International Journal of Public Opinion Research Advance Access published March 12, 2015

International Journal of Public Opinion Research

doi:10.1093/ijpor/edv005

Collective Dynamics of the Spiral of Silence: the Role of Ego-Network Size

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Abstract

The spiral of silence persists as a major explanatory mechanism in public opinion research, linking individuals' perception of the opinion climate and their likelihood of speaking out. However, how locally expressed opinions (or, remaining silent) translate into global opinion distributions and the conditions affecting such generative processes have rarely been examined. Using agent-based modeling, this study attempts to explore a boundary condition affecting opinion dynamics—the distributions of individuals' communication network size, which is affected by the widespread use of social media. The results suggest that the spiraling phenomenon on a global scale becomes more likely when enough people exist between those who have different perceptions of the opinion distribution, keeping the population from being polarized.

Since first proposed by Elisabeth Noelle-Neumann (1974), the spiral of silence has remained an intriguing image to many who aspire to grasp complicated public opinion dynamics. The theory posits that a person's expressed opinion is a function of the perception of the proportion of others that express opinions against his or her own, otherwise known as the *opinion climate*. The more others seem to have the opposite opinion, the less likely it is that the individual will speak out (owing to *fear of isolation*). Thus, the spiral of silence begins with individuals' *quasi-statistical senses* (Noelle-Neumann, 1993) of whether they are in a minority. This component has, however, received relatively little scholarly attention, which left it as "probably the most widely misinterpreted concept in the spiral of silence" (Scheufele & Moy, 2000, p. 9). A recent keyword search using the Google Scholar database for the

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past decade returned only two scholarly articles with "quasi-statistical sense" explicitly in the title compared with 20 for "fear of isolation."

Instead, scholars have focused mainly on testing the presumed effects of opinion climate on the likelihood of speaking out in both offline (Glynn, Hayes, & Shanahan, 1997; Shanahan, Glynn, & Hayes, 2007) and online environments (Ho & McLeod, 2008; Yun & Park, 2011). Further, many have attempted to identify related moderating variables, which include the degree of self-censorship (Hayes, 2007), opinion confidence (Lasorsa, 1991), issue knowledge (Shamir, 1997), and communication apprehension (Neuwirth, Frederick, & Mayo, 2007), among many others. Studies of this sort help us better explain how individuals respond to their local opinion climates, but are less than ideal for revealing how such *local* responses (i.e., speaking out or remaining silent) interact over time to generate a *global* pattern—one's quasi-statistical sense is a function of the previous responses of others whose quasi-statistical senses, in turn, depend on others' responses made even before, and so on.

One might think of the construction of nests by termites as an analogy—observing individual termites' characteristics and behaviors in isolation might not reveal how they collectively build such massive structures with no architect overseeing the entire process. As such, public opinion at any moment is hardly an aggregate of choices by isolated individuals, but a collective outcome that arises from the intricate web of distributed local interactions (Huckfeldt, 2014). The sum of individual opinions in isolation might show how they are distributed at a moment, but not how they change over time. Thus, knowing the behavioral tendency (of remaining silent in the minority situation) alone might not necessarily lead to explaining when and how the spiral of silence takes place. A key to understanding such a dynamic process is examining the generative mechanism through which local interactions among multiple actors translate into global patterns that often "fail to match what might be expected based on the properties of an individual agent" (Smith & Conrey, 2007, p. 2).

We believe that *communication network size* and its distribution, which shapes an individual's quasi-statistical sense, play a crucial role in the generative processes underlying the spiral of silence. Will the spiral of silence take place if everyone's network is so constrained that the opinion climates they perceive might differ from one another and are incongruent with the larger collective? What would happen if individuals have bigger communication networks than before, for example, through social media such as Facebook or Twitter? How large should an individual's network in a society be for the spiral of silence to occur on a global scale? The explosive growth of social media enables individuals to have a far wider range of interpersonal communication than one could have possibly imagined 40 years ago when the theory was first outlined (Liu & Fahmy, 2011; Schulz & Roessler, 2012). Therefore, validating the spiral of silence theory requires re-examining its assumptions in relation to the properties of the fast-growing networked environment. Studying how people's varying scopes of opinion-monitoring affect the spiral of silence can be a small, but important, step in that direction.

The current study is an attempt to examine the generative mechanism underlying the spiral of silence using a type of computer simulation called agent-based modeling (ABM). While the traditional factor-based approach focuses on variables that represent the hierarchical structure of a system (e.g., individual, group, or organization) and their relations, ABM is an actor-based approach that regards social collectivity as an emergent outcome of the many-to-many interactions among autonomous actors over time (Macy & Willer, 2001). The key thesis of ABM is that complex and, often, counterintuitive global patterns may arise from the repeated interactions among simple components, not only from highly complex ones (Kauffman, 1995). ABM is a particularly useful approach to studying macroscopic regularities like the spiral of silence that vary depending on the distribution of the characteristics of a large number of actors (Axelrod, 1997). By creating an artificial social setting where individual agents, given simple behavioral rules, interact over time, this study aims at exploring how various statistical distributions of network sizes determine the courses and outcomes of the spiral of silence.

Distribution of Communication Network Size: a Blind Spot

There are two sources from which people normally obtain information regarding what others think about an issue: their immediate social neighbors and mass media portrayals of the larger collective. Prior research has focused primarily on the impact of mass media on the intention to speak out (e.g., McDonald, Glynn, Kim, & Ostman, 2001; Neuwirth et al., 2007), but such a heavy orientation toward mass media has been often questioned. Several studies have found that individuals rely more on their reference groups than mass media not only to gauge the opinion climate, but also to decide whether to express their own opinions (e.g., Krassa, 1988; McDonald et al., 2001; Moy, Domke, & Stamm, 2001; Oshagan, 1997; Scheufele, Shanahan, & Lee, 2001). Further, it has been found in a large-scale survey that the influence of interpersonal discussion on voters' choices outweighs that of mass media (Beck, Dalton, Greene, & Huckfeldt, 2002). Similarly, peer influences on individuals' willingness to express opinions have been also found in an online environment like message boards (Yun & Park, 2011).

Weighing the relative influence of the two information sources, however, is difficult, especially in the contemporary media environment in which interpersonal and mass-mediated communication are merged and less distinguishable (Schulz & Roessler, 2012). Much of the news nowadays are distributed and shared through online social networks and it is no longer unusual to see traditional mass media using personal blogs and social network services (SNSs) as news sources. A recent survey by CNN, a global news corporation, shows that >40% of respondents are exposed to or acquire news through a SNS on a daily basis (Gross, 2010). This situation is not entirely new because mass media have always operated within the social fabric (Katz & Lazarsfeld, 1955; Mutz & Martin, 2001). The key difference between earlier times and now resides in the expansion of interpersonal networks; people are able to interact with numerous others beyond their geographic and social proximity (Barnett, 2011).

Scholars including Noelle-Neumann (1993) have acknowledged that people often fail to correctly perceive the global distribution of opinion, due partly to their inherently bounded scopes of observation. If individuals' communication networks become bigger, then, it is more likely that they will be exposed to diverse sets of opinions than those with smaller networks. This speculation is supported by recent evidence demonstrating that the larger the network, the more likely it contains *weak ties* (e.g., acquaintances) (Eveland, Hutchens, & Morey, 2013). Since Granovetter's (1973) groundbreaking work, it has long been confirmed that novel and diverse information flows in and out of networks mainly through weak ties rather than *strong ties* because people strongly tied tend to share similar, redundant information and/or opinions.

Being exposed to more diverse sets of opinions may, in turn, increase the chances of developing a perception of opinion climate closer to the actual distribution of the larger collective. That is, those who can observe a wide range of opinions are likely to develop more accurate views of whether they are in the minority. If such individuals became the majority, their perceptions would be challenged less frequently and remain consistent across contexts and times, which would accelerate the downward spiraling as the theory predicts. In contrast, people who observe only the opinions of a few neighbors owing to their networks' limited range are likely to develop highly idiosyncratic views of opinion climate. If the opinion climate perceptions are fragmented as such, some might incorrectly perceive the minority opinion to be the majority opinion or *vice versa*, keeping the downward spiraling from occurring globally.

What makes this issue more complex is that most real-world situations fall in between the two extreme cases described above. Network scientists have recently found that a wide variety of networks, including collaboration networks of scientists (Newman, 2001), the Internet (Barabási & Albert, 1999), and even biological metabolic networks (Jeong, Tombor, Albert, Oltvai, & Barabási, 2000), follow a *power law* or *long tail* distribution, meaning that a small number of nodes possess far greater number of connections than the majority has. With such a skewed distribution of connections, then, can the spiral of silence take place? What would be the properties of the distribution of network sizes that make the large-scale spiral of silence most or least likely? Answering these questions requires experimenting with various possible statistical and topological distributions of individuals' communication network sizes in a society. ABM enables this type of research to be accomplished in a simulated environment, while it would be extremely cumbersome to do so with traditional research methodologies (Gilbert & Troitzsch, 2002; Macy & Willer, 2002). In the following sections, a simple mathematical model of attitude formation and opinion expression is developed and the simulation procedures are described in detail.

A Simple Model of Attitude Formation and Expression

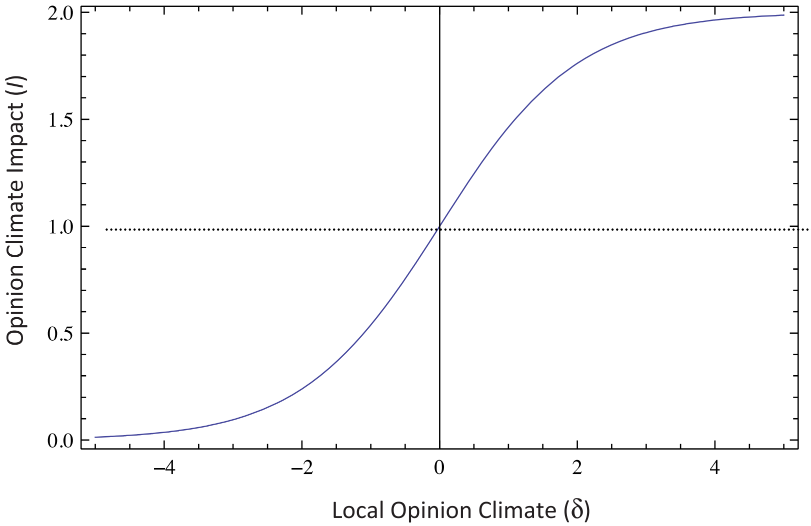
Model of Attitude Formation and Change

Consider a society populated by N individuals who have attitudes toward a controversial issue. Following Fishbein's (1967) attitude model, we assume that a person i's attitude is a product of two elements, *valence* (v_i) and *confidence* (c_i)—valence is a dichotomous variable indicating whether each person has a positive (+1) or negative (−1) attitude toward an issue (e.g., pro or anti-abortion), and confidence is a numerical weight indicating the intensity of the attitude, which ranges between 0 and 1. Thus, person i's attitude toward an issue, denoted by x_i, is represented as a continuous variable ranging between −1 and 1 (i.e., $x_i = v_i \cdot c_i$).

As decades of social psychological research affirm, one's attitude toward an issue is not a purely individual outcome, but partly a function of social context. It has been reported that the conformity pressure on a person in a group situation varies depending on how many congruent or incongruent opinions (to his or her own) exist (Cialdini & Goldstein, 2004). Latané and Wolf (1981), for example, suggested a model that the magnitude of conformity pressure (I) follows the pattern of power function: $I = sN^k$, where N is the number of impact sources (e.g., incongruent opinions encountered), k is an exponent, and s is a constant given. Surveying various conformity studies, they found that the exponent k varies around 0.5, which indicates a decreasing marginal return as N increases. Incorporating this model directly into the current context, however, introduces some problems.

In the spiral of silence, individuals' fear of isolation appears to change not merely because of the absolute quantity of either congruent or incongruent opinions they face (i.e., N in Latané and Wolf's model), but the *relative proportion* of the two (Neuwirth et al., 2007). Thus, what matters is not just how many opposite opinions a person faces, but how many of them exist relative to the supportive ones. This suggests that the opinion climate impact (I) needs to be modeled as a function of the proportional difference

Figure 1
Logistic curve of opinion climate impact



between the supportive and opposite opinions one encounters, denoted here by δ. Merely replacing N with δ in the function above may, however, not solve entirely the problem because the value of exponent k should be specified, but little empirical evidence exists regarding the marginal impact of δ on individuals' fear of isolation. Further, small change in k yields different growth patterns (i.e., it gets steeper as k increases), which might have an impact on the simulation outcomes.

Rather than arbitrarily specifying k, therefore, we adopt a *logistic* function in which the initial exponential growth gradually slows down to asymptotically approach the limit. This function allows the simulation to take into account both the positive and negative impact of the opinion climate in a single model, whereas they should be modeled separately with a power function. In Figure 1, each half of the curve represents a mathematical weight that increases or decreases attitude confidence.[1] Given that the rate of marginal returns for δ is unknown, we think that a logistic function provides a conservative model for an exploratory purpose as it sets an upper and lower limit so as to contain the impact within a predetermined range.

To model δ, let n_s and n_o, respectively, denote the total number of supportive and opposite opinions a person encounters within his or her scope of observation. Then, one's δ at time t in a local neighborhood is represented as follows:

[1]This is valid only with an assumption that the rate of change on both sides is identical. If there were any reason to believe that the marginal rates of the positive (i.e., the majority) and negative (i.e., the minority) impact differ, other functions need to be applied.

$$\delta(t) = \frac{n_s(t) - n_o(t)}{n_s(t) + n_o(t)} \tag{1}$$

Combining the function of opinion climate impact with the elements described earlier, a person i's attitude toward an issue at time t is modeled as follows (v: valence, c: confidence):

$$x_i(t) = v_i \cdot \left[c_i \cdot (t-1) \cdot \frac{l}{1 + e^{-\delta_i(t)}} \right] \tag{2}$$

As shown in Figure 1, the opinion climate impact is largest when the absolute proportional difference (i.e., $|\delta\ (t)|$) is maximal, though the marginal impact decreases as the difference is enlarged. If $n_s > n_o$ within a social network (i.e., the agent is in a majority) at time t, the level of opinion confidence increases from the previous level at time $t-1$, while if $n_o > n_s$ (i.e., the person is in a minority), confidence decreases. We set the limiting value l of the logistic function to 2 so that if $n_s = n_o$ (i.e., $\delta = 0$), the opinion climate impact becomes 1 and makes no change to the confidence level.[2] In sum, a person i's attitude at time t ranges approximately between -2 and 2, $x_i\ (t) \in (-2,\ 2)$ for $i = 1,\ \ldots\ ,\ N$.

Besides individuals' perceived local opinion climate (δ), for a comparative purpose, we let Δ denote the proportional difference between the two opinions at the population level (i.e., the global opinion climate). Then, the amount of error a person makes in perceiving the global opinion climate at time t can be expressed as: $\varepsilon(t) = [|\Delta(t) - \delta(t)|]/2$, which ranges between 0 and 1. Thus, a person's level of accuracy in perceiving the global opinion climate at time t is represented as $\alpha(t) = 1 - \varepsilon(t)$. If a person's perceived local opinion climate is identical to the global opinion climate at time t (i.e., $\Delta(t) = \delta\ (t)$), for example, $\varepsilon\ (t)$ becomes 0.

Threshold Rule of Opinion Expression

In a pioneering study, Nowak, Szamrej, and Latané (1990) examined the dynamic process through which individuals' attitudes are aggregated into public opinion using a computer simulation. Making no distinction between private attitude and expressed opinion, they identified public opinion with the distribution of private attitudes. A key notion in the spiral of silence theory is

[2]In this model, the range of δ, which originally was $-1 \leq \delta \leq 1$, was weighted to be $-5 \leq \delta \leq 5$ so that I_t could approximately range between 0 and 2 (i.e., $0.013 \leq I_t \leq 1.987$). If $\delta > 0$, the impact of opinion climate increases the confidence, while it decreases if $\delta < 0$. If $\delta = 0$, the impact becomes 1. The marginal impact of opinion climate decreases as $|\delta\ |$ increases.

that not everyone with attitudes expresses them, and what influences other people's attitudes are the attitudes expressed rather than those that remain unexpressed (Scheufele, 2008). Because it is the distribution of expressed attitudes, that is, the opinion climate, that people monitor to decide whether to express their own, it is important to model how the decision to speak out is made in relation to the attitude model described earlier.

In this study, each person is assumed to have an expression threshold (ϕ_i). The probability that s/he expresses attitude becomes 1 if the attitude's absolute value at time t (i.e., $|x_i(t)|$) exceeds the expression threshold and becomes 0 otherwise, as shown below:

$$P[\text{expression}] = \begin{cases} 1 & \text{if } |x_i(t)| > \phi_i \\ 0 & \text{if } |x_i(t)| \leq \phi_i \end{cases} \tag{3}$$

In reality, a person's expression threshold (ϕ_i) may vary depending on a variety of personal and situational factors, but here we assume for simplicity that ϕ is given as a constant to all agents following a uniform (i.e., random) distribution, meaning that all values of ϕ are equally likely.[3] Some agents assigned with the minimum ϕ would voice their own attitudes regardless of their degrees of confidence, while those with the maximum value of ϕ would remain silent no matter how high their confidence with attitudes. As a rough analogy, the former may be viewed as the avant-garde individuals who voice their opinions regardless of whether others would agree with them, while the latter are those susceptible to social influence. The rest would fall somewhere between the two extremes: If a person remains in a majority over time, his or her confidence level will continue to increase up to the threshold. Once the absolute value of one's attitude, $|x_i(t)|$, exceeds ϕ, the person reveals his or her own attitude outwardly so as to be observed by others. Since $|x_i(t)|$ ranges approximately from 0 to 2, ϕ_i is set within the same range, $\phi_i \in [0, 2]$ for $i = 1, \ldots, N$.

The Initial Setup of Simulation

The simulation begins with all agents ($N = 1{,}000$) having preassigned characteristics and being randomly distributed over a 40×40 grid created using an ABM programmable environment named *NetLogo* (Wilensky, 1999). In the initial state, all agents are assigned randomly with attitude valence (v), either

[3]Individuals with very high or low expression thresholds should be rare in reality, which might be better represented by a normal than uniform distribution. However, normal distribution has no limit on what range of values it produces, which might yield some nonsensical values (e.g., extremely high, low, or even negative ϕ) possibly affecting the simulation outcomes. Because examining the impact of various threshold distributions is beyond the scope of this study, we used a uniform distribution as a baseline condition with which more sophisticated distributions are to be compared in the future.

of 1 or −1, attitude confidence (c), and expression threshold (ϕ). The simulation starts with a quarter of all agents revealing their attitudes and the rest remaining silent at $t = 1$. At each point in time, every agent in the model randomly chooses a direction of 360 degrees, moves a step, and monitors the distribution of opinions within its network size given as a circled area with a *radius* (r_i). If an agent i's network size is given as $r_i = p$, it observes only those agents within a circled area with radius p or those whose distance from itself is less than or equal to p (Hamill & Gilbert, 2009). This step is repeated 100 times ($t = 100$) for each simulation.

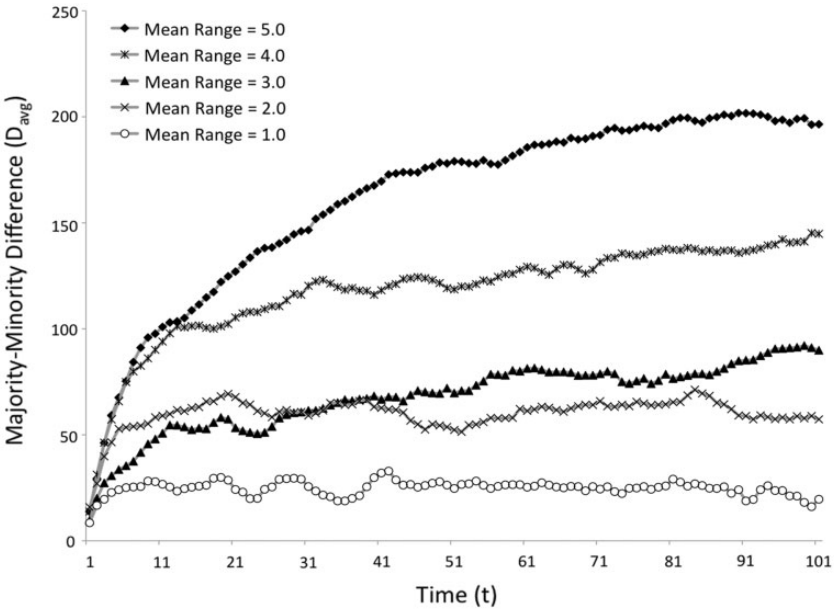
In reality, an individual's network range may vary drastically depending on personal and situational characteristics. Although it is largely unknown how an individual's scopes of observation are actually distributed, it may assimilate the distribution of social relationships, especially in the social media environment. A recent study found that most users of Twitter maintain around 100–200 stable relationships (Goncalves, Perra, & Vespignani, 2011), and Facebook statistics also show that people have, on average, 130 friends. However, it has also been found that people in their 20s tend to have ≥1,000 digital friends, 50 times as many friends as those in their 50s or older (Barnett, 2011). Furthermore, Eveland and his colleagues (2013) found that around 4–7% of respondents have political discussion networks 3.5 times bigger than the rest. This suggests that there exists a serious disparity of connections in human communication networks, as found in other kinds of networks.

To incorporate this distribution into the simulation, it is assumed that an individual's network range is represented by an exponential distribution, $\Phi(r) = \lambda e^{-\lambda r}$, where r denotes the radius of the social network ($r \geq 1$) and λ is the rate parameter. Then, the mean ($\mu = 1/\lambda$) of the distribution was varied from 1 to 5 with an increment of 0.5 to see how the varying distributions of r differentiate the dynamics of the spiral of silence. As the mean (μ) increases, the right tail of the distribution becomes thicker, indicating that the proportion of people with exceptionally large networks increases. When the mean is at its smallest ($\mu = 1.0$), for example, only 0.2% of the population can observe >10% of the entire population. In contrast, a quarter of the population (25%) can do so when the mean is largest ($\mu = 5.0$), which is very unlikely in the real world. Besides the extreme cases, we examined intermediate cases as well by varying the mean (μ), and replicated each simulation 50 times to obtain the averages.

Simulation Results

Figure 2 illustrates how the spiral of silence develops over time depending on the distributions of network sizes (r_i). When the mean network size was the smallest ($\mu = 1.0$), the global majority–minority difference (averaged across 50

Figure 2
Opinion dynamics with variable distributions in network range



repeated simulations), denoted by D_{avg}, was found to be small and consistent over time. Because most individuals in this situation saw others' opinions only in their immediate neighborhood, their majority/minority statuses might have changed irregularly across contexts and times, which kept D_{avg} from increasing in a consistent manner. This pattern did not change significantly until μ became 4.0, meaning that approximately 15% of the agents had networks wide enough to observe >10% of the population. The majority–minority gap became substantial in the early phase of the simulation and increased over time.

Figure 3 illustrates more clearly the growth pattern of majority–minority difference (D_{avg}) by showing how it changed as the mean network size (μ) increased. As indicated in Figure 2, the majority–minority gap did not widen significantly until μ reached 4.0. The trend line shown demonstrates that the growth process was not linear, but followed an exponential pattern ($R^2 = 0.90$). The vertical lines indicating standard deviations reveal that the lowest point at $\mu = 4.0$ was much higher than the highest point at $\mu = 3.5$, which suggests that there was a dramatic jump in D_{avg} between the two values. To further understand what happened, the relationships between an individual's accuracy in perceiving the global opinion climate and the mean network size was examined (Figure 4).

Figure 3
Majority–minority difference by mean networking range

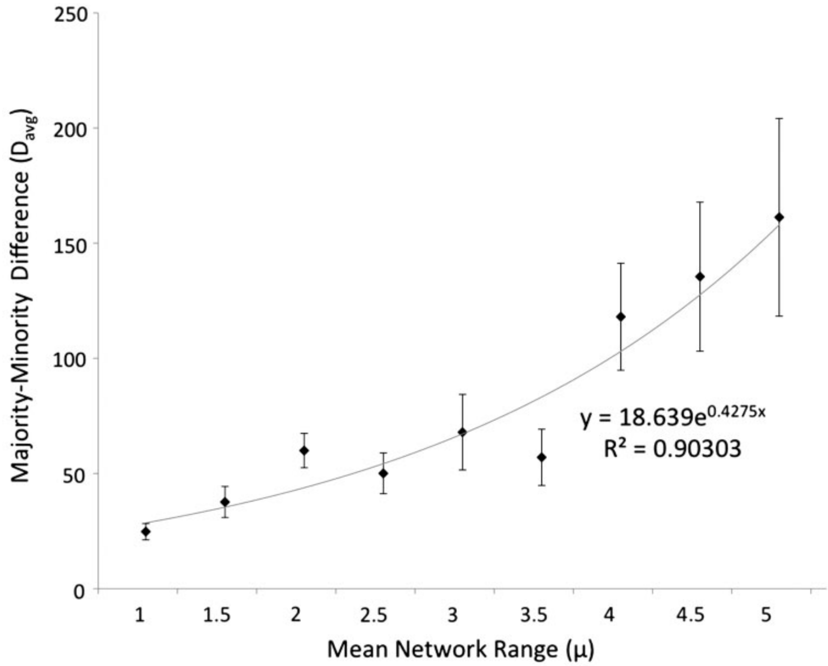
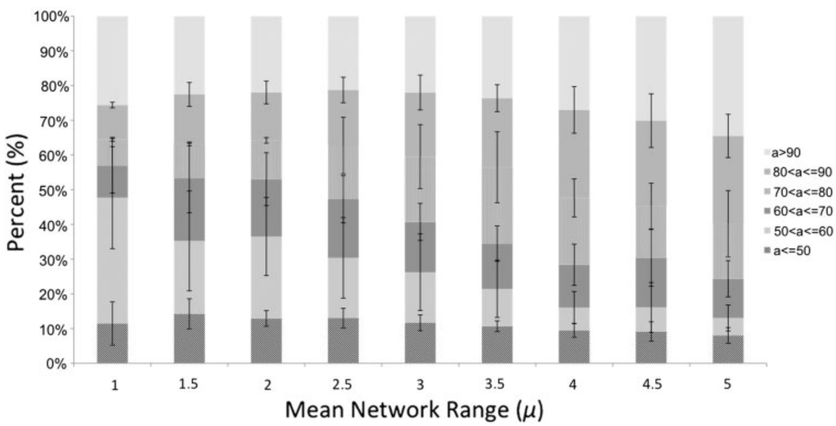


Figure 4
Opinion perception accuracy by mean network range

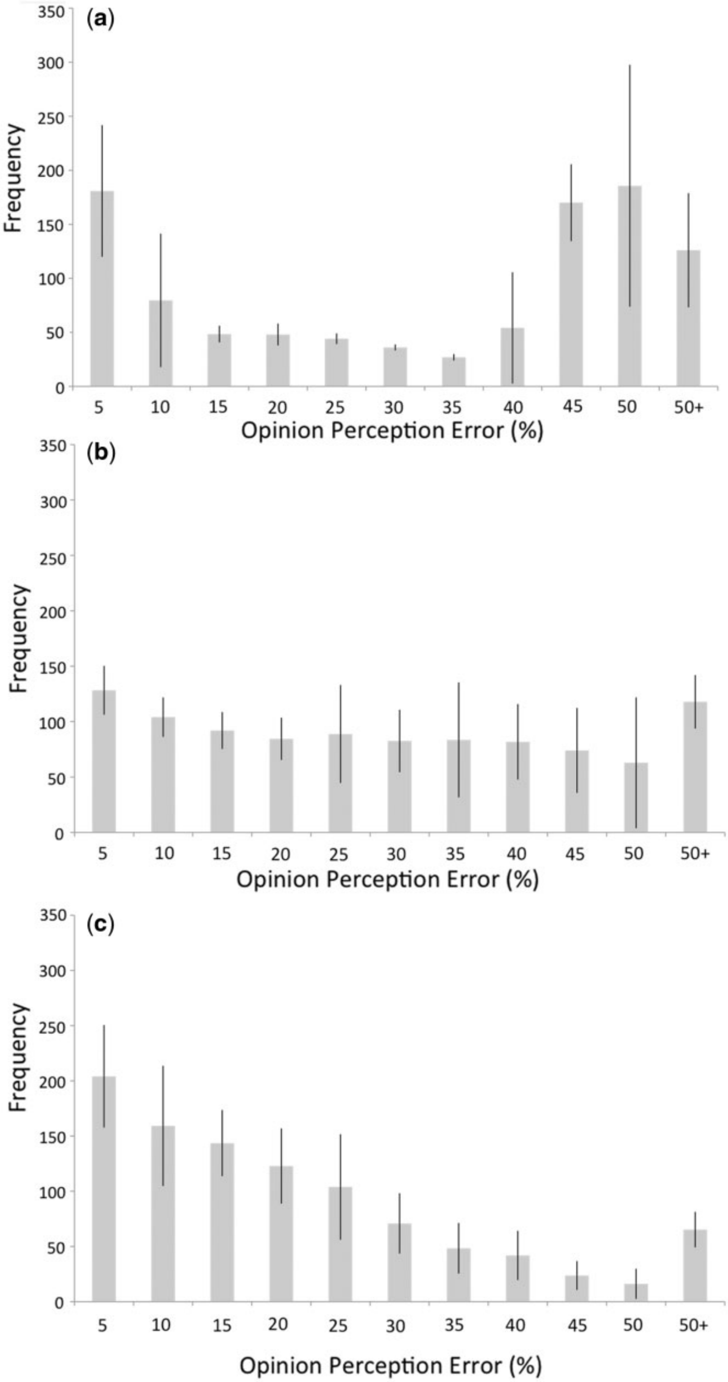


Interestingly, even when the mean network size was at its smallest (i.e., $\mu = 1.0$), approximately 25% of the population was able to perceive the global opinion climate with >90% accuracy ($\alpha \geq 90$) and the proportion did not change much until μ was set to the maximum. Why, then, did the spiral of silence not occur on a global scale even when a quarter of the population had an accurate perception of the global opinion climate? Perhaps this might be because there were too many individuals who had very inaccurate perceptions; approximately 40% of the population had an accuracy level <60% (i.e., $\alpha < 60$). One might infer from this that reducing the size of the least accurate category would proportionally elevate the chance for a large-scale spiraling to occur.

Such an inference, however, is only half-true: While the proportion of those with α <60% gradually shrank >15%p down to 25% as the mean network size increased, the majority–minority gap did not widen until μ exceeded 4.0. Why, then, did the spiral of silence not become gradually more probable as more and more individuals in the population could accurately observe the global opinion climate? A clue can be found in Figure 5, illustrating three cases in the distribution of opinion perception errors by the mean network size. When most individuals were able to observe only their immediate neighborhood ($\mu = 1.0$), the population was divided into two islands of individuals making either virtually no errors or substantial errors, similar to a state called *pluralistic ignorance* (Moy, 2007) (Figure 5a). This polarized situation did not change significantly even when μ reached 3.0, though slightly more appeared in the middle and the proportions at both extremes decreased (Figure 5b). A different picture is, however, shown in Figure 5c—when μ was 5.0, the once polarized population was grouped on one side, while only a few remained on the other side, isolated from the majority. This finding indicates that something happened between the two sides.

In a situation where not enough people are in the middle of the error distribution, individuals are likely be exposed to either of the two very different climates of opinion, in which an opinion winning on one side can be losing on the other side. Because the population is divided into two (almost) remote islands perceiving the global opinion climate in a very accurate or utterly inaccurate way, an opinion embraced by the majority in a setting can subsequently shift to a minority status in another or *vice versa*. When individuals in the middle range become sizeable enough, however, the groups at both extremes of the distribution are less distinctive and more seamlessly connected, which may elevate the chance to be exposed to a wider spectrum of opinions than under the bipartite opinion climates. That is, one might find within his or her networks not only those who have opposite perceptions of the global opinion climate, but also more people who are able to break a tie between the two. Opinion diversity in networks has been found to make

Figure 5
(a) Frequency distributions of opinion perception errors (mean network range = 1.0). (b) Frequency distributions of opinion perception errors (mean network range = 3.0). (c) Frequency distributions of opinion perception errors (mean network range = 5.0)



individuals politically ambivalent and be in line with the majority (Huckfeldt, Mendez, & Osborn, 2004).

As more and more individuals appear in the middle range of the error distribution, the inconsistent shift of majority/minority statuses across time and situations would become less frequent, making it more apparent which opinion is in the minority. The distribution once divided into halves would eventually become merged at one point, leaving a small pocket of minorities on the other side. Why, then, do minorities not simply vanish? Figure 2 reveals the patterns in which the majority–minority gap develops over time. With a constant marginal rate, for example, the spiraling process would continue with the same rate of widening until the minority completely disappeared. The results, however, show that the spiral of silence takes place with a decreasing marginal rate: As the rate of developing the gap gets progressively smaller, it eventually comes close to zero, a state of equilibrium, which illustrates partly why minorities often manage to survive even when majorities' dominance is clear.

Note here that the surviving minorities might result from the collective equilibrium state where the majority–minority gap is already too large for additional differences in the opinion climate to be meaningful, regardless of their individual characteristics like opinion strength. Figure 5c shows that approximately 8% of agents make >50% of the errors even when the great majority is clearly on the opposite side. That is, it might not necessarily be true that *hard cores* (Noelle-Neumann, 1993) survive owing to their psychological immunity to the majority influence. Rather it is also possible that minorities survive simply because of (1) their limited scopes of observation and/or (2) the decreasing marginal return of opinion climate impact.

Discussion

The spiral of silence describes an iterative process where individuals' monitoring of the environment and expression of opinions creates a feedback loop that shapes the environment in which they communicate. Creating an artificial society using ABM, we attempted to examine how the spiraling process varies depending on the way an individual's network size is distributed. The simulation results showed that when most individuals had constrained social networks covering <1% of the population, the large-scale spiraling process did not occur. However, as the network range opened up, the spiraling of opinions became more likely. While this finding may sound self-explanatory, increasing the mean network size did not proportionally increase the chance for the spiral of silence to occur (Figure 3).

The majority–minority gap (D_{avg}) increased dramatically when enough people appeared in the middle range of the error distribution. The simulation results suggest that it is not the respective proportion of those in the top or bottom range of the error distribution, but rather the shape of the distribution itself that holds the key for local social interactions to be translated or amplified into a society-wide phenomenon. That is, a large-scale social event of any kind, including the spiral of silence and the spread of disease, becomes more likely when enough people exist who keep the population from being polarized. As an analogy, we may think of water flowing in a long pipeline: No matter how powerful the pump is, water can not flow to the end if the part in the middle of the pipeline is too short to connect seamlessly.

In a slightly different context, Watts and Dodds (2007) tested the "influentials" hypothesis, first proposed by Katz and Lazarsfeld (1955), using computer simulations and reached a similar conclusion: It is "a critical mass of easily influenced individuals" (p. 454), not the influentials, that play a key role in forming public opinion. That is, influentials can become truly influential on a global scale only if enough other individuals exist whom they can influence. Otherwise, their influence is confined to a local level. Micro-blogging services like Twitter, for example, allow people to "retweet" messages they receive, and the speed and range that messages spread depends not only on the popularity of the initiator (i.e., the influential), but also on the number of those willing to retweet a message in the middle of communication flow.

The results also provide a clue for understanding the difference between the networked environment, such as the environment on social media, and the traditional offline environment in terms of public opinion dynamics. In our simulation, a large-scale spiraling process did not occur until >15% of all agents were able to observe >10% of the population (i.e., $\mu = 4.0$). Such situations are unlikely in an offline environment—imagine people who can monitor 10% of millions, for example. This implies that the spiral of silence might be rarely observed on a global scale in reality had it not been for the presence of a universally accessible information source or aggregator such as mass media. Perhaps this is why many scholars believe mass media are the major reason that the spiral of silence or pluralistic ignorance occurs (Scheufele, 2008). Therefore, in an environment where few individuals possess huge social networks, it may be mass media that are the primary cause of the spiral of silence.

Things may change in an online environment where individuals can possibly reach far more others than ever before: The more people in the population who possess bigger online networks, the more likely they are exposed to a wider range of opinions through weak ties (Eveland et al., 2013). In such an environment, mass media are no longer centralized information sources, but agents competing for attention with a multitude of other information aggregators (e.g., power bloggers, search engines, information curators) that may portray the global opinion climate differently. What matters, therefore, are not just the effects of mass media alone, but also the extent to which the diverse information channels available to individuals show convergent (or divergent) pictures of the opinion distribution. The degree of convergence may, in turn, depend on the size of communication networks—the bigger the networks of individuals, the more likely the opinion distributions shown to them converge to one another.

In a similar vein, Centola, Willer, and Macy (2005) have found through simulations that a large-scale pluralistic ignorance (i.e., global support for a highly unpopular norm) is unlikely to occur in a *small world network* in which distant social clusters are connected through weak ties. This result suggests that pluralistic ignorance may be inversely related to the spiral of silence in an environment where individuals are connected to a wide variety of communication channels; global cascades of one kind (e.g., the spiral of silence) may keep the other kind (e.g., pluralistic ignorance) from occurring. This possibility, of course, should not preclude the possibility that various communication channels converge to a false portrayal of the opinion climate and pluralistic ignorance emerges at a global scale.

The overall simulation results call attention to the notion that the collective patterns can hardly be inferred directly from individual characteristics alone. Instead, the nonlinear growth pattern, equilibrium process, and the survival of minorities are higher-order phenomena that arise in a self-organized fashion from various spatial and statistical distributions of individual characteristics. As shown in our simulation, the roles individuals play in any social process can only be assessed adequately by looking at the composition, structure, and change of a social context in which they are embedded. To grasp the social mechanism underlying any large-scale phenomenon such as the spiral of silence, it is necessary not only to examine the characteristics of individuals, but also to take a macroscopic viewpoint such as the one exemplified in this study, which enables us to figure out the impact of their distributions on collective social outcomes.

Implications and Limitations

Mathematical models and the simulated social environment used in the current study only approximate real individuals and societies, and that inevitably results in the oversimplification and omission of many important elements of reality. Just as a detailed aerial photo of an area is much less useful for finding directions than a simple road map, however, adding more layers of information to make a model more realistic may make the simulation outcomes too complex to interpret, which is why simplicity is emphasized in simulation research (Axelrod, 1997; Gilbert & Troitzsch, 2002). A better strategy for studying a complex phenomenon like the spiral of silence through simulation is to start from a reasonably simple model and gradually move toward a more complex one by adding or modifying assumptions.

Future studies should therefore consider other boundary conditions beyond those examined here. In the current study, for example, it was assumed that all agents could accurately perceive the proportions of supportive and opposite opinions within their networks, while a recent empirical study has found that it might not necessarily be the case (Goel, Mason, & Watts, 2010). The literature on selective exposure and attention shows that people tend to see more of what they want to see (i.e., information congruent to their own) than others (Johnston & Dark, 1986). In addition, McDevitt, Kiousis, and Wahl-Jorgensen (2003) found that people tend to perceive extreme views as more moderate in an online than offline (i.e., face-to-face) environment owing to reduced social cues, which may, in turn, affect their perception of the opinion distribution.

Secondly, while only the *conformity* process (i.e., individuals' views are influenced by those of others) was considered here, people often intentionally select like-minded others based on tastes and/or political opinions. A recent study by Bello and Rolfe (2014) shows some evidence of individuals' conscious selection of peers sharing similar views, though Lazer and his colleagues (2010) found that the conformity tendency was more prevalent than selection in the context of political discussion. If such psychological and social selection processes were considered in the simulation, the outcomes may be different from what was presented here; merely enlarging the size of networks may not increase as much the likelihood of large-scale spiral of silence as expected.

Furthermore, in the current model, individuals' attitude confidence (c) and expression thresholds (ϕ) were assumed to be uniformly distributed, which might not necessarily be the case in reality. Although uniform distribution is often assumed in simulation research for simplicity, it is possible that impact on collective outcomes needs to be explored further.[4] A uniform distribution in the current context, for example, might overrepresent the individuals with extremely low or high ϕ, such as the avant-garde individuals or those too vulnerable to social influence. As little empirical evidence currently exist regarding the distribution of expression threshold, it is necessary to examine the distributional effects by experimenting with various parameters (e.g., standard deviation of a normal distribution) in the future studies, which is beyond the scope of the current study.

[4]Granovetter (1978) mentioned that a slight perturbation in both uniform and normal distribution of thresholds could possibly yield unstable equilibrium outcomes of collective behavior. This sensitivity might be partly because threshold was defined as "the proportion of the group [an actor] would have to see join before he would do so" (p. 1422). Opinion expression threshold (ϕ), defined as the minimum degree of attitude confidence necessary for a person to speak out, is not a direct function of how many have already spoken out, which might make the simulations relatively less sensitive to small changes in the distribution of ϕ.

Lastly, how various properties of communication networks influence the way public opinion is formed and the role of mass media in the process should be considered in future studies. Shibanai et al. (2001), for example, using simulations found that mass media maintained local divergent cultures even as it facilitated cultural convergence. While they did not specify why and how local cultures managed to survive, our simulation results suggest that individuals' network sizes might serve "as a buffer for the [homogenizing] media effect" (p. 93). Considering other network properties other than size would allow us to better grasp the role of mass media embedded deeply in the social fabric. As such, theoretical assumptions like the role of mass media can be effectively tested in simulated environments, which yield further assumptions subject to empirical testing. Through this circular process, theories can be strengthened and to more explanatory and predictive power in the real world. After all, no research method can replace others completely, but only complement their weaknesses.

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