Modeling Information Equality

Social and Media Latency Effects on Information Diffusion

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We live in the "information age. This assertion has developed over the last few decades from a radical reconceptualization of society and power to a clich often mouthed by marketers, politicians, and academics alike. It appears to be one of the few points on which nearly all contemporary social theorists agree.

But what, exactly, does this assertion mean? The answer differs from theorist to theorist. Castells (2000a, 2000b, 2001 a, 2001 b) points to the confluence of three trends: the growing power and pervasiveness of ICT's; the emergence of a global economy; and the increasing social value of free and open communication. To Castells, these factors combine to produce a new social structure that abandons traditional hierarchies for a network model.

Ball-Rokeach (Gibbs, Ball-Rokeach, Jung, Kim, & Qiu, in press; Loges & Jung, 2001; Matei & Ball-Rokeach, 2002) positions information, instantiated in the act of "storytelling, at the center of power relations between individuals, community organizations and global institutions, facilitated by both mass and interpersonal communication media. In her communication infrastructure (CI) model, information is envisioned as the key that allows individuals to achieve crucial personal goals, such as understanding, orientation, and play, both individually and socially.

Bell (1999) distinguishes today's "post-industrial society from the past industrial society on the basis of the shift from a Marxian "labor theory of value to a more current "knowledge theory of value (p. xvii). Information has supplanted labor as the building block of modern societies. Its superiority, he argues, rests in its reflexivity (knowledge begets more knowledge, unlike labor) and in its potential role as a collective good, rather than a scarce resource.

While these theorists, and others, may have different models for discussing the role of information *vis a vis* social, political and economic institutions, each agrees that information, and its exchange, are now fundamental. It follows that access to information – who learns what, and when – is key, especially as the gap between information "haves and "have-nots threatens to grow continually wider. This threat is tacitly addressed in our legal institutions (e.g. laws against insider stock trading), newer social conventions (e.g. file sharing, blogging), and explicitly acknowledged by some communication theorists (Deroian, 2002; Himanen, 2001).

In this study, we address the political ramifications of information-as-currency in interpersonal communication networks. Specifically, we are interested in measuring *information equality,* defined as the extent to which members of a society or social network have access to equivalent information at relatively equivalent speeds. The degree of information equality possessed by a network can be understood as an emergent property generated by the information latencies within that network. Specifically, we identify two network properties, social structure and the communication infrastructure, that impact information latency. We label their effects, respectively, as social latency and media latency.

In an ideal network, every node would have the capacity to communicate instantaneously with every other node. In the real world, social barriers limit the number of possible interlocutors a given person may have access to. The emergent effect of this limitation is an overall lag in the speed with which information can traverse an entire social network – hence, social latency. Similarly, technological limitations and unequal access to, and use of, communication media produce media latency at the network level.

Policy Considerations

The effects of social latency and media latency on a network's information equality have profound policy consequences. Digital divide research (Haythornewaite, 2001; Jung, Qiu, & Kim, 2001; Loges & Jung, 2001; Mansell, 1999; Sidorenko & Findlay, 2001) has previously identified social consequences of the unequal distribution and use of communication media. A policy issue arising from this, specifically from knowledge gap research (Tichenor, Donohue, & Olien, 1970), has been the tendency of newer communication technologies to widen the inherent social inequalities in the system.

The authors point to a number of contributory factors at work in creating this differential effect, including communication skills (attributed to better education—a socioeconomic attribute), existing knowledge, relevant social contact, the nature of the mass medium itself, and selective exposure, acceptance and retention of information. Of particular interest for this paper, research found that social subsystems that benefited the most tended to be those that started with the greatest advantage.

The knowledge gap hypothesis has come under criticism from several quarters since it was first proposed, including the privileging of certain types of information (news and public affairs were the original information topics measured). Gaziano and Gaziano (1999), for example, argue that knowledge gap research has yielded inconsistent results because researchers "combine and confuse concepts from different perspectives that vary in levels of analysis and assumptions (p. 118). However, research on this hypothesis is confounded by these limitations, the premise that new ideas and technologies can increase, rather than close, the gap between information haves and have-nots remains a vital consideration for research, such as ours, focused on the impact of ICT's on social networks. Indeed, the policy considerations arising from the knowledge gap hypothesis found an ally in research concerning the digital divide.

Following the formative years of the World Wide Web, several studies (Basil, Brown, & Bocarnea, 2002; Haythornewaite, 2001; Hoffman, Novak, & Schlosser, 2000; Jung, et al., 2001; Katz & Rice, 2002; Lenhart, 2000; Loges & Jung, 2001; Mansell, 1999; Sidorenko & Findlay, 2001) showed that there were significant differences in terms of access to and use of the Internet with regards to certain key demographic measures — namely, gender, education, race, age, locale, and income — as well as disparities between post-industrial societies and the so-called "developing world. These observations gave rise to the digital divide debate, in which one side argued that disparity would narrow as diffusion increased, and the other side argued that social inequities would only increase with time. Traditional measures of access support the first group, showing gaps narrowing in recent years across incomes, race, and education, and disappearing completely with regards to gender (Howard, Raine & Jones, 2001; Katz & Rice, 2002; Lenhart et al, 2003; Nie & Erbring, 2000).

However, proponents for social equity challenge these findings (Norris, 2001; Schiller, 1999) and question whether diffusion of technology is a meaningful measure. Jung, et al (2001; also see Loges & Jung, 2001; Walther, Slovacek & Tidwell, 2001), for instance, have created an Internet connectedness index (ICI) which reveals continuing inequalities in terms of the intensity and satisfaction of Internet use despite the narrowing gap in basic access. This dissatisfaction with using access to technology and time spent using technology as unqualified barometers of social equality is a theme we echo in our own research. Rather than simply exploring new technology's impact on the *speed* at which members of a network receive information, we are concerned with examining the *differential rates* of access to information, looking for lingering social inequities beneath the surface appearance of uniform benefit.

Several state-sponsored and non-governmental organizations (NGOs) have attempted to address these issues by upgrading, expanding, or democratizing the media infrastructure of communities. These agencies range from the Bill & Melinda Gates Foundation (http://www.gatesfoundation.org) to the World Links for Development Program (http://www.world-links.org), and the United Negro College Fund (http://www.uncf.org). As the knowledge gap and digital divide research shows, the degree to which such efforts can be characterized as successful largely depends on the evaluative mechanism and criteria employed by the researchers.

We believe that these efforts suffer from three principal limitations: focus on media latency at the expense of social latency; lack of an evaluative mechanism that accounts for information equality within the network under study; and lack of adequate predictive power to confidently invest in change. It is our aim to address these limitations, by developing a diffusion of information model that encompasses both social and media latency as independent variables and predicts information equality as a dependent variable. Specifically, we incorporate diffusion research and social network analysis into an agent-based predictive model.

Diffusion Research

Diffusion of innovation research (Granovetter, 1978; Rogers & Shoemaker, 1971; Valente, 1996), and its less common theoretical sibling, diffusion of information research (Rogers, 2000; Wellman & Berkowitz, 1988), consider the multi-level processes whereby messages, attitudes and behaviors are spread through a social system.

Rogers (2003) classifies members of social systems based on the degree to which an individual is relatively earlier to adopt an innovative idea than other members. Of interest from a political standpoint is the observation, mirroring in the findings of knowledge gap research, that earlier adopters tend to have higher socioeconomic status than later ones. Specifically, they tend to have more years of formal education, are more likely to be literate, have higher social status, and a greater degree of social upward mobility.

It is important to note that this social stratification is understood to be an *effect*, as well as a *cause*, of diffusion processes. In the words of Rogers (2003), "the consequences of the diffusion of innovations usually widen the gap between the audience segments previously high and low in socioeconomic status (p. 443). This observation is directly relevant to a network's information equality; to the extent that differential rates of access to communication create separate information classes (i.e. haves and have-nots), these classes tend to map onto preexisting socioeconomic strata.

Diffusion research also focuses on the concept of salience, or the perceived importance of a message to an individual in a network. Researchers such as Rogers (2003) have demonstrated that the perceived salience of a message or innovation has a measurable impact on whether the message is relayed or the innovation is adopted. This is a concept we incorporate into our model, with a variation. Valente (1996) distinguishes between innovation with respect to an individual's personal social system and innovation with respect to the entire network. We apply this bifurcation to our measure of salience, distinguishing between "personal salience (the degree to which a message is perceived as relevant to an individual) and "network salience (the degree to which a message is perceived as relevant to the entire network).

We are hardly the first researchers to apply a political lens to diffusion research. Deroian (2002), for instance, suggests “some political implications of social network formation with regard to diffusion of innovation (p. 845). Rogers (2000), reviewing news diffusion research to date, suggests that “future attention could be given to connecting investigations of news diffusion with such theoretically driven research areas as knowledge-gaps (p. 573). This is exactly the theoretical fusion we strive to accomplish.

Social Network Analysis

Social network analysis encompasses a growing field of methodological and theoretical approaches to communication dynamics within a network of nodes, usually conceived as a group of individuals (Burt, 1992; Monge & Contractor, 2003). One of the distinguishing characteristics is that it analyzes communication within a network based primarily on the emergent structures of links between the nodes, rather than on the qualities of the nodes themselves.

We echo this emphasis in our own model. Most agent-based models in social sciences focus on the way that nodal attributes change as a result of the attributes of other nodes in their immediate environments (Bhargava, Kumar & Mukherjee, 1993; Watt & VanLear, 1996). By contrast, we are primarily interested in modeling message flow as a function of the emergent structures of social links throughout the network.

Another concept we borrow from social network analysis is the distinction between strong and weak ties (Granovetter, 1973; Krackhardt, 1992). Strong ties represent close friendships and family ties, while weak ties represent acquaintances and other lower-intensity relationships. While strong ties are a greater predictor of contact (Koku, Nazer & Wellman, 2001), weak ties have been shown to be “stronger sources of salient information due to their non-redundancy (Granovetter, 1973). We incorporate both of these observations into our model.

Agent-Based Modeling

Typically, research on the diffusion of a message through a network has been conducted through field experiments. This usually entails fielding questionnaires after the fact, attempting to reconstruct the path of a given message through a network, or at least to assess how many individuals had received the message at various discrete points in time (Rogers, 2000). This methodology is insufficient to our needs for a variety of reasons. First, we are attempting not only to observe message diffusion, but to *predict* it, based on two top-level independent variables (social and media latency). Second, we are dealing with extremely large networks consisting of thousands of nodes. Field experimental research on a network of this size would almost certainly require a sampling methodology, and would therefore miss many of the finer details of a network's social structure – one of our primary predictive variables.

Researchers like Moody (2002) argue that relational activity occurs at discrete points in time, rather than in static networks. Accordingly, our research – unlike traditional diffusion research – requires dynamic measurement of a message as it travels through a system; creating a daunting experimental task. Finally, we aim to create a model that may be applied to a broad variety of social networks, and thus demand a tool with a great degree of flexibility. This last point addresses a problem that has dogged diffusion research for years; as Rogers (2000) observes, the majority of diffusion research has not been broadly generalizable, due to the procedural idiosyncrasies of data collection.

The method we choose to best address these needs is agent-based modeling. Sometimes referred to as cellular automata (CA) modeling (there are some differences between the two terms, but it is difficult to draw a clear distinction [Reynolds, 1999]), this method relies upon a computer simulation in which individuals ("agents") interoperate within a given environment according to a set of predefined rules.

This methodology has previously been applied, albeit rarely, to diffusion processes. Bhargava, et al (1993) created a cellular automata model for predicting the successful diffusion of new products in various markets. Similarly, we employ a stochastic, rather than a deterministic, model. This is an essential feature because, as Bhargava, et al write, "in realistic social systems, uniform patterns are rarely seen to persist" (p. 90). Corman (1996) also suggests the viability of this methodology when he writes, "stochastic cellular automata . . . rely on transition probabilities or apply decision rules as constraints on random behavior. Such models describe the innovation diffusion process" (p. 194).

We also draw upon the Bass diffusion model (Bass, 1969) in building our own. Although Bass relied on an ordinary differential equation (ODE) model rather than an agent-based model, his equation included a coefficient accounting for the external effects of the communication media themselves. To our knowledge, Bass' is the only diffusion model prior to our own which explicitly accounts for this factor.

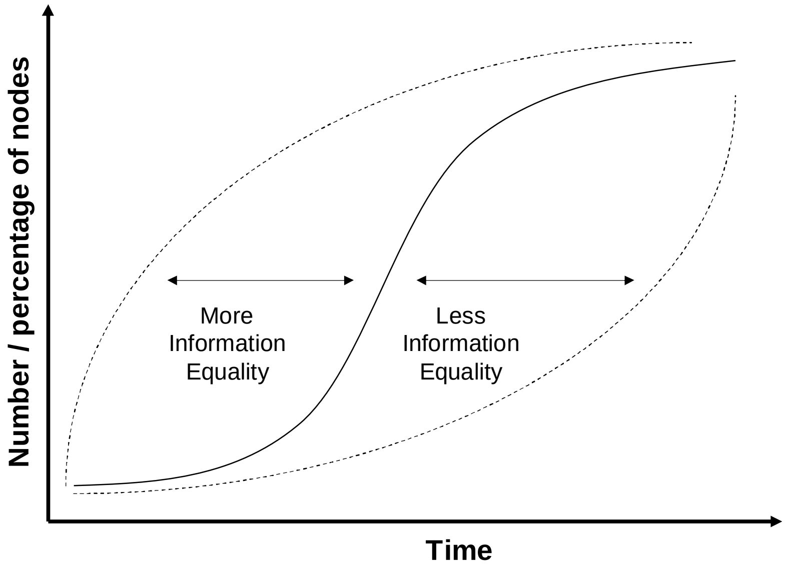
Study Purpose

The purpose of this study is to build and test a preliminary model with the capacity to predict the information equality of social networks, applicable to a variety of groups such as regions, states, etc., using input data regarding social structure and communication media infrastructure. Using such a model, a state or NGO with a budget dedicated to improving the communicative capacity of a given social network could test the effect of different strategies tailored to the network at hand before spending a cent on technology. For the moment, our purpose is to validate the model, rather than create a tool for policy decision-making, a task we leave for the future. In this light, we choose to focus exclusively on interpersonal communication, reserving the effect of mass media for future enhancements to the model.

Our aim in building this model is to examine the emergent effects of social and media latency on a network's overall degree of information equality. Our heuristic for observing information equality is quite simple. As researchers have noted, information diffuses neither universally nor uniformly through a network (Valente, 1995; Wellman & Berkowitz, 1988). As a result, nearly all diffusion processes follow a characteristic "S-curve over time (Bhargava, et al, 1993; Rogers, 2000); a few initial adopters or message recipients are followed by a sudden upsurge of mainstream adopters, followed finally by a smaller number of later adopters. This curve tends to trail off asymptotically as it approaches maximum diffusion – it rarely reaches 100 percent of all possible adoptors or recipients.

We argue that the shape of the S-curve for information diffusion is a veritable map of the gulf that separates information haves from have-nots. To the extent that a few nodes have access to salient information long before the majority, a network lacks information equality. By contrast, the sooner the majority of nodes receive information, the higher a network's level of information equality. This can be observed in the shape of the S-curve, as shown in Figure 1. Greater information equality will "pull the curve to the left, while lower information equality will "pull it to the right. A higher information equality network would be one in which the curve rises sharply and then tapers off as all the members receive the information, at about the same time. A lower information equality network would be one in which the curve rises extremely gradually, as only a few members receive information; and long before the majority.

Figure 1. Diffusion Curves With Greater and Lesser Degrees of Information Equality



The research heuristic, then, involves measuring the impact of two dependent variables, social and media latency, on the information equality of a given network. We aim to develop a model that will first recreate the S-shape of the diffusion curve, and then predict variations in the shape of the curve as a result of changes in the component factors of social and media latency. Specifically, our research questions are:

- Is the degree of information equality dependent on the interpersonal communication infrastructure (media latency)?
- Is the degree of information equality dependent on the social network structure (social latency)?
- Is the degree of information equality dependent on the interaction between the interpersonal communication infrastructure and the social network structure?

Our present task is not to predict the information equality of any specific network, but rather to test the effectiveness of our model. To that end, we are applying it to three separate data sets, culled from the Metamorphosis Project (2002 Data Set), The Pew Internet and American Life Project (March-May 2002 Data Set), and the UCLA World Internet Study (2002 Data Set). The measure of our success will be:

- The degree to which our model predicts S-curve diffusion patterns for each of these data sets.
- The extent to which the dependent variable, information equality, responds to changes in the independent variables, social and media latency.

Method

Our agent-based modeling software, called dFusion, predicts the diffusion of a message through a network by first proposing initial conditions for the network, and then proposing rules governing the ways in which individual nodes within the network may interact.

The initial conditions consist of nodal, relational and environmental attributes. The values for these attributes are determined stochastically at the network level, based on quantitative analysis of the three datasets. Nodal attributes include sociodemographic variables, as well as geographic positioning within a square matrix of 200 x 200 cells. Relational attributes assign and define the links between these nodes, relying in part on their geographic proximity.

Environmental attributes map the external variables onto the social network. In this model sources external to the network include the media vehicles and the message conditions. For present purposes, we are only modeling the use of two communication media: email and phone/face-to-face. We create this dichotomy because these media fall on opposite ends of several relevant axes. Researchers have identified particular qualities that distinguish traditional forms of interpersonal communication from newer forms of computer-mediated communication like email. Prior research (Flanagin & Metzger, 2001) has been conducted upon synchronicity, presence, and the ability to multicast. We merge phone and face-to-face because they exhibit similar characteristics for the axes under analysis.

Email is an asynchronous medium, while phone and face-to-face contact are synchronous. Email is a low-presence medium, offering users little sense of “being there, while phone and face-to-face contact are higher presence media. Email is a multicasting medium, while phone and face-to-face contact are far more likely to occur on a one-to-one basis. Finally, email is a new and only partially diffused medium that requires specialized knowledge to operate, while phone and face-to-face contact are available to almost everybody. Each of these distinctions plays a key role in determining which medium an individual node will use to communicate with another node in our model. Finally, we assign the message a value corresponding to its level of salience—network salience and personal salience.

Once the initial conditions are established, we then set rules stating under which conditions a given node will attempt to relay the message, whom the node will relay it to, which communication vehicle it uses for dissemination purposes, and finally, whether the recipient of the message is available. The decisions made are dependent upon the network conditions, describing the nodes and relations, derived from the datasets. For example, the choice of whether to use email is contingent on whether the sender and recipient have access to the Internet, a factor which is determined for each node in each model network. The rules thus followed are what Monge and Contractor (2003) call “meta-rules :

> a meta-rule may specify that the rules of interaction may depend on agent’s [sic] attributes, thus allowing for the possibility that different agents in the network follow different rules, potentially at different times. (p.87)

The agent-based model is then activated by the introduction of messages with varying degrees of personal and network salience and run under the varying conditions described by the different datasets. The computational modeling technique with stochastic variables requires that we run the same model multiple times and then generate averaged “realized values selected from a probability distribution. Each run of the model thus constructs a unique network created stochastically from the input variables, and the emergent outputs, realized as diffusion curves, are then aggregated over the multiple runs.

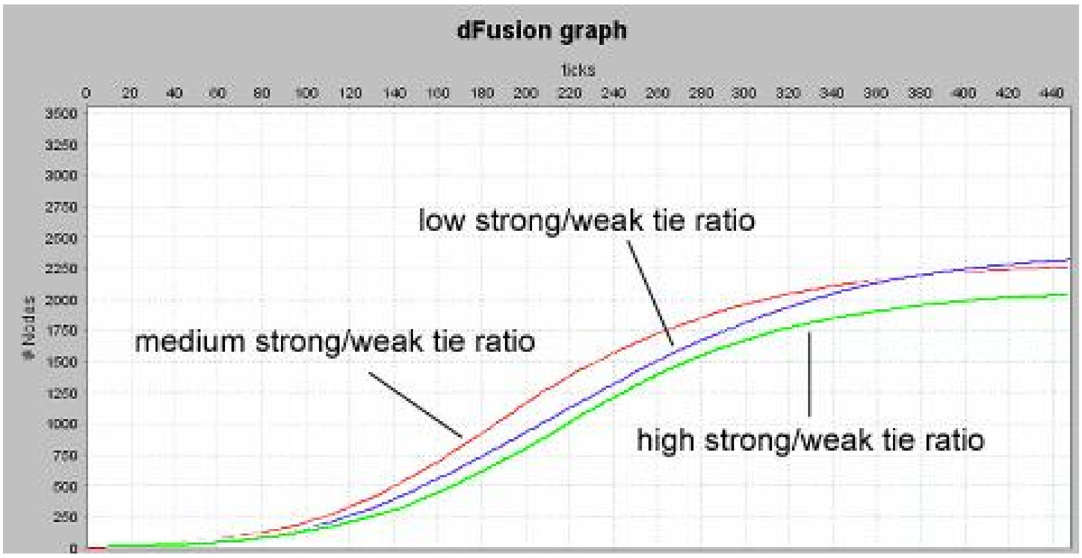
Results

The agent-based model was run for all three datasets. Each dataset was subject to analysis under several permutations of variable values. Specifically, message salience was biased towards high personal salience for half the runs and towards high network salience for half the runs. Social latency was varied between three levels (low, medium and high ratio of strong to weak ties) for half the runs, and controlled for the other half. Similarly, media latency was varied between three levels (corresponding to email usage penetration) for half the runs and controlled for the other half. As a result, each dataset was run with twelve variable permutations at the outset.

The results were markedly consistent across all three datasets. For ease of presentation, we shall only discuss the findings from the Pew Internet and American Life Study here, which are representative of the overall findings. The graphs for the remaining two studies, the UCLA Internet World study and the Metamorphosis Project, are available on request.

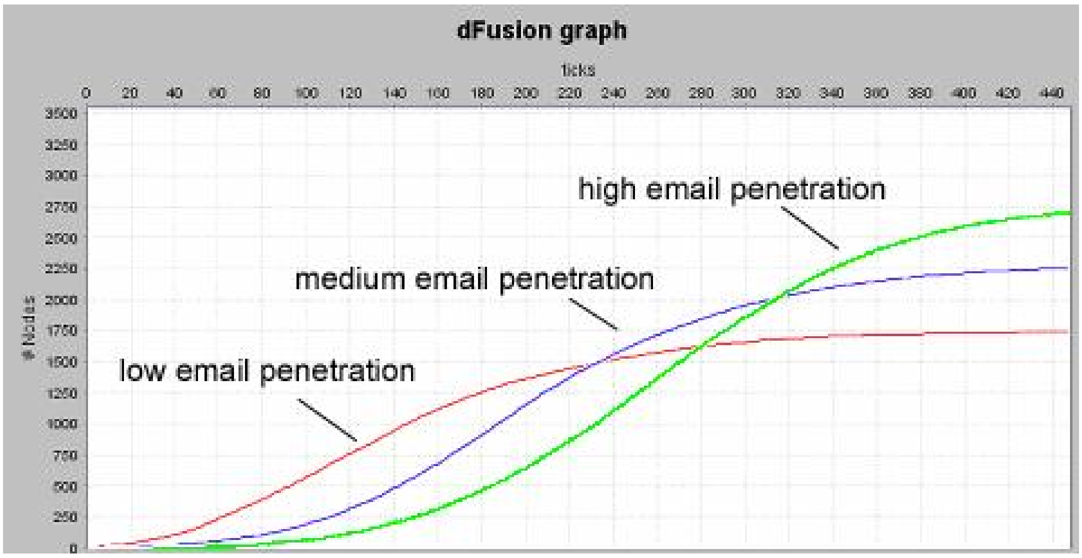
For messages with relatively high network salience, increases in the ratio of strong ties to weak ties led to reduced diffusion of the message, as can be seen in figure 2. The information equality of the curve varied as well, however it did not vary consistently in one direction. The curve demonstrated greatest information equality, moving furthest to the left, in the case of medium-level strength of ties ratio.

Figure 2. High network message salience, varying ratio of strong to weak ties



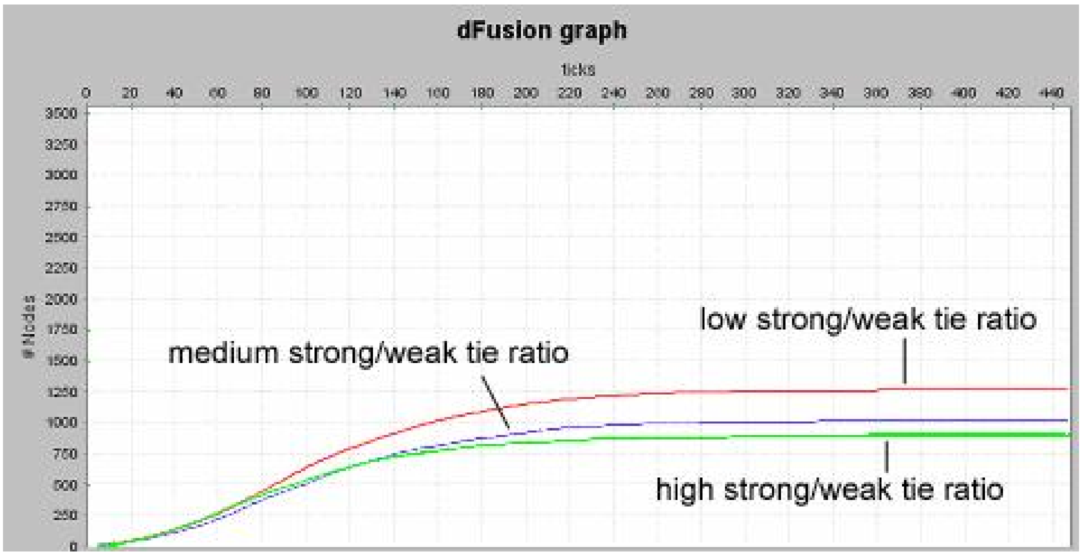
For messages with relatively high network salience, increases in the penetration of email led to increased diffusion of the message, as can be seen in figure 3. Additionally, the curve moved to the right, demonstrating lower information equality, with increased email usage in the network.

Figure 3. High network message salience, varying penetration of email



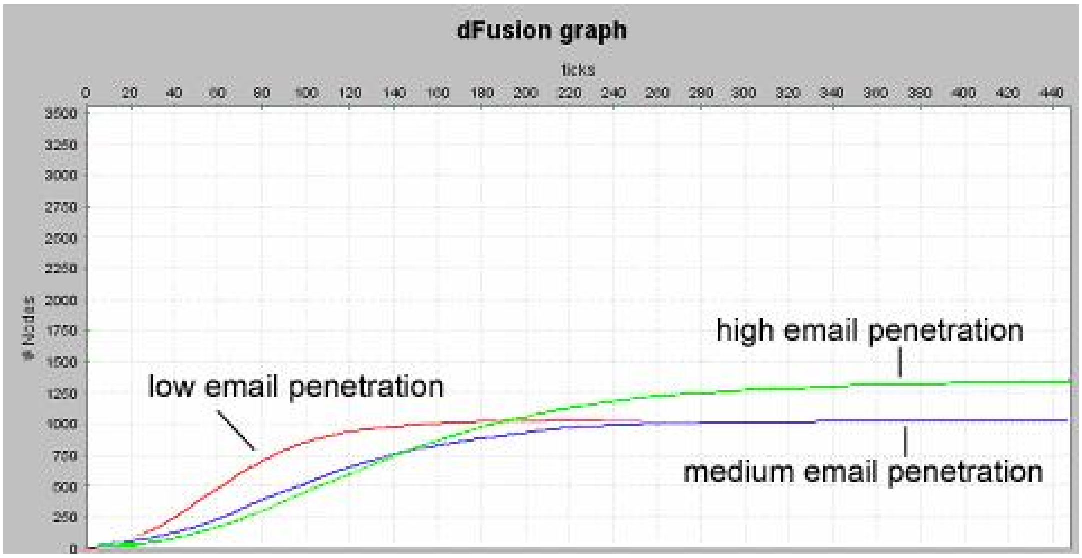
For messages with relatively high personal salience, increases in the ratio of strong ties to weak ties led to reduced diffusion of the message, as can be seen in figure 4. The curve moved to the right, indicating reduced information equality, with increased ratio of strong to weak ties in the network.

Figure 4. High personal message salience, varying ratio of strong to weak ties



For messages with relatively high personal salience, increases in the penetration of email led to increased diffusion of the message, as can be seen in figure 5. The curve moved to the right, indicating reduced information equality, with increased ratio of strong to weak ties in the network.

Figure 5. High personal message salience, varying penetration of email



In all cases, a message with relatively higher network salience achieved greater diffusion as compared to a message with relatively high personal salience. We can observe this result by comparing graphs 2 and 4, and graphs 3 and 5.

Discussion

This study had very promising results. Testing the significance of an agent-based or cellular automata model statistically is difficult at best and virtually impossible in many cases. However, such methods are not required for the current study. As Corman (1996) writes,

> communication scholars should not make the mistake of putting CA models completely under the stricture of traditional, formal statistics. CA models are amenable to testing, but the interpretation of social processes as automata, and

> the intuitive comparison of automatic to actual communication, are equally worthwhile for communication researchers. (p. 209)

Consequently, Corman (1996) recommends an interpretive method relying upon the "qualitative judgments of the modelers and other observers (p. 207). The vital question regarding the model is, "does the automaton look, sound, and/or behave like the phenomenon in question? (p. 207).

Our model does, indeed, look, sound, and behave like the phenomenon in question. In order to produce a model capable of predicting information diffusion patterns through a social network, we incorporated findings from diffusion research and social network analysis into a framework that coupled social latency with media latency as high level independent variables, and replicated the findings of knowledge gap and digital divide research. Our criteria for success were the degree to which the resulting diffusion curves resembled the S-curve typical of diffusion processes, and the degree to which the shape of the curves, representing information equality, would vary as a function of changes to the component variables of social and media latency.

By these standards, our model was quite successful. Under a variety of different initial conditions corresponding with the unique network properties described by our three datasets, the model consistently produced diffusion curves with the "S shape described by Rogers (2000) and Bhargava, Kumar and Mukherjee (1993). Furthermore, by making changes to the initial values in our tests, we were able to predict diffusion patterns with visibly different degrees of information equality.

These findings support our assertion that the degree of a network's information equality is dependent on both social latency and media latency. Additionally, they support Granovetter's

(1973) contention regarding the "strength of weak ties; as the ratio of weak to strong ties rises in our model, the overall message diffusion level increases. Most importantly, they offer promise that stochastic, agent-based models of information diffusion can serve a vital role in predicting the social effects of new technologies before resources are committed to upgrading the interpersonal communication infrastructure.

However, this study is only the beginning of a long process. As Corman (1996) notes, "any good model-building effort involves refinement of the model to make it more consistent with observed phenomena (p. 205). While our current model successfully predicts changes to a network's information equality based on social and technological variables, the scope of those input variables is still rather limited. In order to make the model "more consistent with observed phenomena, we plan to augment it considerably before testing it further. Among the biggest changes we hope to incorporate into future versions of dFusion are:

- Inclusion of more sociodemographic variables (e.g. race, age, gender) as nodal attributes. These variables should influence the model according to patterns predicted by social network analysis (e.g. homophily) and digital divide research.
- Expansion of interpersonal media channels beyond the current dichotomy. While we are confident in the decision to focus on email and phone/face-to-face in our current model, a more diverse array of communication vehicles (e.g. instant messaging, discrete face-to-face interaction) would clearly increase its verisimilitude.
- Inclusion of mass media. Television, radio, print media, and the Web play fundamental roles in diffusion of information, even viewed at an interpersonal

level. Understanding the interplay between these media and interpersonal media will be essential in building a comprehensive model of information diffusion.

- Mobile nodes and geographic clustering. In our current model, nodes inhabit fixed positions within cells, and their locations within the grid are determined randomly at the outset of each model run. In order to tailor the model more effectively to networks under consideration, we plan to geographically cluster nodes based on actual population data, and to allow the nodes to move in space over successive time intervals.
- Dynamic nodal and link attributes. In the real world, the attributes of nodes (e.g. age, education) and links (e.g. strong vs. weak ties) change over time, often as a result of events within the network. Future versions of our model should reflect this potentiality.
- Complex message attributes. Currently, dFusion only allows a single message, introduced at a single moment, with a single probabilistic score for each salience type. Future versions of the model will allow multiple messages, introduced at separate discrete moments, each with additional attributes tailored to interact with nodal attributes (e.g. messages regarding retirement plans are more likely to appeal to older individuals).
- Behavior adoption. Our current model is focused exclusively on information diffusion. This is only the first step in Rogers' (2003) 5-step diffusion of innovation process. Future versions of the model will aim to predict attitudinal and behavioral changes as well.

- Naturalistic time and space coordinates. Our current model relies upon a monolithic timetable for all nodes and a square 200 x 200 geographic grid. Future versions of the model will incorporate more realistic geography, and account for differential schedules (i.e. time zones) for different nodes and regions.

Another change we will eventually have to make is methodological: the inclusion of statistical analysis tools. We agree entirely with Corman's (1996) assertion that CA models may and should be assessed qualitatively, rather than statistically. However, we aim to produce not only binary results ("Which network has greater information equality?), but graded results ("How much greater is the information equality of network X than of network Y?). Toward this end, our next step will be to develop an model for information diffusion that produces a measurable coefficient describing information equality, thus allowing us to compare different networks and conditions mathematically. Such refinements would allow those using our model to make informed cost-benefit analyses regarding the efficacy of investing in new communication technologies.

Finally, we aim to verify our model by conducting controlled field experiments designed to assess the relationships between social latency, media latency and information equality. Micro-level analyses of actual diffusion processes will ultimately aid us in constructing a model that can successfully and consistently predict emergent macro-level diffusion patterns.

References

Alba, R. D. (1978). Ethnic networks and tolerant attitudes. *Public Opinion Quarterly, Vol. 42*(1), 1-16

Baerveldt, C., & Snijders, T. (1994). Influences on and from the segmentation of networks: hypotheses and tests. *Social Networks, 16*(3), 213-232.

Basil, M. D., Brown, W. J., & Bocarnea, M. C. (2002). Differences in univariate values versus multivariate relationships: Findings from a study of Diana, Princess of Wales. *Human Communication Research, 28*(4), 501-514.

Baskerville, R., & Pries-Heje, J. (1998). Information technology diffusion: building positive barriers. *European Journal of Information Systems, 7*(1), 17.

Baskerville, R., & Pries-Heje, J. (2001). A multiple-theory analysis of a diffusion of information technology case. *Information Systems Journal, 11*(3), 181-212.

Bass, F. M. (1969). A new product growth model for consumer durables. *Management Science, 15*, 215-227.

Bell, D. (1999). *The Coming of Post-Industrial Society* (Special Anniversary Edition). New York: Basic Books.

Bergmann, W., & Erb, R. (1992). "I feel uneasy talking about Jews at all". Social latency and the perception of the climate of opinion concerning anti-Semitism. *The German Journal of Psychology, 16*(4), 305-306.

Bhargava, S. C., Kumar, A., & Mukherjee, A. (1993). A stochastic cellular automata model of innovation diffusion. *Technological Forecasting and Social Change, 44*(87-97).

Borgida, E., Sullivan, J. L., Oxendine, A., Jackson, M. S., Riedel, E., & Gangl, A. (2002). Civic culture meets the digital divide: the role of community electronic networks. *Journal of Social Issues, 58*(1), 125-141.

Burt, R. S. (1980). Innovation as a structural interest: rethinking the impact of network position on innovation adoption. *Social Networks, 2*(4), 327-355.

Burt, R. S. (1992). *Structural Holes: The Social Structure Of Competition.* Cambridge, MA: Harvard University Press.

Castells, M. (2000a). *End of Millenium.* Oxford: Blackwell.

Castells, M. (2000b). *The Rise of the Network Society.* Oxford: Blackwell.

Castells, M. (2001a). Information technology and global capitalism. In W. G. Hutton, Anthony (Ed.), *Living with Global Capitalism*. London: Vintage.

Castells, M. (2001b). *The Internet Galaxy*. Oxford and New York: Oxford University Press.

Corman, S. R. (1996). Cellular automata as models of unintended consequences of organizational communication. In J. H. Watt & C. A. VanLear (Eds.), *Dynamic Patterns in Communication Processes* (pp. 191-212). Thousand Oaks, CA: Sage.

De Fleur, M. L. (1988). Diffusing information. *Society., 25*(2), 72.

Deroian, F. (2001). Lock-out in social networks. In A. Kirman & J. B. Zimmermann (Eds.), *Economics with Heterogeneous Interacting Agents: Lecture Notes In Economics And Mathematical Systems* (pp. 77-92). Berlin: Springer.

Deroian, F. (2002). Formation of social networks and diffusion of innovations. *Research Policy, 31*(5), 835-846.

DiMaggio, P., Hargittai, E., Neuman, W. R., & Robinson, J. P. (2001). Social implications of the Internet. *Annual Review of Sociology, 27*, 307-336.

Duff, A. S. (2001). On the present state of information society studies. *Education for Information, 19*(3), 231-244.

Dumlao, R., & Duke, S. (2003). The Web and e-mail in science communication. *Science Communication, 24*(3), 283-308.

Flaherty, L. M, Pearce, K. J., & Rubin, R. B. (1998). The Internet and face-to-face communication: Not functional alternatives. *Communication Quarterly, 46*(3), 250-268.

Flanagin, A., & Metzger, M. (2001). Internet use in the contemporary media environment. *Human Communication Research, 27*(1), 153-181.

Frank, O. (1978). Sampling and estimation in large social networks. *Social Networks, 1*(1), 91-101.

Gaziano, E., & Gaziano, C. (1999). Social control, social change and the knowledge gap hypothesis. In D. Demers & K. Viswanath (Eds.), *Mass Media, Social Control, and Social Change: A Macrosocial Perspective*. Ames, IW: Iowa State University Press.

Gibbs, J., Ball-Rokeach, S. J., Jung, J. Y., Kim, Y., & Qiu, J. L. (in press). The globalization of everyday life: Visions and reality. In M. Sturken, D. Thomas & S. Ball-Rokeach (Eds.), *Reinventing technology: cultural narratives of technological change*: Temple University Press.

Granovetter, M. (1973). The strength of weak ties. *American Journal of Sociology, 81*, 1287-1303.

Granovetter, M. (1978). Threshold models of collective behavior. *American Journal of Sociology, 83*, 1420-1443.

Haythornewaite, C. (2001). Introduction to the Internet in everyday life. *American Behavioral Scientist, 45*, 363-382.

Himanen, P. (2001). *The Hacker Ethic: A Radical Approach to the Philosophy of Business* (A. Hollo and P. Himanen, Trans.). New York: Random House.

Hoffman, D. L., Novak, T. P., & Schlosser, A. E. (2000). The evolution of the digital divide: How gaps in Internet access may impact electronic commerce. *Journal of Computer-Mediated Communication, 5*(3).

Howard, P. E. N., Raine, L., & Jones, S. (2001). Days and nights on the Internet: The impact of a diffusing technology. *American Behavioral Scientist, 45*(3).

Jung, J.-Y., Qiu, J. L., & Kim, Y.-C. (2001). Internet connectedness and inequality: Beyond the "divide". *Communication Research, 28*(4), 507-535.

Kakabadse, A., Kakabadse, N. K., & Kouzmin, A. (2003). Reinventing the democratic governance project through information technology? A growing agenda for debate. *Public Administration Review, 63*(1), 44-60.

Katz, E. (1987). Communications research since Lazarsfeld. *Public Opinion Quarterly, Vol. 51*(Part 2: Supplement: 50th Anniversary Issue. (1987)), S25-S45.

Katz, E., Blumler, J. G., & Gurevitch, M. (1973-1974). Uses and gratifications research. *Public Opinion Quarterly, Vol. 37*(No. 4. (Winter, 1973-1974)), pp. 509-523.

Katz, E., Levin, M. L., & Hamilton, H. (1963). Traditions of research on the diffusion of innovation. *American Sociological Review, Vol. 28*(No. 2. (Apr., 1963)), 237-252.

Katz, J. E., & Rice, R. E. (2002). *Social Consequences of the Internet Use: Access, Involvement, and Interaction.* Cambridge, Massachusetts: The MIT Press.

Kavolis, V. (1964). Economic correlates of artistic creativity. *The American Journal of Sociology, 70*(3), 332-341.

Koku, E., Nazer, N., & Wellman, B. (2001). Netting scholars: online and offline. *American Behavioral Scientist, 44*(10), 1752-1774.

Krackhardt, D. (1992). The strength of strong ties: The importance of Philos. In N. Nohria & R. Eccles (Eds.), *Networks and organizations: Structure, form and action* (pp. 216-239). Boston: Harvard Business School Press.

Lai, G., & Wong, O. (2002). The tie effect on information dissemination: the spread of a commercial rumor in Hong Kong. *Social Networks, 24*(1), 49-75.

Lenert, E. M. (1998). A communication theory perspective on telecommunications policy. *Journal of Communication, 48*(4), 3-23.

Lenhart, A. (2000). *Who's not online: 57% of those without Internet access say they do not plan to log on.* Retrieved November 25, 2003, from http://www.pewinternet.org/reports/toc.asp?Report=21

Lenhart, A., Horrigan, J., Rainie, L., Allen, K., Boyce, A., Madden, M., et al. (2003). *The ever-shifting internet population: A new look at internet access and the digital divide.* Retrieved November 25, 2003, from http://www.pewinternet.org/

Loges, W. E., & Jung, J. (2001). Exploring the digital divide: Internet connectedness and age. *Communication Research, 28*(4), 536-562.

Macy, M. W. (2002). From factors to actors: computational sociology and agent-based modeling. *Annual Review of Sociology, 28*, 143-166.

Mansell, R. (1999). New media competition and access: The scarcity-abundance dialectic. *New Media and Society, 2*(2), 155-182.

Mason, R. O. (1995). Applying ethics to information technology issues. *Association for Computing Machinery. Communications of the ACM., 38*(12), 55-57.

Matei, S., & Ball-Rokeach, S. J. (2002). Belonging across geographic and Internet spaces: Ethnic area variations. In B. Wellman & C. Haythornthwaite (Eds.), *The Internet In Everyday Life.* Oxford, UK: Blackwells.

McGrath, J. E., & Kelly, J. R. (1986). *Time & Human Interaction: Toward a Social Psychology of Time.* New York: Guilford Press.

McLachlan, D. (1961). Communication networks and monitoring. *Public Opinion Quarterly, 25*(2), 194-209.

Michaelson, A. G. (1993). The development of a scientific specialty as diffusion through social relations: the case of role analysis. *Social Networks, 15*(3), 217-236.

Monge, P. R., & Contractor, N. S. (2003). *Theories of communication networks.* New York: Oxford University Press.

Moody, J. (2002). The importance of relationship timing for diffusion. *Social Forces, 81*(1), 25-56.

Moon, Y. (1999). The effects of physical distance and response latency on persuasion in computer-mediated communication and human-computer communication. *Journal of Experimental Psychology - Applied, 5*(4), 379-392.

Myers, M. S. (2001). Missed connections. *Across the Board, 38*(4), 57-59.

Nie, N., & Erbring, L. (2000). *Internet and society: A preliminary report.* Stanford, CA: Stanford Institute for the Quantitative Study of Society.

Norris, P. (2001). *Digital Divide: Civic Engagement, Information Poverty And The Internet Worldwide.* Cambridge ; New York: Cambridge University Press.

Nyblom, J., Borgatti, S., Roslakka, J., & Salo, M. A. (2003). Statistical analysis of network data--an application to diffusion of innovation. *Social Networks, 25*(2), 175-195.

Reynolds, C. (1999, Ocotber 22, 1999). *Individual-Based Models.* Retrieved November 25, 2003, from http://www.red3d.com/cwr/ibm.html

Rice, M. F. (2003). Information and communication technologies and the global digital divide: technology transfer, development, and least developing countries. *Comparative Technology Transfer and Society, 1*(1), 72-88.

Rogers, E. M. (2000). Reflections on news event diffusion research. *Journalism and Mass Communication Quarterly, 77*(3), 561-576.

Rogers, E. M. (2003). *Diffusion of Innovations* (5th Edition ed.). New York: Free Press.

Rogers, E. M., & Kincaid, D. L. (1981). *Communication Networks. Toward a New Paradigm for Research.* New York: The Free Press, A Division of Macmillan Publishing Co., Inc.

Rogers, E. M., & Shoemaker, F. F. (1971). *Communication of Innovations. A Cross-Cultural Approach* (2nd ed.). New York: The Free Press, A Division of Macmillan Publishing Co., Inc.

Schiller, D. (1999). *Digital Capitalism.* Cambridge, Massachusetts: The MIT Press.

Scott, J. (2000). *Social Network Analysis* (2nd ed.). Thousand Oaks, CA: SAGE Publications.

Shah, D., Kwak, N., & Holbert, R. L. (2001). "Connecting" and "disconnecting" with civic life: patterns of Internet use and the production of social capital. *Political Communication, 18*(2), 141-162.

Shah, D. V., McLeod, J. M., & Yoon, S.-H. (2001). Communication, context, and community: an exploration of print, broadcast, and internet influences. *Communication Research, 28*(4), 464-506.

Sherry, J. L. (2002). Media saturation and entertainment-education. *Communication Theory*, 206-224.

Sidorenko, A., & Findlay, C. (2001). The digital divide in East Asia. *Asian-Pacific Economic Literature, 15*(2), 18-30.

Singhal, A., & Rogers, E. M. (2002). A theoretical agenda for entertainment-education. *Communication Theory*, 117-135.

Smith, C. (1994). The spirit and democracy: Base communities, Protestantism, and democratization in Latin America. *Sociology of Religion, 55*(2), 119.

Stross, R. E. (2001, Nov. 12 2001). The rumor mail: spreading rumors via e-mail. *U.S. News & World Report, 131*, 44.

Tardy, R. W., & Hale, C. L. (1998). Getting "Plugged in": A Network Analysis of Health-Information Seeking Among "Stay-At-Home Moms". *Communication Monographs, 65*(4), 336.

Tarjanne, P. (1995). The GII: moving towards implementation. *Telecommunications, 29*, 28.

Thompson, L., & Nadler, J. (2002). Negotiating via information technology: Theory and application. *Journal of Social Issues, 58*(1), 109-124.

Tichenor, P. J., Donohue, G. A., & Olien, C. N. (1970). Mass media flow and differential growth in knowledge. *Public Opinion Quarterly, 34*(2), 159-170.

Valente, T. (1995). *Network Models Of The Diffusion Of Innovations.* New Jersey: Hampton Press, Inc.

Valente, T. W. (1996). Social network thresholds in the diffusion of innovations. *Social Networks, 18*(1), 69-89.

Walther, J. B., Slovacek, C. L., & Tidwell, L. C. (2001). Is a picture worth a thousand words? Photographic images in long-term and short-term computer-mediated communication. *Communication Research, 28*(1), 105-134.

Wasserman, S., & Faust, K. (1994). *Social Network Analysis.* New York, NY: Cambridge University Press.

Watt, J. H., & VanLear, C. A. (1996). *Dynamic Patterns in Communication Processes.* Thousand Oaks, CA: Sage.

Weimann, G. (1983). The strength of weak conversational ties in the flow of information and influence. *Social Networks, 5*(3), 245-267.

Wellman, B., & Berkowitz, S. D. (1988). *Social Structures: A Network Approach* (Vol. 2). Cambridge: Cambridge University Press.

Westmyer, S. A., DiCioccio, R. L., & Rubin, R. B. (1998). Appropriateness and effectiveness of communication channels in competent interpersonal communication. *Journal of Communication, 48*(3), 27-48.

Wilson, E. V. (2002). Email winners and losers. *Association for Computing Machinery. Communications of the ACM., 45*(10), 121.