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14. ABSTRACT

The proposed research explores how message format, errors, and error correction, impact the spread of information and behaviors in social networks. Humans make mistakes but the diffusion of information through social networks is typically modeled as though they do not. We propose to complete development of new experimental software that will permit us to examine the effects of message format, error, and error correction, in networks with complex (i.e., non-linear) structures. The project is innovative in that there has been minimal prior research in this area, and

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Report Title

Final Report: Short-Term Innovative Research (STIR) Program: Testing the Effects of Error and Error Correction in Human Social Networks

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The proposed research explores how message format, errors, and error correction, impact the spread of information and behaviors in social networks. Humans make mistakes but the diffusion of information through social networks is typically modeled as though they do not. We propose to complete development of new experimental software that will permit us to examine the effects of message format, error, and error correction, in networks with complex (i.e., non-linear) structures. The project is innovative in that there has been minimal prior research in this area, and none besides our own that considers semantic meaning. The project is risky in that it is a new area of study that has already proven to require complex methodology. However, greater knowledge in this area would contribute to enhanced communications methodologies and improve models of diffusion in social networks.

Enter List of papers submitted or published that acknowledge ARO support from the start of the project to the date of this printing. List the papers, including journal references, in the following categories:

(a) Papers published in peer-reviewed journals (N/A for none)

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(b) Papers published in non-peer-reviewed journals (N/A for none)

Received Paper

TOTAL:

Number of Papers published in non peer-reviewed journals:

(c) Presentations

3

Number of Presentations: 4.00

Non Peer-Reviewed Conference Proceeding publications (other than abstracts):

Received	Paper

TOTAL:

Number of Non Peer-Reviewed Conference Proceeding publications (other than abstracts):

Peer-Reviewed Conference Proceeding publications (other than abstracts):

Received	Paper

TOTAL:

Number of Peer-Reviewed Conference Proceeding publications (other than abstracts):

(d) Manuscripts

Received		Paper
08/11/2015	1.00	Eric Gladstone, Matthew Brashears. Error Correction Mechanisms in Social Networks can Reduce Accuracy andEncourage Innovation, Social Networks (06 2015)

TOTAL: **1**

Number of Manuscripts:

Books

Received Book

TOTAL:

Received Book Chapter

TOTAL:

Patents Submitted

Patents Awarded

Awards

Best Paper Prize, Academy of Management Meetings, 2014

Graduate Students

NAME	PERCENT_SUPPORTED	Discipline
Kate Watkins	0.25	
Eric Gladstone	0.00	
FTE Equivalent:	**0.25**	
Total Number:	**2**	

Names of Post Doctorates

NAME	PERCENT_SUPPORTED
FTE Equivalent:	
Total Number:	

Names of Faculty Supported

NAME	PERCENT_SUPPORTED
FTE Equivalent:	
Total Number:	

Names of Under Graduate students supported

NAME	PERCENT_SUPPORTED
FTE Equivalent:	
Total Number:	

Student Metrics

This section only applies to graduating undergraduates supported by this agreement in this reporting period

The number of undergraduates funded by this agreement who graduated during this period: 0.00

The number of undergraduates funded by this agreement who graduated during this period with a degree in science, mathematics, engineering, or technology fields:...... 0.00

The number of undergraduates funded by your agreement who graduated during this period and will continue to pursue a graduate or Ph.D. degree in science, mathematics, engineering, or technology fields:...... 0.00

Number of graduating undergraduates who achieved a 3.5 GPA to 4.0 (4.0 max scale):...... 0.00

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The number of undergraduates funded by your agreement who graduated during this period and intend to work for the Department of Defense 0.00

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Names of Personnel receiving masters degrees

NAME
Total Number:

Names of personnel receiving PHDs

NAME	
Eric Gladstone	
Total Number:	**1**

Names of other research staff

NAME	PERCENT_SUPPORTED
Aaron Birkland	0.10
Adam Brazier	0.10
FTE Equivalent:	**0.20**
Total Number:	**2**

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Inventions (DD882)

Scientific Progress

Final Report

Testing the Effects of Error and Error Correction in Human Social Networks

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Appendix B- Gladstone 2015- Completed dissertation detailing software validation research as well as new lattice experiment.

Statement of the Problem Studied:

This research sought to examine the impact of errors in message transmission, and the effect of node-level efforts at error correction, on the spread of information through social networks. A large variety of ideas, beliefs, and behaviors, known as "social contagions," are known to spread through social networks, including fitness activities (Centola 2010, 2011), cigarette, alcohol, and tobacco use (Kirke 2004; Mercken et al. 2010), and technological innovations (Montanari and Saberi 2010; Rogers 2003). What is common to all of these contagions is the transfer of information between individuals; in order for someone to adopt a new behavior they must learn that it exists, what it is, and how to perform it. But while humans make mistakes and often misunderstand each other, existing research treats the "nodes" in social networks as perfect relays rather than fallible individuals, leaving many key questions unanswered. How rapidly do errors accumulate in human networks? Are particular message formats, or ways of transmitting the information, more prone to error than others? And do human efforts to correct errors improve or harm message fidelity? We completed development on a software package that allows us to study how information is changed as it moves through social networks using any of a large variety of arbitrary network structures. This software was further designed to be compatible with crowd sourcing options, including Amazon Mechanical Turk, and we have used it to carry out two experiments to confirm its operation and begin advancing study in this area. This line of research is Army-relevant as effective, accurate communication is essential to successful combined arms operations as well as in preventing blue-on-blue incidents. Similarly, an improved understanding of how information changes as it spreads through social networks would greatly enhance PSYOP/MISO efforts to combat insurgency in a variety of theatres.

Beliefs or behaviors that spread from person to person, intentionally or unintentionally, are known as "social contagions," and their spread is often referred to as "diffusion." The systematic study of diffusion originates with Ryan and Gross' (1943) study of the diffusion of hybrid seed corn and Coleman, Katz and Menzel's (1957, 1959, 1966) investigation of the adoption of a new antibiotic. These studies indicated that decisions to adopt a new technology were often influenced more by peers than by formal assessment of the behavior (See also Burt 1980; Van den Bulte and Lilien 2011). Among individuals, diffusion influences recruitment into activism (McAdam 1986) as well as voting decisions (Bond et al. 2012), and the formation of norms and attitudes appears to be heavily influenced by diffusion (Friedkin 2001; Friedkin and Johnsen 1997, 2011). Organizations have also been shown to adopt the strategies of similar others (Conell and Cohn 1995; Davis 1991; Holden 1986; Soule 1997, 1999; Strang and Soule 1998; Wang and Soule 2012), leading ultimately to organizational isomorphism (DiMaggio and Powell 1983). In short, a huge variety of beliefs and behaviors exhibited by both individuals and groups appear to spread through social networks.

Several efforts have been made to determine the effectiveness of naturally occurring networks for promoting diffusion (Dodds, Muhamad and Watts 2003; Lundberg 1975; Pickard et al. 2011; Travers and Milgram 1969; Watts, Dodds and Newman 2002), often finding that contagions can cross even large networks relatively quickly. However, the diameter of real world networks can be large (Albert, Jeong and Barabasi 1999), and contagions often do not take the shortest path (Golub and Jackson 2010; Liben-Nowell and Kleinberg 2008). As a result, traveling from one side of a network to the other often requires many hops and therefore offers many opportunities for errors to occur and to be transmitted to others. Often these errors are very small, but the consequences of even small mistakes can be quite dire. For example, a miscommunication during the Crimean War led to a light brigade of English cavalry (roughly six hundred men) charging a fortified Russian position, suffering approximately fifty percent casualties in the mistaken attack (Raugh 2004).

The existing research on diffusion and networks has often artificially precluded the possibility of errors. First, research on the small world phenomenon (e.g., Lundberg 1975; Travers and Milgram 1969; Watts, Dodds and Newman 2002) has relied on an experimental design wherein subjects pass fixed packets of information (e.g., a physical letter) from person to person. This is

convenient for the researcher, but most social contagions do not traverse a social network in such a stable format. Second, diffusion studies (e.g., Christakis and Fowler 2007) have often examined an outcome, such as obesity, without measuring the behaviors that lead to this outcome. Because many behaviors can lead to the same end result (e.g., obesity can result from overeating, from insufficient exercise, etc.), changes in the contagion are undetectable so long as they lead to the same consequence. Third, a growing body of research examines contagion using social media, such as Facebook (e.g., Lewis et al. 2008; Lewis, Gonzalez and Kaufman 2012), but in these studies behaviors and preferences are determined by simple on/off choices made by users (e.g., "liking" rock music). As a result, the underlying variation in actions and understandings (e.g., how music is understood or consumed) is undetectable. Finally, theoretical work on contagions (e.g., Barash, Cameron and Macy 2012; Centola and Macy 2007; Rodriguez et al. 2014) has often employed simulation models that implicitly (or explicitly; see Carley 1991: 334) assume that information is passed from node to node without error. The impact of errors is thus excluded a priori and with minimal, if any, theoretical justification. What little research that does exist on errors in networks has focused on the failure or removal of specific nodes or ties (e.g., a member of a terrorist group who is captured by authorities) rather than on errors in the content carried by those networks (e.g., Albert, Jeong and Basabasi 2000; Callaway et al. 2000; Iyer et al. 2013).
If individuals fail to pass on a social contagion accurately (i.e., are sloppy when transmitting or inattentive when receiving) then the social contagion may be changed. The receiver will thus retransmit the now changed version instead of the original social contagion. If several of these mutations occur, the contagion that begins spreading from one side of a network may differ substantially from the contagion that reaches the far side. Moreover, recipients may be unaware that any change has occurred and be unable to identify the original even if it reaches them via another path. The process is analogous to the children's game of "telephone:" just as children whispering a message from ear to ear can change it radically, social networks retransmitting a message can warp it beyond recognition. However, whereas children at a party may knowingly exaggerate the errors for humorous effect, adults in social networks are likely unaware of the extent of change suffered by a contagion and may not be intentionally altering it.
In a prior study (Brashears and Gladstone Forthcoming), we developed and tested a set of hypotheses describing how error occurs in social networks. First, we employed information theory (e.g., Shannon 1948) as a framework for understanding how social contagions would be impacted by message format. If a message is redundant, or low in entropy, then it uses more characters or phonemes to identify the words or ideas than necessary. If there is a certain probability that an error will occur in each letter typed or phoneme uttered, lower entropy messages are more likely to contain an error than higher entropy messages. However, while lower entropy messages are more likely to contain at least one error, their higher level of redundancy means that the intended word or idea can still be recognized using the remaining letters. The same is not true of higher entropy messages; omitting even one character/phoneme introduces considerably more uncertainty about the total message. We therefore hypothesized that lower entropy messages would preserve meaning more effectively. Second, Humans are aware of the meaningfulness (or lack thereof) of the messages they receive and are unlikely to pass on a message that they know to contain an error. However, it is often possible to infer the intended meaning of a message despite the presence of errors. We therefore hypothesized that when permitted to engage in such corrections, the meaning of the message would be preserved over a longer period. Third, human error correction is probably helpful but any attempt to correct errors detected in a message, absent some additional source of information, may fail. And unlike a simple typo, the new message that emerges from a failed error correction will be grammatically and syntactically valid, camouflaging the mutation. We therefore hypothesized that error correction would produce larger fluctuations in the semantic content of a message over multiple transmissions than would an absence of error correction.
We tested these predictions using a 2x2 experiment (higher/lower message entropy by presence/absence of error correction) employing human subjects. The experiment required subjects to read, remember, and then retransmit a series of ten sentences as an analog for receiving and retransmitting a social contagion. Our seed sentences were drawn from popular press books, ensuring that they were not excessively complex, and each contained between 13 and 16 words, keeping the average memory demands of the task constant. Each sentence was presented on a computer screen for five seconds, was then replaced by blank space for five seconds, and finally the subject was given a text field and allowed to type in their new sentence using the keyboard. The time constraints on the stimuli capture the limited time and attentional resources in real social processes. The reproduced sentences became the stimulus sentences for the next subject and all messages were transmitted in a simple linear graph with no contact between lineages (i.e., specific sequences of transmission-reception events sharing a seed and experimental conditions). Ultimately, each seed sentence produced ten to eleven lineages (depending on experimental randomization) in comparable starting conditions. We computed Levenshtein distances (Levenshtein 1965) between all relevant pairs of strings (i.e., parent-child, seed-child), but also had 3-5 human coders rate these pairs for semantic similarity. Ultimately, 8,178 sentence pairs were rated a total of 37,490 times. The results fully supported out hypotheses. First, lower entropy formats were found to preserve meaning better than higher entropy formats. Second, error correction had a substantial positive impact on the similarity of a contagion to its immediate predecessor (parent-child) and to its original progenitor (seed-child). Third, error correction improved the mean fidelity of social contagions, but nevertheless produced more distinct variants than did a lack of error correction. As a result, it appears that the most significant changes in meaning derive from efforts to fix errors, rather than from the original errors themselves.
In order to develop this innovative line of research, we requested funding for two objectives: to complete our experimental software and to carry out the next round of studies. Our initial study relied on informally produced software that can only accommodate simple, linear networks. It initially lacked any client-server architecture and now remains unstable when operating outside of a stand-alone mode. This allowed us to generate our initial data and serves as a proof-of-concept, but is inadequate for study of more complex network structures. Additionally, it is in principle quite practical to conduct this research online, which both allows the rapid recruitment of subjects and improvements in external validity. However, the original software lacked a

robust way to do so as it had limited client-server functionality. It would be beneficial to integrate the platform with services such as Amazon Mechanical Turk, that allow large amounts of experimental data to be produced from broader populations than are typically available for academic research (i.e., college students) in short periods of time.

The new software allows thorough investigations of arbitrary networks structures and leverages crowdsourcing via Mechanical Turk to gather and code data quickly and efficiently. Conceptually, the software is composed of two separate, but related, components. The first component is used to generate our data. We configure the software to present participants with our desired network structure and message seeds. Participants then access the software either via Mechanical Turk (or similar service), or in our Lab, and are assigned to a position in the network. Due to the nature of the experiment, participants can complete the task asynchronously, greatly reducing logistical challenges. After completing the task, participants are paid, and their data is stored within a database. The second component of the software is used to obtain ratings of semantic similarity between messages. Our coders log into the system and enter numerical codes of the meaning similarity of pairs of strings, with the pairs chosen in random order to prevent learning effects. By obtaining multiple ratings per pair we avoid individual bias, but greatly increase the total size of the task.

Second, we would like to fund the next round of studies. What happens when a single individual receives multiple copies of the same contagion? In principle one of four things might occur: they might combine the messages into one, they might discard one and retransmit the other, they might discard both, or they might class them as separate messages. Which of these outcomes occurs will have a substantial impact on the ability of a social contagion to spread but it is unknown which option most individuals prefer. Moreover, we hypothesize that the option selected will depend to some extent on how similar the incoming messages are. If they are quite similar, they will likely be combined into a single message. If they are moderately distinct, one may be discarded as flawed and the other retransmitted. If they are somewhat more distinct, they both may be discarded as neither is clearly viewed as correct. And if they are very different they may be treated as entirely separate messages.

In sum, very little is known about how errors in messages impact the diffusion of social contagions within networks. Current models generally ignore error and error correction, and no experiments that we know of other than our own address these issues. As we have discovered, the very complex and time-consuming nature of such investigations may be a principle reason why. The proposed software streamlines the entire process, allowing us to quickly increase our knowledge of how network structure interacts with the information passing through it. Ultimately, we hope to make our software available to the general community, thus further increasing the speed at which new discoveries are made.

Summary of the Most Important Results:

At the conclusion of our funded period we have accomplished the majority of our objectives. Despite disruption to software development process stemming from an illness in the team, we have completed the software, including the crowd sourcing functionality. We have use a simple html-based interface to specify arbitrary network structures, specify sets of messages to be delivered to initial nodes, indicate the number of steps for the messages to iterate before reset, and have included functionality to automatically code the resulting strings using Levenshtein distance metrics. We have also included the needed human coding functionality, allowing us to code the semantic differences between strings using human judgment. Finally, all of these features can be crowd sourced, allowing us to generate the original data, and to code it, comparatively rapidly. As a result, we have produced the software package to proposed and have included all desired features. We are continuing development outside the funded period in order to complete an adequate manual and to add a more straightforward installer package.

Upon completing the software we have begun executing experiments with it. Initially we performed a partial duplication of our original research in this area (see Appendix A) using respondents drawn from Amazon Mechanical Turk to confirm that the software was functioning as intended. While we have not completed the human coding of the generated data yet, the Levenshtein distance patterns from the new data match our earlier data quite closely. This adds to the reliability of our previous findings (by showing that they are replicable using a different population), validates the software (by showing that it doesn't produce anomalous results), and indicates that Mechanical Turk workers are capable of producing reliable data in this type of experiment. Following this validation, we performed a second data collection to assess the more advanced functions of the software. In this study we utilized a lattice network, comprised of two linear graphs with forward cross-connections at each step. As a result, each subject receives two versions of a diffusing contagion at each time step, following the first. The software performed well and the Levenshtein distance results suggest that the lattice structure substantially reduces the opportunity for contagion drift during transmission. This is a sensible result, but must await confirmation via the semantic codings generated by humans, which are not complete at this time. Both of these studies are discussed in detail in my student, Eric Gladstone's, dissertation (Appendix B). We had hoped to have completed at least one experiment using clustered networks by this point, but plan to proceed to this experiment next.

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Technology Transfer

Final Report

Testing the Effects of Error and Error Correction in Human Social Networks

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Appendix B- Gladstone 2015- Completed dissertation detailing software validation research as well as new lattice experiment.

Statement of the Problem Studied:

This research sought to examine the impact of errors in message transmission, and the effect of node-level efforts at error correction, on the spread of information through social networks. A large variety of ideas, beliefs, and behaviors, known as "social contagions," are known to spread through social networks, including fitness activities (Centola 2010, 2011), cigarette, alcohol, and tobacco use (Kirke 2004; Mercken et al. 2010), and technological innovations (Montanari and Saberi 2010; Rogers 2003). What is common to all of these contagions is the transfer of information between individuals; in order for someone to adopt a new behavior they must learn that it exists, what it is, and how to perform it. But while humans make mistakes and often misunderstand each other, existing research treats the "nodes" in social networks as perfect relays rather than fallible individuals, leaving many key questions unanswered. How rapidly do errors accumulate in human networks? Are particular message formats, or ways of transmitting the information, more prone to error than others? And do human efforts to correct errors improve or harm message fidelity? We completed development on a software package that allows us to study how information is changed as it moves through social networks using any of a large variety of arbitrary network structures. This software was further designed to be compatible with crowd sourcing options, including Amazon Mechanical Turk, and we have used it to carry out two experiments to confirm its operation and begin advancing study in this area. This line of research is Army-relevant as effective, accurate communication is essential to successful combined arms operations as well as in preventing blue-on-blue incidents. Similarly, an improved understanding of how information changes as it spreads through social networks would greatly enhance PSYOP/MISO efforts to combat insurgency in a variety of theatres.

Beliefs or behaviors that spread from person to person, intentionally or unintentionally, are known as "social contagions," and their spread is often referred to as "diffusion." [1] The systematic study of diffusion originates with Ryan and Gross' (1943) study of the diffusion of hybrid seed corn and Coleman, Katz and Menzel's (1957, 1959, 1966) investigation of the adoption of a new antibiotic. These studies indicated that decisions to adopt a new technology were often influenced more by peers than by formal assessment of the behavior (See also Burt 1980; Van den Bulte and Lilien 2011). Among individuals, diffusion influences recruitment into activism (McAdam 1986) as well as voting decisions (Bond et al. 2012), and the formation of norms and attitudes appears to be heavily influenced by diffusion (Friedkin 2001; Friedkin and Johnsen 1997, 2011). Organizations have also been shown to adopt the strategies of similar others (Conell and Cohn 1995; Davis 1991; Holden 1986; Soule 1997, 1999; Strang and Soule 1998; Wang and Soule 2012), leading ultimately to organizational isomorphism (DiMaggio and Powell 1983). In short, a huge variety of beliefs and behaviors exhibited by both individuals and groups appear to spread through social networks.

Several efforts have been made to determine the effectiveness of naturally occurring networks for promoting diffusion (Dodds, Muhamad and Watts 2003; Lundberg 1975; Pickard et al. 2011; Travers and Milgram 1969; Watts, Dodds and Newman 2002), often finding that contagions can cross even large networks relatively

[1] The term "contagion" can refer either to a thing that spreads between individuals, or to the process of spread itself. For clarity, we use "contagion" to refer to the thing that spreads, and "diffusion" to refer to the process as a whole.

quickly. However, the diameter of real world networks can be large (Albert, Jeong and Barabasi 1999), and contagions often do not take the shortest path (Golub and Jackson 2010; Liben-Nowell and Kleinberg 2008). As a result, traveling from one side of a network to the other often requires many hops and therefore offers many opportunities for errors to occur and to be transmitted to others. Often these errors are very small, but the consequences of even small mistakes can be quite dire. For example, a miscommunication during the Crimean War led to a light brigade of English cavalry (roughly six hundred men) charging a fortified Russian position, suffering approximately fifty percent casualties in the mistaken attack (Raugh 2004).

The existing research on diffusion and networks has often artificially precluded the possibility of errors. First, research on the small world phenomenon (e.g., Lundberg 1975; Travers and Milgram 1969; Watts, Dodds and Newman 2002) has relied on an experimental design wherein subjects pass fixed packets of information (e.g., a physical letter) from person to person. This is convenient for the researcher, but most social contagions do not traverse a social network in such a stable format. Second, diffusion studies (e.g., Christakis and Fowler 2007) have often examined an outcome, such as obesity, without measuring the behaviors that lead to this outcome. Because many behaviors can lead to the same end result (e.g., obesity can result from overeating, from insufficient exercise, etc.), changes in the contagion are undetectable so long as they lead to the same consequence. Third, a growing body of research examines contagion using social media, such as Facebook (e.g., Lewis et al. 2008; Lewis, Gonzalez and Kaufman 2012), but in these studies behaviors and preferences are determined by simple on/off choices made by users (e.g., "liking" rock music). As a result, the underlying variation in actions and understandings (e.g., how music is understood or consumed) is undetectable. Finally, theoretical work on contagions (e.g., Barash, Cameron and Macy 2012; Centola and Macy 2007; Rodriguez et al. 2014) has often employed simulation models that implicitly (or explicitly; see Carley 1991: 334) assume that information is passed from node to node without error. The impact of errors is thus excluded a priori and with minimal, if any, theoretical justification. What little research that does exist on errors in networks has focused on the failure or removal of specific nodes or ties (e.g., a member of a terrorist group who is captured by authorities) rather than on errors in the content carried by those networks (e.g., Albert, Jeong and Basabasi 2000; Callaway et al. 2000; Iyer et al. 2013).[2]

If individuals fail to pass on a social contagion accurately (i.e., are sloppy when transmitting or inattentive when receiving) then the social contagion may be changed. The receiver will thus retransmit the now changed version instead of the original social contagion. If several of these mutations occur, the contagion that begins spreading from one side of a network may differ substantially from the contagion that reaches the far side. Moreover, recipients may be unaware that any change has occurred and be unable to identify the original even if it reaches them via another path. The process is analogous to the children's game of "telephone:"[3] just as children whispering a message from ear to

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[2] There has been some study of the propagation and mutation of memes online, but this has not examined the semantic contact (i.e., meaning) of the messages and thus can only speak to the characteristics of the text, not to the information the text conveys.

[3] Also known as "operator," "Chinese whispers," "grapevine," "pass the message," "whisper down the lane," "broken telephone" and numerous other names.

ear can change it radically, social networks retransmitting a message can warp it beyond recognition. However, whereas children at a party may knowingly exaggerate the errors for humorous effect, adults in social networks are likely unaware of the extent of change suffered by a contagion and may not be intentionally altering it.

In a prior study (Brashears and Gladstone *Forthcoming*), we developed and tested a set of hypotheses describing how error occurs in social networks. First, we employed information theory (e.g., Shannon 1948) as a framework for understanding how social contagions would be impacted by message format. If a message is redundant, or low in entropy, then it uses more characters or phonemes to identify the words or ideas than necessary. If there is a certain probability that an error will occur in each letter typed or phoneme uttered, lower entropy messages are more likely to contain an error than higher entropy messages. However, while lower entropy messages are more likely to contain at least one error, their higher level of redundancy means that the intended word or idea can still be recognized using the remaining letters. The same is not true of higher entropy messages; omitting even one character/phoneme introduces considerably more uncertainty about the total message. We therefore hypothesized that lower entropy messages would preserve meaning more effectively. Second, Humans are aware of the meaningfulness (or lack thereof) of the messages they receive and are unlikely to pass on a message that they know to contain an error. However, it is often possible to infer the intended meaning of a message despite the presence of errors. We therefore hypothesized that when permitted to engage in such corrections, the meaning of the message would be preserved over a longer period. Third, human error correction is probably helpful but any attempt to correct errors detected in a message, absent some additional source of information, may fail. And unlike a simple typo, the new message that emerges from a failed error correction will be grammatically and syntactically valid, camouflaging the mutation. We therefore hypothesized that error correction would produce larger fluctuations in the semantic content of a message over multiple transmissions than would an absence of error correction.

We tested these predictions using a 2x2 experiment (higher/lower message entropy by presence/absence of error correction) employing human subjects. The experiment required subjects to read, remember, and then retransmit a series of ten sentences as an analog for receiving and retransmitting a social contagion. Our seed sentences were drawn from popular press books, ensuring that they were not excessively complex, and each contained between 13 and 16 words, keeping the average memory demands of the task constant. Each sentence was presented on a computer screen for five seconds, was then replaced by blank space for five seconds, and finally the subject was given a text field and allowed to type in their new sentence using the keyboard. The time constraints on the stimuli capture the limited time and attentional resources in real social processes. The reproduced sentences became the stimulus sentences for the next subject and all messages were transmitted in a simple linear graph with no contact between lineages (i.e., specific sequences of transmission-reception events sharing a seed and experimental conditions). Ultimately, each seed sentence produced ten to eleven lineages (depending on experimental randomization) in comparable starting conditions. We computed Levenshtein distances (Levenshtein 1965) between all relevant pairs of strings (i.e., parent-child, seed-child), but also had 3-5 human coders rate these pairs for semantic similarity. Ultimately, 8,178 sentence pairs were rated a total of 37,490 times.

The results fully supported out hypotheses. First, lower entropy formats were found to preserve meaning better than higher entropy formats. Second, error correction had a substantial positive impact on the similarity of a contagion to its immediate predecessor (parent-child) and to its original progenitor (seed-child). Third, error correction improved the mean fidelity of social contagions, but nevertheless produced more distinct variants than did a lack of error correction. As a result, it appears that the most significant changes in meaning derive from efforts to *fix* errors, rather than from the original errors themselves.

In order to develop this innovative line of research, we requested funding for two objectives: to complete our experimental software and to carry out the next round of studies. Our initial study relied on informally produced software that can only accommodate simple, linear networks. It initially lacked any client-server architecture and now remains unstable when operating outside of a stand-alone mode. This allowed us to generate our initial data and serves as a proof-of-concept, but is inadequate for study of more complex network structures. Additionally, it is in principle quite practical to conduct this research online, which both allows the rapid recruitment of subjects and improvements in external validity. However, the original software lacked a robust way to do so as it had limited client-server functionality. It would be beneficial to integrate the platform with services such as Amazon Mechanical Turk, that allow large amounts of experimental data to be produced from broader populations than are typically available for academic research (i.e., college students) in short periods of time.

The new software allows thorough investigations of arbitrary networks structures and leverages crowdsourcing via Mechanical Turk to gather and code data quickly and efficiently. Conceptually, the software is composed of two separate, but related, components. The first component is used to generate our data. We configure the software to present participants with our desired network structure and message seeds. Participants then access the software either via Mechanical Turk (or similar service), or in our Lab, and are assigned to a position in the network. Due to the nature of the experiment, participants can complete the task asynchronously, greatly reducing logistical challenges. After completing the task, participants are paid, and their data is stored within a database. The second component of the software is used to obtain ratings of semantic similarity between messages. Our coders log into the system and enter numerical codes of the meaning similarity of pairs of strings, with the pairs chosen in random order to prevent learning effects. By obtaining multiple ratings per pair we avoid individual bias, but greatly increase the total size of the task.

Second, we would like to fund the next round of studies. What happens when a single individual receives multiple copies of the same contagion? In principle one of four things might occur: they might combine the messages into one, they might discard one and retransmit the other, they might discard both, or they might class them as separate messages. Which of these outcomes occurs will have a substantial impact on the ability of a social contagion to spread but it is unknown which option most individuals prefer. Moreover, we hypothesize that the option selected will depend to some extent on how similar the incoming messages are. If they are quite similar, they will likely be combined into a single message. If they are moderately distinct, one may be discarded as flawed and the other retransmitted. If they are somewhat more distinct, they both may be discarded as neither is clearly viewed as correct. And if they are very different they may be treated as entirely separate messages.

In sum, very little is known about how errors in messages impact the diffusion of social contagions within networks. Current models generally ignore error and error correction, and no experiments that we know of other than our own address these issues. As we have discovered, the very complex and time-consuming nature of such investigations may be a principle reason why. The proposed software streamlines the entire process, allowing us to quickly increase our knowledge of how network structure interacts with the information passing through it. Ultimately, we hope to make our software available to the general community, thus further increasing the speed at which new discoveries are made.

Summary of the Most Important Results:

At the conclusion of our funded period we have accomplished the majority of our objectives. Despite disruption to software development process stemming from an illness in the team, we have completed the software, including the crowd sourcing functionality. We have use a simple html-based interface to specify arbitrary network structures, specify sets of messages to be delivered to initial nodes, indicate the number of steps for the messages to iterate before reset, and have included functionality to automatically code the resulting strings using Levenshtein distance metrics. We have also included the needed human coding functionality, allowing us to code the semantic differences between strings using human judgment. Finally, all of these features can be crowd sourced, allowing us to generate the original data, and to code it, comparatively rapidly. As a result, we have produced the software package to proposed and have included all desired features. We are continuing development outside the funded period in order to complete an adequate manual and to add a more straightforward installer package.

Upon completing the software we have begun executing experiments with it. Initially we performed a partial duplication of our original research in this area (see Appendix A) using respondents drawn from Amazon Mechanical Turk to confirm that the software was functioning as intended. While we have not completed the human coding of the generated data yet, the Levenshtein distance patterns from the new data match our earlier data quite closely. This adds to the reliability of our previous findings (by showing that they are replicable using a different population), validates the software (by showing that it doesn't produce anomalous results), and indicates that Mechanical Turk workers are capable of producing reliable data in this type of experiment. Following this validation, we performed a second data collection to assess the more advanced functions of the software. In this study we utilized a lattice network, comprised of two linear graphs with forward cross-connections at each step. As a result, each subject receives two versions of a diffusing contagion at each time step, following the first. The software performed well and the Levenshtein distance results suggest that the lattice structure substantially reduces the opportunity for contagion drift during transmission. This is a sensible result, but must await confirmation via the semantic codings generated by humans, which are not complete at this time. Both of these studies are discussed in detail in my student, Eric Gladstone's, dissertation (Appendix B). We had hoped to have completed at least one experiment using clustered networks by this point, but plan to proceed to this experiment next.

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Appendix A

Error Correction Mechanisms in Social Networks can Reduce Accuracy and Encourage Innovation

Matthew E. Brashears,* Eric Gladstone**

Abstract: Humans make mistakes but diffusion through social networks is typically modeled as though they do not. We find in an experiment that high entropy message formats (text messaging pidgin) are more prone to error than lower entropy formats (standard English). We also find that efforts to correct mistakes are effective, but generate more mutant forms of the contagion than would result from a lack of correction. This indicates that the ability of messages to cross "small-world" human social networks may be overestimated and that failed error corrections create new versions of a contagion that diffuse in competition with the original.

Approximately 15,158 words.

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Introduction

How do errors in a social contagion, and attempts to correct them, impact diffusion over social networks? A substantial body of research examines diffusion, or the tendency for ideas, beliefs, and behaviors to spread through human social networks (e.g., Centola 2010, 2011; Coleman, Katz and Menzel 1966; Montanari and Saberi 2010; Rogers 2003; Wang and Soule 2012). What is common to all of these contagions is the transfer of information between individuals; in order for someone to adopt a new behavior they must learn that it exists, what it is, and how to perform it. [4] But while humans make mistakes and often misunderstand each other, existing research treats the "nodes" in social networks as perfect relays rather than fallible individuals, leaving many key questions unanswered. How rapidly do errors accumulate in human networks? Are particular message formats, or ways of transmitting the information, more prone to error than others? And do human efforts to correct errors improve or harm message fidelity?

We address these questions with a unique laboratory experiment using human subjects exchanging textual messages as a model for information diffusion. We find that semantic errors (i.e., mistakes that compromise meaning) can accumulate rapidly as messages pass through a network. When taken as a model of error in information spread more generally, our results suggest that the effective reachability in small-world and scale-free social networks (Watts and Strogatz 1998; Watts, Dodds and Newman 2002) may be lower than previously thought and that social contagions may have difficulty saturating a large network, even when given ample time. We also find that the error rate is influenced by message format; longer (i.e., lower entropy) messages (e.g., standard English) are able to preserve meaning more effectively than shorter (i.e., higher entropy) messages (e.g., text messaging pidgin) even though they include more characters, and therefore more opportunities for errors to occur upon retransmission. This suggests that increasing usage of communications technologies that encourage the use of shorter messages (e.g., text messaging) may impede the diffusion of social contagions. Finally, while individual efforts to correct error generally improve accuracy, over the course of diffusion they also result in diversification (i.e., accumulation of grammatically valid but semantically distinct versions) of the diffusing message. In contrast, transmission without error correction results in corruption (i.e., accumulation of grammatically invalid but semantically similar versions). This suggests a new mechanism through which cultural diversity can be maintained: efforts to imitate others lead to unintended innovation, generating distinction as a direct result of efforts to conform. Paradoxically, innovation may often be the result of imitation.

Background

Diffusion and Social Contagion

Beliefs or behaviors that spread from person to person, intentionally or unintentionally, are known as "social contagions," and their spread is often referred to as

[4] Some studies of diffusion focus on how attitudes towards an innovation diffuse, but these fundamentally rely on the movement of information (i.e., how others feel about something) and thus are consistent with our perspective.

"diffusion." [5] While many entities can spread via social networks, relatively few are regarded as "social contagions". Schaefer (2007) argues that entities passing through social networks can be distinguished based on their transferability, and their duplicability. An entity that is transferable can be received from one person, and passed on to a different individual; a person can receive a book from one associate, and pass it on to a second associate. In contrast, an entity that is non-transferable can be received from one person but not transferred to a second; a person can receive an affectionate touch from a spouse, but cannot pass that same touch on to another individual. An entity that is duplicable can be copied, with the giver retaining the entity even as it is given to another; if I share a rumor with an associate, I do not as a consequence forget the rumor myself. An entity that is non-duplicable is given up in the process of transferring it to another; if I give an associate five dollars, I cannot have that same five dollars myself. In general, research on diffusion and social contagion concerns itself with entities that are transferable and duplicable. If they are not transferrable then diffusion, as usually conceived, is impossible, and if they are not duplicable then there can be no sustained diffusion process. However, it should be kept in mind that transferability and duplicability overlap in complex ways. For example, a book in common usage is a transferable, non-duplicable artifact, and thus not a social contagion, while the information contained in the book is both transferable and duplicable, and therefore is a social contagion.

The study of diffusion as a larger phenomenon originates with both Gabriel Tarde's (1903[1969]) "The Laws of Imitation" and Georg Simmel's (1908[1964], 1922[1964]) essays on the stranger and connections between groups. However, truly systematic study of diffusion did not commence until the middle of the twentieth century, with Ryan and Gross' (1943) study of the diffusion of hybrid seed corn and Coleman, Katz and Menzel's (1957, 1959, 1966) investigation of the adoption of a new antibiotic. These studies indicated that decisions to adopt a new technology were often influenced more by peers than by formal assessment of the behavior (See also Burt 1980; Van den Bulte and Lilien 2011). Diffusion influences recruitment into activism (McAdam 1986) as well as voting decisions (Bond et al. 2012). The formation of norms and attitudes appears to be heavily influenced by contagion (Friedkin 2001; Friedkin and Johnsen 1997, 2011), and many health-related behaviors respond to diffusion, including fitness activities (Centola 2010, 2011), cigarette, alcohol, and tobacco use (Kirke 2004; Mercken et al. 2010), obesity (Christakis and Fowler 2007; But see also Cohen-Cole and Fletcher 2008a), and happiness (Fowler and Christakis 2008; But see also Cohen-Cole and Fletcher 2008b). A substantial literature has developed on the spread of innovations through social networks (Montanari and Saberi 2010; Rogers 2003), explaining how a novel invention can become ubiquitous throughout a community. The spread of information was pivotal for women attempting to obtain illegal abortions (Lee 1969), allowing them to identify covert practitioners. Even organizations have been shown to adopt the strategies of similar others (Conell and Cohn 1995; Davis 1991; Holden 1986; Soule 1997, 1999; Strang and Soule 1998; Wang and Soule 2012), leading ultimately to organizational isomorphism (DiMaggio and Powell 1983). In short, a huge variety of

[5] The term "contagion" can refer either to a thing that spreads between individuals, or to the process of spread itself. For clarity, we use "contagion" to refer to the thing that spreads, and "diffusion" to refer to the process as a whole.

beliefs and behaviors exhibited by both individuals and groups appear to spread through social networks.

Scholars have attempted to determine the effectiveness of naturally occurring networks for promoting diffusion (Dodds, Muhamad and Watts 2003; Lundberg 1975; Pickard et al. 2011; Travers and Milgram 1969; Watts, Dodds and Newman 2002), often finding that contagions can cross even large networks relatively quickly. However, while contagions may cross networks quickly, the diameter of real world networks can be large (Albert, Jeong and Barabasi 1999), and even when the network structure provides shortcuts, contagions often do not take the shortest path (Golub and Jackson 2010; Liben-Nowell and Kleinberg 2008). As a result, traveling from one side of a network to the other often requires many hops. Significant effort has also been devoted to exploring how different types of network ties, and structures, can accelerate or retard the diffusion process. One stream of research has shown how weak (Granovetter 1973, 1995), bridging (Burt 1992), and high bandwidth (Aral and Van Alstyne 2011) ties can accelerate the diffusion of social contagions. Other research (Centola and Macy 2007) has complicated this picture by suggesting that the "complexity" of the contagion can impact diffusion, at least initially (Barash, Cameron and Macy 2012), and favor strong ties over weak ties. Research has also striven to identify the individuals in networks who are most susceptible to contagions (Aral and Walker 2012), as well as to distinguish tendencies to adopt the behaviors of our associates from tendencies to associate with those to whom we are similar (Aral, Munchnik, and Sundararajan 2009; Lewis, Gonzalez and Kaufman 2012).

The existing research on diffusion and networks is rich, but has often artificially precluded the possibility of errors. First, research on the small world phenomenon (e.g., Lundberg 1975; Travers and Milgram 1969; Watts, Dodds and Newman 2002) has frequently relied on an experimental design in which subjects pass fixed packets of information (e.g., a physical letter) from person to person. This is convenient for the researcher, but many of the social contagions most interesting to social scientists probably do not traverse a social network in such a stable format (i.e., transferable/non-duplicable). Certainly researchers in this area have noted the frequency with which the packets failed to reach their targets, and this could be viewed as an extreme form of error, but the outcomes have remained binary. In other words, either a message reaches the target intact, or fails to reach the target, but never arrives with modification. Second, diffusion studies (e.g., Christakis and Fowler 2007) have often examined an outcome, such as obesity, without measuring the behaviors that lead to this outcome. Because many behaviors can lead to the same end result (e.g., obesity can result from overeating, from insufficient exercise, etc.), changes in the contagion are undetectable so long as they lead to the same consequence. Third, a growing body of research examines contagion using social media, such as Facebook (e.g., Lewis et al. 2008; Lewis, Gonzalez and Kaufman 2012), but in these studies behaviors and preferences are determined by simple on/off choices made by users (e.g., "liking" rock music). As a result, the underlying variation in actions and understandings (e.g., how music is understood or consumed) is undetectable. Finally, theoretical work on contagions (e.g., Barash, Cameron and Macy 2012; Centola and Macy 2007; Rodriguez et al. 2014) has often employed simulation models that implicitly (or explicitly; see Carley 1991: 334) assume that information is passed from node to node without error. The impact of errors is thus excluded a priori and with minimal, if any, theoretical justification. Error is therefore a relatively neglected issue in the study of diffusion.

<u>Errors and Diffusion</u>

In his 1977 presidential address to the American Statistical Association Leslie Kish remarked, "…to err is human, to forgive divine but to include errors in your design is statistical." In other words, humans make mistakes because they are human, and effective research must take account of them in order to achieve valid results. However, errors do not just occur during the research process (e.g., errors in data collection), but in the social processes under examination (e.g., intermittent failure to follow formal organizational procedures), and therefore represent an important part of those social processes. Often these errors are very small, but the consequences of even small mistakes can be quite dire. For example, a miscommunication during the Crimean War led to a light brigade of English cavalry (roughly six hundred men) charging a fortified Russian position, suffering approximately fifty percent casualties in the mistaken attack (Raugh 2004). More recently, an error in the conversion of Imperial measures (pounds-force) into metric (newtons) caused NASA's Mars Climate Orbiter to impact the atmosphere and disintegrate during Mars orbital insertion (National Aeronautics and Space Administration 1999). Similarly, contact was permanently lost with the Mars Global Surveyor probe due to a sequence of errors in the entry of flight-critical data (National Aeronautics and Space Administration 2007). Mistakes happen in a variety of settings and these mistakes, however trivial at the time, can have substantial consequences.

The failure to integrate errors and their consequences into social theory is especially pernicious in the study of diffusion. Social contagions are duplicated either by processes endogenous to transfer (e.g., rumors are duplicated in the process of being transferred), or exogenous to transfer (e.g., influenza duplicates via cellular mechanisms distinct from transfer). For cases of endogenous duplicability, if individuals fail to pass on a social contagion accurately (i.e., are sloppy when transmitting or inattentive when receiving) then the social contagion may be changed.[6] The receiver will thus retransmit the now changed version instead of the original social contagion. If several of these mutations occur, the contagion that begins spreading from one side of a network may differ substantially from the contagion that reaches the far side. Moreover, recipients may be unaware that any change has occurred and be unable to identify the original even if it reaches them via another path. The process is analogous to the children's game of "telephone:"[7] just as children whispering a message from ear to ear can change it radically, social networks retransmitting a message can warp it beyond recognition. However, whereas children at a party may knowingly exaggerate the errors for humorous effect, adults in social networks are likely unaware of the extent of change suffered by a contagion and may not be intentionally altering it.

Social contagions may either be informational (e.g., rumors, news, etc.), shaping beliefs, or behavioral (e.g., smoking, adopting a new statistical package, etc.), shaping actions, but both are subject to error. Individuals may misspeak, mistype, mishear, or

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[6] Similar processes may play out for exogenous duplication (e.g., mutation in a bacterium), but are beyond the scope of this paper.

[7] Also known as "operator," "Chinese whispers," "grapevine," "pass the message," "whisper down the lane," "broken telephone" and numerous other names.

misread messages and thus introduce error into the spread of information. Likewise, a person can learn a new behavior by observing another individual perform it, and humans have a highly developed ability to learn new behaviors from observation (Byrne 1995), but we are not automatically successful, and true behavioral mimicry is exceedingly difficult (ibid). Thus, efforts to adopt a behavior one has observed will not invariably succeed. Moreover, behaviors are often partially symbolic (e.g., Goffman 1959, 1967), and derive much of their impact from context (e.g., Eliasoph 1997). Enacting a behavior correctly, but at the wrong time or in regards to the wrong individuals may produce unintended, and potentially hostile, responses (e.g., Milgram and Sabini 1978; Milgram, Liberty, Toledo and Wackenhut 1986). Similarly, the cultural dimensions of a contagion may be far more important for its spread than the behavior itself (Goldberg and Koning 2013). Thus, even if a behavior is easy to perform correctly, acquiring the necessary cultural and symbolic tools (Swidler 1986) to employ it effectively is much more difficult and provides ample opportunities for mistakes to occur. Finally, many behaviors (and artifacts) cannot be employed effectively without developing a host of new ways of understanding the world and interpreting stimuli. For example, Rogers (2003: 1-5) summarizes the failure of an innovation, water boiling for reduction of disease transmission, to diffuse in a Peruvian village. In this case, while the behavior itself (i.e., heating water) was understood and widely available, diffusion of its use was hindered by local cultural understandings about connections between temperature and health. What mattered was not the behavior, but the set of skills and meanings associated with the behavior. The meanings that humans give to phenomena can be crucial even when we confront technological artifacts with stable properties. For example, Becker (1953) found that enjoying the psychoactive properties of marijuana required users to develop skill in smoking it properly, learn to interpret sensations that indicated it was effective, develop a favorable appreciation of its effects, and maintain these skills and understandings against unpleasant events. While transferring a marijuana cigarette from one person to another is trivial, transferring the collection of skills and meanings that allow a user to enjoy using that cigarette is far more time consuming and complex. Even the recognition of the properties of an artifact can be impacted by prevailing meanings. For example, Bakelite, an early and commercially successful plastic, was synthesized a number of times prior to its "discovery", but was not recognized as valuable because it did not have the characteristics that chemists were looking for (Bijker 2002: Ch. 3). Likewise, growing indications of technical faults in the space shuttle program were documented over a series of launches but went unrecognized by engineers who had grown accustomed to them, ultimately leading to the loss of the *Challenger* (Vaughan 1997). While it is certainly true that the adoption of artifacts can diffuse, and that these artifacts can be functionally identical, it is nevertheless the case that the knowledge of how to utilize these artifacts, and indeed even the recognition of the characteristics and behaviors of those artifacts in the first place, is a social contagion subject to endogenous duplication. As such, errors should impact the spread of all types of social contagions that are, or depend upon a component that is, transferable and endogenously duplicable.

What little research that does exist on errors in networks has focused on the failure or removal of specific nodes or ties (e.g., a member of a terrorist group who is captured by authorities) rather than on errors in the content carried by those networks (e.g., Albert, Jeong and Basabasi 2000; Callaway et al. 2000; Iyer et al. 2013). Much of the existing work on errors in diffusion is found in the literature on "distortion," which examines how individuals modify information before they transmit it so as to produce favorable results. For example, individuals are likely to modify information when they are feeling insecure or threatened (Athanassiades 1973), so as to protect their jobs or promotion opportunities. Similarly, employees who do not trust their superiors are more likely to distort messages in several ways, including "puffing," or making their accomplishments seem more impressive, and "withholding," or omitting key facts (Gaines 1980). Withholding has also been implicated in the sharing of information about past abortions (Cowan 2014); consistent with earlier work (Lee 1969), individuals are more likely to share abortion histories with those whom they expect to be supportive. The global result of withholding is that certain kinds of information are channeled only into particular parts of a network, preventing wide diffusion and biasing the perceptions of network members (See also Lusher and Robins 2013). Distortion can also occur between organizations (e.g., Lee, Padmanabhan and Whang 1997).

The research on distortion is important but has three main drawbacks for understanding error transmission in networks generally. First, its emphasis on intentional manipulation of information means that it is concerned with falsification rather than error. Even in the case of pure withholding (e.g., Cowan 2014), individuals are acting strategically to produce favorable reactions from others rather than making mistakes. Second, identification of distortion relies on close qualitative examination of the source materials, and thus is difficult to connect to more general diffusion processes. Finally, with a handful of notable exceptions (e.g., Lee, Padmanabhan and Whang 1997), studies of distortion have been concerned primarily with the immediate effects of changes to the information, rather than its ramifications throughout the network as the information spreads from node to node.

Most of the remaining work on errors in diffusion processes is found in computer science. Leskovec, Backstrom and Kleinberg (2009) developed a procedure for tracking short phrases, or memes,[8] as they diffuse in online settings. They recognize that these memes, "…undergo significant mutation" (2009: 2), but view these changes as a methodological hurdle to be overcome (i.e., changes in a diffusing meme make computerized tracing more difficult) rather than as an interesting phenomenon. Liben-Nowell and Kleinberg (2008) traced the flow of information using internet chain-letters, and observed that these letters do accumulate errors, but also treat the errors as a methodological impediment. Simmons, Adamic and Adar (2011) conducted the most directly relevant research, attempting to track the mutation of memes in both online newspaper articles and blog posts. They found among other things that shorter phrases are less likely to be modified over time as compared to longer phrases. More recent work on Facebook memes (Adamic et al. 2014) finds that their spread is consistent with the Yule process, likely resulting from simple mutation and replication, and that there is a lack of a clear selection mechanism.

[8] Memes are more generally defined as self-replicating informational units analogous to genes (Dawkins 1976 [2006]), and there is an interesting body of theory dealing with the competition among these replicators for memory space and attention (e.g., Blackmore 2001). Our work could obviously be applied to memetics, but we are not interested in how ideas compete with each other, but rather in how errors, and the efforts of human actors to correct those errors, impact the spread of social contagions. We therefore set aside discussion of issues of interest to meme theory for the present.

While all of these studies make serious efforts to identify and track errors, they have a number of difficulties in common. First, with two exceptions (i.e., Adamic et al. 2014; Simmons, Adamic and Adar 2011), changes in the diffusing contagion are viewed as a methodological obstacle, rather than an important factor in its own right. As a result, all efforts are devoted to identifying a contagion despite errors, rather than to understanding how errors change the contagion or how humans respond to those changes. Second, all of the studies rely on automatic text parsing and are unable to distinguish the structure of the sentences from their semantic content (i.e., meaning). For example, the sentence "Bob threw the blue ball," would be coded as different from the sentence, "The ball, which is blue, was thrown by Bob," even though the semantic content is identical. Third, this stream of research relies on identifying diffusion chains in natural settings, primarily relying on online archives. This yields large sample sizes (though not necessarily reliable samples; see Lazer et al. 2014), but requires that news reports, blog posts, and tweets that relate to the same topic be readily identifiable using a computer algorithm. Errors that substantially alter the structure of a sentence, or that translate the information into a restricted code (see Bernstein 2008), will not be identified as part of the diffusion chain. As a result, these studies are based on a biased sample consisting of messages that have changed, but not so much that the algorithm can no longer recognize them as belonging to a particular social contagion. Fourth, because the contagions are being tracked in natural settings, mutations cannot be readily distinguished from incremental updates (e.g., changes to a news story as more information becomes available). Finally, existing research (Adamic et al. 2014) has found that online memes often spread via offline channels, preventing accurate tracking of diffusion using purely online data. Thus, while this stream of research is interesting, it leaves many questions unanswered about how errors in social networks impact diffusion.

Theory and Hypotheses

We employ information theory as a framework for developing our hypotheses. Information theory traces its roots to the work of Claude Shannon (1948), who introduced a method for quantifying the information contained in a message, known as "entropy" or "Shannon information." If there are a finite number of possible messages that can be sent via a communications channel (e.g., an interpersonal tie), then these potential messages constitute a set. The number, or a monotonic function of the number, of messages in a set determines the amount of information that is conveyed when a message is selected from the set and transmitted to a receiver. The information conveyed is proportional to uncertainty reduction; as there are more members of a set, the uncertainty as to which of them will be selected is greater, and thus the selected message contains more information.

The basic logic of Shannon's theory is easier to grasp if one imagines solving a crossword puzzle.[9] If we view all possible English phrases the same length as the crossword phrase as the set of possible messages, then initially there is a great deal of uncertainty about the outcome. The first few letters filled in greatly reduce the size of the allowable message set and therefore convey a great deal of information. However, each additional letter conveys proportionately less information because the remaining set of possible messages is smaller. Ultimately, the phrase may be solved when some letters remain unidentified; the set of possible messages has been reduced to one, making the

[9] Or, if the reader prefers, an episode of the television program *Wheel of Fortune.*

additional letters redundant and unnecessary. Shannon's entropy[10] is thus similar to the more familiar concept of degrees of freedom; each additional letter reduces the set of values the phrase can take on, much as each additional entry in a contingency table constrains the values that other cells may accept.

The same logic can be applied to the information content of a language: in any given sequence of letters (or phonemes), each additional letter (phoneme) resolves some of the uncertainty about what word is being spelled (or spoken). Shannon (1950) determined that written English is approximately 75% redundant, meaning that roughly three-quarters of the letters in a message can be deleted without meaningfully impacting the ability of a reader to discern the content. For example, the first phrase of this paragraph could easily be rendered as, "Th sme lgc cn b appld to th info contnt of a lnguage," and remain perfectly understandable (if unattractive) even though it contains fewer characters. Similarly, it seems likely that physical actions and behaviors could be modeled using information theory. In this case, high entropy actions might be those that are quick and involve multiple discreet elements in quick succession while low entropy actions are slower, more sequential, and more exaggerated.[11] Information theory is thus a useful framework for thinking about error in diffusion and below we use the term "messages" broadly to refer to ideas, behaviors, and cultural meanings that spread as social contagions.

The main difficulty in using information theory for our purposes is that the meaningfulness of a message (i.e., semantic content) is distinct from, and irrelevant to, the information of a message (Shannon 1948: 379). For example, Shannon algorithmically generated a sentence that has the same entropy (i.e., the same information) as an English sentence of the same length (1948: 385):

"THE HEAD AND IN FRONTAL ATTACK ON AN ENGLISH WRITER THAT THE CHARACTER OF THIS POINT IS THEREFORE ANOTHER METHOD FOR THE LETTERS THAT THE TIME OF WHO EVER TOLD THE PROBLEM FOR AN UNEXPECTED"

This generated sentence strongly resembles English but is clearly not meaningful, and we cannot infer that a message is meaningful merely because it is high in information. Subsequent similar work (e.g., research on "fault tolerance") has followed Shannon's lead in ignoring the meaningfulness of a message (e.g., Castro and Liskov

[10] Some readers may be more familiar with entropy as a measure of the disorder in a system rather than as a measure of information, but the term relies on the same logic in either case. Perfectly ordered signals are low in entropy and therefore low in information, whereas disordered signals are high in entropy and therefore high in information. For example, an endless sequence of one number (e.g., 111111…) is perfectly ordered (low entropy) and all uncertainty about subsequent digits is resolved once the first digit is known (low information). In contrast, an endless sequence of random numbers is perfectly disordered (high entropy) and uncertainty about subsequent digits is unaffected by knowledge of the preceding digits (high information). Signals that convey meaning (e.g., human speech) typically display intermediate levels of entropy; they are not as predictable as a repeating number sequence, but are not purely random either.

[11] A full information theoretic treatment of behaviors is beyond the scope of this paper. For present purposes it is sufficient to note that for a behavior to diffuse the knowledge of how to perform that behavior must be transferred, and it is almost certainly possible to express the character of this knowledge in terms of information theory.

1999; Chen and Avizienis 1978; Laprie 1985; von Neumann 1956; West 1990) and as a result we know surprisingly little about semantic error.

While Shannon information is not the same as semantic content, it still provides a useful foundation for our investigation. If a particular message is redundant, or low in entropy, then it uses more characters or phonemes to identify the words or ideas than are strictly necessary. If there is a certain probability that an error will occur in each letter typed (e.g., a typo) or phoneme uttered, then lower entropy messages are more likely to contain an error than higher entropy messages. However, while lower entropy messages are more likely to contain at least one error, their higher level of redundancy means that the intended word or idea can still be recognized using the remaining letters. The same is not true of higher entropy messages; because they use a minimum number of characters or phonemes, omitting even one introduces considerably more uncertainty about the total message (i.e., enlarges the set of potential messages). Returning to our earlier example, if an error converted the lower entropy phrase, "The same logic…" into "The same lgic…," the message would remain intelligible. In contrast, if an error converted the higher entropy phrase, "Th sme lgc…" into "Th sme lg…," the semantic content would be compromised. Similar logic suffices for behavioral mimicry: slower, more exaggerated actions provide more time for inattention or distraction to impair learning, but also provide more context with which to reconstruct the needed motions. In contrast, faster, compound motions are completed more quickly and with fewer opportunities for distraction, but are more likely to be disrupted by even brief periods of inattention. This leads to the following hypothesis:

- **Entropy Meaning Hypothesis:** Errors impact the semantic content of a lower entropy message to a smaller extent than a higher entropy message.

Every time a social contagion diffuses from one person to another there is an opportunity for error and these errors can produce a variety of potential outcomes. The simplest outcome is what we term "corruption,": random errors accumulate until the original message is rendered unintelligible. For example, in a network with an extraordinarily high error rate, "The same logic…" might first become, "Tye sqme lohic…," then "Tyw wqme kohic…," and continue mutating into complete unintelligibility. Similarly, when attempting to mimic an action, small misunderstandings could gradually disrupt the behavior at each step. Corruption is thus a straightforward degradation of the message over time and the presence of corruption would impose a simple limit on the ability of social contagions to spread.

A second, and more interesting, outcome is what we term "diversification." Humans are aware of the meaningfulness (or lack thereof) of the messages they receive and are unlikely to pass on a message that they know to contain an error.[12] In other words, if one receives the message, "Tye sqme lohic…" from an associate, the presence of errors is obvious. The recipient might discard the message, concluding that it is unintelligible, but may also engage in error correction and attempt to reconstruct the original message. Thus, while the individual receives "Tye sqme lohic…" they might

[12] Humans may also refrain from passing on a message for other reasons (e.g., appropriateness) but this is beyond the scope of the current paper. Likewise, humans may deliberately falsify information for their own benefit; see our earlier discussion of the literature on distortion.

transmit “The same logic…” in response. Similarly, individuals attempting behavioral mimicry may substitute in actions with which they are already familiar (i.e., they will attempt to correct an error) when the behavior seems incomplete or ineffective as observed (e.g., when attempting to duplicate a meal whose preparation was only partially seen, a cook may add spices that seem appropriate to their own palette). Therefore, when humans are able to correct the errors they perceive in messages they will preserve their meaningfulness more effectively than when they are unable to correct them. While this assertion might seem obvious it has never, to our knowledge, been tested, leading to the following hypothesis:

- **Error Correction Hypothesis:** Human efforts to correct error will tend to preserve the semantic content of a message over multiple transmissions.

Finally, human error correction is probably helpful but, “…it is not in general possible to reconstruct the original message or the transmitted signal with *certainty* by any operation on the received signal, [emphasis original]” (Shannon 1948: 398). In other words, an attempt to correct errors detected in a message, absent some additional source of information, may fail. For example, the phrase, “Tye sqme lohic…” might be corrected to read, “The same tonic…” which has a different meaning from the original message. And unlike the case of corruption, the new message that emerges from a failed error correction will be grammatically and syntactically valid, camouflaging the mutation. As a result, there is no way for subsequent recipients of the mutated contagion to realize that a mutation has occurred unless they have access to information beyond the message itself (e.g., contextual information), which itself may also contain errors or ambiguities. Likewise, when corrections are made to behaviors the resulting set of actions will appear complete and more familiar to those who have similar repertoires, making it more difficult to detect a change without outside knowledge. While the presence of error correction stabilizes a contagion in the short run, periodic failed corrections can transform the contagion into something dramatically different, which can then diffuse in competition with the original. Whereas corruption leads to a gradual degradation of the contagion, diversification causes it to periodically, suddenly, and silently mutate into legible variant forms.[13] This leads to the following hypothesis:

- **Diversification Hypothesis:** Human efforts to correct error will tend to produce larger fluctuations in the semantic content of a message over multiple transmissions than will an absence of error correction.

In summary, we hypothesize that the diffusion of messages without error correction will result in a gradual degradation of meaningfulness that we term “corruption.” Diffusion with error correction will prevent corruption and preserve meaning, but only at the cost of introducing “diversification,” or sudden transformations of one message into another, valid mutant version.

[13] There are obvious similarities between this mechanism and evolutionary models, such as Dawkins’ “weasel program,” (Dawkins 1986: Ch. 3). However, whereas Dawkins’ program selects for strings that are closer to the target phrase and thus produces gradual change, our diversification mechanism can produce sudden, dramatic changes in the strings.

Methods

Study Design

We tested our hypotheses using a randomized laboratory experiment. An experiment is appropriate for the problem because, unlike previous efforts to track error in diffusion (e.g., Adamic et al. 2014; Leskovec, Backstrom and Kleinberg 2009; Simmons, Adamic and Adar 2011), it allows us to precisely measure all of the inputs to an individual as well as the subsequent outputs. Thus, we can positively link all mutants to their progenitors no matter how extreme the change and experimental control enables us to determine the origins of any effects that we detect.

The experiment required subjects to read, remember, and then retransmit a series of ten sentences as an analog for receiving and retransmitting a social contagion. This task most closely models the movement of verbal/written contagions through networks, but should provide broadly accurate insights into behavioral contagions as well as these also involve the spread of knowledge (e.g., the existence of a behavior and how to perform it). Our seed sentences were drawn from popular press books, ensuring that they were not excessively complex, and each contained between 13 and 16 words, keeping the average memory demands of the task constant. Each sentence was presented on a computer screen for five seconds, was then replaced by blank space for five seconds, and finally the subject was given a text field and allowed to type in their new sentence using the keyboard. The time constraints on the stimuli capture the limited time and attentional resources in real social processes. However, subjects were given as much time to enter their new sentences as desired to compensate for the unfamiliar nature of the task. The reproduced sentences became the stimulus sentences for the next subject and all messages were transmitted in a simple linear graph with no contact between lineages (i.e., specific sequences of transmission-reception events sharing a seed and experimental conditions). Messages were transmitted until they had been read and retransmitted eleven times by different subjects at which point the software reset to the original seed sentences (i.e., the sentence presented to the first respondent in a lineage). The experiment then repeated with new subjects, allowing us to essentially rewind the clock and produce multiple lineages using the same seed sentences and identical starting conditions. Ultimately, each seed sentence produced ten to eleven lineages (depending on experimental randomization) in comparable starting conditions. We are thus able to observe multiple outcomes of a diffusion process using the exact same starting conditions.

Our experiment crosses a message format manipulation and an error correction manipulation in a two by two design. Message formats with low entropy/high redundancy require more characters to transmit a given idea, but are robust against error because the loss of any particular character has a minimal impact on meaning. High entropy/low redundancy formats use fewer characters to transmit the same idea, but are more vulnerable to errors as a result. Given that standard English is approximately 75% redundant (Shannon 1950), it should be relatively robust against errors and we adopt standard English as our "lower entropy" message format. Recent variants of English such as text messaging pidgin (e.g., "See you later" becomes "C u l8r") use fewer characters to transmit the same information and are therefore less redundant. We use text messaging pidgin as our example of a "higher entropy" message format, both because it fits the definition and because the popularity of this format (Ito, Okabe and Matsuda 2005; Ling

2004), and the growing use of electronic data for diffusion studies (e.g., Lewis et al. 2008; Lewis, Gonzalez and Kaufman 2012; Salathe et al. 2013), makes it interesting in its own right. Two undergraduate research assistants with experience in this method of communication independently converted the English stimulus sentences into text messaging pidgin form and then resolved any disagreements to produce the final sentences. We manipulate message format by presenting the same message either in standard English (i.e., English condition) or in text messaging pidgin (i.e., Text condition), and subjects were instructed to retransmit the sentences in the same format as they were received.

Humans are imperfect relays and therefore will occasionally make mistakes when transmitting or receiving social contagions. Without error correction, a flawed (i.e., mutated) contagion will be retransmitted as-is, and the presence of errors will often be obvious to the next recipient, resulting in corruption over time. When error correction is present, recipients will attempt to reconstruct the original message from what is received. However, repairs will sometimes yield valid (i.e., not obviously flawed) messages whose meaning deviates from the original (loosely analogous to the autocorrect feature on many cellphones). Because the repaired message is valid, the next recipient is unlikely to detect the changes (unless they have information from another source) and will transmit the new mutant, resulting in diversification. In the No Correction condition, human subjects were exposed to a series of ten sentences on a computer terminal and asked to reproduce each sentence exactly as seen. In the Correction condition, subjects were exposed to a series of ten sentences and asked to generate a sentence reproducing the intended meaning of each stimulus sentence rather than the exact text (i.e., paraphrase).

Human subjects were recruited from the student population of a large northeastern university using flyers and an electronic subject pool. All subjects completed the experiment in a laboratory sitting at a prepared computer terminal and were unaware of the study hypotheses or goals. Subjects were not permitted to interact before or during the experiment and all subjects were informed that their compensation depended on the accuracy of their retransmitted sentences. In fact, all subjects were compensated equally but the deception ensured that subjects were engaged in the task and followed the instructions as given.[14] Subjects were randomized into a condition ensuring that between-condition differences cannot be the result of individual variation. No subject was used more than once, ensuring that subject fatigue was not an issue and a total of 490 subjects completed the experiment. All procedures were approved by the IRB and all subjects gave their informed consent.

It should be noted that our experiment represents a sort of "best case" scenario for diffusion. The information to be transmitted is simple and unambiguous, individuals are motivated in all cases to be as accurate as possible, and distractions are kept to a minimum. Thus, our results represent the lower bound on the amount of error likely to creep into diffusing social contagions.

Dependent Variables

[14] Qualitative inspection of the generated messages indicates that those in the no correction condition tended to reproduce messages verbatim, while those in the correction condition engaged in more paraphrasing, as planned.

To analyze message fidelity, we subdivide it into two types: consecutive and evolutionary fidelity (See Figure 1). Consecutive fidelity is the meaning similarity of each child sentence to its parent sentence (i.e., how closely each respondent's output matches their input). Evolutionary fidelity is the meaning similarity of each child sentence to the original seed sentence (i.e., how closely each respondent's output matches the original stimulus). Evolutionary fidelity provides a measure of the *total amount of error* that has crept into the contagion over the course of its diffusion, whereas consecutive fidelity provides a measure of the *rate of mutation* over the course of the diffusion. Evolutionary and consecutive fidelity are different ways of examining the same data, rather than totally separate datasets or different experimental conditions.

Figure 1 about here

Earlier research on the accumulation of errors in diffusion (e.g., Adamic et al. 2014; Leskovec, Backstrom and Kleinberg 2009; Mei and Zhai 2005; Simmons, Adamic and Adar 2011) relied on Levenshtein distance (Levenshtein 1965) or string length. Levenshtein distance quantifies the number of characters that would have to be changed in order to convert one string into another, while string length compares the number of characters in each string, and thus both methods focus on the text of the message, rather than the meaning it conveys. However, humans are capable of recognizing the intended meaning in a message even if many of the message's characters are changed. As a result, Levenshtein distance and string length can easily over- or underestimate the amount of semantic mutation that has occurred. To avoid this problem we measure the semantic fidelity of messages using a set of human coders. All coders were current undergraduate students and native English speakers who were trained by the authors in how to code sentences, but remained blind to the study hypotheses and goals. The coders were instructed to read each sentence pair and provide a rating of how similar the meaning of the sentences were, regardless of spelling errors or grammatical mistakes. Four to five human coders independently read and scored each sentence pair on similarity of meaning from 0 (i.e., different meanings) to 100 (i.e., identical meaning). The presentation of sentence pairs to the coders was random and thus no two coders rated the pairs in the same order. Coders were compensated on an hourly basis, rather than per sentence pair scored, in order to prevent rushed work. Inter-coder reliability was very high (α=0.8601 to 0.9597), indicating that the ratings are consistent. In total, 8,178 transitions (i.e., sentence pairs) were scored a total of 37,490 times.

We use the results of the coding process in two ways. First, we take the mean of the scores for each comparison and use this as our measure of fidelity. Higher means indicate that the coders generally viewed the messages as similar in semantic content, while lower means indicate that the coders viewed the messages as dissimilar. These means allow us to evaluate the impact of message format (Entropy Meaning Hypothesis) and error correction (Error Correction Hypothesis) on fidelity.

Second, we take the standard deviation of both consecutive and evolutionary fidelity (i.e., the means described in the prior paragraph) across lineages that share the same seed and experimental condition (i.e., comparable lineages) as our measure of diversification. We anticipate that error correction will preserve meaning over time, but it should also periodically give rise to a drastically different mutant version. These diversification events are not purely the result of steady accumulation of errors, but occur unpredictably when error corrections are faulty. Therefore, to detect them we examine comparable lineages by finding the dispersion of their fidelity scores after the same number of transmissions. When the standard deviation of consecutive fidelity across comparable lineages is small, each lineage is experiencing roughly similar levels of change at each step (e.g., corruption), while larger standard deviations indicate greater variety in the amount of change at each step (e.g., diversification). Similarly, when the standard deviation of evolutionary fidelity across comparable lineages is small, each lineage is experiencing roughly similar total levels of change over the course of diffusion (e.g., corruption), while larger standard deviations indicate that each lineage is experiencing different total amounts of change over the course of diffusion (e.g., diversification). Thus, in both cases, small standard deviations are consistent with a corruption-like process of gradual decay, while larger standard deviations are consistent with unpredictable and substantial changes in meaning resulting from diversification. If error correction is associated with the production of a wider variety of mutants (Diversification Hypothesis), we should observe more differences between lineages (i.e., larger standard deviations) when error correction is present than when it is absent.

While the mean and the dispersion of the scores are related, these values capture different aspects of the diffusion process. The mean measures the central tendency of the coder scores; for example, if error correction improves fidelity, then the typical message will reflect its progenitor more closely. In contrast, dispersion measures how much each lineage typically varies from comparable others. Thus, error correction can both produce greater mean fidelity, while nevertheless also leading to diversification between lineages.

Independent and Control Variables

Our independent variables are the number of transmissions a message has experienced, as well as a pair of binary variables for our experimental manipulations. “Transmissions” codes the number of times that a message has been read and retransmitted by a distinct human subject, and ranges from one to eleven. “Format” equals one when the English (low entropy) manipulation was used, and zero when the Text (high entropy) manipulation was used. “Correction” equals one when the Error Correction manipulation was used, and zero when the No Correction manipulation was used.

Several interaction effects are also fit. First, we include a squared term for Transmissions to test for the possibility that error accumulation may accelerate, or decelerate, as diffusion progresses. Second, we interact both our Format and Correction variables with the Transmissions variable, to determine if their effects vary over the course of diffusion. Third, we interact Format with Correction to determine if error correction moderates the effect of the message format. Finally, we fit the three-way interaction between format, correction, and the number of transmissions experienced by a message.

Lastly, we include a control for the Levenshtein distance between the messages (i.e., between parent and child for consecutive fidelity, and seed and child for evolutionary fidelity). While semantic content is distinct from changes in the text, sufficiently large changes in the strings will impact their meaning (e.g., enough typos will make it difficult to infer the intended meaning). By including this control, we are able to evaluate the effect of our manipulations on semantic fidelity net of changes in the structure of the messages that carry that meaning. This in turn means that we are studying the impact of error net of the effects identified by previous research (e.g., Simmons, Adamic and Adar 2011). In models examining the standard deviation of fidelity scores across lineages, we control for the standard deviation of the Levenshtein distance across lineages, so as to capture differences in meaning net of the fluctuation in the strings themselves.

Analytic Strategy

We estimate a series of regression models predicting consecutive fidelity, evolutionary fidelity, the dispersion of consecutive fidelity across comparable lineages, and the dispersion of evolutionary fidelity across comparable lineages. Models analyzing dispersion across lineages are adjusted for the clustering of observations on these dispersion scores and all results are presented in Table 1.[15] Given that models containing several interactions are difficult to interpret, we also present, and focus on, a series of marginal plots (i.e., predicted value plots). All marginal plots exhibit a relatively pronounced decline in fidelity with the transition from the seed to the first child sentence, but this simply results from working memory limitations in our subjects.

Experimental Scope

We argue that the diffusion of a social contagion requires the transmission of information from person to person, which we refer to in the preceding with the generic term "messages". This can take the form of verbal or textual communication, or can result from observation of behaviors. This information may be flawed at transmission or reception, as when someone misspeaks or an observer misses an important detail, and that the format in which information is transmitted (i.e., high vs. low entropy) impacts its durability against error. Finally, we argue that when errors occur individual humans may attempt to correct them, essentially adding in words or actions that seem appropriate in the available context. Thus our overall theory applies broadly to transferable, endogenously duplicable social contagions. However, we adopt an experimental design that aligns most closely with the exchange of spoken or written/typed language, and as such our results apply most specifically to this case. Nevertheless, as information must be transferred in some form (i.e., it cannot spread through some form of "social telepathy": see Erbring and Young 1979) we expect that this experiment provides an abstract empirical model for format, error, and error correction processes across a variety of domains. Thus, while readers should be cautious in directly applying our results to non-linguistic areas, we view their implications as extending beyond this limited domain.

Results

How do errors, message format and the use of error correction impact social contagions? Modeling indicates that the number of transmissions a message experiences significantly affects fidelity. Beginning with consecutive fidelity (Table 1, Model 1), the number of transmissions (-1.840, $p<0.001$) reduces fidelity at a decreasing rate (0.155,

[15] We do not present raw results because the complex interactions between experimental conditions and the number of transmissions, as well as the necessity of controlling for Levenshtein distance, make them difficult to interpret.

$p<0.001$); each child sentence resembles its parent less closely than the parent resembles the grandparent, but to a diminishing extent. The main effect of message format is non-significant, but its interaction with number of transmissions is positive and significant (0.659, $p<0.05$), indicating that, consistent with our Entropy Meaning hypothesis, English lineages experience smaller amounts of change over time than the Text lineages. Error correction does dramatically improve consecutive fidelity (8.311, $p<0.001$) but to a diminishing extent as the contagion continues to diffuse (-0.484, $p<0.10$), suggesting that error correction can impede consecutive fidelity in sufficiently lengthy diffusion chains. These findings are consistent with our Error Correction Hypothesis, which predicts that error correction mechanisms will generally preserve semantic content. The three-way interaction between format, error correction and transmissions is also significant (-0.848, $p<0.05$). Finally, Levenshtein distance has a negative effect on consecutive fidelity (-1.089, $p<0.001$), indicating that changes to the characters used in a message tend to degrade its fidelity. Even so, the remaining significant effects confirm that semantic content is substantially independent of the specific characters used to convey it, confirming the usefulness of our approach. Even when the specific characters, or phonemes, in a message are changed, the semantic content may nevertheless be transferred successfully, and our results confirm the need to study the meaningfulness of a message rather than just its entropy.

Table 1 about here

The marginal effects of format and error correction on consecutive fidelity are illustrated in Figure 2, with all control variables set to their means. These values indicate the predicted change in fidelity at a particular transition, rather than total change over the course of the lineage. Messages passed with error correction display consistently high levels of consecutive fidelity throughout the course of the diffusion, though this advantage erodes over time. Early in the diffusion process error correction allows messages to be passed with nearly ninety-five percent accuracy, but this diminishes to a low of roughly eighty-seven percent after eight transmissions before recovering. Text and English messages in the correction condition appear to diverge slightly in their levels of consecutive fidelity, but this difference is not significant. In contrast, the consecutive fidelity of messages passed without error correction remains stable or actually increases over the course of diffusion. Consecutive fidelity without error correction starts at roughly eighty-five percent accuracy, declines to a low of approximately eighty-four percent after six transmissions, and then recovers to a maximum of over ninety percent after eleven transmissions. English without correction increases the most in consecutive fidelity, achieving a maximum of over ninety percent, significantly more than the other conditions. These results suggest that without error correction, a message may rapidly lock-in on a stable, though mutated, form. In contrast, messages passed with error correction tend to diverge more and more substantially from their immediate predecessors the longer they have been diffusing.

Figure 2 about here

The preceding results indicate how message format and error correction impact the rate of mutations, but what are their impacts on the accumulation of errors over time? Modeling indicates that evolutionary fidelity (Table 1, Model 2) decreases linearly with the number of transmissions (-1.365, $p<0.01$); the more often a contagion has been transmitted, the less it will resemble its progenitor. Surprisingly, standard English initially degrades fidelity (-5.471, $p<0.01$) but has a positive interaction with the number of transmissions (1.814, $p<0.001$). The net result is that over the course of diffusion, the redundancy of correct English grammar preserves meaning better than lower entropy alternatives (i.e., text messaging pidgin). This result supports our Entropy Meaning Hypothesis. Error correction has an extremely strong and positive effect on evolutionary fidelity (16.126, $p<0.001$), which supports our Error Correction Hypothesis. Message format and error correction do not interact, but the three-way interaction between format, correction, and transmissions is marginally significant (-0.813, $p<0.10$). Finally, Levenshtein distance is negatively related to evolutionary fidelity (-1.191, $p<0.001$), confirming that while character changes degrade semantic fidelity, they are not equivalent to semantic fidelity.

The marginal effects of format and error correction on evolutionary fidelity are illustrated in Figure 3, with all control variables set to their means. The most striking finding is that messages in standard English that are transmitted with error correction exhibit very little mutation over the course of diffusion. Indeed, the predicted loss of fidelity over eleven transmissions is less than five percent, though a substantial loss of fidelity is incurred at the first transmission. This indicates that, on average, messages transmitted in lower entropy formats with error correction arrive at a distant node with very similar meaning as when they departed. However, error correction does not provide the same benefits for messages passed in higher entropy formats, with fidelity declining from a bit under seventy percent to only a bit over fifty percent. Thus, the success of error correction appears to rely to some extent on higher redundancy message formats that provide more of a basis for human inference. Lower entropy message formats (i.e., standard English) diffusing without error correction show relatively stable levels of fidelity, hovering around fifty percent, while higher entropy formats (i.e., text messaging pidgin) show a linear decline in fidelity from a bit over fifty percent to somewhat less than forty percent. This is particularly interesting as the subjects in our study, college students, should be experienced with, and proficient at, using text messaging pidgin. Nevertheless, it still shows a more pronounced decline in fidelity than standard English. On the whole, these results are consistent with both our Entropy Meaning Hypothesis and our Error Correction Hypothesis: lower entropy formats and error correction both provide advantages for preserving meaning. At the same time, error correction works best when combined with lower entropy message formats, and is less effective otherwise. In order for humans to successfully infer the meaning of a message, they must have access to information on which to base such inferences. When higher entropy message formats deny this information, the inferences tend to be less effective, even when the population is comfortable with these formats.

Figure 3 about here

We now turn to analysis of the dispersion of fidelity scores across comparable lineages, enabling us to test our Diversification Hypothesis. The cross-lineage standard deviation of the consecutive fidelity scores (Table 1, Model 3) is not significantly related to the number of transmissions or to the square of the number of transmissions. Lower entropy formats (i.e., English) have no obvious effect, but error correction reduces the standard deviation of coder scores (-4.319, $p<0.05$), contrary to our Diversification Hypothesis. However, the three-way interaction between format, correction, and transmissions is significant (1.452, $p<0.01$), suggesting that over several transmissions likelihood of diversification may be growing. Finally, the Levenshtein distance is positively related to the dispersion of coder scores (0.870, $p<0.001$); unsurprisingly, the greater the difference in the strings, the less similar the semantic similarity of those strings.

The marginal effects of format and error correction on the cross-lineage dispersion of consecutive fidelity are illustrated in Figure 4, with all control variables set to their means. This again is dealing with the change at each step, rather than the total change over the entire diffusion chain. Text messages transmitted with correction, as well as both types of messages transmitted without correction, show gradual decreases in cross-lineage consecutive dispersion. This indicates that in these conditions, the amount of change from parent to child in one lineage grows more similar to the change in a comparable lineage as the length of the diffusion chain increases. In contrast, English sentences transmitted with error correction show the opposite trend, with initially small differences across lineages that increase over the diffusion chain. This is consistent with our Diversification Hypothesis and suggests that in the English-Correction condition there is an increasing tendency to generate new, and very different, mutant forms of a social contagion with each new transmission.

Figure 4 about here

Finally, the standard deviation of the cross-lineage evolutionary fidelity scores (Table 1, Model 4) increases with the number of transmissions (1.070, $p<0.05$) at a decreasing rate (-0.104, $p<0.01$). Thus, there is less cross-lineage consensus over the similarity between a descendant contagion and its original progenitor the longer that contagion has been diffusing. Message format and error correction have no significant main effects, but have a strongly negative interaction (-8.744, $p<0.001$), suggesting that English sentences transmitted with error correction tend to produce very similar levels of change over the course of diffusion. However, the three-way interaction between format, correction, and transmissions is significant and positive (1.182, $p<0.01$), suggesting that the picture is more complex. Finally, the Levenshtein distance is once more positively associated with the dispersion in evolutionary fidelity (0.639, $p<0.001$). This once more confirms that the semantic content of a message is distinct from the code used to convey it.

The marginal effects of format and error correction on the cross-lineage dispersion of evolutionary fidelity are illustrated in Figure 5, with all control variables set to their means. The predictions are, in general, similar to Figure 4. Text messages transmitted with correction, and text and English messages transmitted without correction, show similar trends in cross-lineage dispersion in evolutionary fidelity across the diffusion chain. However, English messages transmitted with correction both exhibit very low levels of cross-lineage dispersion initially, and increase substantially over the diffusion chain. Thus, while error correction benefits English messages initially, over the course of diffusion it produces more widely varying descendant messages than do the other conditions. By eleven transmissions, English lineages with correction differ from each other significantly more than any other type except for text lineages with correction. In other words, after lengthy diffusion chains, the presence of error correction actually produces more variability in the meaning of a message rather than less. This is consistent with our Diversification Hypothesis and shows that while correction improves the average fidelity of a message, it also produces more widely varying mutants.

Figure 5 about here

In total, the preceding results provide partial support for the Entropy Meaning hypothesis, but stronger support for both our Error Correction and Diversification Hypotheses. Higher entropy messages and error correction consistently improve fidelity, while simultaneously giving rise to diversified mutant versions.

For robustness, we also estimated a series of models predicting the standard deviation of the coder scores within each lineage for each comparison. Larger standard deviations indicate less agreement among coders, while smaller standard deviations indicate more agreement. Evaluating the meaning similarity of diversified mutants ought to be more difficult, and thus will give rise to more disagreement among the coders than simple corruption. Therefore, if error correction is associated with the production of a wider variety of mutants (Diversification Hypothesis), we should observe increasing dispersion in the coder scores over the course of the diffusion when error correction is present. The results (omitted to save space, but available on request) are consistent with our hypotheses, and confirm that while error correction preserves the meaning of a message over time, it also increases the likelihood that very different descendant messages will be produced. Both across lineages, and within a single lineage, our results show that diversification can and does occur.

Discussion

We examined the impact of message format and error correction on both the preservation of meaning and the diversification of a single social contagion into multiple contagions. We found that lower entropy formats like English are better at preserving meaning than higher entropy alternatives like text messaging pidgin. This implies that part of the reason why Human languages, such as English, are redundant (e.g., English is roughly 75% redundant; Shannon 1950) is that this redundancy allows communication to occur in the midst of error and noise. However, new communications technologies including cellular phones and email are making higher entropy formats like text messaging pidgin more common. The consequence may be that social contagions that spread through this medium will be more vulnerable to mutation than contagions that spread through face-to-face contact. These weaknesses are likely to remain even when copy-and-paste functionality is available, as humans will not always make use of it, and may insert or delete content at their discretion. This suggests that studies of contagion that make use of electronic or online data (e.g., Aral and Walker 2012) should consider the potential impact of error on their models.

Humans are self-aware entities and are often capable of detecting, and repairing, errors in contagions. This error correction has a substantial positive impact on the similarity of a contagion to its immediate predecessor (consecutive fidelity) and to its original progenitor (evolutionary fidelity). Remarkably, when paired with a lower entropy message format, error correction was able to keep the evolutionary fidelity of a contagion stable over a fairly lengthy diffusion chain, suggesting that humans are quite adept at spreading social contagions when using conventional formats (e.g., standard English). At the same time, the effectiveness of error correction is greatly reduced when the message format is higher entropy. By eleven transmissions, high entropy social contagions transmitted with error correction have preserved roughly the same amount of fidelity as lower entropy formats without error correction. This implies again that social contagions moving through electronic networks may experience greater amounts of mutation than we might otherwise expect, even if humans are attempting to correct errors.

Error correction improves the fidelity of social contagions, but also results in the diversification of messages and the concealment of such mutations. The downstream messages resulting from error correction generally cluster around the original meaning, but nevertheless spread out as failed repairs produce ever more distinct variants. For example, in one lineage a seed sentence, "During the session on service, the group discussed the differences between philanthropy and volunteering," ultimately diversified into, "During group service, members of the group found that they are not that close to each other." In a comparable lineage, the same seed transformed into, "During the debate the philosophers discussed the difference between philanthropy and volunteering." Despite the effectiveness of error correction at protecting social contagions from corruption, it nevertheless introduces the likelihood of diversification. Message mutation has been viewed as self-serving "distortion" (e.g., Athanassiades 1973; Gaines 1980; Lee, Padmanabhan, and Wang 1997), but our results suggest that good faith efforts to preserve meaning can have the opposite effect. While distortion is doubtless a real phenomenon, the efforts of individuals to pass on messages as accurately as possible can still result in substantial mutation in a social contagion.

Our observation of diversification suggests that the diffusion of information over real world social networks will result in a proliferation of messages, preventing any one message from saturating the network. This is particularly the case given that we observed substantial diversification even in our linear graphs, where the messages were simple and distractions kept to a minimum. Real social networks offer more complex paths and thereby more opportunities for error corrections to exert an effect, and are usually active in more cluttered and noisy environments. As a result, even connected social network graphs can contain substantial diversity, and our results likely represent the lower bound for this phenomenon. This helps to explain how diversity can be maintained even in the face of pressure to reach conformity (e.g., Friedkin and Johnsen 2011); the tendency for contagions to diversify prolongs the time required for a network to reach consensus. Yet, diversification likely also plays a role in generating diversity in the first place. Because contagions can be radically altered by failed repairs, they can inadvertently transform into new ideas, beliefs, or behaviors that may then spread on their own. Diversification thus represents an important engine for the generation of new social contagions and shows how innovation can result from attempts at imitation.

While most research on contagions has artificially designed out the potential for error (e.g., Centola 2010, 2011), our results suggest that error and mutation are important social processes that can have significant impacts on diffusion. The practical reachability in many social networks is lower than we might expect because diversification impedes effective communication; the message that arrives at one side of the network can be quite different from the message that departed from the other. Identification of the critical driver nodes for control of a social network (Liu, Slotine and Barabasi 2011) will also be complicated if error correction diversifies the control signals. The clear implication is that processes occurring on social networks cannot be accurately modeled unless the behavior, and limitations, of the human components are understood. Likewise, it is clear that message format cannot be ignored as the medium helps to shape the message as it diffuses.

Our experiment focused on textual contagions and our results are most directly relevant to linguistic diffusion. Yet, the implications of this work are more far reaching. The spread of behaviors and technologies, even if these can be reproduced in exactly the same format (e.g., purchase of an identical product), requires the spread of knowledge about the existence of the product and its characteristics. This secondary information is crucial to the way that behaviors and technologies are used and are subject to error and error correction even if the entities they are associated with are not. As such, while our results apply narrowly, our theory has the potential be to relevant to a wide variety of social contagions of interest to researchers.

Beyond their relevance to the study of diffusion, our results have significant implications for our understanding of social networks more generally. Networks have often been viewed as "pipes," through which information and resources flow, or as "prisms," that alter the perceptions of observers (Podolny 2001). Our work suggests that networks should also be regarded as "processors," or structures that alter the information and resources that flow through them. By making mistakes and engaging in error correction the human nodes in social networks fundamentally impact the nature of the contagions that they spread. At a minimum, as we have shown, this can diversify a contagion into new forms. However, errors can be unintended and yet still be non-random. Individuals who expect to receive certain messages, either due to priming or their ideology, may tend to correct errors so that messages conform to their expectations. If such biases are not randomly distributed throughout a graph, then the information and practices available in different portions of a network may vary systematically. Moreover, if the network is relatively centralized, the biases of the central actors may broadly influence the content of the network. Different network structures can therefore interact with the tendencies of human nodes to systematically alter the information that flows through them, even without conscious intent.

We evaluated only linear networks because these provide a necessary baseline against which to judge more complex effects, but in most natural contexts information will not be spreading through isolated, separated linear graphs. In more natural networks individuals will often have associates in common, and therefore individuals may receive multiple examples of a contagion, which may allow them to identify, and correct, diversified variants of a message. However, contagions that traversed different paths will diversify in distinct ways. The ability of recipients to recognize two diversified messages as having a common ancestor will depend to a significant extent on their relative levels of diversification; two heavily diversified variants are likely to be interpreted as distinct contagions. If the two versions are recognized as variants, individual responses will likely vary depending on how distinct the variants are. Relatively small distinctions between mutants will likely result in attempts to combine the messages. These efforts may be successful, but also may produce another mutant form as the attempted error correction will not invariably succeed. Alternatively, if the distinction between the mutants is great, individuals may adopt an either/or strategy and simply disregard the mutant they believe to be flawed. This suggests that nodes within the same cluster should harbor similar message variants, while nodes in different clusters, particularly when the clusters are widely separated, should not. Alternatively, a network with minimal clustering (e.g., a random network) should exhibit a great number of variants as it will be uncommon to receive multiple versions that have diversified to a similar extent, and thus each variant will often be treated as a distinct message. Finally, the characteristics of the sending/receiving nodes are likely to be of critical importance. Variants received from high status or prestige nodes may be less likely to be questioned, regardless of their apparent quality, then variants received from low status or prestige nodes.

Second, in natural social networks it is sometimes (but not invariably) possible for individuals to request clarification, which could greatly reduce the error rate. However, it is an open empirical question how often individuals attempt to clarify an apparently garbled message. Asking for clarification will often require more time and effort than simply applying an error correction and, given the relatively strong performance of error correction in our results, error correction will often be sufficient. As a result, satisficing may often lead individuals to prefer error correction to requesting clarification even when they have the ability and need. Moreover, differences in status and authority may often prevent such attempts. A subordinate or lower status individual may fear antagonizing a superordinate or higher prestige individual by requesting clarification, or may fear the loss of face stemming from their failure to understand in the first place. Alternatively, higher status or prestige individuals may refuse to provide clarification to those of lower prestige or status. Thus, even though it is technically possible to clarify a garbled message, social actors may lack the motivation to do so. In any event, asking for a message to be repeated will slow the spread of a social contagion. Finally, asking for clarification requires that the individual recognize the error in the first place, meaning that corruption will be reduced without necessarily impeding diversification. As such, we expect bi-directional ties to be used only infrequently for error reduction, and that their usage will be conditioned on the distribution of status within the network.

Third, the trustworthiness of contagions is likely determined to some extent by the prestige or status of the person from whom the contagion is received. Thus, even if having multiple copies in general reduces diversification, obtaining multiple copies in the presence of a prestige hierarchy may lead to a consistent bias in error correction. In other words, copies of a contagion received from a high status other are more likely to be accepted, or preferred, than copies received from a low status other. Such an effect would be magnified if high prestige others tend to be more central in communications networks, as seems likely (e.g., de Sola Pool and Kochen 1978). In this case messages received by network members will often have passed through a central, high prestige actor even if they did not originate there, and as a result the error correction behavior of these individuals will have a disproportionate impact on the network as a whole. Thus we might expect networks that are relatively centralized, and in which central actors are high in prestige, will also exhibit relatively uniform distributions of variants deriving from these central actors.

Fourth, some mutants may be more appealing (for whatever reason) than, and thereby enjoy a competitive advantage over, the original message, and will therefore tend to spread even when more accurate versions are available (e.g., Nyhan and Reifler 2010). Put differently, humans are not disinterested observers, but come to information with existing biases and understandings of the world. As a result, networks that are relatively homogeneous in their contents to begin with are likely to suppress variants relative to networks that are more diverse, as error corrections will tend to follow similar paths.

For all of the above it should be borne in mind that information processing is costly (Turner 1976), and therefore even if multiple versions of a contagion are available for comparison, individuals may not choose to use them all to attempt a correction. In other words, humans are satisficers and may choose a variant to accept arbitrarily in many cases rather than carry out the extensive comparison processes we describe above, or may allow their error correction efforts to be heavily shaped by their preconceptions. Thus researchers should be cautious of adopting a view of humans in natural environments as informational detectives cautiously searching through every clue. We are likely to find that most humans engage in quick, heuristic driven error correction because it is frequently easy and accurate, and as a result generate unanticipated and undetected diversification.

Conclusion

We set out to evaluate how message format, error, and error correction impact social contagion and diffusion. Our results indicate that redundant communication formats are important for preserving the content of social contagions, that error correction helps to counteract the corruption of social contagions, and that error correction produces diversification. The implications are that the diffusion of social contagions cannot be understood without a better understanding of how the human "relays" in a network actually process and manipulate the information that they are passing on.

We believe that future empirical study of more complex networks along the lines described above is advisable, though researchers embarking on such a project should keep the logistical difficulties in mind. Our simple linear networks generated over eight thousand sentence pairs and more than thirty-seven thousand ratings. Moving to a similar design where each respondent receives two stimulus sentences would essentially double the number of sentence pairs to be rated, and more complex designs will increase the size and complexity of the data still further. Research in this area can thus be time-consuming and potentially expensive, even with access to crowd sourcing services (e.g., Amazon Mechanical Turk or the Zooniverse), and researchers must be prepared for such challenges.[16] At a minimum we strongly recommend that researchers carefully plan their experiments as the data are non-trivial to generate and code.

We also believe future research should consider employing simulation models to study the system-level implications of these processes. Simulations represent an economical way to explore the impact of different network configurations on corruption and diversification. At the same time, the amount of data and coding generated by this type of research is quite large, and it is unclear how to adequately simulate human attention to meaning and meaning-based error correction. Regardless of how these issues are addressed, we do not believe that such models will be useful until additional experimental work shows how individuals deal with multiple copies of a contagion. Without an empirical understanding of this process, any simulation model will be fatally dependent on the assumptions built into its operation, which may or may not reflect reality with any level of fidelity.

Ultimately, our research shows that mistakes, errors, and attempts to correct those errors can play a significant role in the diffusion of social contagions. The bad news is that by omitting errors and error correction from consideration, existing models of diffusion have likely drawn unreliable conclusions. However, the good news is that such deficiencies can be remedied, and in so doing we will gain a better understanding of an important, and currently unstudied, source of novelty.

[16] We suspect that these logistical difficulties account for the relative lack of earlier, similar work in this area.

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Table 1- Models of consecutive ratings, evolutionary ratings, cross-lineage SD of consecutive ratings, and cross-lineage SD of evolutionary ratings

Model Number:	1	2	3	4
DV:	Consecutive Rating	Evolutionary Rating	Consecutive Lineage SD	Evolutionary Lineage SD
Transmissions	-1.840***	-1.365**	0.174	1.070*
	(0.356)	(0.471)	(0.569)	(0.417)
Format (English=1)	-2.129	-5.471**	-2.401	-1.778
	(1.371)	(1.846)	(2.018)	(1.895)
Correction	8.311***	16.126***	-4.319*	1.028
	(1.342)	(1.806)	(2.094)	(1.466)
Transmissions^2	0.155***	0.003	-0.039	-0.104**
	(0.028)	(0.037)	(0.045)	(0.033)
Format x Transmissions	0.659*	1.814***	-0.311	-0.284
	(0.282)	(0.379)	(0.421)	(0.373)
Correction x Transmissions	-0.484~	-0.059	-0.298	0.262
	(0.253)	(0.340)	(0.408)	(0.285)
Format x Correction	2.460	-0.166	-4.488	-8.744***
	(1.819)	(2.447)	(2.918)	(2.337)
Format x Correction x Transmissions	-0.848*	-0.813~	1.452**	1.182**
	(0.335)	(.451)	(0.528)	(0.428)
Levenshtein Distance	-1.089***	-1.191***	0.870***	0.639***
	(0.016)	(0.019)	(0.067)	(0.087)
Constant	99.273***	100.726***	12.545***	13.849***
	(1.185)	(1.558)	(1.775)	(1.636)
Observations	4089	4089	4089	4089
R-squared	0.551	0.578	0.348	0.207

*** p<0.001, ** p<0.01, * p<0.05, ~ p<0.10. Standard errors in parentheses.

Figure 1: Consecutive Fidelity (Panel A) and Evolutionary Fidelity (Panel B). Solid arrows are network ties through which sentences are transmitted. Dashed arcs are parent-child (Panel A) and seed-child (Panel B) comparisons scored by coders to produce fidelity measures. All sentence pairs (i.e., dashed arcs) were rated by 4-5 independent coders.

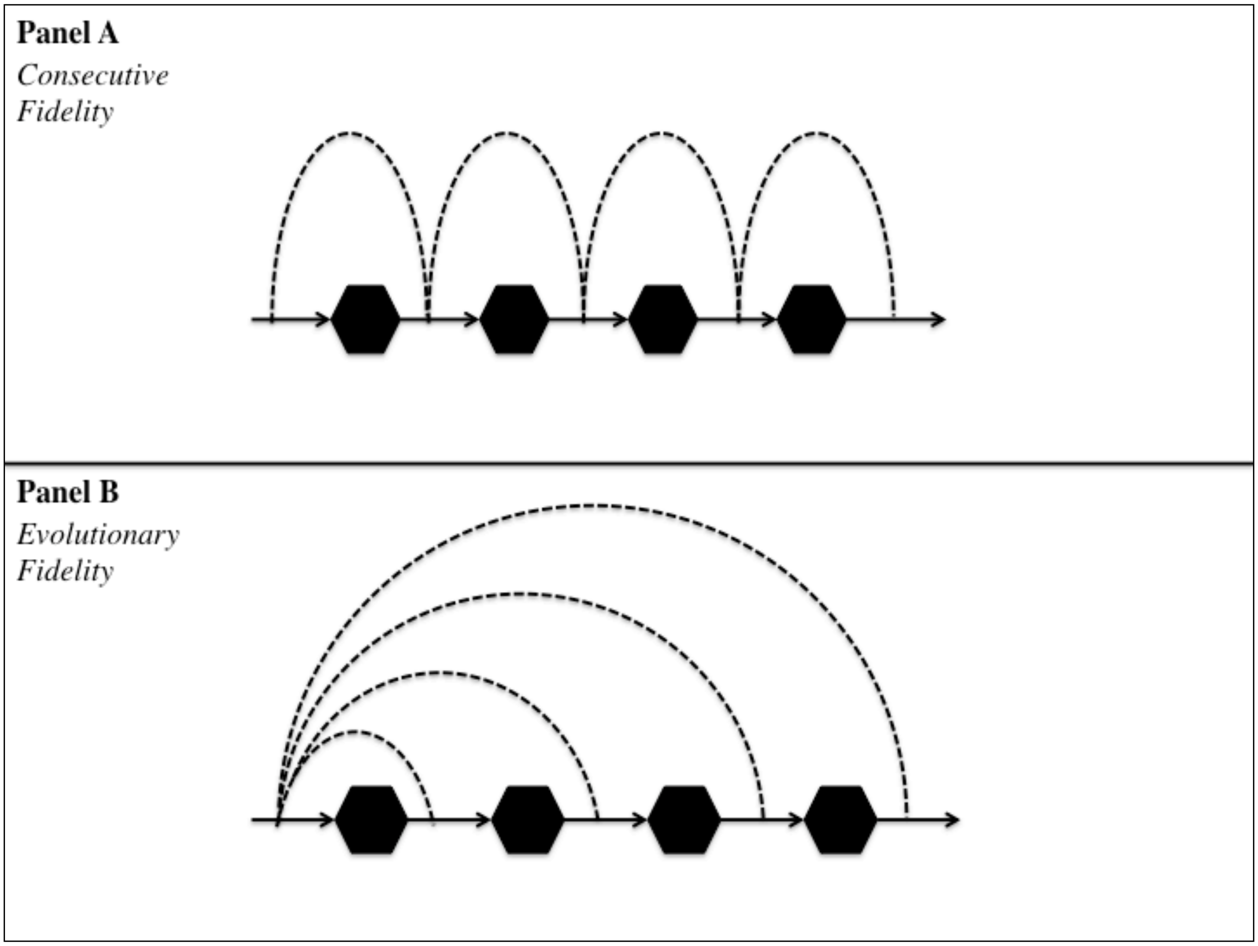


Figure 2: Marginal plot of number of transmissions, error correction and message format on consecutive fidelity.

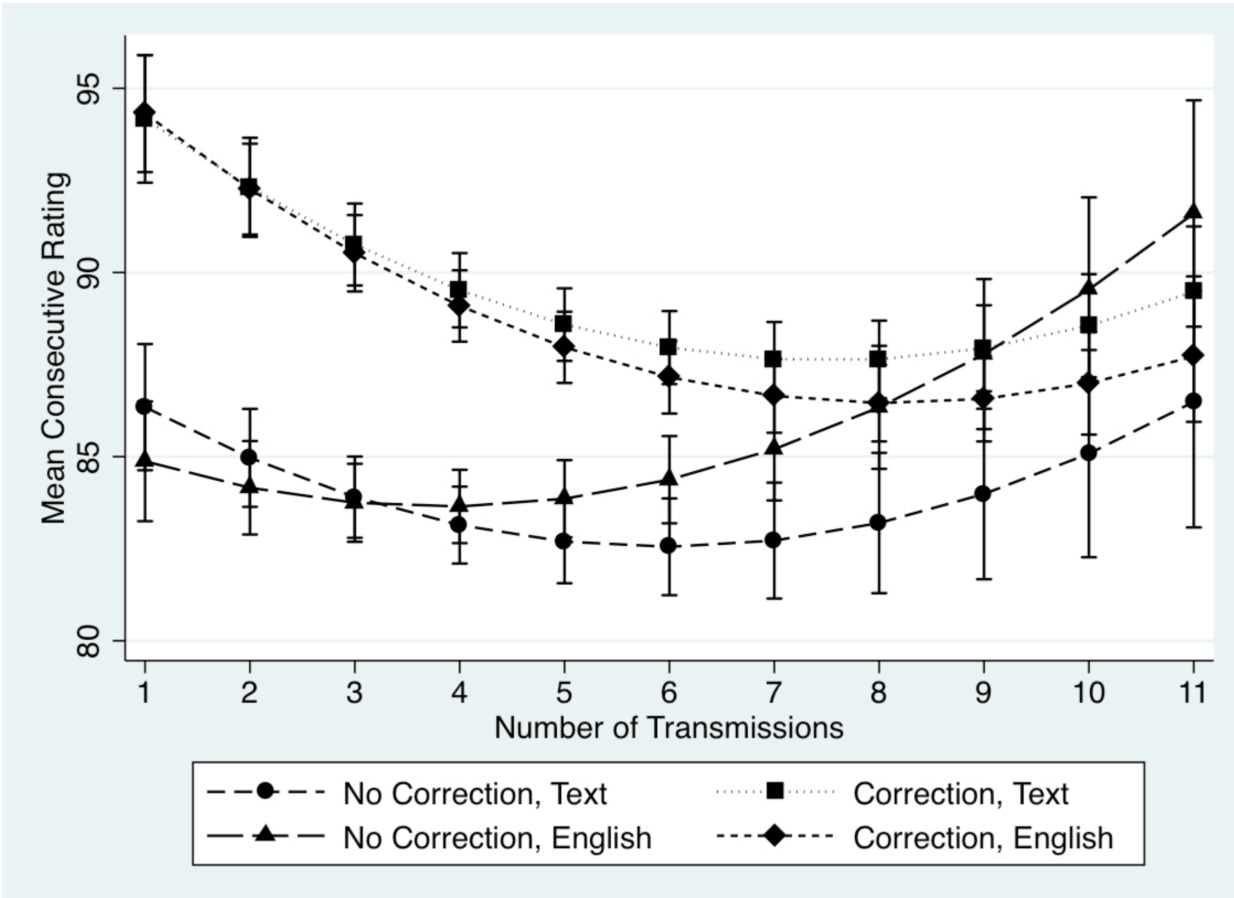


Figure 3: Marginal plot of number of transmissions, error correction and message format on evolutionary fidelity.

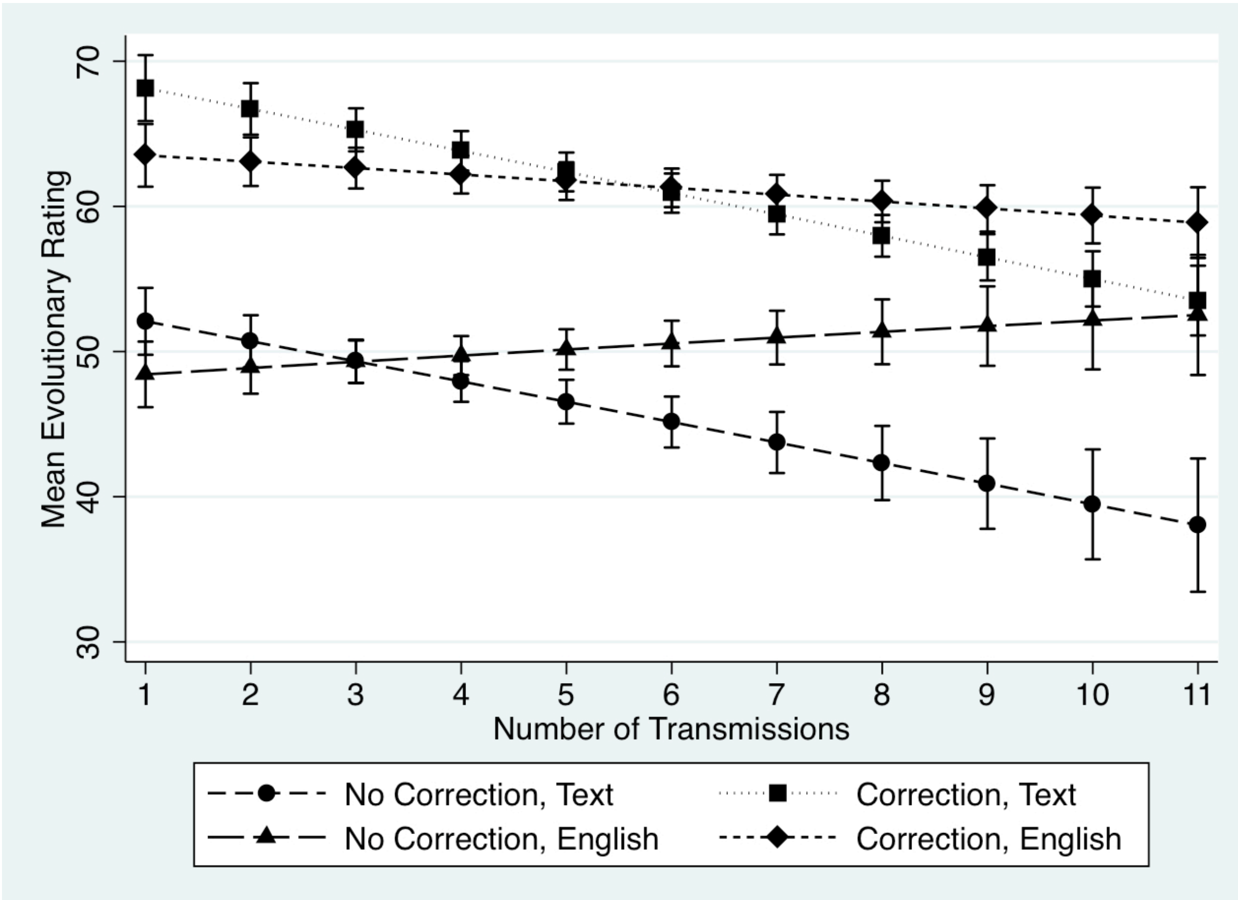


Figure 4: Marginal plot of number of transmissions, error correction and message format on the cross-lineage standard deviation of consecutive fidelity scores.

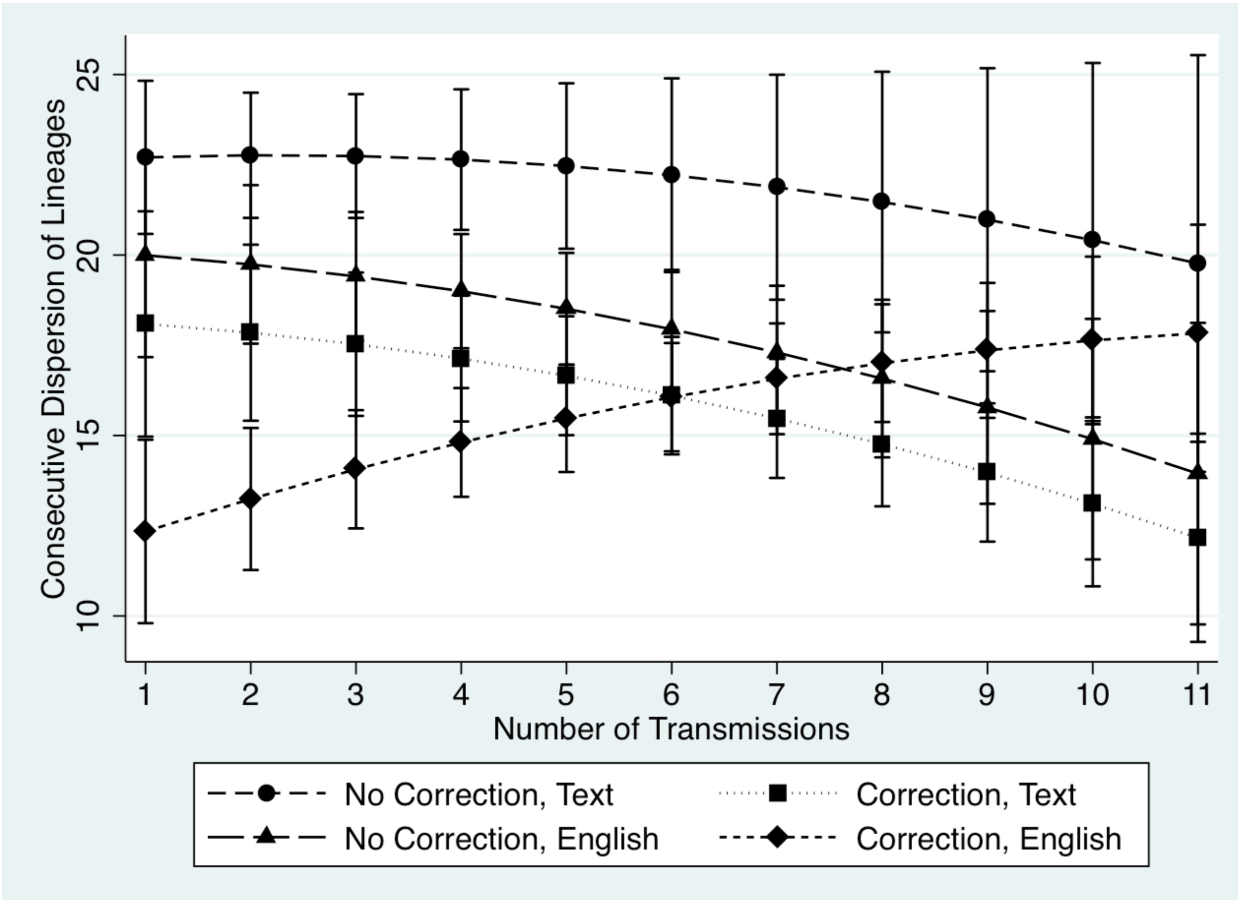
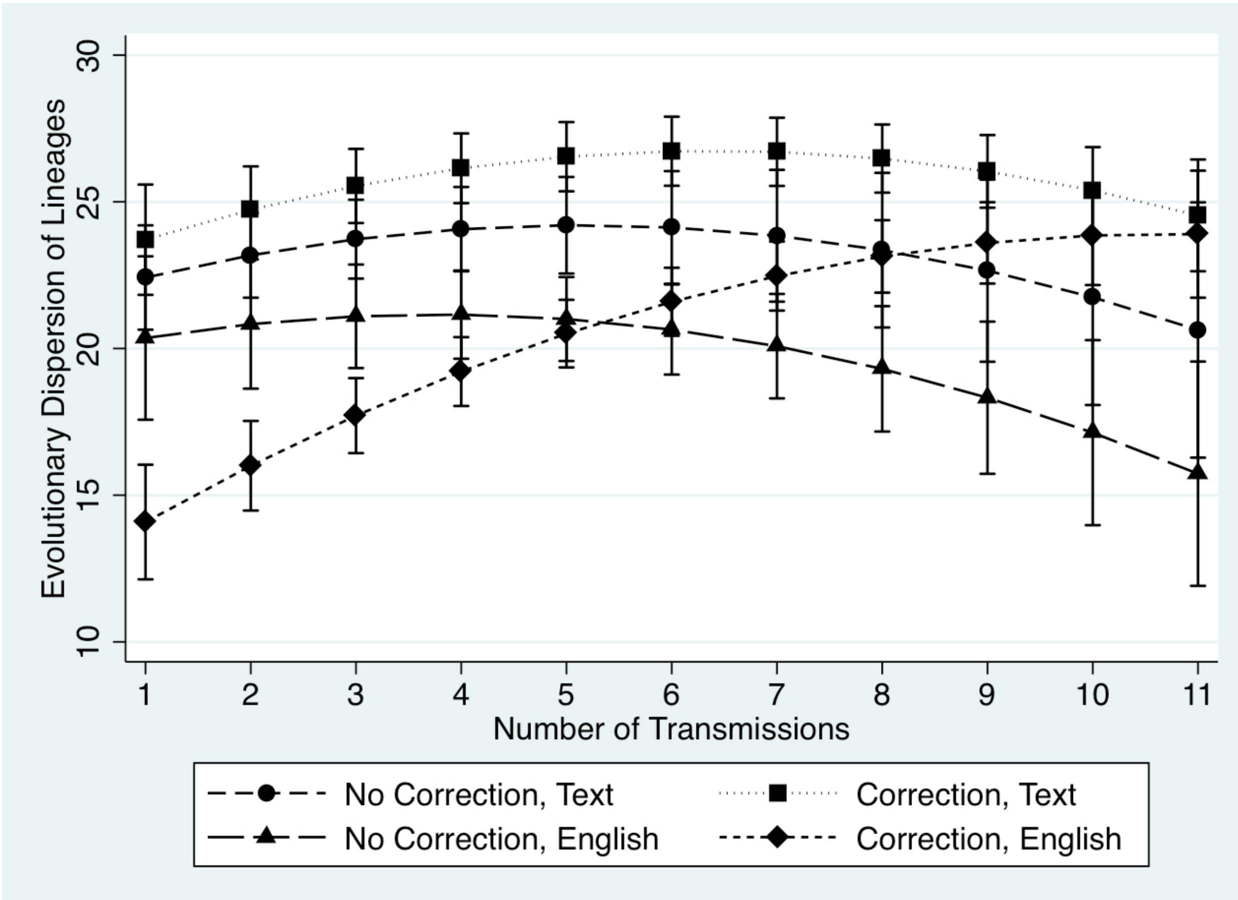


Figure 5: Marginal plot of number of transmissions, error correction and message format on the cross-lineage standard deviation of evolutionary fidelity scores.



Appendix B

Innovation from Imitation: Error in Diffusion Processes
Eric Gladstone
B-Exam, Dissertation
July 28th, 2015

Special Committee:

Kathleen M. O'Connor (Chair)
James R. Detert
Matthew E. Brashears

Abstract

Humans are cognitively limited and make errors, yet the modeling of diffusions through social networks assume they do not. Results across 3 studies suggest that 1) the format of the communication impacts the process of error accumulation, 2) the presence of human beings attempting to correct flawed communications generates mutant forms of the original contagion, and 3) the nature of the network structure itself impacts the process of error accumulation. These findings indicate that the ability of real world diffusions to fully cross and saturate a given network is likely over-estimated. Further, the process of error accumulation during diffusion events can generate competing forms of the original contagion. Last, particular attention should be paid to the very nature of the structure through which a given contagion is spreading.

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Table of Contents:

1: Background and Introduction

Before continuing to the background and introduction, it is important to give credit where credit is due. This research program—the examination of error accumulation in network diffusions—is an ongoing collaboration between myself and Dr. Matthew E. Brashears (Department of Sociology, the University of South Carolina). As such, the general theory and ideas are the products of collaboration. Study 1 of this dissertation is a joint endeavor, with the resulting paper about to go to press. Studies 2 and 3, while drawing on the same shared background theory and logic, work to extend our understanding of error in diffusion by considering new means of data collection, and new network structures. Studies 2 and 3 were conceived, conducted and analyzed by the author.

The network paradigm is increasingly prevalent within studies of management, organizations, and social movements (Borgatti & Foster, 2003). A substantial subset of that work examines network contagions[17], or the tendency for ideas, beliefs, and behaviors to spread through and between networks, both organizational and human social networks (e.g., Centola 2010, 2011; Coleman, Katz and Menzel 1966; Montanari and Saberi 2010; Rogers 2003; Wang and Soule 2012). Models of diffusion have been used to explain organizational performance and innovation from patent production, new policy adoption, and culture (Ilinitch, D'Aveni, & Lewin, 1996; Kale et al, 2000; Kogut, 2000; Oliver, 2001; Powell et al., 1996) as well as information and knowledge sharing (Kogut, 2000; Oliver, 2001; Powell et al., 1996). Common to all of these studies is a focus on information transfer between two entities.

For dyadic contagion to occur, one party must receive information (e.g., via communiques and behavioral observation) pertinent to the idea or behavior in question. To show that behavior or belief to another, one party must then transfer this information to the target (again, for instance, via behavioral demonstration, communique). At any of these points, errors can occur; individuals can misunderstand each other due to human cognitive limitations or they can misinterpret the information they receive. Despite the likelihood of these errors, existing research treats the "nodes" in social networks—the individuals—as perfect relays rather than as fallible people (Travers & Milgram, 1969; Lundberg, 1975; Wattds, Dodds, & Newman, 2002; Christakis & Fowler, 2007; Lewis, Gonzalez, & Kaufman, 2012; Carley, 1991; Centola & Macy, 2007; Barash, Cameron, & Macy, 2012; Rodriguez, 2014), leaving many key questions unanswered.

Indeed, theoretical and empirical research in social psychology, behavioral economics, cognitive psychology, evolutionary psychology, management science, and neuroscience indicates that the core assumption of contagion models—the perfect relay of information between actors in a network—is nigh impossible (Frank, 1988; 1996). It was Simon (1947) who first set forth a model of bounded rationality wherein human beings are considered not as perfect information processors but as cognitive misers and cognitive optimizers. In short, bounded rationality rests on the assumption that non-trivial human constraints exist regarding the reception, storage, retrieval, and transmission of information. Individuals, in large part due to their limited cognitive abilities, operate largely on heuristics where quick and dirty computations are the norm. Continued research on bounded rationality has taken many forms, and includes work on cognitive biases and decision heuristics (Tversky & Kahneman, 1972), as well as the

[17] The term "contagion" can refer either to a thing that spreads between individuals, or to the process of spread itself. Diffusion, more generally, refers to the overall process.

emotional biases that can distort cognitive processes (for a review, see Angle, Connelly, Waples, & Kilgyte, 2011). As Jones (1999) notes, there is no longer any "doubt about the weight of the scientific evidence" (p. 38) concerning human rationality: the general expected rationality model once utilized by psychology, economics, and organization studies is not supported in the lab or in the field. From the lab, he notes, "comes failure after failure" (p. 31) when rational behavior models are put to the test. In organizational settings, too, results appear no more promising, as there is "scant to zero" (p. 32) evidence that employees or managers behave in line with classical rationality models.

To understand how the idea of bounded rationality impacts the transmission and reception of information—thus significantly impacting diffusion events—one need look no further than the children's game of telephone. In this game, composed of a simple linear graph, the first child is given a message to whisper into the ear of another child. This child, in turn, must repeat that same message to the child next to her. This process continues until the end of the graph has been reached—and the message is often far different than its original form. The source of this corruption stems from the requirements of perfect relay fidelity and the limits of the human mind[18]. In this case, the first child must encode the original message, retrieve it accurately, and communicate it with zero phonetic error to the next child. Further, this must all be done while the exterior environment presents various processes vying for the cognitive attention of the child (random noise, conversations by others, etc.). The next child, then, must also function in an identical manner if she is to perfectly encode the message, retrieve it, and pass it along. Indeed, in their seminal work on the process of communication, Shannon and Weaver (1948) imply that perfect information transmission requires a sender with one hundred percent fidelity, a medium or message format that does not allow for corruption, a receiver who perfectly encodes the message with no distortion, and an environment that does not interfere in any way with the transmission process. These conditions are difficult to meet, and as the simple game above suggests, even the simplest contagion process is easily corrupted. One can imagine how, in a real-world setting, a message sender can be distracted or biased or the message format does not convey perfect information (email, for example, lacks all visual and vocal components of normal face-to-face interaction) or the receiver suffers from the same problems as the sender or the environment contains distraction.

2: Objectives

The goal of this research is to account for the human element present in diffusion and contagion processes. Put differently, this work investigates how human limitations in perfectly receiving and transmitting information result in the accumulation of error throughout the contagion process. For theoretical and methodological reasons, previous research has assumed no possibility of error in contagion processes (Milgram, 1961; Centola, 2010; 2011). In contrast, this work extends existing work on diffusion by placing error at the forefront. In short, it is asserted that bounded rationality and the error it generates during diffusion events are inherent in diffusion processes and carry significant and predictable consequences for network theory.

In addition to attempting to understand and quantify the process and consequences of error accumulation during contagion events, this project also examines

[18] Children also likely exaggerate errors for comedic effect.

other factors that interact with the basic process of error accumulation. First, this project explores the impact that message format has on predicting diffusion events. Despite the likely important role that format plays in diffusion events, it has not been studied in the context of network contagions.

A number of researchers interested in contagion processes have called for greater theoretical and empirical attention to be given to the process of error accumulation—from the "Originator of Information Theory" Shannon, (1948), to more contemporary researchers such as Rodgers (2002), and Strang and Meyer (1998). Yet, their calls have largely have been ignored. The current work heeds that call by examining how the accumulation of error throughout a diffusion event differs when that source material is formatted as Standard English, or as Internet Pidgin/Text messaging pidgin. These comparisons are especially pertinent given the increasingly prevalent use of abbreviated English (Internet/Text pidgin) in both the workplace (Smith & Jones, 2013; Jones & Barbosa, 2012), and in general everyday life (Donnel, 2011; Annara & Walker, 2004).

A second goal stems directly from the first--the quantification of error produced during organizational and social contagions as it results from human cognitive limitations. While actors are cognitively limited in their ability to accurately send and receive communications, they are nonetheless capable of restructuring and adding meaning to garbled and corrupt communications. Indeed, individuals and organizations look for meaning in the world around them--from behaviors to speech to written text (i.e., Blumer's symbolic interactionism, 1962; 1971; 1973; Weick's organizational sense-making, 1995; Salancik & Pfeffer, 1978). Given this tendency, it is likely that individuals will construct meaning in flawed communications.

However, as noted by Shannon, "it is not in general possible to reconstruct the original message or the transmitted signal with *certainty* by any operation on the received signal, [emphasis original]" (Shannon 1948: 398). In other words, absent additional information, an attempt to correct errors detected in a message, only may be partially successful. That is, the repair has only altered the original communication into something similar, but different. Similar, but different is key—the repair has effectively masked the mutation such that a receiver would have no idea the message was flawed to begin with. This process then, in theory, continues for the next message recipient, and so on and so forth. Thus, the interaction of cognitive limitations in the process of receiving and transmitting information coupled with individuals' tendency to actively look for meaning and pass along meaningful communications may very well generate new forms of the original contagion.

As is elaborated further in this dissertation, and as initial collaborative work with coauthor Matthew E. Brashears demonstrates, when individuals are unaware of the original contagion, and thus cannot compare it to the version they are currently seeing, they are unlikely to recognize that they are viewing a mutant form[19]. Unaware, they will pass along the new version and it will roam about the network where it competes with the original form of the contagion for peoples' attention and interest. Indeed, the idea that diffusion events can change over time was touched upon by Rodgers when he discussed the concept of reinvention (2012). While Rodger's theory understands reinvention to be a

[19] The presence of slight, but not drastic errors in the communique could alert the receiver that they are viewing a potentially mutated form of the original contagion.

purposeful act wherein the received information is "changed or modified by the…" (p. 108) potential receiver, it is suggested here that reinvention can result from overt attempts at imitation. Thus, as the title of this dissertation suggests, innovation and reinvention can occur from imitation.

A third goal of this project is to understand what role network structure itself plays in the accumulation of error throughout a contagion event. That network structure is crucial to the flow of information in diffusion processes is recognized by many scholars, albeit without an emphasis on the way structure impacts error. Rodgers (2003) defines network structure as a social system, which is composed of "...a set of interrelated units engaged in joint problem solving to accomplish a common goal" (p. 231). And because diffusion occurs within a social system, it necessarily occurs within a structured social system--or, as Rodgers (2003) states "...the patterned arrangements of the units within a system (p. 231). Thus, one must pay attention to the very arrangements of the ties between actors or firms to properly understand the way in which a diffusion event will unfold. Arguably, the same logic holds for understanding how error will accumulate during a diffusion event.

A fourth goal of this project to develop and implement a stable software program that allows for the easy collection and analysis of data related to information decay. As discussed in sections to come, one of the primary reasons work of this variety has not been attempted is the sheer trouble and inefficiencies associated with data collection and analysis. To this end, in collaboration with Dr. Matthew E. Brashears, I have contracted out, and assisted in, the creation of automated software capable of leveraging crowdsourced populations. Currently, the software package allows for N size networks of arbitrary structure. This software is largely funded by the Department of Defense.

Last, and related to the fourth contribution, is the continued use of crowdsourcing techniques to efficiently gather data. As suggested in Studies 2 and 3, using online populations such as Mechanical Turk result in data that is consistent with findings achieved via more traditional sources such as the laboratory.

3: Theoretical Contributions

By considering 1) the role that error plays in network diffusion events, 2) the manner in which information format impacts the accumulation of error, 3) how network structure interacts with error accumulation to increase or retard the error process, 4) how attempts to repair information error impact the diffusion processes, and 5) how modern data collection techniques, coupled with custom software, can allow new and more complex network-oriented questions to be asked, this program of study will contribute to the fields of management and organizational behavior, network theory, and studies of diffusion processes. In addition, this research also has significant practical implications for organizations and managers alike.

In contrast to work that views distortions in contagion processes as intentional acts designed to gain advantage (e.g., Athanassiades 1973; Gaines 1980; Lee, Padmanabhan, and Wang 1997), we argue that corrupted diffusions can occur in the absence of intention, and regardless of whether those intentions are nefarious. Good faith attempts at preserving information during reception and transmission can lead to corruption, and in fact, may increase the likelihood that a given communication mutates.

Conventional diffusion research suggests (Barash, Cameron, & Macy, 2012; Christakis & Fowler, 2012; Centola & Macy, 2007) that diffusions either die out and are removed from the graph, or fully saturate the network in their original form. This is because current diffusion theorizing does not take into consideration human limitations in reception and transmission processes. An actor is exposed to a contagion, receives it perfectly, and transmits it with equal perfection. In contrast to existing perspectives on diffusion, this argument suggests that the likelihood of mutated information will result in a proliferation of messages, preventing any one message from saturating the network. Thus rather than a given diffusion simply dying off, or being omnipresent in the network, that diffusion mutates and multiple forms can emerge to occupy the same network. If this is the case for simple experimental networks, then the likelihood of this in even more complex structures will be greater, as there will be more opportunities for error corrections. As a result, even in graphs with numerous shortcuts and jumps that allow the easy dispersion of information (i.e., small world networks), it is unlikely that a singular belief or behavior can fully saturate the network in its original form.

Information mutation represents an important engine for the generation of new organizational and social beliefs and behaviors without the need for humans attempting to be overtly novel or innovative. Because contagions can be radically altered by failed repairs, they can inadvertently transform into new ideas, beliefs, or behaviors that may then spread on their own. Further, this work suggests how diversity can be maintained even in the face of pressure to reach conformity (e.g., Friedkin & Johnsen 2011); the tendency for contagions to diversify prolongs the time required for a network to reach consensus. Indeed, the very small world graphs that typify human and organizational interaction likely further increase the time required for network consensus. That is, the many hops and skips (i.e., transmission→reception events) present in small world graphs suggest that error and mutation are powerful forces which keep any one idea or behavior from dominating. This work suggests that new ideas, beliefs, and behaviors can be generated in the absence of overt attempts at being creative or novel—rather, the processes inherent to human communication of information will, at random, generate new forms of information.

Further, existing network theory suggests that a given diffusion event can easily cross from one side of a network to the other (i.e., Travers & Milgram, 1969; Christakis & Fowler, 2007). This research suggests that estimates of practical reachability—e.g., the six degrees of separation between any two people—are likely underestimated when it comes to diffusion events. This is because mutation impedes effective communication; the information that arrives at one side of the network can be quite different from the information that departed from the other. Thus, while a contagion may reach across a network in 6 steps, there is no guarantee that the end state of the contagion is identical to its original form.

4: Practical Implications

The ultimate proof of our understanding of networks, and the diffusions and contagions that move through them, is reflected in our ability to control patterns of information flow. Indeed, this kind of work has already begun (Liu, Slotine, & Barabasi, 2011). Initial attempts to capitalize on diffusion processes have been met with limited success when using networks composed of human actors, though. It could be that the failure to quantify error accumulation, and to take network structure into consideration may account for this. Thus, the practical implications of this work extend to many facets of organizational and managerial life. From a marketing standpoint, the ability to selectively target areas of a network for product adoption would greatly minimize advertising costs while increasing the probability that a given good or service is adopted (for a discussion on this, see Centola & Macy, 2011). Similarly, firms must transmit key cultural values and practices to new employee (Rubineau & Gladstone, forthcoming). Being able to selectively target critical nodes for this process would become a more realistic possibility if one could understand the ways in which the diffusion event is likely to change, and move, over time. While current theorizing suggests that targeting a central node in a firm will result in the dissemination of a new behavior or belief, current results show that this may only be partly true. If one doesn't consider error accumulation as a potential process, then central nodes are adept at perfectly disseminating new information. However, if one does consider error accumulation, then targeting a central node as a starting point for a diffusion event can have quite the opposite outcome—the many points of information transfer between the central actor and her exterior ties provide increase the likelihood of flawed transmission. Further, even without any transmission→reception errors, this node could nonetheless color the original information in ways which correspond to her own personal biases, emotions, and expectations.

As this dissertation title suggests, innovation and creativity can be generated without intention. This process can occur in mundane communication structures as error accumulates and humans restructure communiques to imbue semantic meaning. Given this, savvy managers and firms can intentionally structure communication networks in such a way as to promote the likelihood that mutation and innovation occur, or conversely, structure networks in such a way as to minimize mutation and innovation and preserve the status quo.

5: Bounded Rationality

Prior models of human mental capacity—our cognitive power—viewed humans as limitless information processing machines, with extensive reasoning and processing power, boundless knowledge, and limitless amounts of time with which to make decisions (Kahneman, 2003). Herbert Simon challenged these assumptions about human cognitive ability, instead painting a picture of individual decision makers as having finite processing power, very limited time to make decisions, and operating with access to insufficient information (1947; 1991; 1987). Coining the term bounded rationality, Simon devised a model with two interlocking components: the limitations of the human mind, and the structure of the environments in which the mind operates. Simon's model (1947) states simply that models of human judgment and decision making should account for known limits to human cognition. Because of these limitations, humans must "…use approximate methods to handle most tasks." (Simon, 1990, p. 6). These methods include recognition processes that largely eliminate the need for information search, heuristics that guide information processing, and additional heuristics which dictate behavior based on the information that was processed. Because these methods are adapted to work well enough—not perfectly—they sometimes are inadequate for the task at hand.

5.1: Network Diffusion and Network Contagion

Social contagions refer to opinions or behaviors that spread, intentionally or not, from person to person. Generally, the spread of social contagions is known as a network "diffusion" or "contagion." While all manner of entities may spread throughout a social network, relatively few are considered true "social contagions." A more pointed discussion of what constitutes a social contagion comes from Schaefer (2007). Schaefer notes that information passing through a social network can be categorized in a 2x2 square composed of (yes/no) transferability, and duplicability. Transferability is a straight forward concept: a book is transferable as it can be given to one person, and then from that person, to another. In contrast, a hug from mother to child is non-transferable in that the hug itself cannot be passed on from that child to another person. Duplicability refers to whether a given piece of information can be copied. A rumor, or an electronic dissertation manuscript, can be held by multiple people at the same time. In contrast, a non-duplicable entity refers to an entity that must be given up during the process of transmission to another person. If I give a colleague a piece of art from my home, I cannot have that same piece of art myself. As noted, relatively few diffusion events are considered "true" social contagions, and this is because network researchers generally focus on only 1 of the 4 possible cells: network diffusions that are composed of entities which are transferable and duplicable. Non-transferable entities effectively preclude network contagions, whereas non-duplicable entities are not sustainable over time. Obvious counter-arguments exist, and point out the rough cut this approach takes to categorizing social contagions: a hard-copy book is a transferable, non-duplicable entity and thus not considered a true social contagion. Yet, the information contained within the book is both transferable and duplicable. Thus, it is important to consider the assumptions employed when one defines what is, and what is not, a social contagion.

Social network research has strong roots in the work of Grabriel Tarde (1903). Tarde invoked many concepts and ideas that gave rise to more contemporary social network analysis as he sought to understand the dynamics of group cognition and group behavior. Further, the work of George Simmel (1908[1964], 1922[1964] examined the ties between disparate groups, and how individuals (now known as "brokers") between groups can facilitate or hamper the flow of information. More modern forms of systematic analysis of network dynamics and diffusion began with the study of hybrid corn seed adoption (Ryan & Gross, 1943). Building on this work, Coleman, Katz, and Menzel (1957, 1959, 1966) investigated the spread of new antibiotics throughout medical networks. These researchers concluded that rather than relying on rational assessments of whether a new technology was useful, individuals were instead most influenced by the behavior of their peers (See, also, Burt, 1980; Van den Bulte & Lilien, 2011). From this point in time, research on network diffusion fanned out broadly and explored a wide variety of topics. Scholars have used board interlock structures to explain the spread of so-called "poison pills" (Davis, 1991), firm acquisition behavior (Haunschild, 1993), organizational structure and restructuring (Palmer, Jennings, & Zhou, 1993), and CEO pay patterns across time (Geletkanycz, Boyd, & Finkelstein, 2001). Additional research has focused on recruitment in to activism (McAdam, 1986), and voting behaviors (Bond et al., 2012). Belief and behavior norms are heavily impacted by contagion processes (Friedkin, 2001; Friedkin & Johnsen, 1997; 2011). Indeed, some of the more popular research on network contagions has concerned the spread of health-related behaviors and beliefs such as fitness (Centolla, 2010; 2011), drug use (Kirke, 2004; Mercken et al., 2010), obesity (Christakis & Fowler, 2007; however, see Cohen-Cole & Fletcher, 2008a), and happiness (Fowler & Christakis; again however, see Cohen-Cole & Fletcher, 2008b). From an organizational perspective, substantial attention has been paid to the spread of innovation and new practices (Montanari & Saberi, 2010; Rogers, 2003). Indeed, the tendency of organizations to resemble "similar" others both in organizational form and function has been traced to network influence effects (Conell & Cohn, 1995; Davis, 1991; Holden, 1986; Soule, 1997; 1999; Strang & Soule, 1998; Wang & Soule, 2012). This review of network diffusion processes is by no means exhaustive—it is meant to be suggestive of the extremely wide variety of beliefs and behaviors which spread throughout social and organizational networks.

A fundamental question for diffusion researchers concerns the ability, and speed, by which contagions can cross social networks (Dodds, Muhamad, Watts, 2003; Lundberg, 1975; Pickard et al., 2011; Travers & Milgram, 1969; Watts, Dodds, & Newman, 2002). These researchers find that generally, contagions can cross networks relatively quickly. However, networks can be quite sizeable and contagions do not always take a geodesic from one end to the other (Albert, Jeong, & Barbasi, 1999; Golub & Jackson, 2010; Liben-Nowell & Kleinberg, 2008). As such, the journey from one side of a network to the other can require many hops and stops—and is especially pertinent to the focus of this dissertation. If crossing a given network is often inefficient with many jumps from node to node, then the likelihood of transmission→reception errors becomes increasingly important to assume. Indeed, research also examines how the very nature of the network structure itself impacts the spread of diffusions. Granovetter, 1973; 1995) shows how weak ties can facilitate exposure to new information. In a similar vein, Burt (1992) examines brokerage positions within networks and how they impact the accumulation of social capital. Additionally, Aral & Val Alstyne (2011) look at bandwidth of the relations--the information carrying capacity of the ties themselves. Turning the question on its head to some extent, some researchers have found that the nature of the contagion itself—whether it is simple or "complex"—requires different types of structures and ties to spread efficiently (Barash, Cameron, & Macy, 2012). Further research has examined those more or less likely to be susceptible to contagions (Aral & Walker, 2012), as well as attempted to disentangle social influence patterns from homophily patterns (Aral, Munchnik, & Sundararajan, 2009; Lewis, Gonzalez, & Kaufman, 2012).

While existing research on diffusion is rich, and quite varied, one significant commonality is present: the continued omission of error. This occurs for three general reasons. First, work on the small-world phenomenon (Travers & Milgram, 1969; Lundberg, 1975; Watts, Dodds, & Newman, 2002) relied on an experimental design which instantiated a social contagion in the form of a message or letter. Effectively, this fixed communique locks the information in question into a form which can then be passed from person to person with no fear of error during transmission→reception. While this is surely convenient for the researcher, it is unlikely that most social contagions traverse real-world networks in such a stable format, or do so without relying on cognitive processes such as memory, or interpersonal communication. While work in the small-world phenomenon does find that messages occasionally fail to find their intended target, this is an extreme form of error and is binary. In these studies, a message either arrives or does not—there is not potential for the message to arrive, but to also have changed and mutated throughout its travels. A second way in which error has been ignored as a possibility in diffusion research is that outcomes such as happiness were examined without consideration or measure of the behaviors which lead to this outcome (Christakis & Fowler), 2007). In other words, a running assumption hidden in this type of work is that each outcome has only one process when leads to it. However, feelings of happiness can be generated by a variety of behavioral and attitudinal processes. As a result of this, changes in the contagion processes which lead to a given outcome are not detectable so long as they lead to the same consequence. Last, theoretical work network diffusion often assumes, overtly or implicitly, that information is passed perfectly from person to person. While the exclusion of error in earlier studies is done for practical reasons (i.e., Travers & Milgram), here it is done for no obvious theoretical reason. In any of the 3 examples above, error is simply and conveniently ignored.

5.2: Error in Network Diffusion and Contagion

Given the overwhelming evidence that humans are limited in their cognitive ability, it is only reasonable that error is taken to be a fundamental component of the research process itself—mistakes are made in research. However, what is less often considered and in turn, researched, are the errors occurring in the social processes under study themselves. These errors take many forms from interpersonal communication problems to failures to follow organizational protocols. And indeed, history shows that small errors can produce significant consequences. For example, in the Crimean War a small communication error led to a light brigade of 600 English soldiers walking into a slaughter (Raugh, 2004). More recently, a simple failure in conversion of Imperial measures to metric caused NASA's Mars Orbiter Climate to impact the Martian atmosphere and disintegrate (National Aeronautics and Space Admiration, 1999). More tragically, a failure to observe engineering concerns over the cold-weather durability of fuel tank o-rings led to the complete destruction of the Space Shuttle Challenger (National Aeronautics and Space Admiration, 1987). Errors, however small, happen and they can have severe consequences. The point is straightforward: even in small, relatively small and simple networks with relatively few opportunities for transmission→reception events to occur, noticeable error creeps into the system.

The potential for error within social processes is particularly interesting when one considers social diffusion. If a given individual, for whatever reason, transmits a flawed (but plausible) contagion to another individual, then the contagion has effectively mutated. And this person, believing the contagion to be plausible, will in turn transmit to another individual. As these mutations pile up and accumulate over time, the entity contained in one part of the network may not resemble its parent contained in another part of the network. Further, individuals are unlikely to know when they are receiving a mutated contagion, even if they encounter said mutation at a latter point via a different network path. A good analogy for the above example is the children's game of "telephone."[20] Just as a group of children whispering playful messages to one another can result in big changes to the message, social networks can also severely warp messages. And further, whereas children within the game expect to receive flawed communiques from their peers, adults in the real world do not. This only further exacerbates the problem of contagion mutation.

Contagions may either be informational (rumors, news, gossip) or behavioral (smoking, running, gaining weight)—both are equally subject to error. Informational error can result from flawed key inputs when typing, or from misinterpretations during interpersonal communications. And while observing and transmitting behavior may seem

[20] Also known as "Chinese whispers," "Grapevine," "Pass the message," "Whisper down the line," "Broken telephone," and numerous other names.

relatively easy on the surface, it is not—true behavioral mimicry is exceedingly rare and difficult (Byrne, 1995). In part, this is because accurate behavioral imitation invokes sets of complex symbolic meanings and norms which are largely context dependent (Goffman, 1959; 1967; Eliasoph, 1997). Timing itself is a component of accurate behavioral enactment (e.g., laughing at a funeral), and getting this component of behavioral mimicry incorrect can elicit negative and hostile responses (Milgram & Sabini, 1978; Milgram, Liberty, Toledo, & Wackenhut, 1986). Last, there are cultural components to enacting a behavior correctly—appropriate levels of intoxication often vary by culture, for example. Thus, above and beyond the purely cognitive barriers in contagion transmission, there are numerous cultural, temporal, and symbolic barriers which make accurate contagion transmission quite unlikely.

The "small set of studies" that focus on error in the contagion process tend to center on how the failure of or the removal of particular nodes can affect the process (the removal of a terrorist cell leader, for example; Albert, Jeong, & Basabasi, 2000; Callaway et al., 2000; Iyer et al., 2013). rather than examine how the content of the contagion changes and mutates, this research examines how the removal of parts of the network impact information flow. Aside from this type of research, the bulk of the remainder of work on diffusion error examines "distortion"—how individuals intentionally modify content in the information flow in an effort to produce favorable outcomes for themselves or negative outcomes for others. Note that this is different from the kind of unintentional error proposed in this study.

Research on distortion shows that individuals are likely to modify information for self-gain when they feel insecure or threatened (Athanassiades, 1973) so as to help protect their professional or promotional opportunities. A lack of psychological safety or distrust in superiors is also linked to distortion attempts (Gaines, 1980). These forms of distortion take the form of "puffing" (emphasizing and embellishing one's accomplishments) and withholding key pieces of information from competing parties (Gaines, 1980). At a global level, the gross impact of withholding is that different types of information are likely present in different parts of the network. Similar individuals may group together, and these similarities may drive patterns of information withholding. Mechanisms such as trust between parties, and homophily tendencies, likely underlay this process. Withholding is not just limited to individuals, as organizations engage in the same behaviors (Lee, Padmanabhan, & Wang, 1997).

The insights this literature offers the present studies is limited in three ways: First, the this work is focused on intentional efforts to falsify information. A second issue with the distortion literature is that it relies on qualitative studies with relatively few participants. While such methods are valuable, they also rely on small, non-representative samples which make connecting their results to more general network processes difficult. Last, studies of distortion examine the immediate downstream effects of information manipulation—not the ways in which these behaviors impact processes throughout the entire network (however, see Lee, Padmanabhan, & Wang, 1997).

Largely, the remaining studies of error in network contagion are found in computer science, and they, too, consider errors to be noise rather than the focus of research. Leskovec, Backstrom, & Kleinberg (2009) developed an automated procedure for tracking short phrases, or memes[21], as they travel throughout online networks. While the authors do note that the memes undergo forms of mutation, these changes are viewed as methodological hurdles to be overcome, rather than a focus of study itself. Similarly, Liben-Nowell, & Kleinberg (2008) examined chain letters and again, observed forms of mutation among the letters as they passed from person to person. Most relevant to the tracking of contagion mutation is the work by Simmons, Adamic, & Adar, 2011) who find that shorter phrases contained in print articles and blog posts are less likely to mutate than longer phrases.

While the aforementioned studies all employ different perspectives and methods for tracking errors, they have a number of important similarities. First, all view changes in the diffusion process as a methodological hurdle, rather than an important and interesting subject of study in and of itself (for exception, see Adamic et al., 2014; Simmons, Adamic, & Adar, 2011). The result of this is that most if not all effort is put towards identifying and tracking a contagion despite error—rather than attempting to understand how error impacts the contagion and how, in turn, humans react to these errors. A second similarity held by these studies is the use of automatic text parsing algorithms which cannot distinguish changes in character structure from changes in meaning. For example, the sentence "Eric is a tall man who walked into the room." would be recognized as "different" by the algorithms in use than the sentence "Into the room walked a tall man whose name is Eric." While it is clear that significant changes in character content are likely associated with changes in semantic content, there are times when this is not the case. A third similarity held by the studies is the study of diffusion chains in naturalistic settings—often online archives. While this certainly produces large sample sizes (for quality concerns, see Lazer et al., 2014), it also requires that online repositories (blogs, news sites, tweets) contain chains that are easily identified as similar by whatever algorithm is in use. As a result of these limitations, these studies are based on large, biased samples consisting of messages which have changed—but only so far as the algorithms in play can recognize them as being from the same original contagion[22]. Finally, due to the naturalistic settings of these studies, small and discrete changes in the contagion cannot easily be observed. In the same vein, research suggests that online contagions are often spread both online and offline, preventing effective tracking of the diffusion as it mutates (Adamic et al., 2014). In sum, this stream of research is interesting and useful in its own right, but leaves many questions unanswered regarding how errors impact diffusion events within social networks.

6: Theory and Main Hypotheses

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[21] Memes are more generally defined as self-replicating informational units analogous to genes (Dawkins 1976 [2006]), and there is an interesting body of theory dealing with the competition among these replicators for memory space and attention (e.g., Blackmore 2001). Our work could obviously be applied to memetics, but we are not interested in how ideas compete with each other, but rather in how errors, and the efforts of human actors to correct those errors, impact the spread of social contagions. We therefore set aside discussion of issues of interest to meme theory for the present.

[22] Dr Mor Namaan, Professor of Computer Science at Cornell University, once remarked to me that he typically excludes roughly 50% of his data due to this very problem.

We employ information theory as a framework for developing the main effect hypotheses which are directly investigated in Study 1. The next chapter attempts to replicate the results founds in Study 1 using a different metric of analysis and a different study population. Following this, a new type of network structure is explored (a lattice) and differences in information decay between linear and lattice networks are discussed.

Information theory is rooted in the work of Claude Shannon (1948), who developed a method for quantifying the amount of information contained within a message—known ultimately as "Shannon Information." Information theory begins by defining a set, which is the finite number of possible message that can be sent via communications channel (i.e., a tie). This number, or the monotonic function of this number, of messages within a set determine the total amount of information that is conveyed when the message is pulled from the set and transmitted to a given receiver. Here, the information conveyed is proportional to uncertainty reduction—as the number of messages in a set increases, so too does the uncertainty as to which of them will be selected for transmission. In this scenario, the more messages contained within a set, and the greater the uncertainty as to which message is chosen, the greater the amount of information contained within the chosen message.

Shannon information is perhaps easier to grasp when we view it as a cross word puzzle. If one considers all possible English phrases of the same length as the crossword puzzle phrase as the set of possible messages, then initially there are a great deal of possible messages and thus a great deal of uncertainty. With the first few letters filled in, the size of the allowable message sets reduces significantly—this indicates that the first few letters convey a great deal of information. Each additional letter inserted into the crossword message, then, conveys proportionally less information because the remaining set of possible messages has reduced. That each additional letter conveys less and less information is what allows phrases to be solved despite some letters being absent—the allowable message set has been reduced to one, and other possibilities are not allowed.

Shannon Information logic can be applied to information content of language, too. In any given sequence of letters (phonemes), each additional letter (phoneme) resolves some of the uncertainty about what word is being spelled (or spoken). English, for example, is roughly 75% redundant, meaning that approximately three-quarters of the characters in a message can be removed without the "readability" of the message being drastically altered.

The main problem with employing information theory for the purposes of tracking changes in contagions across networks is that the meaning of a given message (semantic content) is distinct to, and independent from, the information of a message (Shannon, 1948; 379). To illustrate, Shannon generated a sentence that has the same information content as an English sentence of the same length (1948; 385):

> *"THE HEAD AND IN FRONTAL ATTACK ON AN ENGLISH WRITER THAT THE CHARTACTER OF THIS POINT IS THEREFORE ANOTHER METHOD FOR THE LETTERS THAT THE TIME OF WHO EVER TOLD THE PROBLEM FOR AN UNEXPECTED."*

While the above sentence appears to resemble normal English, it is clearly not meaningful—one cannot simply infer that a message is meaningful simply because it is high in information content. Following Shannon's lead, subsequent researchers tended to also neglect the meaningfulness of a given message (Castro & Liskov, 1999; Chen &

Avizienis, 1978; Laprie, 1985; von Neuman, 1956; West, 1990), and as a result, we know very little about semantic error.

While Shannon information cannot determine semantic content, it does serve as a useful jumping off point. When a particular message is redundant, or low in entropy, it utilizes more characters to identify the word or concept than is strictly necessary. Therefore, if there is some probability that an error will occur when a letter is keyed, or a phoneme spoke, then more redundant messages are more likely to contain errors than less redundant messages. While low entropy messages (high redundancy) are more likely to contain at least a single error, these higher levels of redundancy also mean that other letters or phonemes are present which can help the individual understand the intended meaning of the message. This cannot be said of higher entropy (less redundant) messages: omitting just a single crucial letter or phoneme may render the message unintelligible as no additional letters or phonemes are present to account for the missing information. From this, the first main effect hypothesis is generated. H1 is investigated directly in Study 1, and by proxy in Study 2:

H1: *Entropy/Redundancy Meaning Hypothesis: Errors will impact the semantic content of lower entropy message to a smaller extent than a higher entropy message.*

With each transmission of a social contagion from person to person, there are opportunities for transmission→reception errors to occur. These errors can result in several different outcomes. The first outcome is likely the most intuitive one, and is termed "corruption." Here, random error accumulates over time with each transmission and reception. Ultimately, the original contagion is left unintelligible. In a network with significantly high levels of corruption, the sentence "Buddy is a dog" decays over time to "Uddy is a og" and ultimately to a meaningless statement such as "ddy is a g." Corruption is thus a simple and cumulative degradation of a given contagion over time, and necessarily imposes an upper limit on the number of steps a meaningful contagion may take within a network before being dropped.

While the above scenario may seem intuitive, it is not the most interesting or likely scenario. Humans are aware of meaningfulness, and will likely not send along a message they know to contain a fatal error. In other words, if one receives "Buddy th doug" from a colleague, the presence of error is quite clear. The recipient may simply discard the message, concluding its meaning is not clear. The recipient might also engage in very human behavior, and attempt to correct the message by restoring what she believes is the intended meaning. Thus, while the individual receives "Buddy he doug," she may reconstruct the message and transmit "Buddy the dog." Therefore, when humans are able to correct the meaningfulness of a given message, the message will preserve its meaningfulness over time to a greater extent than when correction is not allowed. This logic leads to the second main effect hypothesis. H2 is investigated directly in Study 1, and by proxy in Study 2.

H2: *Error Correction Hypothesis: Individuals efforts to correct error will work to preserve the semantic content of a message over multiple transmissions when compared to a lack of individual efforts to preserve semantic content*[23]

While the ability of humans to correct flawed messages is surely useful, it is relatively limited. As Shannon notes (1948), any attempt to correct errors detected within a message, absent additional information external to the message itself, may fail. For example, the phrase "Buddy he doug" might be corrected to read "Buddy has Doug" which has a meaning distinct from its original form. And because the new message is syntactically and grammatically correct, the mutation is effectively camouflaged. Thus, there is no sure-fire way for downstream recipients to know they are receiving a mutation unless they have access to information outside the message itself (context, personal knowledge of the sender, etc). Thus, while the presence of correction works to stabilize a contagion in the short run (H2), it will also give rise to periodic and dramatic failed correction attempts in the long run. Whereas corruption leads to a gradual and visible decay of the message over time, diversification generates quick, silent, and dramatic changes to the message which are grammatically and syntactically valid. This leads to the third main effect hypothesis. H3 is investigated directly in Study 1, and by proxy in Study 2.

***H3**: Diversification Hypothesis: Human efforts to correct error will tend to produce larger fluctuations in the semantic content of a message over multiple transmissions than will an absence of error correction.*

Existing work on behavioral and attitudinal adoption finds that the structure of a network—that is, the pattern of relational linkages between nodes—predicts whether a given node adopts a behavior or belief (Macy & Centola, 2012). In particular, this vein of research suggests that multiple sources of exposure to a new practice, belief, or behavior are required before the actor in question adopts the new practice. This is in contrast to more traditional models of diffusion and contagion where exposure to a single source of new information is sufficient for adoption. This work strongly suggests that the structure of the network itself will impact the degree to which error accumulates, and the extent to which corruption or mutation occurs.

More theoretically, this work argues that each transmission→reception event contains a probability for error. Different network structures contain differing amounts of transmission→reception events, wherein a given actor may receive two different forms of the original contagion, or may be exposed to the contagion at multiple times throughout the diffusion event. If error is, in part, a function of transmission→reception events, and structure impacts the amount of transmission→reception events available in a network, then it stands to reason that structure and error are intimately related.

This project aims to explore, in totality, 6 types of network structure. While this dissertation explores linear and lattice networks, it may prove prudent to briefly discuss additional types of structures as this speaks to the wide breadth and practicality of structure→information decay theory. The first type, as shown in Figure 1, is a simple linear graph. Here, the first participant sends a message to the second, who in turn sends a message to the third. Messages are directed, and each node receives and transmits a given message only once. This is, arguably, the most simple of possible graphs, and allows for baseline estimates of error accumulation to be made. This the first structure to be investigated in this dissertation. The second type of structure to be investigated is a parallel crossing network—otherwise known as a lattice structure (Figure 2). Here, messages pass through two parallel linear networks. After the first transmission, however, each node will receive 2 variations of the original seed sentence—one from a predecessor in their own lineage, and one from a predecessor in the other lineage. This is an elaboration on the current linear graph, and allows for the estimation of how individuals respond to possibly conflicting versions of the same communication. The third type of network to be investigated is a bi-directional ring (Figure 3). Here, nodes are arranged in a connected circle, with no central hub. Any given node can communicate with its direct neighbor, and any given communication must go through many transmission→reception events to reach the other side. Compared to the simple linear network, this graph has a connected end and beginning, and all ties are bi-directional versus uni-directional. The fourth graph of future inquiry is similar to the bi-directional ring—the only difference is that this graph has shortcuts (Figure 4). Here, nodes have shortcuts through which communications can avoid the numerous transmission→reception events present in the unmodified bi-directional ring. The fifth graph (Figure 5) of interest is a slight modification on graph 3. Here, a bi-directional ring is utilized, but with a central hub. This is akin to a staff member in a large department disseminating information to faculty who then speak amongst themselves. The next graph (Figure 6) to be investigated is known as a bi-directional lattice network. Here, nodes are arranged on a grid surface, and are connected only to their immediate neighbors. As is typical in most research using lattice graphs, each node is connected to two neighbor nodes and has no shortcuts. Similar to the parallel graph, this network utilizes parallel sequences but increases their number while also introducing bi-directionality. The next graph to be analyzed mirrors the structure of the aforementioned, but introduces shortcuts (Figure 7). This is an elaboration on the lattice network, and allows for cross-network connections (thus reducing the number of steps a communication needs to cross the network). Figure 8 represents a directed hierarchy. Here, communications originate from a central, top-down source. Within each "level," nodes can speak to one another, and then send communication down the line. This represents an organization with multiple tiers. Last, a clustered unidirectional hierarchy (Figure 9) will be explored. Here, individual hierarchies (similar to units in a firm) are arranged on a graph. Individual nodes within hierarchy are able to communicate with similarly placed nodes from other hierarchies. This mirrors, to an extent, the communication patterns in large firms with multiple, autonomous departments.

> *Structure Research Question: How does the structure of the network impact the rate at which error accumulates, and thus, the extent to which information corruption or mutation occurs?*

To this end, the decay rates of information across linear networks, and parallel crossing/lattice networks are compared. These are contained in Table 4.

The sections to come describe the general methods, experimental design, and analytic strategy by which H1, H2, and H3 are tested in Study 1

7: Linear Network Using Laboratory Population, Methods and Experimental Design

Study 1 addresses H1, H2, and H3 using experimental methods. Unlike previous efforts in tracking error during diffusion processes (Adamic et al., 2014; Leskovec, Backstrom, & Kleinberg, 2009; Simmons, Adamic, & Adar, 2011), experimental methods afford a degree of control and precision not available in naturalistic studies. Because tracking the progression of the contagion mutation relies on linking all parent and child pairings, experimental controls are a must.

A social contagion is instantiated via series of ten sentences which participants had to read, remember, and retransmit (Figure 1). Specifically, this task resembles the movement of informational, online contagions keyed via a computer terminal, but should serve as a broad demonstration of how all contagions change and mutate over time. The "seed" sentences (first node, Figure 1) were drawn from popular press books, ensuring each was not overly difficult to read or remember. Further, the word length of each of the ten sentences was kept roughly equivalent.

Participants entered the experiment, and after providing informed consent, were shown ten sentences. Each sentence was presented on the screen for five seconds, followed by a blank screen of five seconds. Participants were then asked to rekey the sentence they had just seen. The time limits were designed to resemble the limited time and cognitive resources available during a contagion process. Each subject, however, was given as much time as she needed to rekey each sentence. The reproduced sentence then became the next input stimuli for the next participant.

The study used specially designed software engineered by a colleague. The software allows one to configure the type of network structure in which the messages were passed. For example, Study 1 used a network structure that was linear: a->b->c->d. Here, 'a' is the first subject and receives the "seed" sentence. She then views and rekeys this sentence for the next participant (b) who sees her rekeyed sentence. B then transmits, to c, c to d, and so on and so forth (Figure 1, for an example of how a linear network works). The software utilized for this project allows the simulation of any type of network graph--lattice, hub and spoke, small world, scale free, and so on.

For Study 1, messages were transmitted until they had been read and retransmitted across eleven rounds by different subjects at which point the software reset to the original seed sentences (i.e., the sentence presented to the first respondent in a lineage). In a linear network, each node (starting from the left and moving to the right) represents a round. Thus, as depicted in Figure 1, Study 1 had eleven rounds. The experiment then repeated with new subjects, allowing one to essentially rewind the clock and produce multiple lineages using the same seed sentences and identical starting conditions. One is thus able to observe multiple outcomes of a diffusion process using the exact same starting conditions.

Study 1 uses a linear network, and is crossed by message format manipulation. As previously discussed, message formats with low entropy/high redundancy require more characters to transmit a given idea, but should be more robust to error because the loss of any given character has minimal impact on meaning. Conversely, high entropy/low redundancy formats utilize fewer characters to transmit a given idea—effectively making each character within the sentence more important. Thus, the loss of any given character in this condition will impact message meaning to a greater degree. Here, Standard English is adopted as the low entropy/high redundancy format given that it is roughly 75% redundant (Shannon, 1950). Other forms of English, such as texting or internet pidgin use fewer characters to transmit the same information ("See you later" becomes "C u l8r") and thus fit the definition of high entropy/low redundancy. In addition to working well as experimental instantiation, the use of internet pidgin is also becoming increasingly prevalent (Ito, Okabe & Matsuda, 2005; Ling, 2004; Lewis et al., 2008; Lewis, Gonzalez & Kaufman, 2012; Salathe et al., 2013), thus making the study of it within the context of social diffusion interesting in and of itself.

Undergraduate research assistants with experience in this method of communication independently converted the English stimulus sentences into text messaging pidgin form and then resolved any disagreements to produce the final sentences. Message format was manipulated by presenting the same message either in Standard English (i.e., English condition) or in text messaging pidgin (i.e., Text condition), and subjects were instructed to retransmit the sentences in the same format as they were received.

In the No Correction condition, participants were exposed to a series of ten sentences on a computer terminal and asked to reproduce each sentence exactly as seen. In the Correction condition, subjects were exposed to a series of ten sentences and asked to generate a sentence reproducing the intended meaning of each stimulus sentence rather than the exact text (i.e., paraphrase).

For Study 1, participants were recruited from the student population of a large northeastern university using flyers and an electronic subject pool. All subjects completed the experiment in a laboratory sitting at a prepared computer terminal. Subjects were not permitted to interact before or during the experiment if in the laboratory, and all subjects were informed that their compensation depends on the accuracy of their retransmitted sentences. In truth, all subjects were compensated equally but the deception ensures that subjects were engaged in the task and followed the instructions as given. Subjects were randomized into a condition ensuring that between-condition differences cannot be the result of individual variation. No subject was used more than once, ensuring that subject fatigue is not an issue. In total, Study 1 produced 4,089 unique observations. All procedures were approved by the IRB and all subjects were given their informed consent.

7.1: Experimental Logic and Experimental Scope

Given that the connection between experiments and the real-world is not always immediately clear, it may prove useful to discuss the initial conditions, instantiations, and overall scope of the experiments. At base, the diffusion of information within any network requires the passing of information (here, instantiated as “messages”) between two or more people. The form of these messages can be verbal or textual, or can result from behavioral observation and demonstration. As noted previously, individuals may make mistakes when sending information (typos, etc), or may make mistakes when receiving information (mishearing someone during a conversation)—in either case, an error has been introduced into the contagion. Further, and as discussed, the format of the information conveyed (high/low redundancy) makes it more or less robust to error accumulation. When presented with messages containing errors, individuals may attempt to correct these flaws by introducing new characters into the message in an attempt to repair meaning. Taken as a whole, the theory and experimental procedures represent a best-case scenario as the information to be received and transmitted is minimal, and entities competing for attentional and cognitive resources kept to a minimum. While the instantiations and conditioning of the phenomena are relatively specific, the broader implications shed light on the fundamental processes occurring in any type of verbal, written, or behavior contagion involving two or more human beings who are able to perceive and correct flaws in received communiques.

7.2: Linear Network Using Laboratory Population, Dependent Variables

The analyses are subdivided into two separate, but related, components: evolutionary and consecutive fidelity (Figures 10 and 11, respectively). Consecutive fidelity is defined as the semantic similarity of each child sentence to its parent. In a contagion composed of nodes A-B-C, the consecutive similarity would be measured as the meaning similarity of A to B, and of B to C. In other words, consecutive similarity is the degree to which a participant's input matches her output. Evolutionary fidelity is perhaps the more intuitive of the analytical frameworks. Here, evolutionary fidelity is defined as the meaning similarity of each child sentence to the original seed sentence. In a network composed of nodes A-B-C, evolutionary fidelity would be defined as A to B, and A to C. Whereas evolutionary fidelity provides the total amount of error that has crept into the contagion over the course of the diffusion, consecutive fidelity gives the rate of error accumulation. These are not separate datasets or experimental conditions—rather, evolutionary and consecutive fidelity are different analytic approaches to examining the same data.

The vast majority of research on error in diffusion processes (Adamic et al., 2014; Leskovec, Backstrom & Kleinberg, 2009; Mei & Zhai, 2005; Simmons, Adamic & Adar, 2011) relies on some variety of string length, or Levenshtein distance, to assess error accumulation (Levenshtein, 1965). Levenshtein distance quantifies the number of strings that would have to change to convert a given string into another string, and string length quantifies the number of strings within a message. Both methods focus on the characters within a message, and not the meaning of the message itself. Humans, unlike algorithms, are able to recognize messages that mean similar things despite being composed of different characters. The result of this is that Levenshtein distance and string length can easily over- or under- estimate the rate of semantic error accumulation during a diffusion. Study 1 avoids this problem by using a set of semantic coders to assess message meaning. The coders were native English speakers, and were instructed how to code the sentences. All coders were blind to the hypotheses of the study. Coders were instructed to read each sentence pairing, and rate their similarity on a 0-100 scale (1 being least similar, 100 being most similar). Four to five human coders independently read and scored each pair, and the presentation of sentence pairs was randomized. To combat fatigue, coders were paid on an hourly basis—versus a per sentence scored rate.

The results of the coding process are used in two ways. First, the mean of the scores for each comparison are used as a measure of meaning fidelity (Figure 12). The higher the mean, the more the coders viewed the messages as similar in semantic content. Assessing semantic similarity means allows for the testing of Hypotheses 1 and 2.

H3 is assessed by taking the standard deviation of both evolutionary and consecutive fidelity across lineages that share the same seed and experimental condition (Figure 13). This serves as the measure of diversification. In short, error correction should preserve meaning over time, but should also periodically give rise to drastically different forms of the contagion. This process should not result from gradual accumulation of error, but instead from unpredictable failures in error correction. In order to observe these unpredictable failures, one selects comparable lineages and finds the dispersion of their fidelity scores after the same number of transmissions. When the standard deviation of consecutive fidelity across comparable lineages is small, each lineage is experiencing roughly similar levels of change at each step (e.g., corruption), while larger standard deviations indicate greater variety in the amount of change at each step (e.g., diversification). Similarly, when the standard deviation of evolutionary fidelity across comparable lineages is small, each lineage should be experiencing roughly similar total levels of change over the course of diffusion (e.g., corruption), while larger standard deviations indicate that each lineage should be experiencing different total amounts of change over the course of diffusion (e.g., diversification). Thus, in both cases, small standard deviations would be consistent with a corruption-like process of gradual decay, while larger standard deviations would be consistent with unpredictable and substantial changes in meaning resulting from diversification. If error correction does in fact give rise to mutant forms of the contagion, analyses should reveal greater differences between lineages when error correction is present than when it is not.

It is important note that while the mean and dispersion scores are related, they capture different elements of the contagion and mutation process. The mean measures the general or central tendency of the coders. In contrast, the dispersion score measures how much each lineage varies from comparable others. As a result, error correction can both improve mean fidelity, as well as generate increased dispersion scores between lineages.

7.3: Linear Network Using Laboratory Population, Independent and Control Variables

Study 1 codes the number of transmissions a message has experienced, as well as the proposed experimental condition. “Transmissions” refers to the number of times a message has been read and transmitted by a distinct participant, and ranges from one to ten. “Format” equals one when the English condition is used, and zero when the Text condition is used (used only in Table 1). Correction equals one when Error Correction is present, and zero when No Error Correction is present.

Study 1 also employs Leveshtein distance to examine changes in character composition. While semantic content and character composition are likely related, sufficiently large changes in character content may change the meaning of a given sentence.

7.4: Linear Network Using Laboratory Population, Analytic Strategy

A series of regression models were run, which predict consecutive character fidelity, evolutionary character fidelity, the dispersion of consecutive character fidelity, and the dispersion of evolutionary character fidelity across comparable lineages. Results are presented in Table 1. Due to the interdependence of observations in models examining dispersion across lineages, models are adjusted for the clustering of observations.

7.5: Linear Network Using Laboratory Population, Results and Discussion

Error correction does dramatically improve consecutive fidelity (8.311, $p<0.001$) but to a diminishing extent as the contagion continues to diffuse (-0.484, $p<0.10$). These findings are consistent with the Error Correction Hypothesis, which predicts that error correction mechanisms will generally preserve semantic content. Finally, Levenshtein distance has a negative effect on consecutive fidelity (-1.089, $p<0.001$), indicating that changes to the characters used in a message tend to degrade its fidelity. Even so, the remaining significant effects confirm that semantic content is substantially independent of the specific characters used to convey it, confirming the usefulness of our approach; even in the presence of changing characters, semantic meaning can be effectively transferred throughout a network. This, in turn, suggests that the study of message meaning is important and contributes above and beyond the study of character change during diffusions.

The effects of format and error correction on consecutive fidelity are illustrated in Figure 14. These values indicate the predicted change in fidelity at a particular transition, rather than total change over the course of the lineage. Messages passed with error correction display consistently high levels of consecutive fidelity throughout the course of the diffusion to a diminishing extent. Text and English messages in the correction condition appear to diverge slightly in their levels of consecutive fidelity, but this difference is not significant. In contrast, the consecutive fidelity of messages passed without error correction remains stable or actually increases over the course of diffusion. English without correction increases the most in consecutive fidelity. These results suggest that without error correction, a message may rapidly lock-in on a stable, though mutated, form. In contrast, messages passed with error correction tend to diverge more and more substantially from their immediate predecessors the longer they have been diffusing.

The preceding results indicate how message format and error correction impact the rate of mutations, but what are their impacts on the accumulation of errors over time? Modeling indicates that evolutionary fidelity (Table 1, Model 2) decreases linearly with the number of transmissions (-1.365, $p<0.01$). Surprisingly, standard English initially degrades fidelity (-5.471, $p<0.01$) but has a positive interaction with the number of transmissions (1.814, $p<0.001$). The net result is that over the course of diffusion, the redundancy of correct English grammar preserves meaning better than lower entropy alternatives (i.e., text messaging pidgin). This result supports the Entropy Meaning Hypothesis. Error correction has an extremely strong and positive effect on evolutionary fidelity (16.126, $p<0.001$), which supports the Error Correction Hypothesis. Message format and error correction do not interact, but the three-way interaction between format, correction, and transmissions is marginally significant (-0.813, $p<0.10$). Finally, Levenshtein distance is negatively related to evolutionary fidelity (-1.191, $p<0.001$), confirming that while character changes degrade semantic fidelity, they are not equivalent to semantic fidelity.

The marginal effects of format and error correction on evolutionary fidelity are illustrated in Figure 15, with all control variables set to their means. The most striking finding is that messages in standard English that are transmitted with error correction exhibit very little mutation over the course of diffusion. Indeed, the predicted loss of fidelity over eleven transmissions is less than five percent, though a substantial loss of fidelity is incurred at the first transmission. This indicates that, on average, messages transmitted in lower entropy formats with error correction arrive at a distant node with very similar meaning as when they departed. However, error correction does not provide the same benefits for messages passed in higher entropy formats, with fidelity declining from a bit under seventy percent to only a bit over fifty percent. Thus, the success of error correction appears to rely to some extent on higher redundancy message formats that provide more of a basis for human inference. Lower entropy message formats (i.e., standard English) diffusing without error correction show relatively stable levels of fidelity, hovering around fifty percent, while higher entropy formats (i.e., text messaging pidgin) show a linear decline in fidelity from a bit over fifty percent to somewhat less than forty percent. This is particularly interesting as the subjects in the study, college students, should be experienced with, and proficient at, using text messaging pidgin. Nevertheless, it still shows a more pronounced decline in fidelity than standard English. On the whole, these results are consistent with both the Entropy Meaning Hypothesis and the Error Correction Hypothesis: lower entropy formats and error correction both provide advantages for preserving meaning. At the same time, error correction works best when combined with lower entropy message formats, and is less effective otherwise. In order for humans to successfully infer the meaning of a message, they must have access to information on which to base such inferences. When higher entropy message formats deny this information, the inferences tend to be less effective, even when the population is comfortable with these formats.

Examining the dispersion of fidelity scores across comparable lineages, allows for the testing of the Diversification Hypothesis. The cross-lineage standard deviation of the consecutive fidelity scores (Table 1, Model 3) is not significantly related to the number of transmissions or to the square of the number of transmissions. Lower entropy formats (i.e., English) have no obvious effect, but error correction reduces the standard deviation of coder scores (-4.319, $p<0.05$), contrary to the Diversification Hypothesis. However, the three-way interaction between format, correction, and transmissions is significant (1.452, $p<0.01$), suggesting that over several transmissions likelihood of diversification may be growing. Finally, the Levenshtein distance is positively related to the dispersion of coder scores (0.870, $p<0.001$); unsurprisingly, the greater the difference in the strings, the less similar the semantic similarity of those strings.

The marginal effects of format and error correction on the cross-lineage dispersion of consecutive fidelity are illustrated in Figure 16, with all control variables set to their means. This again is dealing with the change at each step, rather than the total change over the entire diffusion chain. Text messages transmitted with correction, as well as both types of messages transmitted without correction, show gradual decreases in cross-lineage consecutive dispersion. This indicates that in these conditions, the amount of change from parent to child in one lineage grows more similar to the change in a comparable lineage as the length of the diffusion chain increases. In contrast, English sentences transmitted with error correction show the opposite trend, with initially small differences across lineages that increase over the diffusion chain. This is consistent with the Diversification Hypothesis and suggests that in the English-Correction condition there is an increasing tendency to generate new, and very different, mutant forms of a social contagion with each new transmission.

Finally, the standard deviation of the cross-lineage evolutionary fidelity scores (Table 1, Model 4) increases with the number of transmissions (1.070, $p<0.05$) at a decreasing rate (-0.104, $p<0.01$). Thus, there is less cross-lineage consensus over the similarity between a descendant contagion and its original progenitor the longer that contagion has been diffusing. Message format and error correction have no significant main effects, but have a strongly negative interaction (-8.744, $p<0.001$), suggesting that English sentences transmitted with error correction tend to produce very similar levels of change over the course of diffusion. However, the three-way interaction between format, correction, and transmissions is significant and positive (1.182, $p<0.01$), suggesting that the picture is more complex. Finally, the Levenshtein distance is once more positively associated with the dispersion in evolutionary fidelity (0.639, $p<0.001$). This once more confirms that the semantic content of a message is distinct from the code used to convey it.

The marginal effects of format and error correction on the cross-lineage dispersion of evolutionary fidelity are illustrated in Figure 17, with all control variables set to their means. The predictions are, in general, similar to Figure 16. Text messages transmitted with correction, and text and English messages transmitted without correction, show similar trends in cross-lineage dispersion in evolutionary fidelity across the diffusion chain. However, English messages transmitted with correction both exhibit very low levels of cross-lineage dispersion initially, and increase substantially over the diffusion chain. Thus, while error correction benefits English messages initially, over the course of diffusion it produces more widely varying descendant messages than do the other conditions. By eleven transmissions, English lineages with correction differ from each other significantly more than any other type except for text lineages with correction. In other words, after lengthy diffusion chains, the presence of error correction actually produces more variability in the meaning of a message rather than less. This is consistent with the Diversification Hypothesis and shows that while correction improves the average fidelity of a message, it also produces more widely varying mutants.

In total, the preceding results provide partial support for the Entropy Meaning hypothesis, but stronger support for both the Error Correction and Diversification Hypotheses. Higher entropy messages and error correction consistently improve fidelity, while simultaneously giving rise to diversified mutant versions.

8: Linear Network Using Crowdsourced Population, Methods and Experimental Design

Here, a linear network is employed (Figure 1) once more, but uses Amazon Mechanical Turk[24] workers as the study population. Much like Study 1, experimental methods are appropriate in that they allow for the control of all inputs, and to track the subsequent outputs. Unlike the software used in Study 1, Study 2 (and Study 3) use specially designed software supported in part by the Department of Defense.

The implementation of Study 2 is identical to that of Study 1—participants are required to read, remember, and retransmit a series of ten sentences across eleven Rounds. Upon reaching the eleventh round, the software rewinds the social clock, and a new lineage begins at Round 1. The seed sentences used were identical to Study 1, and each sentence was presented on a computer screen for five seconds, and then replaced by blank space for five seconds. The subject was then given a prompt to rekey the sentence into a text box.

The manipulations used in Study 2 differ slightly from those used in Study 1. Whereas Study 1 was a 2x2 design—message format crossed by Correction v. No Correction—Study 2 manipulates only Correction V. No Correction. In both Correction and No Correction, standard English is used. In the No Correction condition, participants were exposed to a series of ten sentences on a computer terminal and asked to reproduce each sentence exactly as seen. In the Correction condition, subjects were exposed to a series of ten sentences and asked to generate a sentence reproducing the intended meaning of each stimulus sentence rather than the exact text (i.e., paraphrase).

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[24] MTurk was developed as an online labor market. It is being used by experimentalists as a source of experimental data (Kraut, Olson, Banaji, Bruckman, Cohen & Couper, 2003; 2004). Comparisons of laboratory data and participants (Buhrmeister, Kwang, & Gosling, 2011; Gosling & Johnson, 2010; Gosling, Sandy, John, & Potter, 2011; Gosling, Vazire, Srivastava, & John, 2004) indicate that the AMT samples are more representative than traditional college samples, and the data are at least as reliable. Results from experiments conducted via AMT were consistent with those collected in the lab of a Midwestern university, and collected on Internet boards (Paolacci, Chandler, & Ipeirotis, 2010).

The use of only Correction v. No Correction is done for several reasons. First, as discussed in the results section prior, the majority of the action occurred in the Correction conditions. More redundant information packets should always maintain their integrity to a greater extent than lower redundancy formats. Further, and from a purely theoretical standpoint, the contribution of message format is relatively small compared to that of Correction conditions. This becomes increasingly true as more complex networks (Study 3) are explored where multiple versions of the same message must be reconciled.

As noted, participants were recruited from Amazon's Mechanical Turk population. As with Study 1, subjects were informed that their compensation depended on the accuracy of their retransmitted sentences. In reality, all subjects were compensated equally. Subjects were randomized into Correction v. No Correction conditions, and no subject was earned more than once. Subjects were compensated $0.75 for participation, and Study 2 produced 2,115 unique sentence transition observations. All procedures were approved by the IRB.

Unlike Study 1, the environment of Study 2 is more similar to that of a real-world. Given that I lack total control over the environment in which participants took the study, there is a strong chance that everyday processes were competing for subjects' attention and cognitive resources. In this way, Study 2 provides a more realistic link to the external world.

Whereas Study 1 controlled for Levenshtein distance and relied on human coders to distinguish changes in semantic content, it is employed here as a dependent variable. This is done for several reasons. First, significant delays in the development of this very useful software resulted in a limited time for data collection and analysis. While using human coders to determine semantic similarity is the best measure of meaningful information decay, the use of Levenshtein distance provides a reasonable estimation of information error accumulation. The results of the Levenshtein distance analysis for the crowdsourced linear network should follow a predictable trend. Should this trend be present, it suggests that crowdsourced populations are sufficient to produce valid observations, and that Levenshtein distance is in fact an adequate proxy for the effects of information decay on semantic change. Second, further analysis of the data generated in Study 1 showed Levenshtein distance, on average, to be correlated with coder ratings of semantic similarity. Last, semantic change in the sentences is inherently tied to character change—not perfectly, but within reason.

8.1: Linear Network Using Crowdsourced Population, Dependent Variables

As with Study 1, the analyses are subdivided into evolutionary and consecutive perspectives (Figures 10, and 11). Unlike Study 1, this method of analysis employs Levenshtein character similarity rather than semantic similarity. Thus, consecutive fidelity is the character similarity of each child sentence to its parent sentence (i.e., how closely each respondent's output matches their input). Evolutionary fidelity is the character similarity of each child sentence to the original seed sentence (i.e., how closely each respondent's output matches the original stimulus). Evolutionary fidelity provides a measure of the *total amount of character error* that has crept into the contagion over the course of its diffusion, whereas consecutive fidelity provides a measure of the *rate of character mutation* over the course of the diffusion. Evolutionary and consecutive character fidelity are different ways of examining the same data, rather than totally separate datasets or different experimental conditions.

As with Study 1, the results of the Levenshtein distance analyses are used in two separate ways. First, the mean Leveschtein character distance of both consecutive and evolutionary perspectives is taken, and this is used as a measure of character fidelity (similar to the meaning fidelity use in Study 1). Higher Levenshtein means suggest that any two given messages were more, versus less, similar in their character composition.

In addition to examining Levenshtein mean character distances, the analyses also look at the standard deviation of both consecutive and evolutionary Levenshtein distance means across comparable lineages—lineages that share the same seed sentence and experimental condition. Much like Study 1, it is anticipated that error correction will preserve character content over time, but should also periodically give rise to drastically different messages, as measured from a character content perspective. When the consecutive standard deviations across lineages are low, each lineage is experiencing roughly similar levels of character alteration at each time step (i.e., decay). When the consecutive standard deviations are high, each lineage is experiencing greater amounts of character decay at each time step. Similarly, when the evolutionary standard deviations are relatively low, each lineage is experiencing low levels of character decay throughout the course of the diffusion. When the evolutionary standard deviations are high across comparable lineages, each lineage is experiencing different amounts of total character change. In both cases, and similar to Study 1, low standard deviations are suggestive of a gradual process of decay and high standard deviations are indicative of unpredictable and substantial changes in message character composition.

8.2: Linear Network Using Crowdsourced Population, Independent and Control Variables

Similar to Study 1, a number of independent variables are employed during model estimations. "Transmissions" codes the number of times a message has been read and retransmitted by a unique participant, and ranges here from 1-11. Unlike Study 1, the experiment is not conditioned by message format and thus this variable is not included. "Correction" equals one when the Error Correction manipulation was used, and zero when the No Correction manipulation was used.

In addition, several interaction variables are fit. First, a squared term for Transmissions is included to test whether character decay within each message is stable, accelerates, or decelerates throughout the course of the diffusion. Second, Correction and Transmissions are interacted to determine whether their effects vary throughout the course of the diffusion event.

8.3: Linear Network Using Crowdsourced Population, Analytic Strategy

A series of regression models predicting consecutive character fidelity, evolutionary character fidelity, the dispersion of consecutive character fidelity, and the dispersion of evolutionary character fidelity across comparable lineages are estimated. Results are presented in Table 2. All models are adjusted for the clustering of observations.

8.4: Linear Network Using Crowdsourced Population, Results

Turning to the results of the linear network which used crowdsourcing techniques and utilizes only Levenshtein distance, we find that the number of transmissions significantly impacts character decay. Beginning with consecutive Levenshtein character fidelity (Table 2, Model 5, Figure 18), analysis reveals that transmission impacts character decay (-3.530, $p<0.01$) at a decreasing rate (0.193, $p<0.05$, one tailed). Each child sentence, from a character standpoint, resembles its parent less closely than the parent resembles the grandparent, but to a diminishing extent. Levenshtein mean distances are considerably higher in the Correction condition v. the No Correction condition (11.121, $p<0.01$). The interaction of transmission with correction yields a non-significant effect (-0.303, p=ns). Moving to evolutionary Levenshtein character fidelity, (Table 2, Model 6), Figure 19, analysis suggests that the number of transmissions increases Levenshtein distance (8.865, $p<0.001$) at a decreasing rate (-0.433, $p<0.001$). The evolutionary comparison results suggest that the message characters are locking into a stable format where character alterations are occurring less and less frequently. Correction has a significant impact on Levenshtein character fidelity (15.557, $p<0.05$)--the use of Correction results in more character alteration than when No Correction is present. As with Model 5, the interaction of Correction and transmission is non-significant (-0.845).

Next, the consecutive dispersion of Levenshtein character scores across comparable lineages is analyzed (Table 2, Model 7), Figure 20). The cross lineage standard deviation, as measured consecutively, reduces with each successive transmission (-1.697, $p<0.001$), and does so in a roughly linear fashion. Similar to Model 6, the presence of Correction significantly increases the the standard deviations across comparable lineages (6.41, $p<0.001$). That is, the standard deviations of the Levenshtein scores, in the presence of Correction v. No Correction, increase when Correction is present. This speaks, in part, to the Diversification Hypothesis. As participants are asked to correct potentially flawed messages, they introduce new characters which the standard deviations of the Levenshtein scores pick up. Of course, without semantic codings, it is not possible to determine whether these changes are gravitating towards, or away from, the original sentence meaning. As with prior models, the interaction of transmission and correction yields a non-significant effect (-0.011). Examining the evolutionary dispersion of Levenshtein character change (Table 2, Model 8), Figure 21), results show that each transmission significantly reduces the standard deviation of the Levenshtein distance scores (-2.533, $p<0.001$) at an increasing rate (0.174, $p<0.001$)--though the rate of change is much greater in the presence of Correction. Similar to Model 7, the presence of Correction initially and significantly increases the Levenshtein standard deviations across lineages increase (4.756, $p<0.001$). Unlike Models 5, 6, and 7, the interaction of Correction and transmission does yield a significant result (-1.584, $p<0.001$). With each additional transmission in the presence of Correction, Lev distances across comparable lineages decrease.

As noted, Figures 18, 19, 20, and 21 graphically depict these results. On the left axis are the Levenshtein distance means or standard deviations, and the bottom axis is the transmission number.

8.5: Linear Network Using Crowdsourced Population, Discussion

Here, the network structure used in Study 1 was replicated, and employed crowdsourcing to quickly and efficiently gather data. Without speaking to human rated measurements of sentence similarity, the analyses of Levenshtein character alterations suggest that 1) the software is performing as expected, and 2) that crowdsourced populations are sufficient to generate valid observations.

Turning to the main trends revealed in the analyses, several general processes are noted. First, the general pattern of Levenshtein distance means and standard deviations is negative. Viewed from the consecutive and evolutionary frameworks, and either within or between comparable lineages, the character distance between comparable sentences tends to decrease with each successive transmission—this could be interpreted as meaning the semantic meaning of each comparable sentence is increasing. It should be noted, however, that interpreting character change from perspective of semantic meaning is cloudy at best. The manners in which the characters are "locking-in" in terms of their decreasing change may have something to do with the structural properties of English (or any language for that matter). That is, the grammatical structure of language likely places upper and lower limits on the extent to which characters can change in meaningful ways. The effect of Correction produces positive and significant coefficients across all models. That is, Correction tends to increase the character distance of all comparable sentences. This, viewed from the perspective of semantic similarity, suggests that Correction increases the difference in message meaning.

9: Lattice Network Using Crowdsourced Population, Methods and Experimental Design

Study 3 marks the first of many structure oriented questions this project will ask. Here, a lattice network structure (Figure 2) is examined. The lattice structure is composed of two parallel crossing linear networks. Unlike the linear network, each individual transmits to two additional nodes. The lattice network structure is the theoretical and practical next step in this program because it addresses a fundamental question in this research program—how does the presence of multiple versions of the same seed sentence, from which the participant must output a single sentence, impact the accumulation of character decay? Understanding this process is crucial in exploring additional networks where multiple messages arrive at the same node. Further, understanding this process will help in the production of agent based models which can quickly generate insights and assumptions into how error accumulation processes operate in the real world and thus, how to better design future experiments. As with Studies 1 and 2, experimental methods are appropriate in that they allow for control of the inputs, and to track the subsequent outputs.

The implementation of Study 3 is nearly identical to that of Study 1 and 2—participants are required to read, remember, and retransmit a series of ten sentences across five rounds. Upon reaching the fifth round, the software rewinds the social clock, and a new lineage begins at round 1. The use of five rounds (versus eleven in Studies 1 and 2) is the result of a methodological decision. Each round of the lattice network is composed of two nodes—in order to keep the number of nodes relatively comparable across different structures, a reduction in rounds in Study 3 was necessary. The seed sentences used were identical to Studies 1 and 2, and each sentence was presented on a computer screen for five seconds, and then replaced by blank space for five seconds. The subject was then given a prompt to rekey the sentence into a text box. Further, Study 3 is conditioned in the same manner as Study 2—by Correction and No Correction. The logic for dropping the format condition remains the same as that stated in Study 2. Additionally, the recruitment, informed consent process, and compensation of participants from Mechanical Turk was identical to that used in Study 2. Study 3 produced 3,561 unique sentence transition observations. Last, Study 3 utilizes only Levenshtein character distance as a primary dependent variable, for the same reasons noted in Study 2.

9.1: Lattice Network Using Crowdsourced Population, Dependent Variables

As with Studies 1 and 2, analyses are subdivide into evolutionary and consecutive perspectives (Figures 10, and 11). As with Study 2, the method of analysis employed in Study 3 uses Levenshtein character similarity rather than semantic similarity. As with the previous studies, analyses are divided into consecutive and evolutionary perspectives. In the same vein as Studies 1 and 2, the results of the Levenshtein distance analyses are used in two separate ways: 1) within lineage changes in the mean of the Levenshtein distance scores, and 2) across lineage changes in the standard deviations of mean Levenshtein distance scores.

9.2: Lattice Network Using Crowdsourced Population, Independent and Control Variables

The independent and control variables used in Study 3 are identical to those used in Study 2. "Transmissions" codes the number of times a message has been read and retransmitted by a unique participant, and ranges here from 1-5. As with Study 2, message format is not included. All sentences are presented in standard English. "Correction" equals one when the Error Correction manipulation was used, and when the No Correction manipulation was used.

In addition, several interaction variables are fit. First, a squared term for Transmissions is included to test whether character decay within each message is stable, accelerates, or decelerates throughout the course of the diffusion. Second, Correction and Transmissions are interacted to determine whether their effects vary throughout the course of the diffusion event.

9.3: Lattice Network Using Crowdsourced Population, Analytic Strategy

The analytic strategy for Study 3 is identical to those of Studies 1 and 2. A series of regression models predicting consecutive character fidelity, evolutionary character fidelity, the dispersion of consecutive character fidelity, and the dispersion of evolutionary character fidelity across comparable lineages are fit. Results are presented in Table 3.

9.4: Lattice Network Using Crowdsourced Population, Results

We now move to the lattice network configuration described previously (Table 3, Model 9, Figure 22). As noted, participants receive multiple versions of the same seed sentence, and must somehow synthesize them into a single sentence. In order to control for the number of nodes across different types of networks (i.e., linear and lattice), the number of rounds in the lattice network is limited to 5, whereas the number of rounds in the linear network was 10. This is because the lattice network requires more nodes per round. The effect of transmission, from the consecutive perspective, is non-significant (3.226), and there is no significant change in the rate of decay throughout the duration of the message transmission (-0.508, p=ns). Correction significantly increases Levenshtein distance scores (20.46, p<0.001). The interaction of transmission with Correction reveals no impact on Levenshtein distance scores (-1.011, p=ns).

Looking at evolutionary Levenshtein distance scores (Table 3, Model 10, Figure 23), analyses show that each transmission significantly increases character alteration within the message (14.464, p<0.001), and that this process significantly decreases over time (-1.601, p<.01). The presence of Correction also significantly increases character alteration as participants try to reconcile different, and potentially flawed, messages

(25.663, p<0.001). The interaction of Correction and transmission does not significantly impact Levenshtein distance scores (-1.312, p=ns).

Turning to the standard deviations of Levenshtein distance scores across comparable lineages (Table 3, Model 11, Figure 24) from the consecutive perspective, results suggest that each transmission significantly increases the standard deviations of the Levenshtein distance scores (5.098, p<0.001), and this occurs at a significantly decreasing rate (-0.613, p<0.01). That is, with each successive transmission of a given message, the standard deviations of the mean Levenshtein distance scores is decreasing. This suggests less and less dramatic changes in the message's character content. The presence of Correction decreases the standard deviations across comparable lineages (-0.923, p<0.001). Last, analyses show that the interaction of Correction and Transmission significantly decreases the standard deviations of Levenshtein distance scores across lineages (-1.277, p<0.001).

We now turn to the evolutionary model of Levenshtein distance score standard deviations across lineages (Table 3, Model 12, Figure 25). Here, results show that transmission count does not impact standard deviations (-1.376, p=ns). As expected, the effect of transmission squared is similarly non-significant (-0.414). The model shows an effect for the interaction of Correction and transmission count, however (-0.548, p<0.001). The presence of Correction works to reduce the Levenshtein distance standard deviations across lineages (-0.548, p<0.001). With multiple opportunities at properly correcting flawed sentences, Correction is particularly effective.

As noted, Figures 22, 23, 24, and 25 graphically depict these results. On the left axis are the Levenshtein distance means or standard deviations, and the bottom axis is the transmission number.

9.5: Lattice Network Using Crowdsourced Population, Discussion

Coupled to Study 2, Study 3 provides additional evidence that the software is operating as expected and that Mechanical Turk is a valid resource for gathering data points. Examination of the models 9, 10, 11, and 12 reveal several general patterns. First, character distance between comparable sentences tends to increase with each transmission. As noted in the discussion of Study 2, this suggests that semantic similarity is decreasing. Though, as noted, direct interpretations of the relationship between semantic meaning and character change are difficult to assess. The effect of Correction dramatically increases the character distance between comparable pairs (Models 9 and 10), and decreases the standard deviations between comparable sentences across lineages (Models 11 and 12). Across all models, analyses show that the rate of change of characters across comparable sentences is negative, suggesting a lock-in process whereby characters are slowly ceasing to alter. Whereas Study 2 revealed no effect for the interaction of Correction and Transmission, Study 3 finds one. Examining the standard deviation scores of Levenshtein distance means, results show that Correction has an impact, but that this effect decreases with each successive transmission.

10: A Comparison of Linear and Lattice Networks Using a Crowdsourced Population

The ultimate goal of this project is to understand how network structure impacts the process of error accumulation throughout the course of a diffusion event. When examining Tables 2 and 3, several differences are present. Within a linear network, each successive transmission tends to decrease the amount of character change between comparable sentences. For the lattice network structure, the opposite holds true. For the linear network, the effect of Correction is uniformly positive—that is, Correction increases the character distance and character change standard deviations between comparable sentences. In comparison, Correction increases the character distance means between comparable sentences, but decreases the character change standard deviations between comparable sentences. While comparing and contrasting main effects across the different models is useful and informative, it does not allow one to test for differences in the two network structures.

In order to do this, a full model containing the data from both linear and lattice structures (Table 4) is produced. Here, Correction is coded as one when Correction is present, and as zero when No Correction is present. The variable "Structure" is coded as 1 when referencing the lattice network, and as zero when referencing the linear network.

As noted, the ultimate aim of this dissertation, and the work to follow, is to understand how different network structures impact error accumulation. Table 4 provides the first analysis of this inquiry, and arguably, the first analysis of its kind. Turning to the consecutive analysis of mean character change (Model 13, Table 4, Figure 26) analyses reveal no effect for the number of transmissions on Levenshtein character change across linear and lattice networks (-1.909, p=ns). As expected, there is no effect for the transmission squared term (4.034, p=ns). The presence of Correction, however, does significantly increase the measure of Levenshtein character change distance across both types of networks (13.475, p<0.001). Turning to the focal point of the model, results show that the nature of the structure does significantly impact the rate of Lev distance change. Compared to linear networks, the baseline of Levenshtein character change is significantly higher in lattice networks (12.719, p<0.001). This is most likely due to the fact that participants must synthesize multiple versions of the same seed sentence and create one single output sentence. While character change, and not semantic meaning is measured here, the presence of notable differences across two basic network structures is suggestive that the accumulation of error is dependent on the pipes through which it flows.

The interaction of network structure and Correction is significant at the one-tailed level (5.65, p<.05). The interaction of Correction and transmission number is not significant (-0.595).

Model 14, Table 4 depicts the analysis of Levenshtein character change score from the evolutionary framework (Figure 27). Unlike Model 13, the effect of transmission number is positive and significant (14.311, p<0.001), and this process decreases at a significant rate (-1.559, p<0.001). Unlike Model 13, analyses show no effect for nature of the network structure (-2.113, p=ns), the interaction of structure with Correction (7.781, p=ns), or the interaction of Correction with transmission number (-0.419, p=ns). As with the Figure 26, the Correction lattice condition does have the highest overall Levenshtein baseline. Similarly, both No Correction conditions across both types of networks have the lowest baseline Levenshtein distances.

Turning to Model 15, Table 4, the consecutive perspective on standard deviation changes across lineages (Figure 28) is examined. The number of transmissions, here, has no impact on changes in the Levenshtein distance score standard deviations across lineages (1.181). Correction does has a powerful impact on Levenshtein character change standard errors--in the presence of Correction across both types of networks, Correction significantly increases Levenshtein score standard deviations (10.843, $p<0.001$). As with Model 14, the nature of the network structure has a powerful effect on standard deviation character error change (8.962, $p<0.001$). Compared to linear networks, lattice networks generate greater standard deviations across comparable lineages. This is, in part, likely due to the effect of the No Correction lattice condition. Unlike the other three conditions, this cell is marked by increasing amounts of Levenshtein distance standard deviations. The interaction of network structure and Correction yields a significant effect (-11.341, $p<0.001$). Here, the presence of Correction generates more standard deviation in the Levenshtein score standard deviations when operating in the linear network. Last, results show that Correction and Transmission count significantly impact consecutive scores of Levenshtein distance standard deviation (-1.407, $p<0.001$). When Correction is present, standard deviations in the Levenshtein scores increase across lineages.

Last, we turn to Model 16, Table 4, which examines standard deviations scores from the evolutionary perspective across linear and lattice networks (Figure 29). The number of transmissions experienced by the message significantly impacts its Levenshtein score standard deviation (-1.512, $p<0.05$). With each successive transmission of a message, standard deviations across lineages decrease. Correction is strongly and positively associated with increased standard deviations (4.332, $p<0.001$), and this effect remains relatively stable throughout the life of the message (0.031, $p<ns$). Unlike Models 13, and 14, the nature of the network structure does not impact the standard deviations of the Levenshtein scores (0.046). The interaction of structure and Correction is strong, and negative (-5.826, $p<0.001$). This suggests that Correction, in the presence of the linear network, generates more standard deviations in Levenshtein distance scores than in the presence of lattice networks. No Correction across network structure has a virtually indistinguishable effect. Last, analyses show that Correction and Transmission count is negatively and strongly associated (-1.371, $p<0.001$). This suggests that with each successive transmission, in the Correction condition, Levenshtein score standard deviations across lineages decrease.

As noted, Figures 26, 27, 28, and 29 graphically depict these results. On the left axis are the Levenshtein distance means or standard deviations, and the bottom axis is the transmission number.

11: General Discussion

This research placed error in diffusion events front and center, as opposed to artificially precluding error. The theory and results contained in this manuscript suggest that error is a fundamentally important component of social processes, and in particular, network diffusion. Given the wide amount of diversification observed throughout these studies, the ability of contagions to reach disparate ends of a given network may be overestimated. This is because the message which originated on one side of the network may quickly mutate and become something quite unlike its original self. The most glaring finding from these studies is that error matters—models of processes occurring within social networks must take into account human inabilities. Additionally, the medium through which a communique is transmitted matters, and this suggests that blanket models of diffusion which cover all forms of communication are inaccurate, at best.

The experiments here focused on textual, written communiques and are thus most directly relevant to linguistic diffusion in a textual form. This should not be seen as a negative, however, as a great deal of modern diffusion events take place in exactly this form. More generally, however, is the fact that virtually all contagions require some form of human communication (face to face, email, etc). Even in the case of contagions involving static and duplicable entities such as sharing a song on the internet, the ways in which we consume and experience these duplicable entities is heavily influenced by the knowledge we share with one another about them. This knowledge is, often, transmitted either verbally or via written text. More generally, these results shed light on the ways in which social networks can shape our perceptions and information flows. Podolny (2001) likens networks to pipes which impact the manners in which information flows. Different arrangements of pipes yield different flows of information. This work shows that different arrangements of pipes yield different patterns of error accumulation during contagion events.

Yet, it may not just be the pipes that matter. Pipes connect nodes—otherwise known as humans—and humans come with all variety of mechanisms that can further shape and mutate the information they receive. When faced with different or competing incoming communications, factors such as interpersonal trust, or status distinctions, will likely impact the mutation process. Indeed, even when the potential for communication clarification is present, significant status differentials may result in the receiver opting to "play it safe" and make a best guess. Further, human beings do not simply approach incoming information sets without internal preference or want—this suggests that certain contagions and diffusions may enjoy a competitive advantage simply because they are more "appealing" than others. From this perspective, it could be the case that similar others share similar preferences for various contagions. It would then stand to reason that in the case of a diffusion event, homophily mechanisms would lead different forms of the same contagion to be clustered across a network.

The intentional manipulation of diffusion events is becoming increasingly popular. The published empirical studies in this vein have yielded poor results (Carrell, Fullerton, & West, 2009; Carrell, Sacerdote, & West, 2013; Sacerdote 2011), Yet, a recent meta-analysis (Thomas, McLellan, & Perera, 2013) finds attempts at leveraging contagion effects quite unsuccessful. While this is no doubt due to the many exogenous factors not under the researchers control, the results of these studies also suggest a different interpretation. The work on leveraging contagion implicitly assumes that the information they insert into the network at a strategic location remains static and unchanged as it travels throughout the network. As demonstrated, this is very likely not the case. Instead, the null results found by these researchers may stem from contagion corruption and mutation. Put simply, what they're looking for either dropped out of the network, or has assumed a new form.

An additional consequence for organizational behavior is the logic by which people may be given, or ask for, information. It stands to reason that in more directed organizational forms, informational transfer occurs between individuals with differing levels of authority, prestige, or trust. In contrast, in more informal networks such as social groups, individuals often seek out information from peers who they are similar to authority and prestige levels. In the latter, individuals likely feel relatively comfortable asking for and providing clarity should a suspected information error occur. In the former, however, an opposing process likely occurs. Due to reputational concerns such as appearing competent, or due to status differences between individuals, people may be hesitant to ask for clarification when an information error is suspected to have occurred. Thus, it is the networks we intentionally structure for efficient and reliable communications that may be most prone to error accumulation. From this perspective, open and trusting interpersonal relations among super and subordinates are particularly important. Concepts such as psychological safety (Detert & Martin, 2014)—a cognitive and emotional state where individuals feel secure in asking questions and reporting mistakes—thus become highly relevant to the study of error accumulation.

This perspective also has implications for the savvy manager who wishes to efficiently distribute information through a firm. While it may be tempting to simply locate a relatively central actor and insert a communique to be distributed, caution should be practiced as the message being diffused may be significantly different than what is intended. Practioners, then, may be wise to check in on their diffusions, and make sure what is being circulated throughout the network is accurate and intended.

One question that remains is how individuals reconcile competing communications. While the use of a lattice network in Study 3 sheds light on this, the actual decision making process remains unobserved. A simple, yet informative, experiment could provide answers. The sentence codings used in Study 1 could be strategically handpicked and then presented to participants in an effort to understand their mental calculus. For example, randomized presentations of sentence pairings coded at quartiles—0-25% similar, 26-50% similar, 51-75% similar, and 76-100% similar—would be presented to participants. From here, they would be asked to provide a detailed account of why they generated the output sentence they did. Further elaborations on this design could instantiate other node level qualities such as relative trust of the sender, or status differentials. More generally, little is known about the cognitive processes by which people make communication decisions—who they ask for information from or how node and tie characteristics impact how information is received. Receiving multiple input communications from similar, trusted parts of one's network may result in improved error correction, whereas receiving different or competing messages from disparate parts of one's network may reduce the ability to correct errors.

12: Conclusion

I, in an ongoing collaboration with Dr. Matthew E. Brashears, set out to understand how message format, human abilities to correct flawed messages, and network structure impacted the accumulation of error during contagion processes. In doing so, we give error the front stage and treat it as a fundamental social process. The most general implication is that with any model of a complex process, care must be taken in what is omitted and what is included. The results presented here suggest that the omission of error from diffusion models may be a serious problem which significantly limits our understanding of how diffusion events occur. As noted, attempts at leveraging contagions have been largely unsuccessful—flawed models due to error omission may contribute to these null findings.

As noted, our simple networks generated a significant amount of data to be coded by human beings. With the advent of crowdsourcing via sites such as Amazon's Mechanical Turk, the time spent on coding semantic similarity can be greatly reduced.

However, researchers are urged to carefully plan their experiments, and pay close attention to the amount of data being generated. While it has been suggested that researchers have chosen to artificially preclude error from their diffusion studies, it may also be the case that the investigative process is time intensive, difficult, and generally not appealing. Ideally, a careful balance may be struck between the automation and speed of algorithms which track changes in character content, and the semantic abilities of human coders. Indeed, work in machine learning is headed in just this direction.

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14: Figures

Figure 1: Experimental Design of Linear Telephone Game

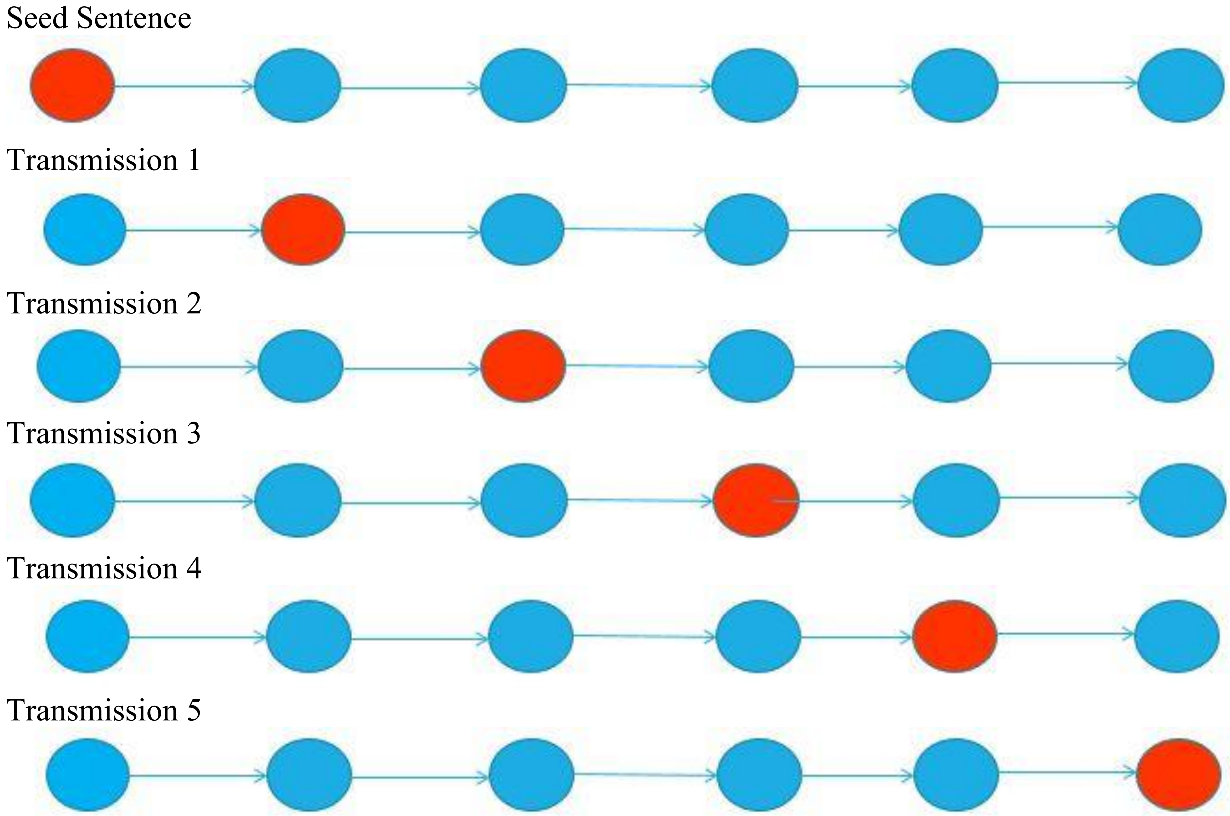


Figure 2: Parallel Crossing Network

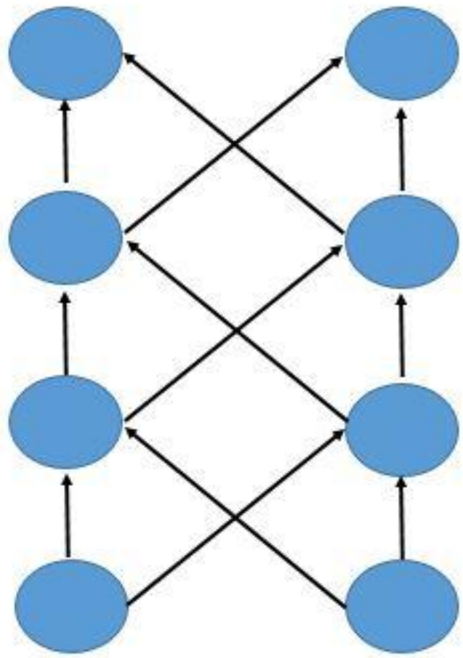


Figure 3: Bi-Directional Ring

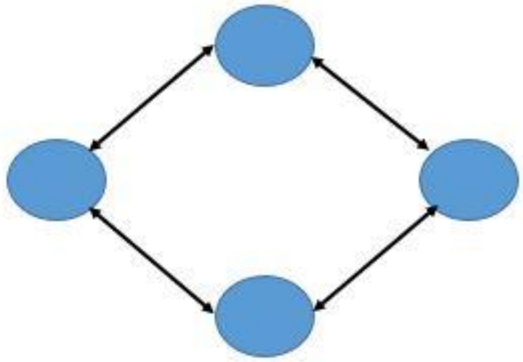


Figure 4: Bi-Directional Ring with Shortcut

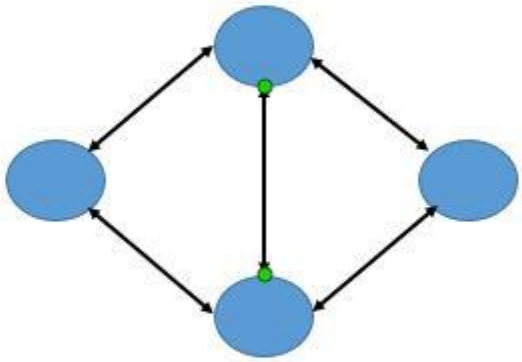


Figure 5: Bi-Directional Hub and Spoke

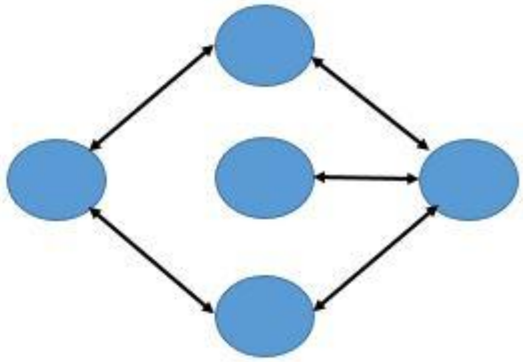


Figure 6: Bi-Directional Lattice

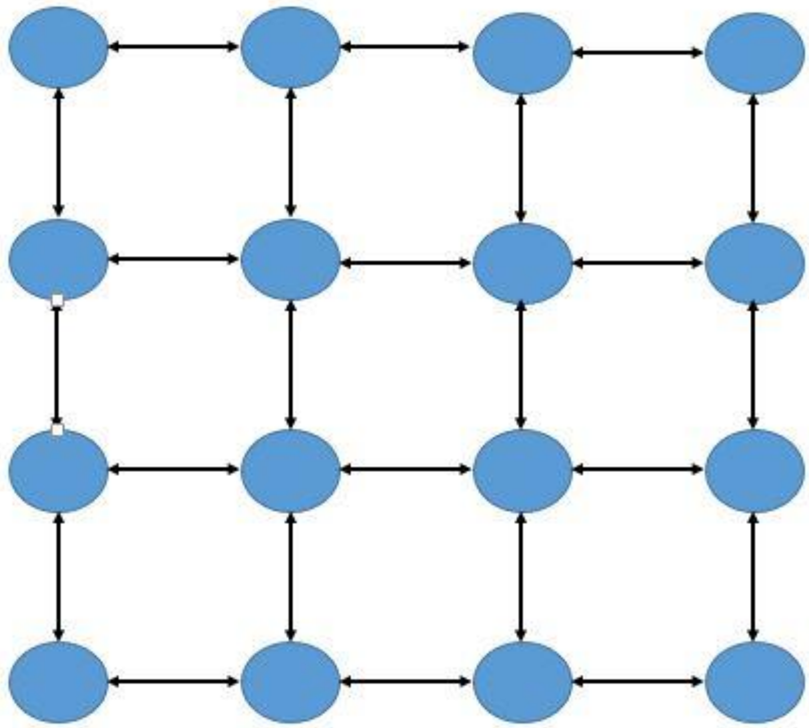


Figure 7: Bi-Directional Lattice with Shortcut

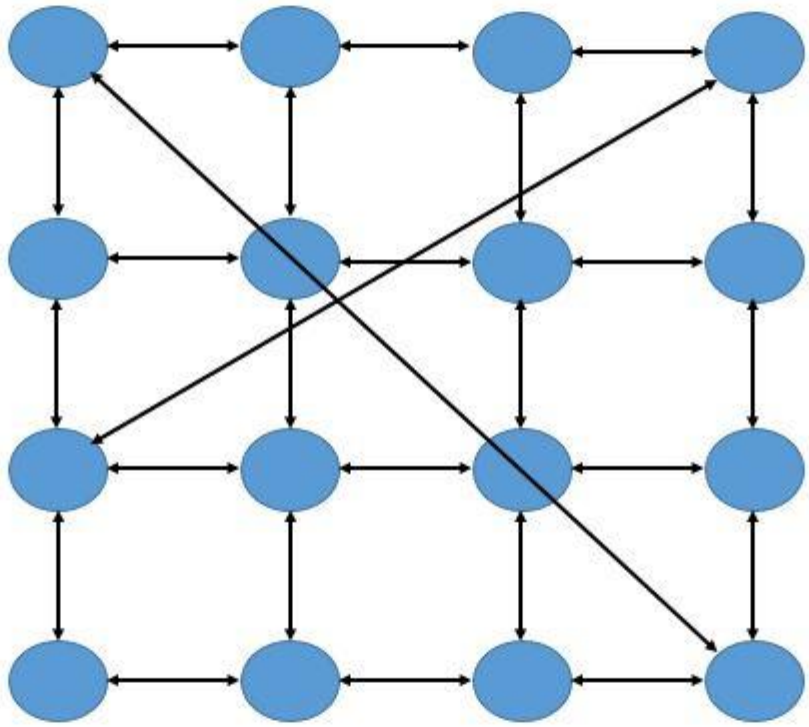


Figure 8: Directed Hierarchy

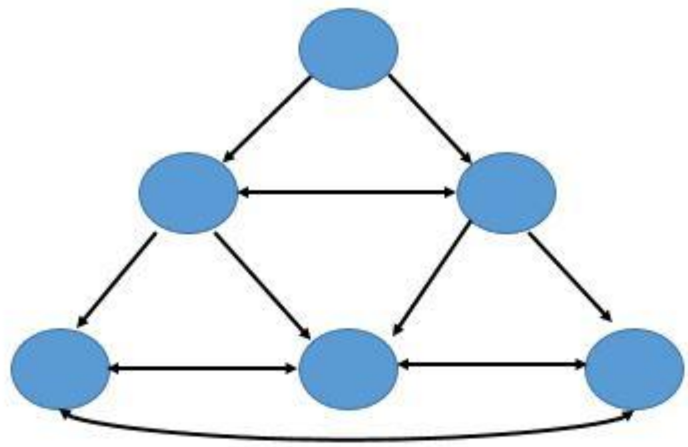


Figure 9: Clustered Directed Hierarchy

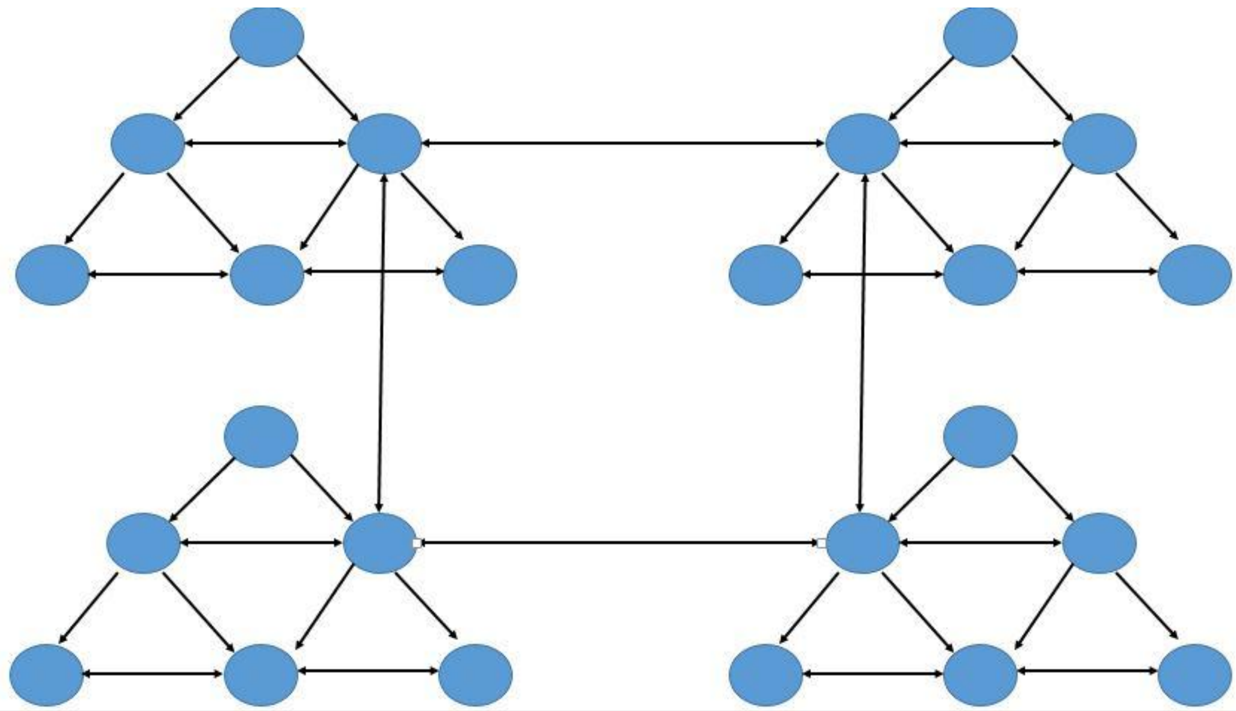


Figure 10: Evolutionary Comparisons

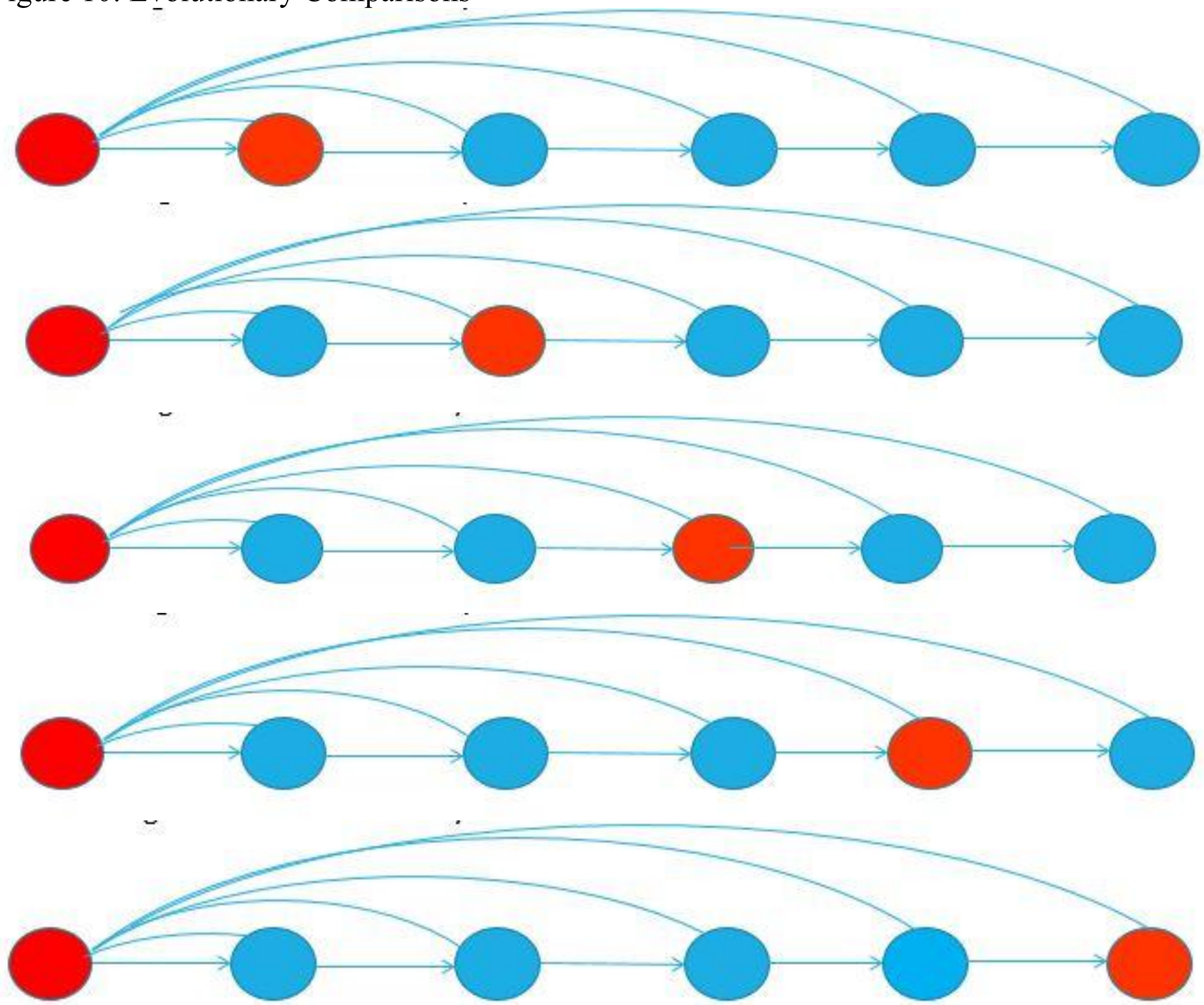


Figure 11: Consecutive Comparisons

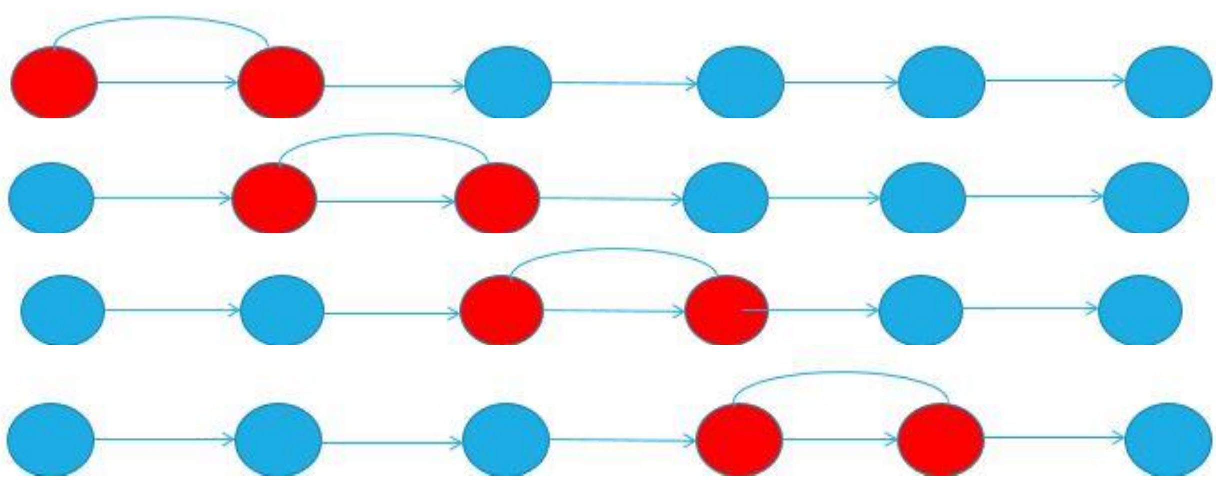


Figure 12: Semantic Similarity

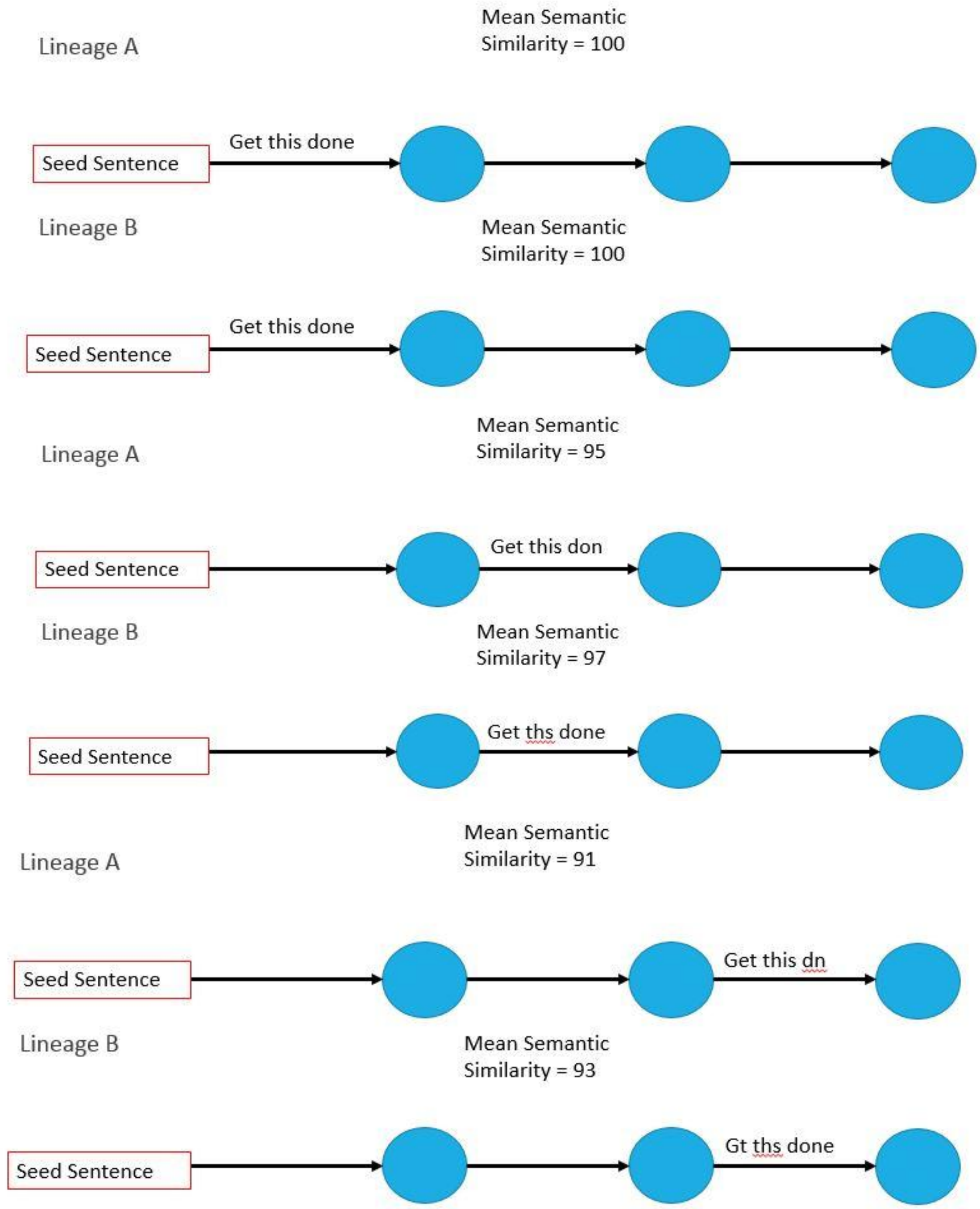


Figure 13: Semantic Diversification

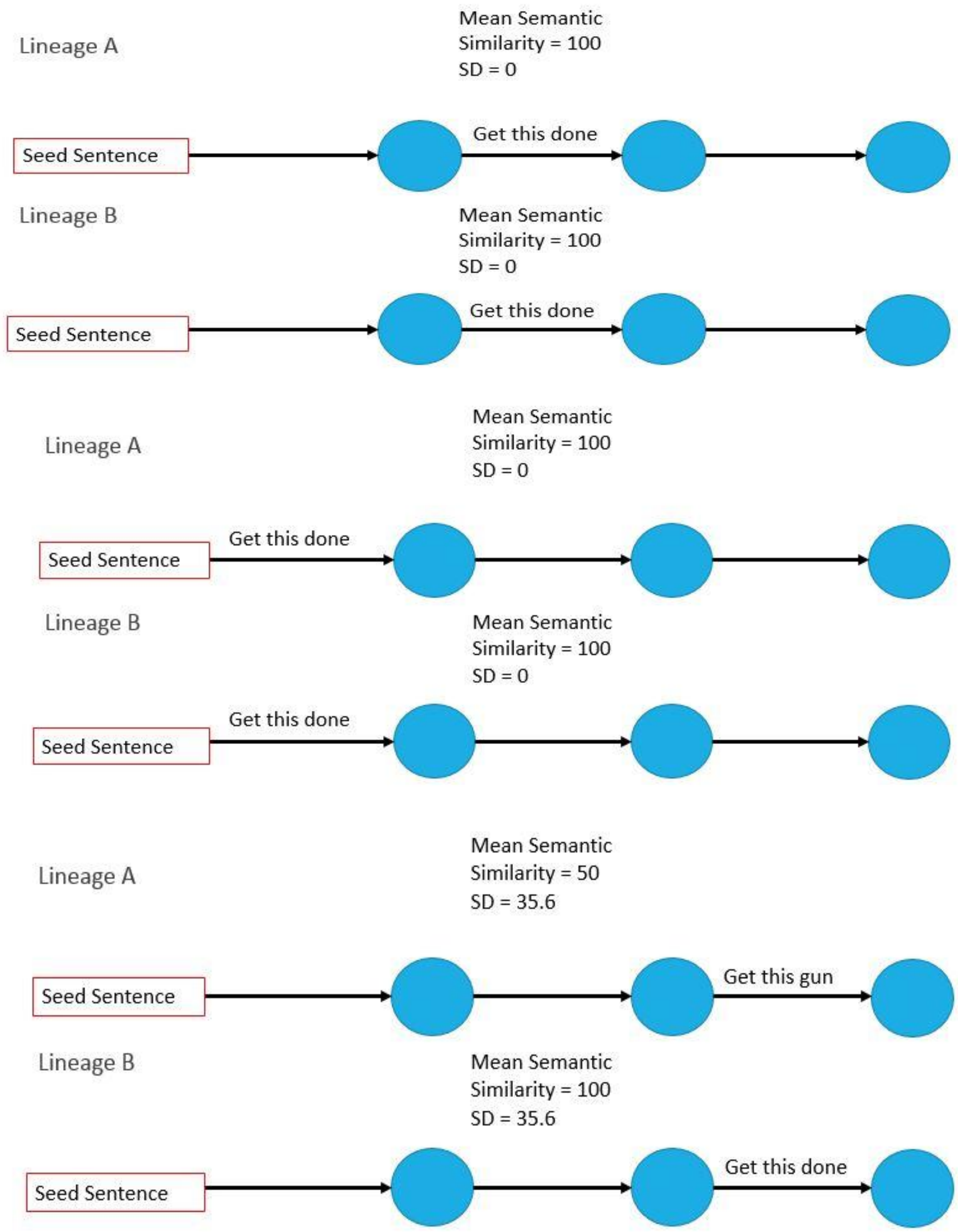


Figure 14: Marginal plot of number of transmissions, error correction and message format on consecutive fidelity.

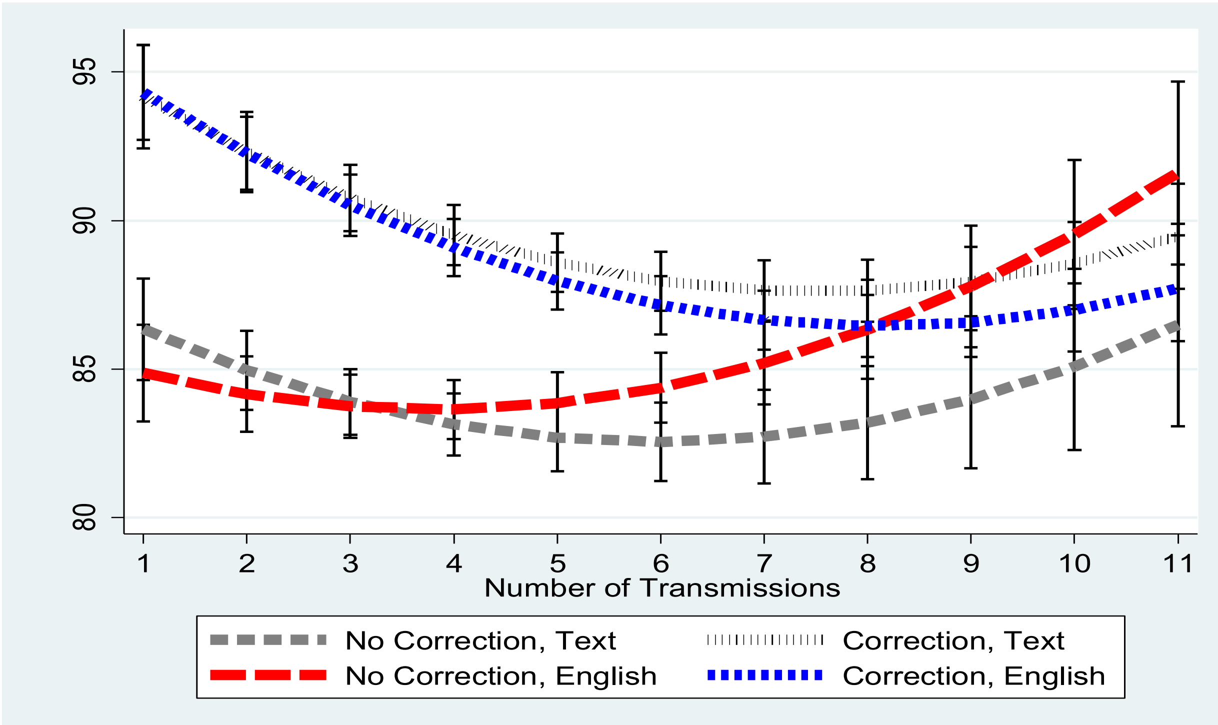


Figure 15: Marginal plot of number of transmissions, error correction and message format on evolutionary fidelity.

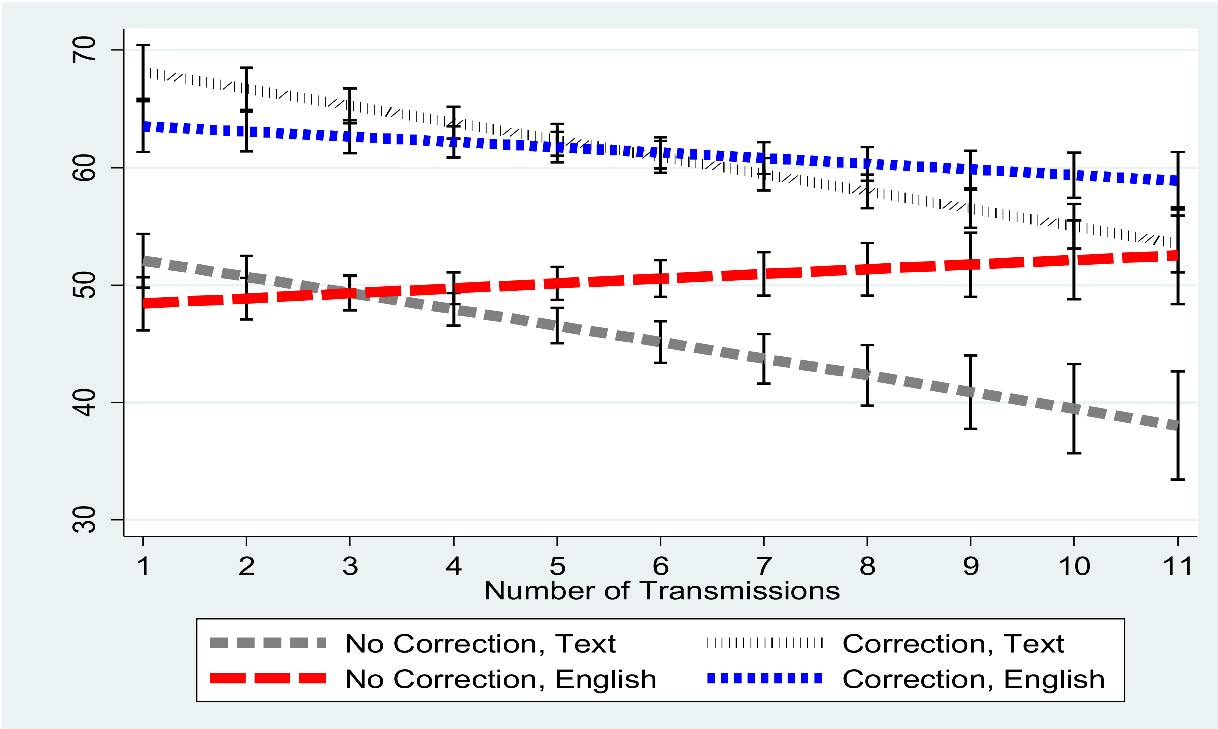


Figure 16: Marginal plot of number of transmissions, error correction and message format on the cross-lineage standard deviation of consecutive fidelity scores.

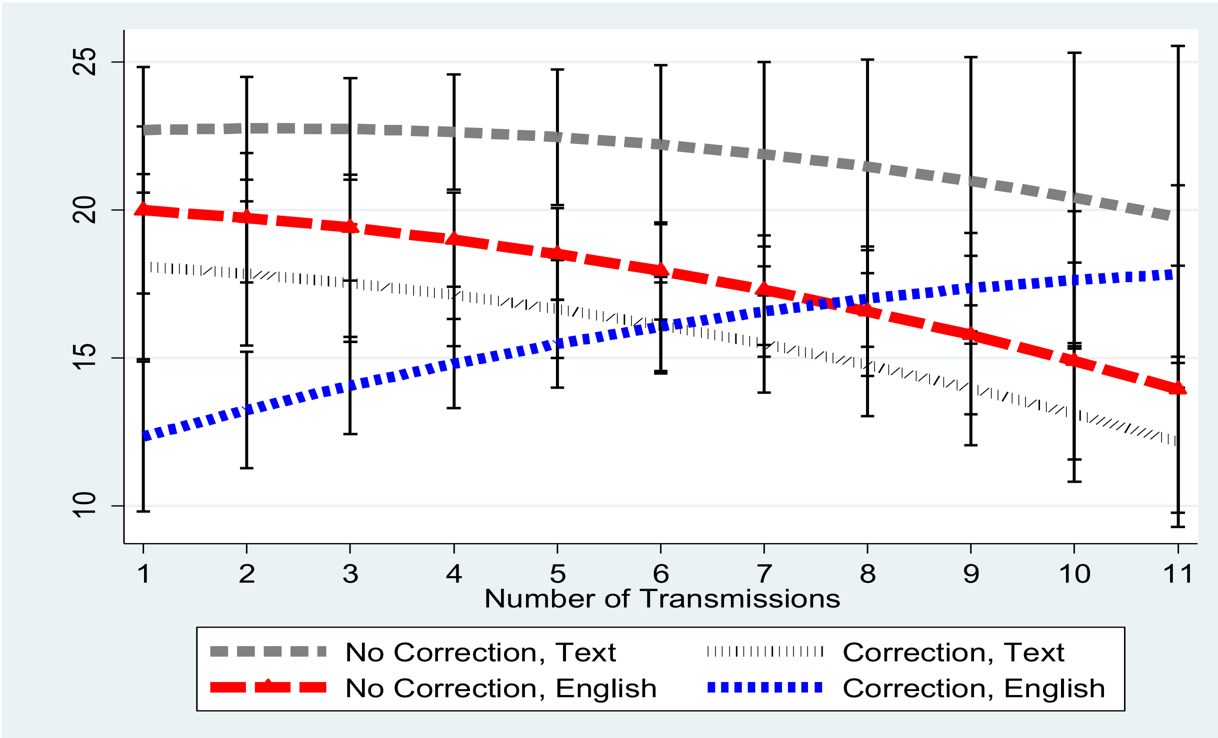


Figure 17: Marginal plot of number of transmissions, error correction and message format on the cross-lineage standard deviation of evolutionary fidelity scores.

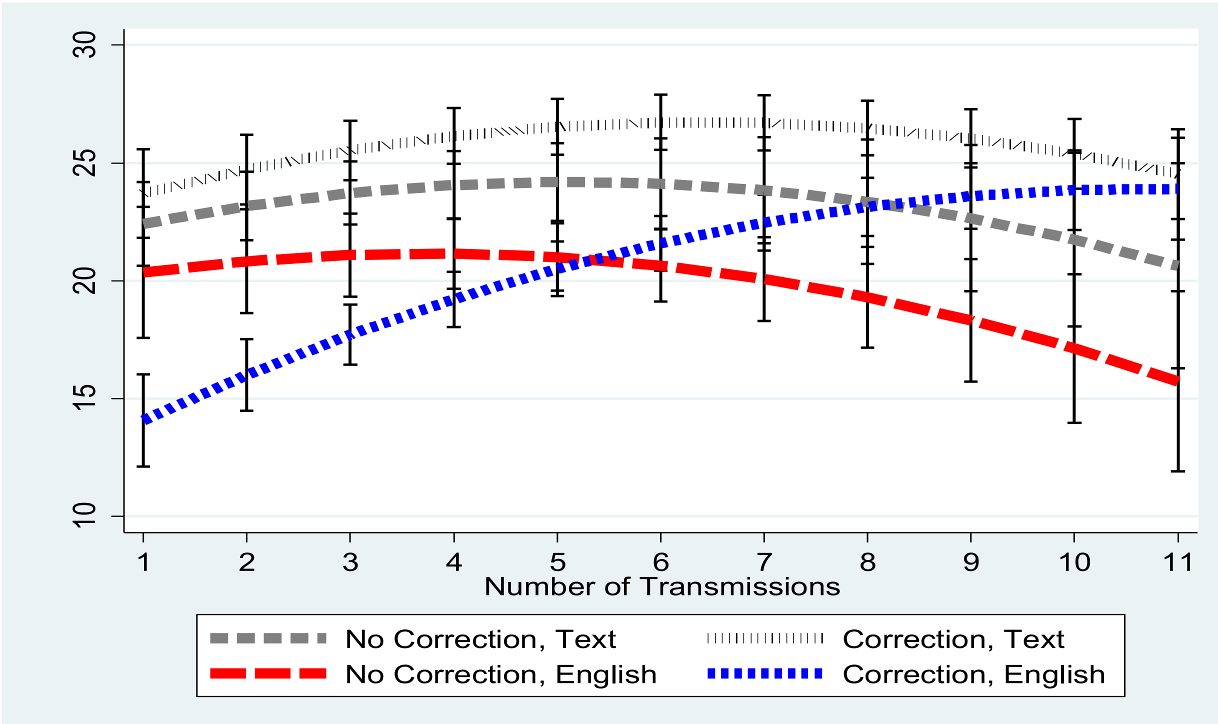


Figure 18:

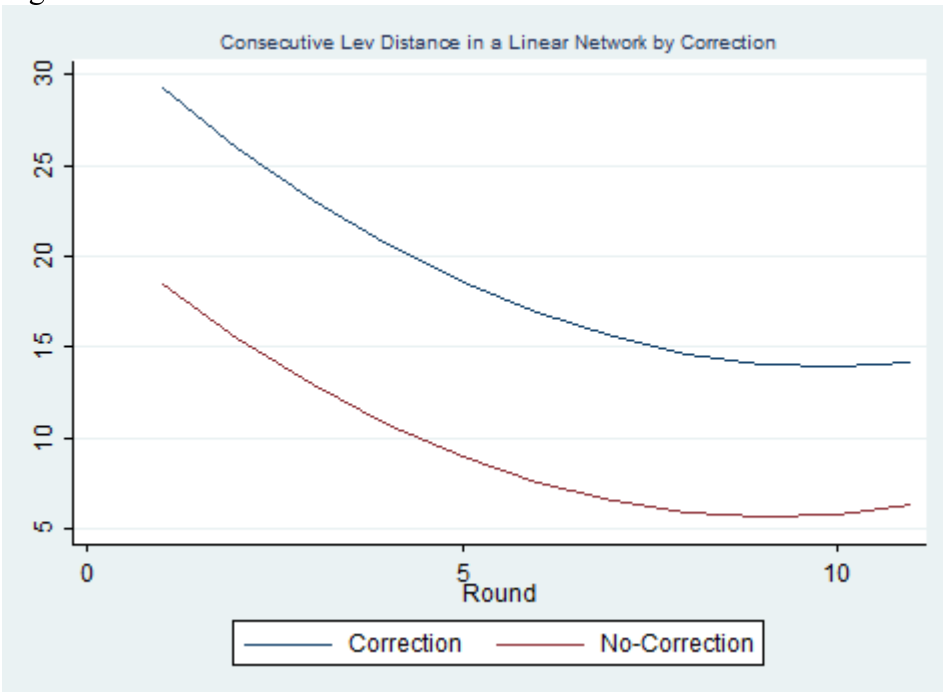
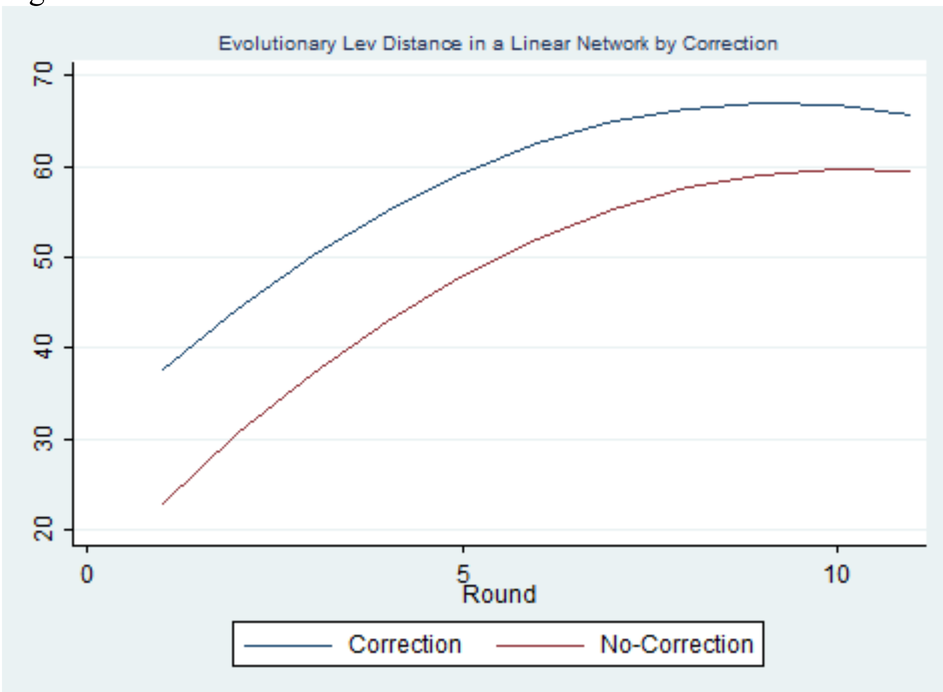
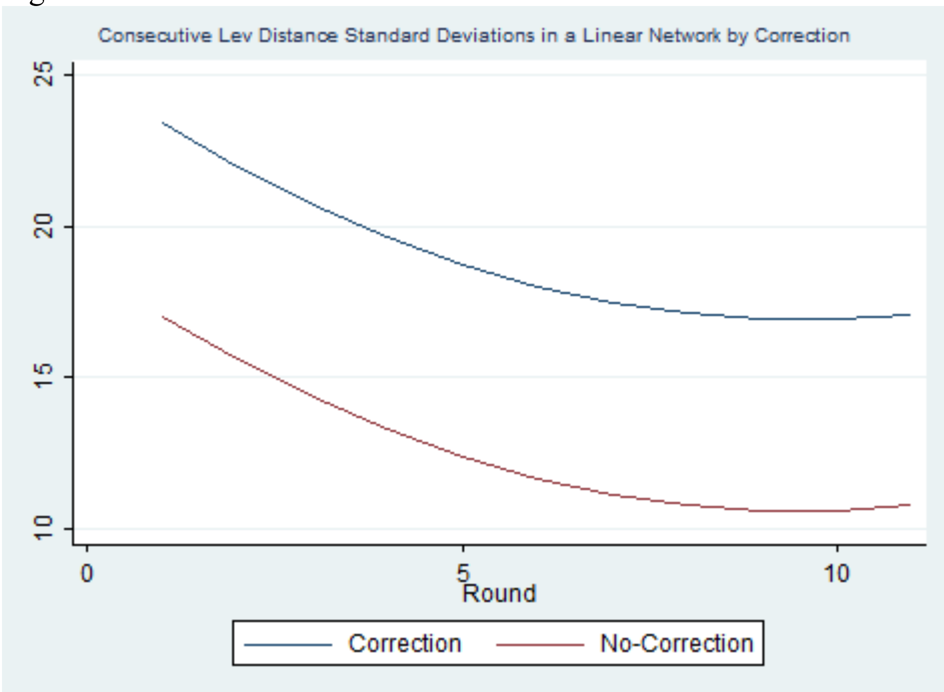

Consecutive Lev Distance in a Linear Network by Correction
30
25
20
15
10
5
0
5
10
Round
Correction
No-Correction

Figure 19:



Evolutionary Lev Distance in a Linear Network by Correction
70
60
50
40
30
20
0
5
10
Round
Correction
No-Correction

Figure 20:



Consecutive Lev Distance Standard Deviations in a Linear Network by Correction
25
20
15
10
0
5
10
Round
Correction
No-Correction

Figure 21:

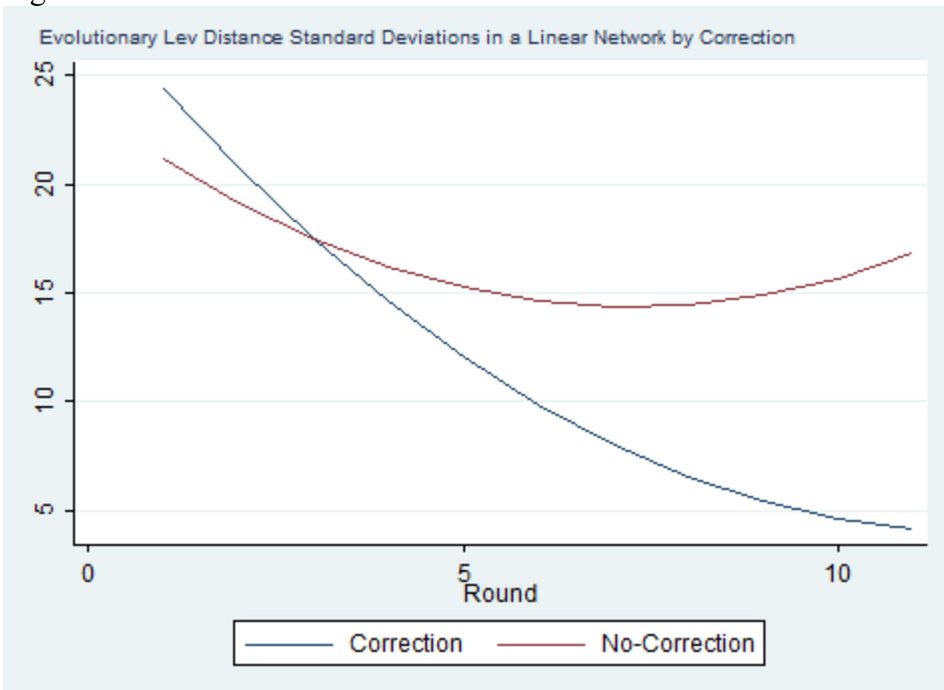
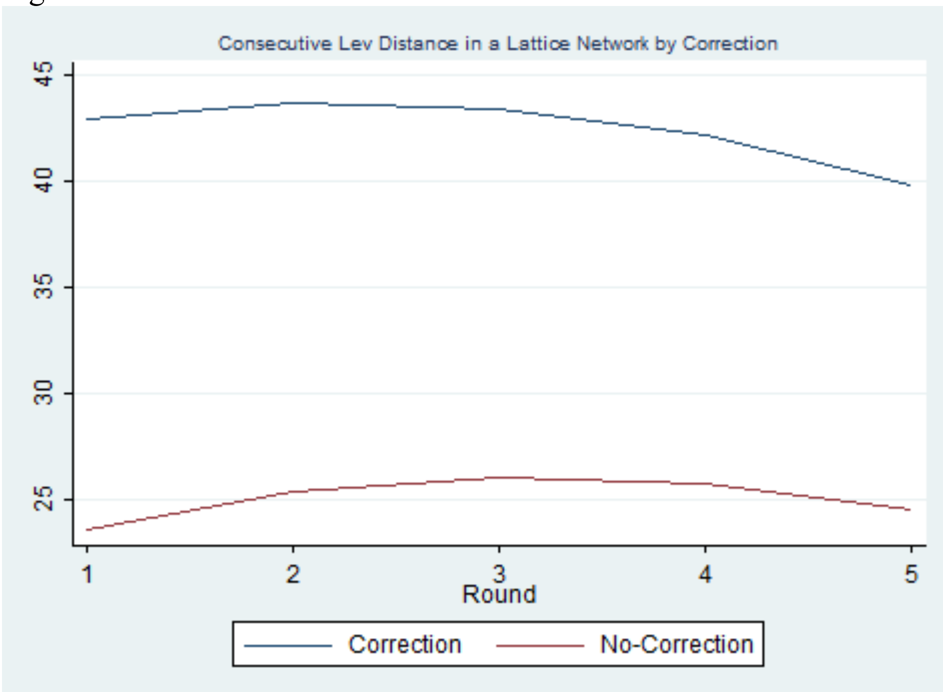
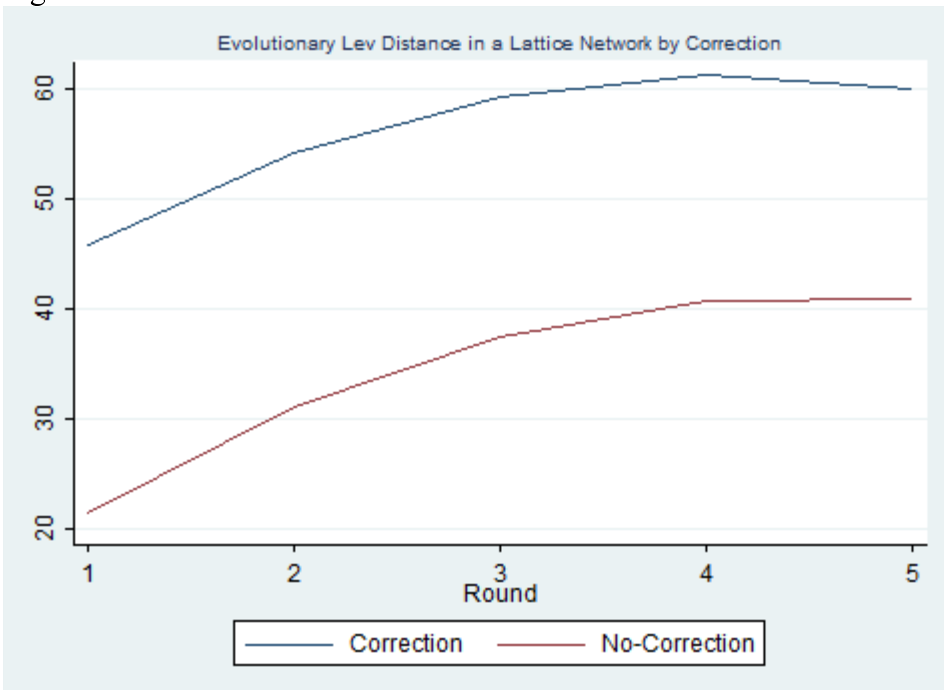

Evolutionary Lev Distance Standard Deviations in a Linear Network by Correction
25
20
15
10
5
0
5
10
Round
Correction
No-Correction

Figure 22:



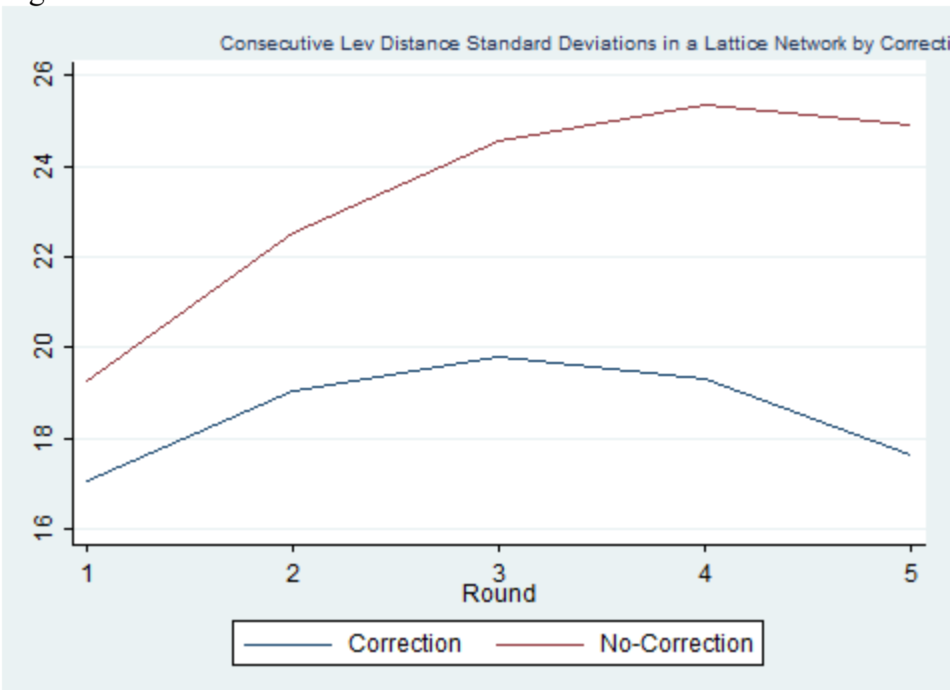
Consecutive Lev Distance in a Lattice Network by Correction
45
40
35
30
25
1
2
3
4
5
Round
Correction
No-Correction

Figure 23:



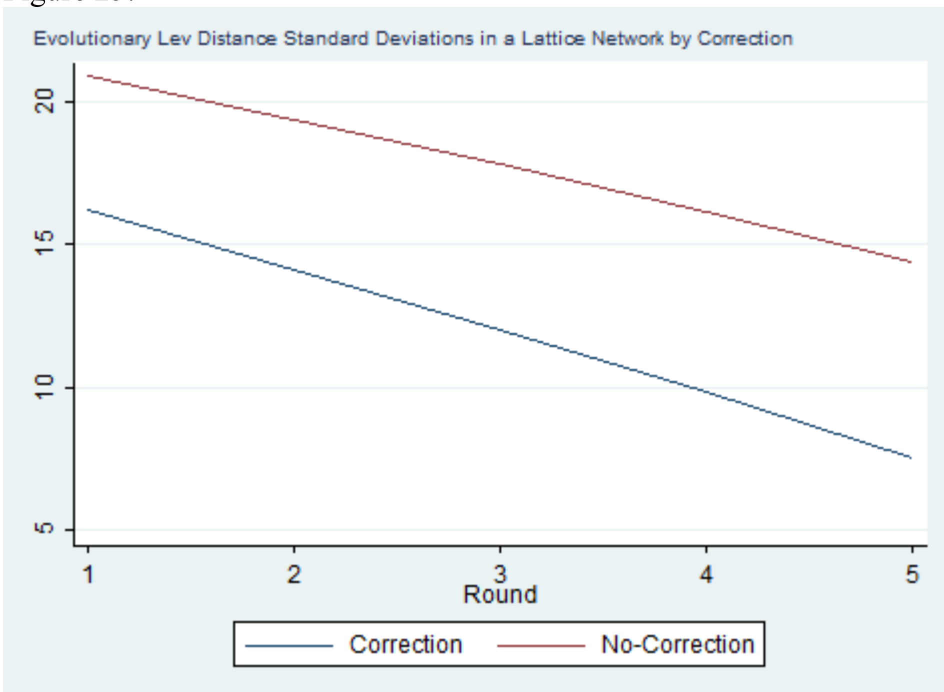
Evolutionary Lev Distance in a Lattice Network by Correction
60
50
40
30
20
1
2
3
4
5
Round
Correction
No-Correction

Figure 24:



Consecutive Lev Distance Standard Deviations in a Lattice Network by Correcti
16
18
20
22
24
26
1
2
3
4
5
Round
Correction
No-Correction

Figure 25:



Evolutionary Lev Distance Standard Deviations in a Lattice Network by Correction
20
15
10
5
1
2
3
4
5
Round
Correction
No-Correction

Figure 26:

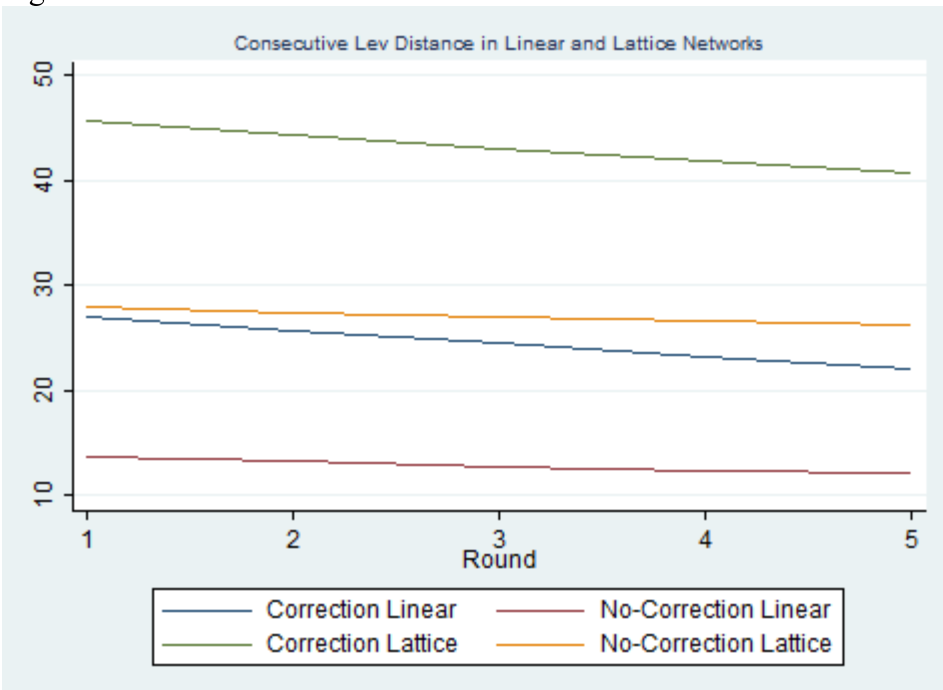
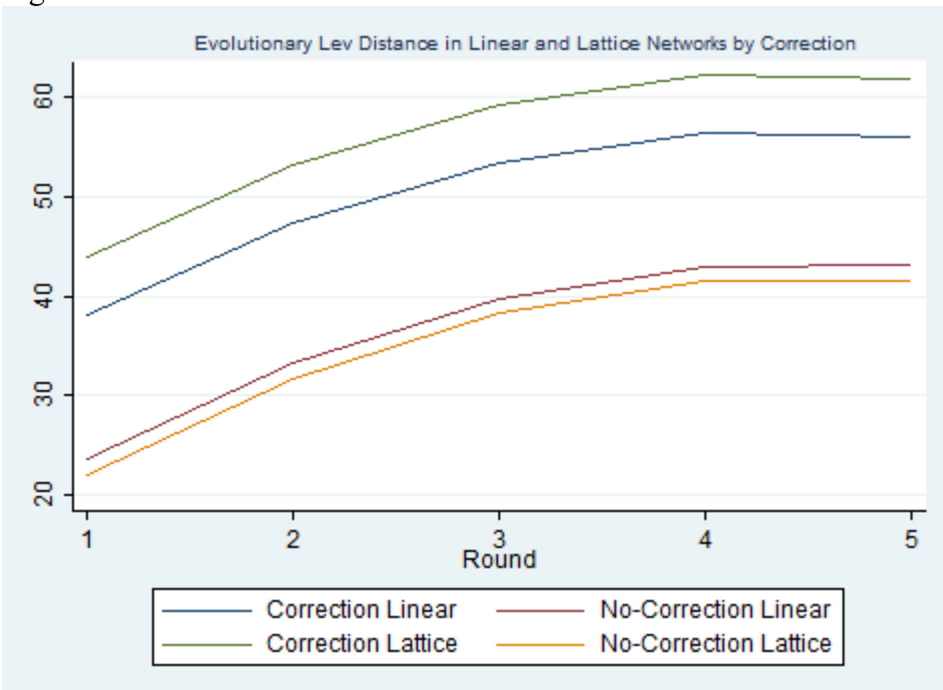
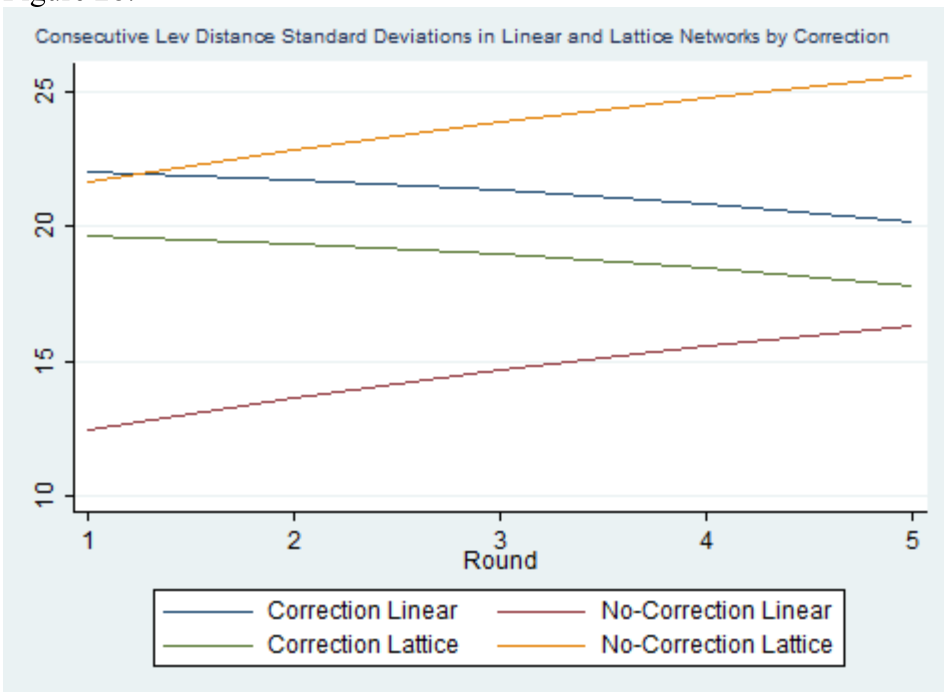

Consecutive Lev Distance in Linear and Lattice Networks
50
40
30
20
10
1
2
3
4
5
Round
Correction Linear
No-Correction Linear
Correction Lattice
No-Correction Lattice

Figure 27:



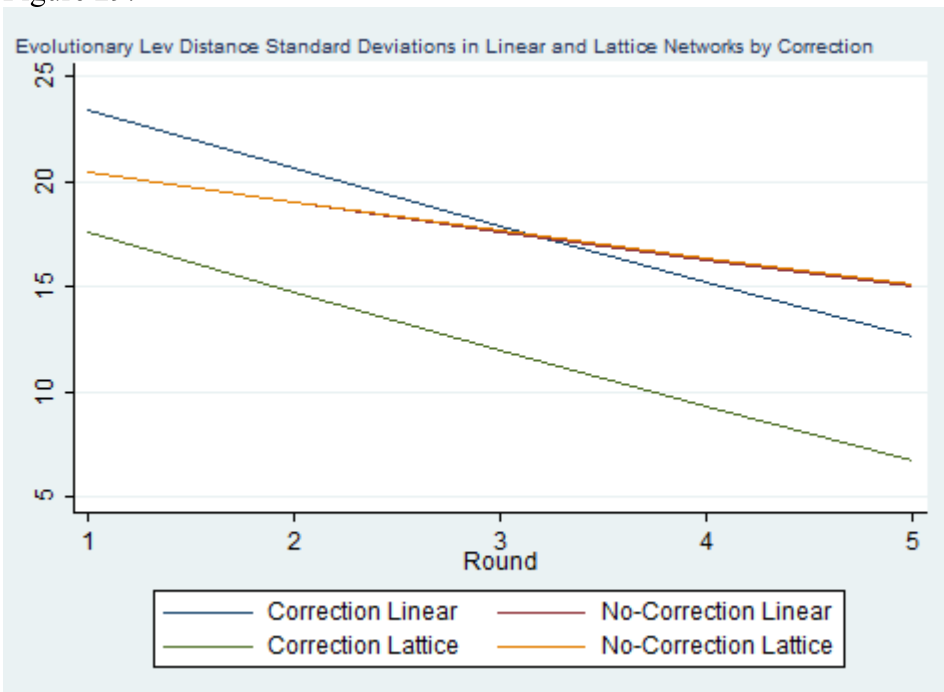
Evolutionary Lev Distance in Linear and Lattice Networks by Correction
20
30
40
50
60
1
2
3
4
5
Round
Correction Linear
No-Correction Linear
Correction Lattice
No-Correction Lattice

Figure 28:



Consecutive Lev Distance Standard Deviations in Linear and Lattice Networks by Correction
25
20
15
10
1
2
3
4
5
Round
Correction Linear
No-Correction Linear
Correction Lattice
No-Correction Lattice

Figure 29:


Evolutionary Lev Distance Standard Deviations in Linear and Lattice Networks by Correction
25
20
15
10
5
1
2
3
4
5
Round
Correction Linear
No-Correction Linear
Correction Lattice
No-Correction Lattice

15: Tables

Table 1- Models of consecutive ratings, evolutionary ratings, cross-lineage SD of consecutive ratings, and cross-lineage SD of evolutionary ratings

Model Number:	13	14	15	16
DV:	Consecutive Semantic Rating	Evolutionary Semantic Rating	Consecutive Semantic Rating Lineage SD	Evolutionary Semantic Rating Lineage SD
Transmissions	-1.840***	-1.365**	0.174	1.070*
	(0.356)	(0.471)	(0.569)	(0.417)
Format	-2.129	-5.471**	-2.401	-1.778
	(1.371)	(1.846)	(2.018)	(1.895)
Correction	8.311***	16.126***	-4.319*	1.028
	(1.342)	(1.806)	(2.094)	(1.466)
Transmissions^2	0.155***	0.003	-0.039	-0.104***
	(0.028)	(0.037)	(0.045)	(0.033)
Format x Transmissions	0.659*	1.814***	-0.311	-0.284
	(0.282)	(0.379)	(0.421)	(0.373)
Correction x Transmission	-4.84~	-0.059	-0.298	0.262
	(0.253)	(0.34)	(0.408)	(0.285)
Format x Correction	2.461	-0.166	-4.488	-8.744***
	(1.819)	(2.447)	(2.918)	(2.337)
Format x Corrections x Transmissions	-0.848*	-0.813	1.452***	1.182***
	(0.335)	(0.451)	(0.528)	(0.428)
Levenshtein Distance	-1.089***	-1.191***	0.870***	0.639***
	(0.016)	(0.019)	(0.067)	(0.087)
Constant	99.273***	100.726***	12.545***	13.849***
	(1.185)	(1.558)	(1.775)	(1.636)
Observations	4089	4089	4089	4089
R-Squared	0.551	0.578	0.348	0.207

***p<0.001, **p<0.01, *p<0.05, ~*p<0.05 one-tailed. Standard errors in parentheses.

Table 2 - Models of consecutive Lev distance, evolutionary Lev distance, cross-lineage SD of consecutive Lev distance, and cross-lineage SD of evolutionary Lev distance for linear network using crowd sourcing

Model Number:	5	6	7	8
DV:	Consecutive Lev Distance	Evolutionary Lev Distance	Consecutive Lev Distance Lineage SD	Evolutionary Lev Distance Lineage SD
Transmissions	-3.530**	8.865***	-1.697***	-2.533***
	(-1.234)	(-1.271)	(-0.381)	(-0.464)
Correction	11.121**	15.557*	6.41***	4.756***
	(-2.922)	(-6.364)	(-0.155)	(-0.851)
Transmissions^2	0.193~*	-0.433***	0.089*	0.174***
	(-0.101)	(-0.087)	(-0.031)	(-0.038)
Correction x Transmissions	-0.303	-0.845	-0.011	-1.584***
	(-0.378)	(-0.717)	(-0.027)	(-0.014)
Constant	21.783***	14.491**	18.63***	23.561***
	(-2.983)	(-4.67)	(-0.821)	(-1.001)
Observations	2115	2115	2115	2115
R-Squared	0.131	0.281	0.263	0.611

***p<0.001, **p<0.01, *p<0.05, ~*p<0.05 one-tailed. Standard errors in parentheses.

Table 3 - Models of consecutive Lev distance, evolutionary Lev distance, cross-lineage SD of consecutive Lev distance, and cross-lineage SD of evolutionary Lev distance for lattice network using crowd sourcing

Model Number:	9	10	11	12
DV:	Consecutive Lev Distance	Evolutionary Lev Distance	Consecutive Lev Distance Lineage SD	Evolutionary Lev Distance Lineage SD
Transmissions	3.277	14.464***	5.098***	-1.376
	(3.226)	(2.487)	(0.968)	(1.047)
Correction	20.46***	25.663***	-0.923***	-4.149***
	(4.361)	(4.408)	(0.145)	(0.062)
Transmissions^2	-0.508	-1.601***	-0.613**	-0.414
	(0.448)	(0.309)	(0.153)	(0.167)
Correction x Transmissions	-1.011	-1.312	-1.277***	-0.548***
	(1.243)	(0.968)	(0.028)	(0.017)
Constant	20.771***	8.52	14.767***	22.307***
	(5.935)	(5.362)	(1.243)	(1.365)
Observations	3561	3561	3561	3561
R-Squared	0.153	0.292	0.171	0.461

***p<0.001, **p<0.01, *p<0.05, ~*p<0.05 one-tailed. Standard errors in parentheses.

Table 4 - Models of consecutive Lev distance, evolutionary Lev distance, cross-lineage SD of consecutive Lev distance, and cross-lineage SD of evolutionary Lev distance for linear and lattice networks using crowd sourcing

Model Number:	13	14	15	16
DV:	Consecutive Lev Distance	Evolutionary Lev Distance	Consecutive Lev Distance Lineage SD	Evolutionary Lev Distance Lineage SD
Transmissions	-1.909	14.311***	1.181	-1.513*
	(2.944)	(1.949)	(1.212)	(0.622)
Correction	13.475***	15.001*	10.843***	4.332***
	(4.034)	(5.897)	(0.548)	(0.622)
Transmissions^2	0.211	-1.559***	-0.037	0.031
	(0.411)	(0.258)	(0.179)	(0.128)
Structure	12.719***	-2.113	8.962***	-0.046
	(2.142)	(4.094)	(0.163)	(0.041)
Structure x Correction	5.65~*	7.781	-11.341***	-5.826***
	(3.179)	(5.302)	(0.161)	(0.065)
Correction x Transmissions	-0.595	-0.419	-1.407***	-1.371***
	(1.112)	(0.9122)	(0.181)	(0.207)
Constant	15.051**	10.655*	11.448***	21.941***
	(4.753)	(4.767)	(1.659)	(0.826)
Observations	4553	4553	4553	4553
R-Squared	0.214	0.271	0.191	0.453

***p<0.001, **p<0.01, *p<0.05, ~*p<0.05 one-tailed. Standard errors in parentheses.

REPORT DOCUMENTATION PAGE (Standard Form 298)

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13. SUPPLEMENTARY NOTES

14. ABSTRACT

The proposed research explores how message format, errors, and error correction, impact the spread of information and behaviors in social networks. Humans make mistakes but the diffusion of information through social networks is typically modeled as though they do not. We propose to complete development of new experimental software that will permit us to examine the effects of message format, error, and error correction, in networks with complex (i.e., non-linear) structures. The project is innovative in that there has been minimal prior research in this area, and none besides our own that considers semantic meaning. The project is risky in that it is a new area of study that has already proven to require complex methodology. However, greater knowledge in this area would contribute to enhanced communications methodologies and improve models of diffusion in social networks.

15. SUBJECT TERMS

Social Networks; Social Contagions; Diffusion; Error; Error Correction; Information Theory; Software

16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
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Unclassified	Unclassified	Unclassified			19b. TELEPHONE NUMBER *(Include area code)* 607-280-2728

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Prescribed by ANSI Std. Z39.18

Enclosure 1

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1. Submissions:
(a) Papers published in peer reviewed journals: No papers supported by this grant have yet been published.
(b) Papers published in non-peer reviewed journals: No papers supported by this grant have yet been published.
(c) Presentations:
i. At meetings, but not given in conference proceedings: American Sociological Association Annual Meeting- August 19, 2014
ii. Non-peer reviewed conference proceedings: None.
iii. Peer-reviewed conference proceedings: Academy of Management Meeting- August 4, 2014
iiii. Invited talks: University of South Carolina, Department of Sociology, February 27, 2015; Stanford University, Graduate School of Business, January 28, 2015.
(d) Manuscripts: Innovation from Imitation: Error in Diffusion Processes (Ph.D. Dissertation; See Appendix B)
(e) Books: None
(f) Honors and Awards: Best Paper Prize, Academy of Management Meetings, 2014
(g) Patents disclosed: N/A
(h) Patents awarded: N/A

2. Students/Supported Personnel
(a) Graduate Students: Watkins, Kate, One semester, 0.50 FTE.
(b) Post-Doctorates: None.
(c) Faculty: PI drew no support from this grant.
(d) Undergraduate Students: None
(e) N/A
(f) Masters Degrees awarded: None
(g) Ph.D.s Awarded: None (Eric Gladstone defended in July of 2015)
(h) Other Research Staff: Eric Gladstone, Grad student Collaborator, not supported on grant

3. Technology Transfer: N/A.

4. Scientific Progress: Developed proposed software for collection of novel data. Completed validation studies to demonstrates usefulness of software. Executed lattice study to determine effect of multiple, closely-related information channels on error propagation (See full report and appendices).

5. Copies of Technical Reports: See appendices.