average opinion of their influencers at every time step, agents may only partially move towards this value while retaining some of their original position. The strength of the external influence is controlled by a conformity parameter. Basically, this is an updating rule such that new opinion is developed based on a neighborhood average minus the old opinion and this multiplied a conformity parameter, which is has an initial value that is randomly assigned to each individual
2. **Probabilistic speech:** Agents are only receptive to the opinions of some agents at a given time, since not all agents are airing their views at all times. An agent must be speaking in order to influence the opinion of another agent at that time. Some agents are more outspoken than others. Agents always speak their true opinions, and any listening agent also hears the same true opinions.
3. **Small-world network:** A small-world network of communication that is initialized independently of opinion positions. Over time, agents can make changes to their neighborhood by rewiring their links - this is done by removing a link to the most dissimilar neighbor and replacing them with a link to the most similar speaking agent. These changes are made with the assumption that agents may prefer to be in a neighborhood of like-minded agents.
4. **Bounded communication:** Even within their own network an agent is limited to communicating with only those other agents that are similar enough to themselves. Depending on a model parameter, an agent may either not be able to speak to or to listen to another agent whose dissimilarity exceeds the agent’s communication boundary. This is adapted from the HK model’s Ε parameter.
5. **Social identity groups:** At the beginning of every time step all agents classify other agents into social identity groups based on their clustering in the opinion space. Agents are only influenced by other agents in their own identity group.

See Appendix 1 for a technical description of how we approached our modeling efforts.

**Can we model cohesion using this simplified model?**

The next step in developing this model is describing whether or not this simplified model can impact cohesion/polarization. To describe cohesion/polarization, we report a spatial model. In this model, when nodes (individuals) occupy a geographically near or identical space they are treated as having agreement. When individuals occupy more distant spaces, the agreement is less. Our results suggest that variations on the HK model did, in fact, impact how cohesive or polarized our results were in this context.

FRANCESCO, CAN YOU PUT IN WHATEVER YOU USE TO DESCRIBE THIS HERE?

**How do individual agent decision points impact overall model development?**

Once we established a fundamental model that could describe polarization in this context, we tested the impact of a series of theoretically driven variables on measures of cohesion. Our predictor variables were boundary (0-1 scale) with a boundary closer to 1 indicating a greater ability to reach out to others and connect. Agents determine the existence of identity groups in the entire network by applying the Louvain community detection algorithm {De Meo, 2011 #30}on a subset of the whole agent set, selecting only (what they view as) tightly connected agents. Our second variable is identity threshold (0-1 scale) which determines minimum similarity between two agents for them to be included in part of a community. Before every step the social identity group are identified based on the physical network structure. An agent is required to have two agents that are similar enough to themselves. tolerance level for difference (0-1) with 1 indicating a greater tolerance for difference, probability of speaking (0-1) with 1 indicating a greater probability of speaking, conformity level (0-1) with 1 indicating a greater preference for network partners to conform, and p-random, which is a randomized example of the probabilistic speech from the original HK model. We had two binary variables, use identity (0=, 1=) and modevaglue speak (0=, 1=). To test this we subjected our data to a series of regression analyses with our manipulated predictor variables predicting our two different measures of cohesion. Because of this large sample size, we required out differences to be significant at the .005 level since the likelihood of spuriously detecting meaningless effects is high.

**Do fundamental model parameters impact our results**

We also compared the impact of two basic types of simulation studies to understand cohesion, ESBG, which has a fundamental assumption that our individuals preferentially join into two separate groups and the normalized condition, where we allow the number of groups to vary to a greater extent. Further, in order to test the sensitivity of our analyses to sample size, we ran the analysis two ways 1) with a sample of 360 simulations and 2) with a sample of 3650 simulations. If the results look similar across statistical models and sample sizes, it would suggest that the small sample size may adequate for future analyses.

**Results**

*Can we model cohesion/fragmentation?* 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.

*How do individual agent decision points impact our model overall?* Across our four analyses, our results suggest that the variables included in our models explain a significant proportion of the variance (R2=.495-.628) but also that there is variance left to be explored beyond the variables we have included in our model. Due to the large sample sizes, we felt that statistical significance was not meaningful unless the variable was explaining additional variance in the model, we therefore submitted our variables to stepwise regression across models. We report the results of those stepwise regressions here.

There are three variables that explained the majority of the variance across models. These were, identity threshold (positively associated with our outcome variables), boundary condition (negatively associated with our outcome variables) and use identity (positively associated with our outcome variables).

*Do our fundamental model parameters impact model results.* Generally, our models are robust to sample size. There are minor differences depending on sample size but these differences do not appear to significantly impact the results.

**Discussion**

Though this model is incomplete, our result suggest that we can effectively use ABM to model 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. Group identity as a social dynamic also is a strong predictor of polarization and fragmentation. We interpret the predictive strength of these factors relative to other network parameters more conventionally explored in H-K network studies both as supportive of the RSM theoretical arguments and as providing useful variables to explore for students of network processes.

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 simulating the dynamics of RSM and Spiral of Silence. Later steps will involve simulation of various forms of media impact on network dynamics. Indeed, past research has suggested the importance of willingness to post disagreeable content on social media and the development of SoS.

Limitations

This paper is a step toward utilizing agent-based modeling to define the complex system that underlies SoS and other Communication theories that consider polarization.

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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’.

**Table 2. Assumptions of the model:**

|  |
| --- |
| **Summary of all seven assumptions:** |
| Communication processes are dynamic and longitudinal in nature. |
| Individuals are impacted both by internal states and interactions with the environment. |
| Network experiencing RSM and SoS processes may reach an equilibrium state. |
| 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. |
| Individuals are able to recognize true opinion position of communication partners when these partners speak out their opinion. |
| Individuals listen only to speaking partners with opinions not too far from theirs, i.e. inside a tolerance interval. |
| Individuals update their opinions to the average value of listened opinions. |

**Figure 1. Summary of simulation results.**

Chart

Description automatically generated

**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 closeed 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.

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