Title: A simulation model of diffusion with schemas

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Abstract

Although models for network diffusion have proliferated over the last 25 years, few have accounted for a fundamental truth about diffusion: ideas, information, and innovations change as they diffuse. This study develops a simulation model that incorporates two of the ways that ideas can change as they spread from person to person. First, ideas can be misinterpreted, or repeated to another person with error. Second, people can generate new ideas by recombining two schemas, meaning two frameworks for ideas that they already know. To simulate this, I seed a population with a set of 3 bit idea frameworks, which I refer to as schemas, and then simulate communication by letting a person draw a 5 bit string from the 3 bit schema, or by creatively recombining 2 3-bit frameworks into a 5 bit string. The recipient of the 5-bit string matches the received string to the set of schemas that he or she already knows. If he or she receives several bits that cannot be matched to an existing schema, he or she creates a new one. To explore the parameter space, I vary the probability with which people draw from a single schema versus combining two existing schemas. The results of this simulation suggest, paradoxically, that creatively recombining schemas leads to less diverse outcomes, and that some ideas are more likely to stick than others.

Introduction

Over the last 25 years, the number of formal network diffusion models has proliferated, generating many key insights for sociological research. At their core, formal network diffusion models describe how information, ideas, innovations, or other social contagions spread through a network of connected people. These models have been used to explain how innovations take off in popularity (Rogers 2003), how groups of people come to consensus (Friedkin 1998; Friedkin and Johnsen 2011) or become polarized (Baldassarri and Bearman 2007), how non-communicable diseases, like obesity, spread (Christakis and Fowler 2007), how people find job leads (Granovetter 1973, 1995), and even how organizations become similar to one another (DiMaggio and Powell 1983). Underlying this diverse set of processes is a simple formal model: people pass discrete pieces of information, which represent the ideas, innovations, or other intangible things spreading through the network, to people that they are connected to, who then relay the bits of information to others.

The underlying formal model, however, assumes that people do not process the information as they receive it¹ – an assumption that is violated in virtually every empirical situation. People or companies who adopt innovations modify them to suit their needs (Bartel and Garud 2009; Faulkner and Runde 2009; Strang 2010); people who hear a new idea hear it through the lens of their previous experience (Hunzaker 2014; Sperber 1996); even organizational routines vary as they are transmitted between people (Feldman and Pentland 2003). For each socially meaningful contagion (Strang and Meyer 1993), people introduce their own biases about the diffusing bit into the diffusion process. Actors' biases could lead them to modify the diffusing idea, innovation, or piece of information to suit the bias, or could lead them

¹ Existing studies often assume that information from several others is averaged, but it is not modified based on the recipient's beliefs or mental representations generally.

to reject the diffusing bit altogether. This actor-level processing, in turn, could influence the overall outcome of the diffusion process.

This study addresses this deficiency by introducing a diffusion model that takes into account actors' schemas – that is, their underlying biases about the diffusing bit. The diffusion with schemas model proposed here draws on two distinct notions of schemas: constraints on our beliefs about what actions are possible (Sewell 1992), and cognitive heuristics that aid processing of new information (Sperber 1996; Strauss and Quinn 1997). I construct an agent-based model that integrates both of these views of schemas. In the model, people who are confronted with new information choose from a set of “logics,” meaning schemas that represent constraints on beliefs about what actions are possible, and then create a specific instance of an interaction by drawing from the cognitive heuristic associated with that logic. People receiving the information then build on their existing schemas by learning from the specific information conveyed during the interaction. This follows research from anthropology (Strauss and Quinn 1997) and organizational theory (Feldman and Pentland 2003) that suggests that although the meaning of an idea or the enactment of a ritual is drawn from a relatively stable underlying schema, the meaning or ritual is enacted in a slightly different way at each interaction.

The rest of this study proceeds as follows. I begin by briefly describing how previous formal models of diffusion have treated processing of the diffusing information, noting two recent models that partially address cognitive processing. I follow with a discussion of the two branches of the literature on schemas that the simulation draws on. This is followed by a description of the simulation approach, and an analysis of how the results differ from diffusion models that do not include cognitive processing.

Diffusion models' unthinking averaging

Although formal models of diffusion have proliferated in recent years, most rely on similar epidemiological foundations. In these models, ideas, innovations, or pieces of information are passed without changing from person to person along observed network ties. Typically, formal diffusion models assume that each bit of information spreading between people is independent of the spread of other bits, and therefore the models generally consider the spread of one bit at a time. This process mirrors the process of HIV or another sexually transmitted disease spreading through a sexual contact network, an analogy that is sometimes made explicitly (Moody 2001; Noymer 2001). At best, some models allow people to average the information that they receive together, but virtually none allow people to modify information based on what the person currently believes.

The existing models take one of two approaches to simulating how ideas spread: averaging or replacement. The averaging approach, developed independently in sociology (Friedkin 1998; Friedkin and Johnsen 2011) and statistics (DeGroot 1974), suggests that people update their opinions by taking the weighted average of their network neighbors' opinions and their own opinion. The replacement approach, which also has been adopted both in sociology (Carley 1991; Mark 1998) and physics (Durrett et al. 2012; Holme and Newman 2006), suggests that during a single interaction event, individuals replace an existing piece of information with a piece of information from the person they are interacting with. In both approaches, a person only minimally processes the information that they encounter. In the averaging approach, a person incorporates information proportionally to the number of people they encounter, regardless of the content that is shared. In the replacement approach, a person adopts information from another person with a given probability, without any processing whatsoever. Although these approaches have illustrated how groups reach consensus (e.g. Childress and Friedkin 2012) and how

networks and opinion changes coevolve in theory (Carley 1992; Durrett et al. 2012), they ignore any cognitive processing by actors in the model.

Although they do not capture a dependence between bits, two recent studies have relaxed the assumption that information does not change as it is transmitted. The first study by Dandekar et al. (2013) introduces a cognitive bias, biased assimilation, into the averaging process. Biased assimilation suggests that people are more likely to incorporate information that confirms their previously existing views, and are more likely to disregard information that contradicts their previously existing views (Lord, Ross, and Lepper 1979). Dandekar et al. (2013) suggest that biased assimilation be incorporated by adding a bias parameter, $b_i \geq 0$, as follows:

$$x_i(t+1) = \frac{w_{ii}x_i(t) + (x_i(t))^{b_i}s_i(t)}{w_{ii} + (x_i(t))^{b_i}s_i(t) + (1 - x_i(t))^{b_i}(d_i - s_i(t))}$$

Where $x_i(t) \in [0, 1]$ is the attitude of person i at time t , w_{ij} is the weight that i gives to j 's attitude, $s_i(t) := \sum_{j \in N(i)} w_{ij}x_j(t)$ is the sum of i 's neighbors' opinions, and $d_i := \sum_{j \in N(i)} w_{ij}$ is i 's weighted degree. Thus a person's attitudes at time $t+1$ are the weighted average of their own attitude at time t , $x_i(t)$, and their biased perception of their neighbors' attitudes at time t , $(x_i(t))^{b_i}s_i(t)$. The unbiased averaging processes is a special case of biased assimilation, where $b_i = 1$ for each person i .

A second set of studies, by Shaw (2015) and Weng et al. (2012) suggest a different approach to relaxing the assumption that actors do not process diffusing information. Both studies allow people to choose from a set of representations based on the previous times they used that representation. In the Shaw (2015) model, each person has a set of mental representations, each with an associated weighting. When each simulated person interacts with others, he or she plays the representation with the highest weight. He or she then adds one to the

weight of the representation played by the people that he or she interacted with. This approach diverges from the simple weighted averaging by allowing people to choose which representation to play based on previous interactions. In the Weng et al. (2012) model, people have a set of “tweets” that they can see on their “screen”. Each “tweet” is associated with a given “meme”. As the number of “tweets” about a given “meme” increase, the person is more likely to create a new tweet using the given “meme”. Over time, “tweets” are removed from the “screen”, and therefore the “tweet” and the associated “meme” are forgotten. Both approaches allow people to process information by giving information that they have seen more frequently greater weight.

Although both of these approaches allow some processing by the agents, neither considers how different mental representations influence the spread of a diffusing bit. In both the original weighted averaging approach and Dandekar et al. (2013)’s extension, people are limited to a single mental representation. In the Shaw (2015) and Weng et al. (2012) approaches, people switch between mental representations, but the mental representations do not influence how people incorporate information. The following section addresses how different mental representations may influence the spread of a diffusing bit.

Schemas as mental representations and cognitive heuristics

Although the literature on schemas has become wide-ranging, two primary definitions of schemas have emerged. In the first, schemas are cognitive heuristics, which make understanding new situations and remembering old situations easier (Sperber 1996; Strauss and Quinn 1997). When people encounter a new situation, they attempt to understand it in terms of a familiar situation, and when they forget about parts of a situation, they fill in the gaps in their memories from the underlying schema. In the second, schemas are mental representations, which define the boundaries for the types of action that a person thinks are possible (Sewell 1992). People

draw on different schemas to understand and respond to different situations. Both of these approaches to schemas are likely to influence a diffusion process.

Schemas as cognitive heuristics

One view of schemas describes them as a network of associations between concepts that people use as a cognitive heuristic. In this approach, stemming primarily from anthropology (Strauss and Quinn 1997) and social psychology (Bohner and Dickel 2011), schemas provide a set of stylized stories about how the world works, which serve as guides for understanding new information. When a person encounters new information, he or she tries understand it in terms of one of the schemas he or she holds (Mesoudi and Whiten 2008). If the new information is slightly incongruent, the person may modify it to match the schema; if it is wildly incongruent, the person may disregard it entirely.

The evidence for schemas as cognitive heuristics comes primarily from transmission chain experiments (Mesoudi and Whiten 2008). In a transmission chain experiment, a person at the beginning of the chain is asked to read a story, and then he or she retells the story for the next person in the chain. This process is repeated several times, and at each step, the researcher records changes to the story. Initially, experimenters found that subjects introduce three types of changes most often: omissions, meaning that they forget pieces of the story, rationalizations, meaning that they add explanations that were not present in the original story, and transformations of detail, meaning that they change unfamiliar details to more familiar concepts (Bartlett 1932). Subsequent extensions showed that the dissimilarity of the information and the schema influenced whether a person remembered the information (Barrett and Nyhof 2001). Subjects remembered slightly counterintuitive information substantially more often than common information or bizarre information.

Taken together, these experimental findings suggest that schemas operate as types of compression heuristics, allowing people to remember a large number of stories by simply remembering deviations from a single set of root stories. Mental structures like schemas have long been thought to aid cognitive efficiency, in domains ranging from network structures (Brashears 2013) to organizational routines (Carley 1986; March and Simon 1993). In each domain, the mental structures provide a basic, minimal framework from which specific cases are generated. For example, Feldman and Pentland (2003) describe two parts of an organizational routine: the “ostensive” part, meaning the knowledge of the set of rules about how to perform the routine, and the “performative” part, meaning the actual actions taken to perform the routine. When people in an organization go to perform a routine, they draw on their ostensive ideas about the routine to construct the outlines of how the routine will proceed, and then fill in the gaps while they perform the routine. Thus the underlying mental structure – here, the ostensive routine – forms a basis for a variety of similar actions.

As a compression heuristic, schemas represent a conservative force for diffusion processes. When people encounter a new piece of information, they attempt to fit it in with their existing knowledge, possibly modifying it in the process. This warps the spreading information towards the pre-existing schemas. Sperber (1996) refers to the preexisting schema values as “cultural attractors” and suggests that diffusing information will eventually converge towards these attractors.² Dandekar et al. (2013) show a similar effect in their model of biased assimilation. In both cases, the modifications to the diffusing information caused by the underlying schemas pulls the diffusing bit towards a value that is consistent with those schemas.

² In the limiting case, where schemas are fixed and unchanging, the diffusion process ultimately becomes a very inefficient lookup function, where the diffusing bit eventually converges to the schema values. (I thank Jim Moody for suggesting this colorful phrasing.)

Schemas as mental representations

A second view of schemas holds that schemas are a finite set of mental representations that each person holds, which they can draw on selectively to understand what actions are possible in a given situation. This view stems primarily from Sewell (1992) who suggested schemas served as a form of social structure. Schemas present the unwritten rules for society, held by each person. In this view, however, there is a multiplicity of structures. Instead of a single overriding social structure that everyone subscribes to, there are many social structures, and therefore many schemas, that people draw on selectively. People exercise their agency by choosing which structures to draw from when they take actions in daily life. Significantly, the act of incorporating new information is not necessarily passive; people can integrate multiple schemas to gain social advantages or to acquire additional resources.

This view has taken hold most prominently in the organizations literature, where schemas are described as institutional logics (Friedland and Alford 1991; Thornton, Ocasio, and Lounsbury 2012). Institutional logics are similar to Sewell's multiple structures; instead of having a single logic for how organizations operate, the institutional logics perspective suggests that there are several different logics that guide action for people in organizations. For example, a person operating under the "family" logic might focus on making sure that all of the members of the family have been provided for, while a person operating under the "capitalist" logic might focus instead of making sure the organization generates the most profits possible. New organizational forms arise when people creatively combine different logics – for example, from an institutional logics perspective, the mega-church arises from the combination of the "church" and the "capitalism" logics.

Thus, a second approach to schemas would follow the institutional logics perspective, and would suggest that schemas provide a set of rules that guide, but do not dictate, peoples'

actions. People hold several schemas in their heads at once, and when they interact with new pieces of information, they choose a schema to fit the information into. To reflect this approach, I consider the possibility that people have multiple schemas, which can be used selectively by each person if it improves their social standing.

Although the two views of schemas – cognitive heuristics that aid information processing, and mental representations that define rules for action– are not incompatible with one another, they suggest different effects of schemas on a diffusion process. Unlike the conservative pressure that schemas as cognitive heuristics creates for a diffusion process, the “schemas as mental representations” approach suggests that schemas *increase* the variance in diffusing bits. As people creatively recombine schemas, they introduce new types of bits that, by definition, do not match with existing schema values. As these bits diffuse, however, people reinterpret them through the lens of their existing schemas, which reduces the diversity of the diffusing ideas. The influence of schemas on a diffusion process, therefore, is unclear. To understand how schemas increase or decrease diversity of diffusing bits, I construct an agent-based model where people have multiple schemas that they can creatively recombine, but which also influence how they incorporate new information.

Simulation setup

I construct an agent-based model that simulates people drawing on their schemas when they interact. The underlying model follows the model for competition among memes with limited attention introduced by Weng et al. (2012). In their model, each person has a number of posts, each of which is associated with a meme, available to him or her.³ At each time step, a

³ The model they introduce follows how Twitter users interact. As such, in their model, a user is exposed to posts on a “screen,” and they can choose posts to “repost”.

person in the network sends a post to his or her network neighbors by choosing between reposting a post or generating a new post from a meme in the available list. After a certain number of steps (Weng et al. use the number of actors in the network), every person in the simulation deletes the oldest post and its associated meme from their list of posts. Dropping the oldest post simulates forgetting; if a meme is used infrequently enough, eventually the population will forget that it exists.

The model introduced by this study takes a similar approach. I construct a network of N simulated people, and give each person a “schema” value to start with. Schema values have a similar role to the memes in the Weng et al. (2012) simulation. I encode schemas as a 3 bit binary vector. At each step, I choose an edge in the network, and set one person to update the other along that edge. The person who is updating creates an “interaction bit” to share with the other person. The interaction bit is represented by a 5 bit binary vector. The person who generates the interaction bit sends it to the person that he or she is connected to, and the recipient attempts to match the interaction bit to one of his or her schemas. Each person maintains a list of interaction bits that he or she received, the associated schema, and the order in which they were received. After N steps, I delete the oldest bit/schema pair from each person’s list.

Generating the interaction bit

The interaction bit is constructed in one of two ways, matching the two approaches to how schemas are used. First, an interaction bit can be constructed from a single schema, following the schemas as compression heuristics approach. To construct an interaction bit from a single schema, I choose 2 of the 5 bits at random, and set them randomly to 0 or 1. I then fill in the remaining 3 bits with the 3 bits from the schema, in order. I choose the schema by selecting uniformly at random from the schemas that a person has in their list of interaction bit / schema pairs. Schemas that have been activated more often have more bits associated with them, and are

therefore more likely to be drawn; schemas that have been activated less recently have had more of their associated bit/schema values deleted, and are less likely to be drawn. Constructing the interaction bit in this way simulates adding additional information to the transmitted idea, as, for example, when people rationalize stories that they repeat to others.

Second, to construct an interaction bit from more than one schema, I choose two non-matching schemas, again uniformly at random, and create a bit using the first schema that was drawn as the first 3 bits, and first 2 bits of the second schema that was drawn as the last two bits. This interaction bit represents creatively recombining schemas to generate new ideas. Each simulated person decides whether to draw a bit from a single schema or from multiple schemas according to a tunable parameter, p . That is, at each step, the person makes the following decision:

$$p(\text{draw bit from single schema}) + (1 - p)(\text{creatively recombine two schemas})$$

For a value of $0 \leq p \leq 1$. The focus of this study is considering how variation in the number and type of schemas in the population changes as p varies across its range.

Matching bits

The recipient of a bit attempts to match the bit to one of his or her existing schemas. He or she does this by computing the Levenshtein distance from the bit to each of his or her schemas, and matching the schema with the lowest distance. The Levenshtein distance measures the number of changes that would have to be made to one string to transform it into another string. For example, the Levenshtein distance between “kitten” and “sitting” is 3: “s” is substituted for “k”, “i” is substituted for “e”, and “g” is added. The Levenshtein distance is commonly used for “fuzzy set” matching. This distance measure is appropriate for this application because it allows accurate matching between a bit and the schema that the bit was drawn from. In this case, the Levenshtein distance between a bit and the schema that the bit was

drawn from should be small – at most 2, because two deletions would be necessary to get from the bit to the schema value. Other schemas might also have a distance of 2 to the bit, however. This ambiguity in matching mirrors the ambiguity of social situations found in real life.

The Levenshtein distance between 2 strings is at least the difference in length between the 2 strings (here, 2), and is at most the length of the second string (here, 5).⁴ Bits that are a distance of 4 or 5 from all of a person's schema values are considered not to match. People in the simulation form new schemas when they encounter enough non-matching bits. When a person encounters a first bit that does not match, he or she stores it without an associated schema value. This represents the person encountering an unfamiliar situation – he or she remembers it, but he or she does not know what to make of it, and therefore cannot generate new ideas from it. When a person encounters additional unmatched bits, he or she compares them to the unmatched bits that he or she already has in his or her memory. When he or she encounters a bit that has a distance of 2 to 2 other unmatched bits, he or she creates a new schema value from the similarities between these bits, and stores the new schema value with the new bit. That is, once the person has encountered several similar unfamiliar situations, he or she constructs a model for that type of situation, which he or she can use to generate new ideas. Some variation is introduced, however, because the person does not know, *a priori*, what the most important aspects of the situation are, other than the ones that he or she sees repeatedly.

Taken together, this simulation captures several relevant aspects of how schemas influence diffusion processes. First, as cognitive heuristics, schemas represent situations in the world concisely. They can be used to fill in missing pieces of information, or to make sense of

⁴ For example, a schema value of 111 would have a distance of 2 from the bit 11111 (we would have to delete 2 “1” values) and a distance of 5 from the bit 00000 (we would have to delete 2 “0” values and replace 3 “0” values with “1”).

ambiguous information. As they store the information, however, schemas also lead to distortions. Schemas can lead to incongruent information being dropped, and use of the wrong schema for a situation can lead to distortions in the diffusing information. By representing the schema as a shortened version of the diffusing bits, and attempting to match the bit to the associated schema, I simulate how schemas can both serve as compressed versions of the transmitted information, and can introduce distortions when the schema is incorrectly matched. Second, as mental frameworks, schemas can be a source of new forms of ideas when they are creatively recombined. The simulation captures this generative aspect of schemas by allowing people to recombine two schemas, and to incorporate new schemas when they see similar, unusual patterns frequently enough.

To conduct the simulation, I repeat the simulated interactions 10,000 times, or until the schema values in the simulation converge. I then repeat the simulation many times, to get a sense of the variation caused by the random initial parameters. The primary goal of the simulation is to see how the variety and pattern of the simulated bits changes as the probability of recombination versus reproduction of schemas changes across its range.

Results

Figure 1a and figure 1b show the results from a single set of simulations. The figures show the frequencies of each of the observed, 5 element interaction bit combinations, and each of the observed, 3 element schema values, respectively. Each of the panels shows values from a different simulation, where the parameter p , which gives the probability of drawing a bit from a single schema, was set to a different value. The x-axis gives the number of iterations of the simulation, divided by the number of people in the simulation. This gives a rough estimate of

how many opportunities this simulation has to go through all the people one time.⁵ The y-axis gives a frequency count how many times a bit or schema value was present in the population at the end of a given set of iterations.⁶

[FIGURE 1(A) ABOUT HERE]

Figure 1(a) shows the relative frequency of each bit over the course of 5 simulations, where the parameter p was set to 0, 0.3, 0.5, .7, and 1. At low values of p , meaning that a person was very likely to recombine two schemas, the frequency of a small number of bits increases linearly with time, represented by the number of iterations. In the first panel, representing $p = 0$, the simulation converges on several bits; in the second and third panels, representing $p = 0.3$ and $p = 0.5$, respectively, the simulation converges on a single bit (00000 and 11111 respectively). At higher values of p , the simulation converges less on a single set of bits, and for $p = 1$, the none of the bits develop a different frequency relative to the other bits in the simulation. Overall, figure 1(a) shows clear consolidation on a few circulating bits for low values of p , and little to no consolidation on any particular bit as $p \rightarrow 1$.

[FIGURE 1(B) ABOUT HERE]

Similarly to Figure 1(a), Figure 1(b) shows the frequency of different schema values over time in the population.⁷ Figure 1(b) shows a similarly convergence on a small number of schema values across each of the simulations. These likely correspond to the bits that each of the simulations converge on, suggesting a cumulative advantage process for schemas. That is, as a particular schema value became widespread among simulated actors, many of the actors were

⁵ In using this measure, Weng et al. (2012) refer to it as a “week.”

⁶ Appendix figure 1 shows a similar plot to one of the panels of Figure 1, but with more iterations. Since the pattern of the results do not change with additional iterations after about 100 iterations, the remaining results show 100 iterations of the simulation.

⁷ In Figure 1(a) and 1(b), the panel $p = 0$ represents results from the same, single simulation. 1(a) gives the frequency of the bit values in that simulation, and 1(b) gives the frequency of the schema values associated with those bits. Each panel, $p = 0$, $p = 0.3$, etc., represents a different, single simulation.

able to recognize bits generated from that schema. The actors, in turn, are more likely to generate new bits from that schema themselves, because actors choose schemas to recombine proportionally to the frequency with which they observed those schemas. The particular schema that the simulation converges on appears to be path dependent. In the first simulation, it is 100, in the second simulation, it is 000, and in the third simulation it is 111.

In many of the simulations, a second schema value becomes popular and grows in popularity over time, but does not eclipse the highest schema value. The schema that becomes second most popular varies between simulations, and the particular value similarly appears to result from a path dependent process. These secondary schemas are most prominent at middling levels of p – that is, $p = 0.3$ and $p = 0.5$. At lower levels, the second most popular schema value grows in popularity at a lower rate. This low growth may be an idiosyncrasy of the simulations shown in Figure 1, or it may suggest a difference in how actors in each model process bits. When actors always creatively recombine schemas, the combinations may only match the most popular bit, and therefore other schema values are less likely to become popular. As actors have some probability of drawing from a single schema, the noise introduced by drawing on a single schema may make the bit more likely to be matched to other schema that are not the most popular schema value. As the probability of drawing from a single schema increases, however, the amount of noise introduced into the system increases, and no particular schema value become significantly more popular than the others.

The introduction of noise into the system is shown most clearly by the increase in the frequency of the NULL schema. The NULL schema arises when an actor in the simulation encounters a bit that is not close enough to one of his or her existing schema values to match. Consider, for example, a person who has schema values 111 and 101 in the list of schema values

that he or she has heard before, when he or she hears a new bit, 00000. The actor will calculate the distance from the bit to the schema values, and will find distances of 5 and 4, respectively. 111 and 00000 are 5 changes apart because the actor would have to change 3 bits of the 00000 string to 1, and delete 2 0's, for a total of 5 changes; 101 and 00000 are 4 changes apart because the actor would have to change 0's to 1, and delete 2 0's. Distances of 4 and greater are too far for an actor to match, and therefore he or she stores the bit without a schema. This simulates a person having a social interaction that he or she does not know how to place. He or she remembers the interaction, but does not have a mental framework to associate with it. If he or she encounters more situations like that one, he or she will eventually create a new framework for situations like that. Similarly, in the simulation, the actor will store the bit with a NULL schema value associated with it. The actor cannot simulate new bits from NULL schemas, but whenever he or she encounters a new bit that also can't be placed, the actor attempts to construct a new schema from the common pieces of the unmatched bits.

In the simulations in Figure 1(b), the number of unmatched, NULL schema values is relatively high. At values of $p < 1$, the NULL schema value is the second or third most common schema value. In the simulation where $p = 1$, the NULL schema value increases nearly linearly with time, and becomes the most common schema value. In each of these simulations, the NULL schema value represents situations where the two actors did not understand each other. The high frequency of the NULL schema value in the simulation where the actors always generate bits from a single, existing schema value suggests that adding a small amount of noise to ordinary conversations introduces a considerable amount of ambiguity. That is, the ordinary, daily interactions of actors in this simulated environment are often highly

uncertain, and cannot be placed. Although the NULL schema value is high for the simulations where $p < 1$, the frequency of NULL schemas appears to stabilize in those situations.

This stability suggests that situations where an actor is consciously drawing from an existing schema are more likely to be interpreted correctly, in terms of a single schema. Substantively, one might think of this as the pioneering entrepreneur who attempts to make a new type of restaurant with Mexican and Vietnamese food. Although the entrepreneur might recognize the two cuisines being combined, a patron is more likely to categorize using his or her existing schema for “Mexican restaurant”.⁸ Confusion is more likely to arise when a person creates a restaurant with some Mexican restaurant elements along with other elements, because the person does not necessarily attempt to explicitly explain what type of restaurant he or she has created. Overall the results from the single set of simulations presented in Figure 1 seem to show that recombining schemas *decreases* the number of different schemas in the population, rather than increasing them, as the theory would predict.

[FIGURE 2 ABOUT HERE]

Figure 2 shows the variance in the number of bits and schemas by the iterations of the simulation. I measure the variance in the number of bits and schemas using the Shannon entropy of the bit values, calculated as $-\sum_{i=1}^k p_i \log(p_i)$, where p_i is the proportion of bits or schemas that have the i^{th} value, for each of the $i = 1, \dots, k$ unique values of bits or schemas. The entropy gives a measure of how much uncertainty is present in the bit or schema values. Low values indicate less uncertainty, and therefore lower variance; high values indicate high uncertainty, and therefore higher variance. The figure shows the entropy calculated after each iteration, from

⁸ To use an example that is closer to the institutional logics framework, consider a person who attempts to merge the logics of church and business to create a megachurch. Many attendees would not see the new megachurch as a new organizational form, but would instead lump the megachurch in with their existing logic for “church”.

simulations using a random graph of 25, 50, or 100 people, across different values of p .

Confidence intervals in the figure are taken from the 5% and 95% quantiles of 100 replications of the same simulation.

The results shown in Figure 2 indicate more variation in both the bits and schemas present in the population as the probability of drawing from a single schema increases. The top row shows the entropy of the bits in the population. In the condition where people always recombine schemas, the entropy of the bits in the system starts low and falls rapidly. Very little variation is introduced into the system by recombining schemas, and that variation is reduced further as the bits concentrate on a single value or set of values. As the value of p increases, the entropy of the bits early in the simulation is higher, and the slope of the decline increases as well. As actors are increasingly likely to draw from a single bit with noise, more noise is introduced into the system, and the system is slower to converge on a single set of bits. At its highest value, there is little change in the amount of uncertainty in the bits as the simulation progresses.

The entropy of the distribution of schemas changes similarly over simulated time. At low values of p , where actors almost always recombine schemas to form new bits, the entropy of the distribution of schemas declines over time. Actors in the system converge on a few schemas, and recombine them to draw similar bits repeatedly. At the opposite end of the scale, actors do not converge on a set of schemas, and the entropy of the schema values in the system remains high. These results appear to follow a similar pattern to those in Figure 1. The results in Figure 2 do not show significant differences as the size of the graph changes. Larger graphs have a narrower distribution across replications (indicated by a narrower confidence band), but do not display a different pattern of results.

[FIGURE 3 ABOUT HERE]

Figure 3 shows the entropy of the distribution of bits and schemas at the final iteration of the simulation across the range of values for p .⁹ The entropy of the bits at the end of the simulation appears to increase linearly with p . As before, as the probability of drawing from a single schema with noise increases, the uncertainty in the bits present in the system increases as well. The change appears to be linear; there does not appear to be a phase transition or other non-linear changes in the entropy of the bits as p increases. The entropy of the schemas shows a similar linear increase as p increases. The entropy of the schemas is lower overall because there are fewer possible unique schema values, meaning less randomness in the distribution of schemas is possible. Figure 3 also does not show significant differences by the number of people in the random graph. Larger graphs have slightly less variance between replications, but do not show a different pattern in the randomness of the bits. Overall, Figure 3 shows that the amount of randomness in the bits or schemas in the simulated system is proportional to probability of drawing from a single schema.

[FIGURE 4 ABOUT HERE]

Figure 4 considers the effect of graph structure on the distribution of simulated bits. I compared the results from Figure 2 to an observed graph from a middle school friendship network. Figure 4 shows that the middle school friendship network shows less consolidation on a single set of bits or schemas. In the top row, the friendship network has a slightly less negative slope than the random graphs, and the entropy of the bits appears to level off after several iterations. In the second row, there appears to be a roughly constant level of randomness in the distribution of the schema values throughout the simulation, and the level appears similar across the different levels of p . This difference may be a result of the lower density of observed graphs

⁹ Separate simulations were conducted for $p = 0, 0.1, 0.2, \dots, 0.9, 1$. To construct Figure 3, I plotted the distribution of each of those simulations and connected them.

versus random graphs. As density of the network decreases, a person may be less likely to encounter another person with a similar schema. The resulting lack of communication may prevent a single schema from developing a cumulative advantage over the others.

Discussion

Although diffusion models have many applications in the social sciences, virtually all of the diffusion models have ignored an important component of the diffusion process: individual processing of the diffusing information. This study introduces a diffusion model with schemas to address this deficiency. In the model, each person has a shortened mental representation of the spreading information, and that mental representation shapes both how they receive the information, and how they generate new information to spread to others.

To construct the model for how schemas shape the information that people send and receive, I draw on two distinct, but related, literatures on how schemas influence how people process information. The first literature, which draws on ideas from Sewell (1992) and the institutional logics perspective (Friedland and Alford 1991; Thornton et al. 2012), suggests that schemas define the set of actions that people think are possible in a given situation. Under this framework, people exhibit agency by drawing selectively on different schemas to produce new types of interactions or organizational forms. The second literature, which draws on cognitive anthropology (Sperber 1996; Strauss and Quinn 1997), suggests that schemas are stable mental representations that serve as cognitive heuristics, allowing people to store information concisely, and to fill in gaps in the information that they receive.

These two frameworks represent two potentially contradictory effects of schemas. If schemas are used to generate new types of ideas or organizational forms, then introducing a model where people can recombine schemas should produce a large amount of diversity in set of

ideas spreading through the group. Alternatively, if schemas are used as mental heuristics, then schemas should have a conservative influence, reducing the diversity of the ideas that as spreading through the group by pulling them towards the set of underlying schema values. I illustrate the diffusion model with schemas by assigning a parameter, p , the probability that people will attempt to communicate using information from one schema, versus recombining schemas, and I consider how the diversity of ideas changes as that value is varied across its range.

The simulation showed the opposite conclusion from what the literature predicted. As people attempt to recombine schemas, the diversity of the schemas in the system decreases dramatically. As people draw from a single schema, they introduce a small amount of noise, which represents differences in the retelling of a story, differences in the execution of an organizational ritual, or other small variations that can be introduced by a social situation. This small amount of noise creates diversity in ideas in the system. By contrast, when people attempt to draw on two schemas, they begin by stating one of the schemas in its purest form in the simulation.¹⁰ When people telegraph one of the schemas clearly, it becomes easier for others to match. This matching and retelling process leads to a cumulative advantage process for one of the schemas, which in turn leads to a lack of diversity in the system overall.

These results have important implications for our understanding of how new ideas, rituals, or organizational forms arise. Previous literature assumed that new ideas arise through the creative recombination of different mental models. These simulations suggest the opposite. When people recombine mental models, they must be clear about which mental models they are

¹⁰ To use a currently popular example, an entrepreneur attempts to pitch his new business idea by saying, “It’s like Uber, but for ...”. By beginning the pitch with “It’s like Uber,” the entrepreneur links the organizational form to the organizational form for “Uber” in the other person’s mind.

recombining. This clarity allows people to match the new idea to an existing mental model. Paradoxically, the attempt to create a new model allows people to match the idea to an existing model more easily. Instead, this model suggests that new ideas come from random noise in day to day interactions. The random noise introduced in a day to day interaction may lead to people encountering an idea they cannot understand using their past experience. By encountering enough unfamiliar ideas, a person may develop a new mental model for those ideas, allowing him or her to generate a new set of ideas.

In the simulation, schemas were represented as 3 element vectors of 0 or 1 values. Many of the simulations converged to the schema value 111 or 000. Although not explicitly tested in this study, this pattern of results may lend credence to the cultural evolution perspective (Boyd and Richerson 1985; Mesoudi 2009; Mesoudi and Whiten 2008). The cultural evolution perspective suggests that some ideas have higher levels of evolutionary fitness, making them inherently more likely to be replicated and spread. Proponents of this theory suggest a set of candidate biases for information that are more likely to be replicated, such as social information (meaning information about other people, like gossip; Mesoudi 2009). The convergence of several simulations on a single set of bits may suggest that some bits are indeed more likely to be spread, and that evolution of bits may explain some of the observed diversity of ideas.

This study suffers from several limitations. In particular, this study relies on a very specific measure of schemas and bits transmitted, for a very specific process. If this approach does not reflect how bits and schemas are actually matched, the simulated results may not represent how schemas introduce, or fail to introduce, diversity into a population. A second limitation is that no error correction happens in this simulation. Once people have associated an idea with a schema, they do not change which schema it is associated with in future iterations.

This limitation primarily affects bits that could not be associated with a schema when they were initially received, because it would be difficult to improve on an existing match. Future work might allow people to reassign bits to the best matching schema once they develop a new schema. Finally, this does not allow people to attempt to match the schema that they use to the schemas that they think the person that they are communicating with might have. This sort of “network cognition” may serve to increase the frequency with which random deviations are understood.

In spite of these limitations, this simulation provides an important look at how mental processes can influence the results of a diffusion process. Information is transmitted with error, and people who receive it hear it through the lens of what they already believe. In addition, actors may attempt to strategically create recombine other ideas. Even the small amount of mental processing introduced by these differences proved to be significant, introducing vary amount of uncertainty into the diffusion process. Future diffusion studies will need to take mental processing, both in this form and in others, into account to fully understand how a diffusion process unfolds.

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Figure 1a: Bit values by iteration & probability of single schema, 50 person random graph

Figure 1b: Schema values by iteration & probability of single schema, 50 person random graph

Figure 2: Heterogeneity of bit & schema values by iteration

Figure 3: Heterogeneity of ultimate bit & schema values by p

Figure 4: Heterogeneity of bits and schema values by time for different graph types