

Error correction mechanisms in social networks can reduce accuracy and encourage innovation

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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.

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1. 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 et al., 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.¹ 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 et al., 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.

2. Background

2.1. Diffusion and social contagion

Beliefs or behaviors that spread from person to person, intentionally or unintentionally, are known as “social contagions,” and

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¹ Some studies of diffusion focus on how attitudes toward 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.

their spread is often referred to as “diffusion.”² 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 transferable 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 20th century, with [Ryan and Gross' \(1943\)](#) study of the diffusion of hybrid seed corn and [Coleman et al.'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, 2001](#)). 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 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 et al., 2003](#); [Lundberg, 1975](#); [Pickard et al., 2011](#); [Travers and Milgram,](#)

[1969](#); [Watts et al., 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 et al., 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 et al., 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 et al., 2009](#); [Lewis et al., 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 et al., 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, 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 et al., 2012](#); [Centola and Macy, 2007](#); [Rodriguez et al., 2014](#)) has often employed simulation models that implicitly (or explicitly; see [Carley, 1991](#), p. 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.

2.2. Errors and diffusion

In his 1977 presidential address to the American Statistical Association [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

² 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.

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 50 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.³ 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":⁴ 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 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 et al., 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: Chap. 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 et al., 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 et al., 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

³ Similar processes may play out for exogenous duplication (e.g., mutation in a bacterium), but are beyond the scope of this paper.

⁴ Also known as "operator," "Chinese whispers," "grapevine," "pass the message," "whisper down the lane," "broken telephone" and numerous other names.

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 et al., 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 et al. (2009) developed a procedure for tracking short phrases, or memes,⁵ 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 et al. (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.

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 et al., 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.

3. 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.⁶ 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 additional letters redundant and unnecessary. Shannon's entropy⁷ 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 cntnt 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.⁸ Information theory is thus a useful framework

⁶ Or, if the reader prefers, an episode of the television program *Wheel of Fortune*.

⁷ 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.

⁸ 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

⁵ 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.

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, p. 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, 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.⁹ 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 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, p. 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.¹⁰ This leads to the following hypothesis:

⁹ 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.

¹⁰ 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.

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.

- **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.

4. Methods

4.1. 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 et al., 2009; Simmons et al., 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 10 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 5 s, was then replaced by blank space for 5 s, 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 et al., 2005; Ling, 2004), and the growing use of electronic data for diffusion studies (e.g., Lewis et al., 2008, 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.¹¹ 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.

¹¹ 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.

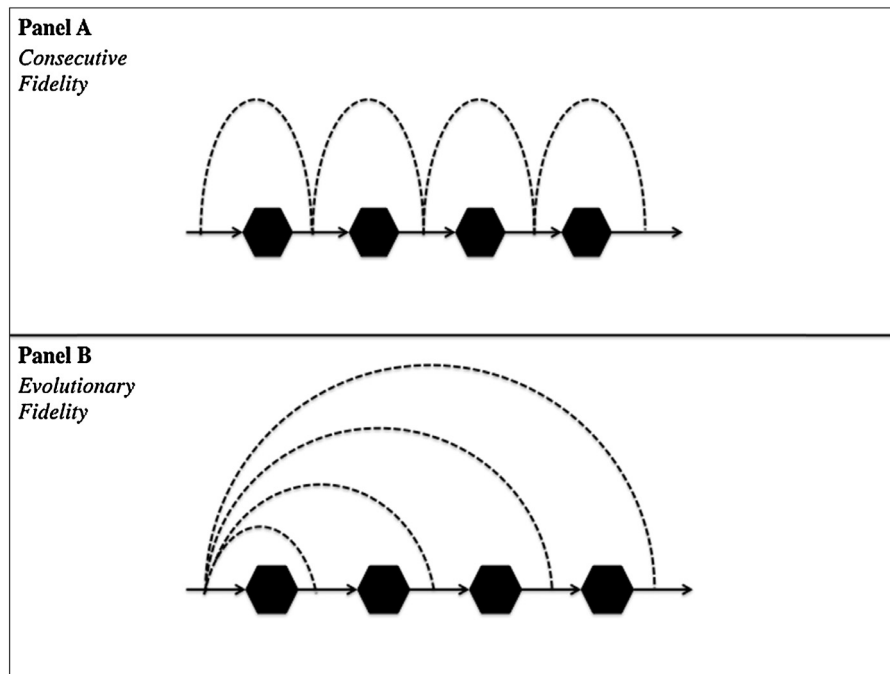


Fig. 1. Consecutive fidelity (Panel A) and Evolutionary fidelity (Panel B). Solid arrows are network ties through which sentences are transmitted. Dashed arcs are parent–child (Panel A) and seed–child (Panel B) comparisons scored by coders to produce fidelity measures. All sentence pairs (i.e., dashed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

4.2. Dependent variables

To analyze message fidelity, we subdivide it into two types: consecutive and evolutionary fidelity (see Fig. 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.

Earlier research on the accumulation of errors in diffusion (e.g., Adamic et al., 2014; Leskovec et al., 2009; Mei and Zhai, 2005; Simmons et al., 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 ($\alpha = 0.8601–0.9597$), 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.

4.3. 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 et al., 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.

4.4. 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 1.¹² 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.

4.5. 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/taped 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.

5. 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 ($0.155, p < 0.001$); 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.

The marginal effects of format and error correction on consecutive fidelity are illustrated in Fig. 2, with all control variables

¹² 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.

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

Model number: DV:	1 Consecutive rating	2 Evolutionary rating	3 Consecutive lineage SD	4 Evolutionary lineage SD
Transmissions	−1.840*** (0.356)	−1.365** (0.471)	0.174 (0.569)	1.070* (0.417)
Format (English = 1)	−2.129 (1.371)	−5.471** (1.846)	−2.401 (2.018)	−1.778 (1.895)
Correction	8.311*** (1.342)	16.126*** (1.806)	−4.319* (2.094)	1.028 (1.466)
Transmissions ²	0.155*** (0.028)	0.003 (0.037)	−0.039 (0.045)	−0.104** (0.033)
Format × transmissions	0.659 (0.282)	1.814*** (0.379)	−0.311 (0.421)	−0.284 (0.373)
Correction × transmissions	−0.484~ (0.253)	−0.059 (0.340)	−0.298 (0.408)	0.262 (0.285)
Format × correction	2.460 (1.819)	−0.166 (2.447)	−4.488 (2.918)	−8.744*** (2.337)
Format × correction × transmissions	−0.848* (0.335)	−0.813~ (.451)	1.452** (0.528)	1.182** (0.428)
Levenshtein distance	−1.089*** (0.016)	−1.191*** (0.019)	0.870*** (0.067)	0.639*** (0.087)
Constant	99.273*** (1.185)	100.726*** (1.558)	12.545*** (1.775)	13.849*** (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 are in parentheses.

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 95 percent accuracy, but this diminishes to a low of roughly 87 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 85 percent accuracy, declines to a low of approximately 84 percent after six

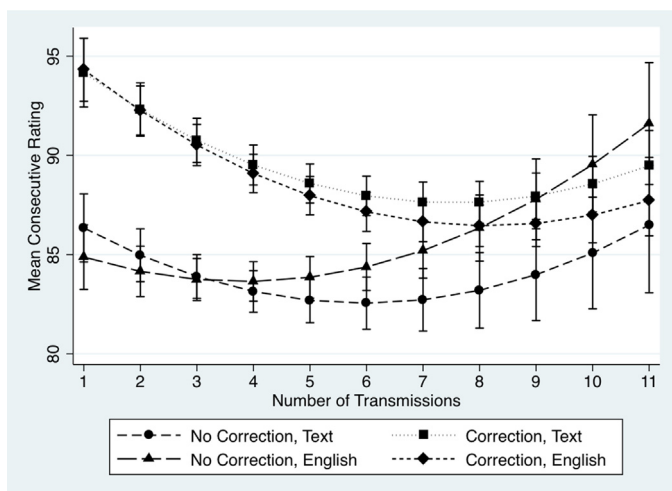


Fig. 2. Marginal plot of number of transmissions, error correction and message format on consecutive fidelity.

transmissions, and then recovers to a maximum of over 90 percent after 11 transmissions. English without correction increases the most in consecutive fidelity, achieving a maximum of over 90 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.

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 Fig. 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 11 transmissions is less than 5 percent, though a substantial loss of fidelity is incurred at the first

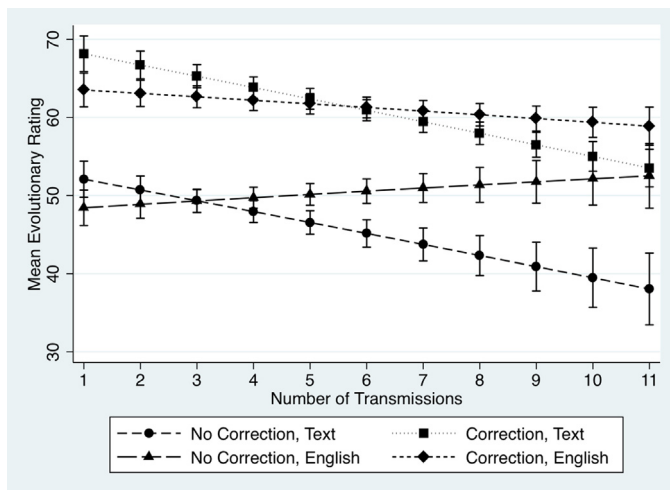


Fig. 3. Marginal plot of number of transmissions, error correction and message format on evolutionary fidelity.

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 70 percent to only a bit over 50 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 50 percent, while higher entropy formats (i.e., text messaging pidgin) show a linear decline in fidelity from a bit over 50 percent to somewhat less than 40 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.

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 Fig. 4,

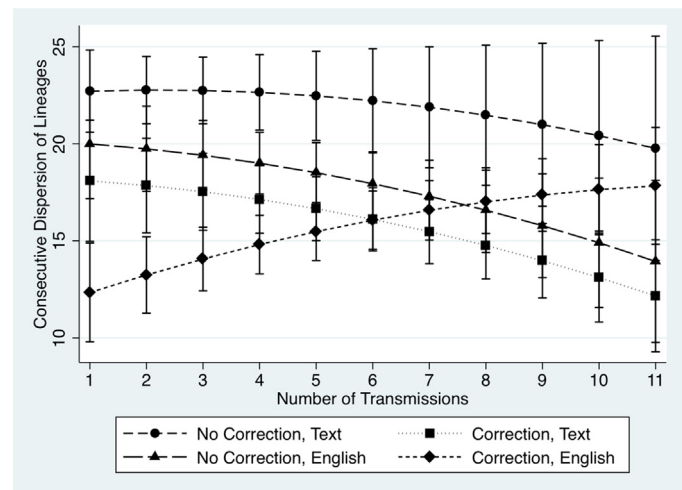


Fig. 4. Marginal plot of number of transmissions, error correction and message format on the cross-lineage standard deviation of consecutive fidelity scores.

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.

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 Fig. 5, with all control variables set to their means. The predictions are, in general, similar to Fig. 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.

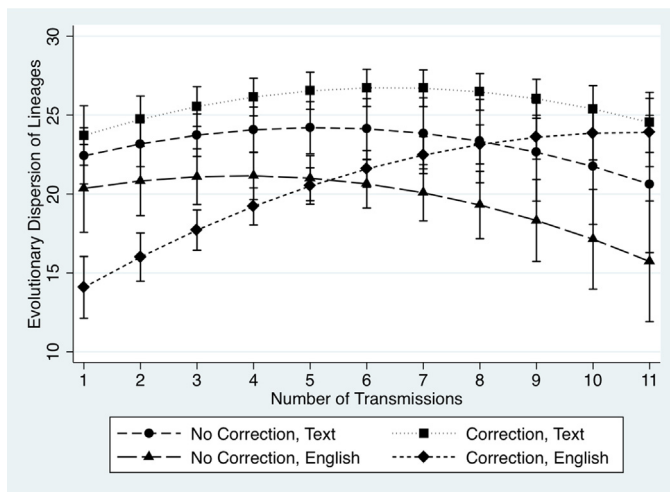


Fig. 5. Marginal plot of number of transmissions, error correction and message format on the cross-lineage standard deviation of evolutionary fidelity scores.

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.

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.

6. 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 11 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 et al., 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 et al., 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 to be 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, than 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.

7. 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 37,000 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.¹³ 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.

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¹³ We suspect that these logistical difficulties account for the relative lack of earlier, similar work in this area.

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