Centers, Peripheries, and Popularity: The Emergence of Norms in Simulated Networks of Linguistic Influence

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1 Introduction

Ties to friends, kin, and acquaintances form the essential architecture of communication in daily life. These networks of individuals bound together by shared goals and socio-cultural practices represent interactional sites where linguistic variation can acquire locally-relevant social meaning (Milroy 2002) and new lexical, phonological or morpho-syntactic variants can emerge and diffuse widely. Social networks have complex structures, in which connection densities and tie strengths define their members' network roles and positions mediating these individuals' influence over others' language use (Labov 1972, 2001, Milroy 1987, Eckert 2000). To date, a wide variety of network roles have been identified by numerous, ethnographically-oriented sociolinguistic studies. *Leaders, loners, lames, brokers,* and *in-betweens* refer to individuals whose more or less centrally-connected positions have been correlated with greater or lesser influence over others in their social networks (see Chambers 1995 and Chambers 2009 for reviews). The more direct (or *first-order*) and indirect (or *second-order*) connections an individual has, the more *centrally-connected* s/he is in the network. Conversely, the sparser and weaker the amount of ties linking an individual to others, the more isolated or *peripheral* is that individual's position.

While previous studies have demonstrated how individuals regulate, or are affected by, the flow of linguistic influence in small-scale social networks, they have also revealed a somewhat contradictory picture of these individuals' actions in the selection and propagation of competing linguistic variants. In Labov's Philadelphia neighborhood studies (cf. Labov 2001) and Eckert's Detroit high-school studies, for instance, centrally-connected leaders proved to be the source of innovative variants. Primarily influenced by other leaders, the influence of these leaders on others' use of the vernacular seemed to percolate through their local personal networks, extending from more to less well-connected members. The Milroys' studies of Protestant enclaves in Belfast (Milroy and Milroy 1985), on the other hand, have shown that individuals with looser ties to the local community were the innovators bringing about change from outside by virtue of their greater distance from the influence of local centers. The wave-like diffusion patterns of vernacular features in Harlem and Detroit supported the *two step flow of influence* model (Lazarsfeld et al. 1949; Katz and Lazarsfeld 1955; Labov 2001, 356–365), while the spread of innovations through individuals connected with loose ties to multiple social networks argued for the well-known weak-tie model of social influence (Granovetter 1973, 1983). The main difference between the two models lies in the source of innovative linguistic variants: the first locating it with influential centers, the second attributing it to strategically-connected peripheries. Based on the two models, centrally-connected members and their cohorts have been shown to act as conservative agents of stability in some contexts (Belfast) and innovative agents of change in others (Harlem, Detroit). Conversely, peripherally-connected individuals sometimes channeled novel variants (Belfast) and other times acted as outer edges of networks barely touched by innovations (Harlem, Detroit). The question is: how can all these scenarios be legitimate? What are the systematic explanations behind these, apparently conflicting, network roles in the introduction and spread of linguistic innovations?

The goal of this paper is to answer some of these questions by investigating the role of centers, peripheries, and the selection of competing linguistic variants in the diffusion of competing linguistic innovations. We present an agent-based computational model simulating the dynamics of emergence, spread, and establishment of a single linguistic variant as norm, i.e. variant adopted by the majority of individuals, in a socially realistic heterogeneous influence network. We carry out the computer simulations in a closed artificial network, whose local characteristics bear close resemblance to properties of small local communities studied by sociolinguists (see Section 2.2), and analogize this network to a large, highly polarized social space, analogous to urban working-class neighborhoods or clusters of adolescent peer groups in school settings. Analogous to real-life scenarios, new phonetic, lexical, and morpho-syntactic forms that possess some indexical value (Silverstein 2003, Eckert 2008), i.e., conveying group membership, speaker stance and style, or any group-based ideology, are adopted over other competing variants in the network.

2 The Computational Model

2.1 Computational Approaches to Language Change

Numerous recent simulations used realistic mathematical and computational models of social networks to model the dynamics of language change (Baker 2008, Troutman et al. 2008), language endangerment (Minett and Wang 2008), societal bilingualism (Sankoff 2008), and new dialect formation (Baxter et al. to appear). Similar to our approach, these computational approaches have treated the sociolinguistic system as a complex adaptive system, in which small, incremental changes can eventually have large consequences, and simple interactions between individuals can lead to complex emergent phenomena (Dras et al. 2003, Harrison and Raimy 2007). In such systems, initial causes are not always proximal to effects, making it difficult to understand causation using traditional methods. Thanks to this influx of ideas from physics, mathematics, and computer science, such simulation-based techniques offer a powerful new methodology of experimenting with large-scale observed phenomena, such as language variation and change. If done judiciously, their advantage is to be able to experiment with "possible worlds" of interacting social agents, and therefore address questions that span large scales in space, time, and/or population size, which cannot be investigated empirically. Two main insights emerging from these approaches is that stochastic models of change are more effective at matching actual observations than deterministic models, and social network structure can have an important influence on the spread of linguistic innovations.

One of the earliest computational studies to demonstrate these crucial insights was Nettle's (1999) work of the threshold problem of language change, i.e., innovative variants becoming "fixed in a language if they can pass a threshold of frequency which in the early stages they never have" (Nettle 1999:98). In Nettle's model, agents arrayed in a grid-like social network had to choose between two competing linguistic variants, p and q. They passed through five "life-stages," analogous to age, in which they could variably influence, and be influenced by, others. An agent decided which variant to adopt based on the number and social status of individual agents and the social distance between agents already using the variant. In addition, agents also had some functional bias, i.e., perceptual or cognitive preference, toward a particular linguistic variant. Nettle showed that minority variants were adopted only when some speakers were socially much more influential than others, and referred to these as "hyper-influential" agents. Although functional bias played a large role in the selection of a variant, without heterogeneous social influence the population still could not overcome the threshold problem, i.e., passing the point at which a given variant begins to propagate and end up being used by the majority.

The main issue to study, still, is how rare variants can become the linguistic norm for the majority of individuals in a large influence network. Nettle has argued that the solution to the threshold problem lies in the variants being taken up by highly influential speakers. He doesn't say, though, what it is that makes some individuals more influential than others. We will show, below, that influence can be interpreted both structurally, as the position of the individual in a so-called scale-free social network, and dynamically, as a probabilistic bias of adoption of those individuals' variants that are the most popular with other agents. As a result, we do not have to artificially impose "hyper-influence," since it is a natural feature of the network structure and preferential copying of competing variants.

2.2 Generating a Scale-free Social Network

We model the social network as a graph, where the nodes correspond to individuals or agents, and the links correspond to *linguistic influence*. This network is a subgraph of the social interaction network. The difference is that the links in this graph are *directed*. When two agents interact, they are not equally likely to be influenced by each other's language. The use of directed links in the graph captures this asymmetry in a linguistic interaction. A link from node A to node B indicates that A listens to, and is influenced by, B. The precise way in which this interaction is modeled is described in Section 2.3.

Social interaction networks are known to have a special structure (Milgram 1967, Barabási and Albert 1999), characterized by three main features:

- a small diameter, which means that most pairs of agents are connected by short chains of acquaintances ("six degrees of separation")
- high clustering, which means that agents that are linked to the same agent are also likely to be linked to each other
- a scale-free degree distribution, which means that there is structure in the network at all scales: some agents are very highly connected (and highly influential), some a little less so, all the way down to agents who are connected to only a few others or possibly no others

Such networks are called scale-free small-world networks. It is not known why social networks (and indeed many other kinds of networks) have these particular structural properties, though models based on spatial distribution (Wong et al. 2005) and competition for limited resources (Anghel et al. 2004) have been proposed.

To model the spread of linguistic variants, we must first generate an artificial social network with the properties listed above. We used the R-MAT algorithm (Chakrabarti et al. 2004) to generate such a network. R-MAT, which stands for Recursive MATrix, works by creating a set of nested communities in the network. The algorithm operates on the adjacency matrix of the network. An adjacency matrix describes a network as follows: if agent x is influenced by agent y in the social network (i.e., there is a link from x to y), then we place a 1 at row x and column y of the adjacency matrix, otherwise we place a 0 at that location.

The R-MAT algorithm uses four parameters, (a, b, c, d), which correspond to four quarters of the adjacency matrix, as shown in Figure 1. We start with an adjacency matrix filled with zeroes. We then choose a quarter of the matrix with probability corresponding to its parameter. We chose the parameters $a = 0.5$, $b = 0.1$, $c = 0.1$, and $d = 0.3$. These parameters mean, for example, that half the time we choose the upper left quarter of the matrix. We then treat the chosen quarter as a new matrix, divide it into quarters, and again choose one quarter with the same set of probability parameters. This process is repeated recursively until we end up with a single cell, whereupon we set the value at that cell to 1.

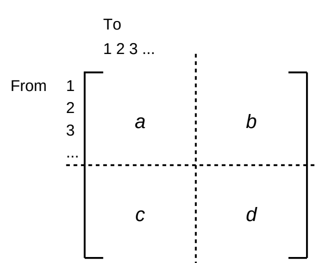


Figure 1: In the R-MAT algorithm, the adjacency matrix is recursively divided into quarters, and each quarter has a probability (a, b, c, d) associated with it. Starting with an empty matrix, we choose quarters recursively according to these probabilities until we get to a single cell, whereupon we set that cell to 1 to indicate a link.

This process is repeated from the beginning a pre-determined number of times to create the network. Any particular cell in the adjacency matrix might end up being chosen more than once, in which case the final number of links in the network will be slightly fewer than the number of times the process is carried out. For example, we created a network with 900 nodes and added links to the adjacency matrix 9000 times, which resulted in 7561 unique links.

2.3 Running the Model

Once we have a realistic social influence network, we model language spread as follows. We assume that there are k possible variants of a certain linguistic features. For example, the intervocalic /t/ in the word 'mittens' can be pronounced as flapped or fully released, yielding $k = 2$ competing variants.

To initialize the model, we assign a uniformly randomly chosen variant to each agent in the network at time $t = 0$. At each time step after that, we choose one of the agents uniformly randomly. This agent updates its variant by copying one of its neighbors. The neighbors of an agent are the ones which are pointed to by links originating at the given agent. It is possible for an agent to have no neighbors, in which case it will never change its variant. This type of agent is a "loner." It is possible for loners to have links pointing to them, however.

One crucial aspect of our model is the rule by which an agent chooses a neighbor to copy. The agent uses an *indegree-biased voter model*. This rule is written formally as follows:

$$P(i) = \frac{D_i}{\sum_k D_k}, \qquad \forall i, k \in N$$

where $P(i)$ is the probability that the agent picks neighbor i, D_i is the indegree of neighbor i, and N is the set of all neighbors of the agent. This rule says that an agent is more likely to copy a neighbor that is highly influential. It assumes that agents know the influence (or popularity) of their neighbors, and is a modification of the *voter model* which assumes that all neighbors are treated equally. The voter model has a long history in the statistical physics literature, and has even been used to model language spread (Castelló et al. 2006, Castellano et al. 2009).

We keep a running count of the number of agents with each variant in the network. If one of the variants is in use by more than 90% of the population, we say that that variant has become the *norm*. Note that this means there can be periods when there is no norm in the population.

3 Results

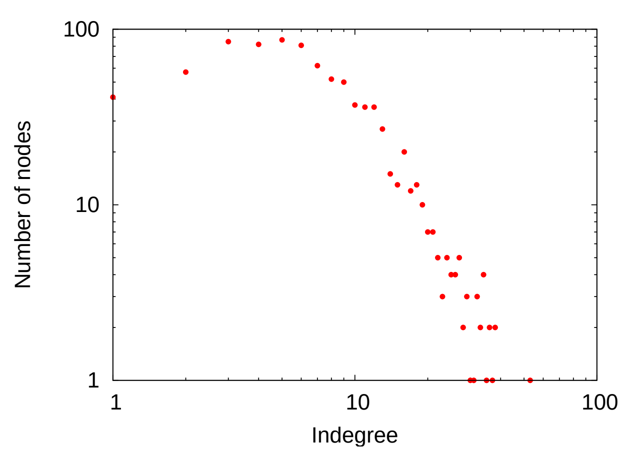


Figure 2: The indegree distribution for the network used for the simulation in Figure 3.

The network in this simulation has 900 agents, and there are 7561 links between them. It was created by choosing parameters $a = 0.5$, $b = 0.1$, $c = 0.1$, and $d = 0.3$ for the R-MAT algorithm, as mentioned earlier. This is a fairly sparse network, since the number of *possible* links, which is the number of ordered pairs of agents, is $900 \times 900 = 810000$. It means that there are 8.4 links per agent, though the distribution is quite skewed, as can be seen in Figure 2.

The maximum indegree and outdegree are 53 and 50 respectively (both for agent 0). Thus no agent has direct influence over a large fraction of the population. There are several agents with a relatively high indegree (in the thirties and forties). These are the hubs in the network. The minimum indegree and outdegree are zero for 21 and 19 agents respectively (not shown in Figure 2 because it is plotted on a log-log scale). The agents with zero indegree are the ones with no influence over the rest of the population. Those with zero outdegree are the loners, i.e., agents that are not influenced by the rest of the population though they may themselves have some (small) influence.

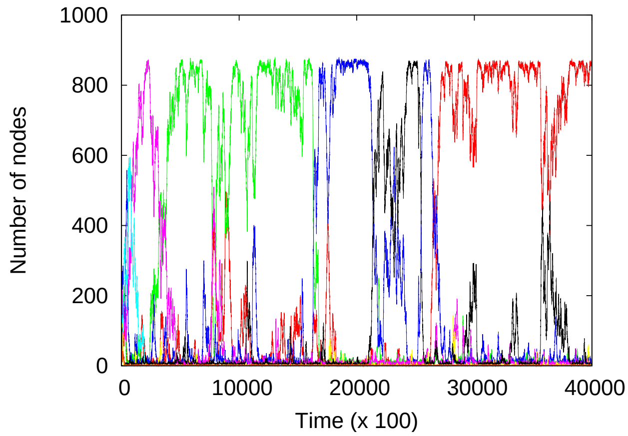


Figure 3: New norms appear one after another in the population. The simulated population has 900 individuals. We say that the population has a norm when more than 90% of the population has the same variant. Three factors are necessary for this to happen: the presence of loners, the presence of hubs, and a bias for listening to more "popular" individuals. The x-axis shows time, and the y-axis shows the number of nodes (agents) in the social network that are using a particular variant.

Our main result is shown in Figure 3. There are $k = 8$ possible variants, and we see the emergence of several norms, one after another. Norms emerge along a "rugged" S-curve trajectory, due to the stochastic nature of the process. Note the x-axis is highly compressed (only every hundredth time step is plotted), and spans a fairly large number of time steps. This makes the slope of the curves seem nearly vertical.

Non-norm variants are typically present in very low numbers in the population. They are never eliminated entirely because the loners are not influenced by the rest of the population. Despite these low numbers, a non-norm variant occasionally rises to displace the norm. This happens due to the probabilistic uptake of a non-norm variant by one or more hubs who then spread it through the rest of the population. Hubs thus play the role of the so-called "hyper-influential" agents in Nettle's model. As pointed out above, though, no single agent in our social network has an influence over a significant fraction of the population (the highest indegree is 53 whereas the population size is 900), thus the language dynamics are really a collective property of the population. In fact, it turns out that there are three important factors that together create the dynamics we observe. We ran a number of simulations to identify these factors. They are:

- the existence of loners
- the existence of hubs
- the indegree-biased voter model

We show next that the removal of any of these factors from the model results in a drastic change in the behavior of the system: norms either fail to emerge, or emerge once and become fixed forever.

3.1 Removing Loners

We can remove loners by making the network more dense. We ran R-MAT with the same parameters as before, only this time we carry out the link addition process 27000 times, resulting in a network with about thrice as many links as before, and no loners.

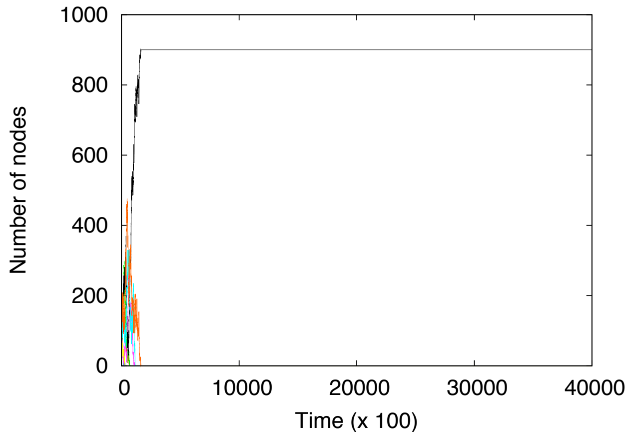


Figure 4: We can remove loners from the population by increasing the number of links in the social network. Here we show what happens when the number of links is increased to 27000. The population very rapidly converges to a norm which then stays fixed forever.

We ran the simulation on this new network, with $k = 8$ as before. The result is shown in Figure 4. We see that the population converges very quickly to a norm, which then stays fixed. This is because all 900 agents have adopted the same variant, and there are thus no other variants remaining. In the previous simulation (Figure 3), there are a few loners whose chosen variants never change and can only match the rest of the population by chance. These loners serve as sources of innovation, or repositories of past norms, and thereby multiple variants can be maintained in the population. This allows the norm to change over time as, probabilistically, a loner's variant gets picked up by some other agents and propagated through the rest of the population. If there are no loners, this clearly cannot happen.

3.2 Removing Hubs

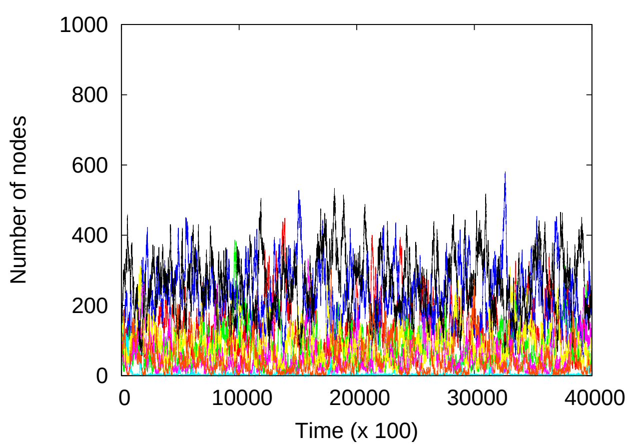
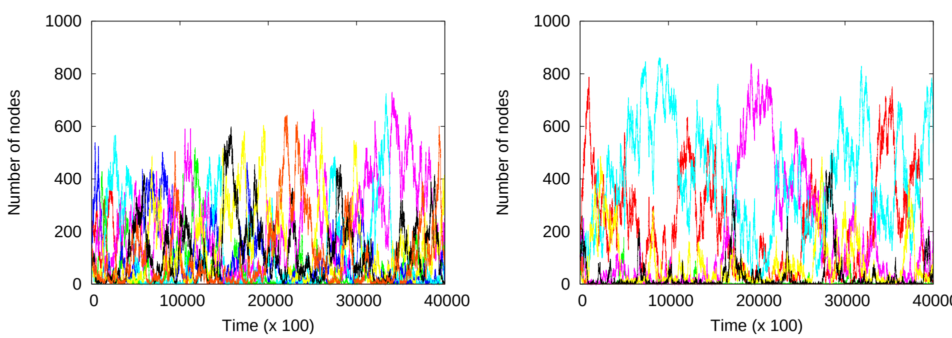


Figure 5: We can remove hubs from the network by changing the topology. Instead of a scale-free network, we construct a random network with approximately the same number of loners as the scale-free network considered in the simulation in Figure 3. We see that in this case, norms fail to appear.

To remove hubs from the network, we have to change the topology of interactions. Instead of a scale-free network, we created a random network with approximately the same number of loners as the network studied in Figure 3. We created a random network by starting with an empty network of 900 agents. We then chose a *from* agent and a *to* agent independently and uniformly randomly and created a link between them, 3000 times. The choice of number of links is dictated by the resulting number of loners in the network. Adding 7500 links (to be comparable with the network in Figure 3) typically results in zero loners. Since the existence of loners is an important factor, we chose to make that as nearly equal as possible so that we could isolate the effect of hubs on the dynamics. Adding 3000 links resulted in 35 loners. The dynamics on the resulting network are shown in Figure 5.

We see that, in this case, norms fail to appear. All the variants remain present in about equal proportions at all times. This suggests that the role of hubs, with their relatively high influence, is to spread variants quickly through a population, thus causing a norm to appear, and also to help in maintaining that norm over a period of time. Thus the hubs, in the initial state, act as innovators, picking up variants from the loners and spreading them through the population, but then also act as stabilizers, since the event of copying a variant from a loner is extremely rare (when indegree-biasing is present). Most of the time, then, other agents are copying the hubs, allowing the hubs' variant to stabilize in the population.

3.3 Removing Indegree-biasing



(a) No biasing. (b) Random biasing.

Figure 6: Here we examine the case where the population is organized in a scale-free network, and both loners and hubs are present. However, agents do not pay attention to indegree when choosing a neighbor to copy. They either treat all neighbors equally (6(a)), or bias their choice on the basis of random numbers assigned to each agent at the beginning of the simulation (6(b)). In both cases norms fail to appear. In the second case different variants become relatively dominant in the population at different times, but none becomes popular enough to be a norm.

Finally, we return to the network studied in Figure 3, and change the update rule. We looked at two cases. In the first case, instead of biasing the choice of neighbor to copy by that neighbor's indegree, agents now treat all the neighbors equally. This is the standard voter model. This has the effect of diminishing the number of times hubs are chosen to be copied, and raising the number of times loners are chosen to be copied. Thus loners' variants enter the population more often. However, it turns out that norms fail to appear, as we can see in Figure 6(a). Essentially, new variants are entering the population *too* often for a norm to emerge.

In the second case, we assign a random number between 0 and 1 to each agent at the beginning of the simulation. The agents thereafter use the numbers assigned to their neighbors to bias their decision of whom to copy. This case falls inbetween the unbiased and indegree-biased cases. If the random numbers chosen had been well-correlated with the indegrees of the agents, then we would expect the same behavior as in Figure 3. However, since they are not well-correlated, we see that norms once again fail to appear, though different variants become dominant at different times in the population. The reason that norms do not appear, once again, is that hubs are hampered in their role of norm spreading and enforcement.

4 Discussion and Conclusion

We have examined the role of network positions, and their influence, in the emergence and change of linguistic norms. The use of a simulation model has allowed us to experiment with the social network architecture and with the diffusion model, to determine the necessary and sufficient conditions for the spread of linguistic variants through the network. Our results show that three factors are necessary for the emergence of linguistic norms. These are: the presence of leaders or hubs in the social network, the presence of loners or peripheral members, and a biased adoption of variants from individuals who are more "popular." The third factor means that individuals are aware of their own relative position in the social hierarchy, and also that of their neighbors. In the absence of any of these features, norms will fail to appear. These findings also indicate that, ultimately, it is some of the most peripheral members of the population who regulate the diffusion dynamics within the population. If the loners are absent, one norm emerges and remains fixed forever.

The model has helped us to reconcile two different empirically-determined views of the role of central and peripheral members in the diffusion phase of language change. We have shown that peripheral members act as both sources of new and repositories of old variants, depending on the state of all other variables in the network.

We have shown that centers (hubs or leaders) and peripheries (loners) represent two facets of the same diffusion dynamics that can be interpreted differently in specific social and historical contexts.

Centrally-connected charismatic leaders can take on the role of advancing a change, e.g., a new and vigorous vowel shift, such as the Northern Cities Shift, in their extended adolescent peer groups, and thus be perceived as agents of on-going change. In other contexts, they can also spread local forms in an extended working-class community, resisting the intrusion of mainstream influence, and thus coming across as safe-keepers of local dialectal norms. As our simulations show, however, they are propagators of linguistic influence rather than innovators of novel variants in each case (for the distinction, see Croft 2001:179). (Recall that in our model, variants were assigned uniformly randomly to all agents; no particular agents were designated to be innovators.)

Similar to centers, peripheral individuals (loners and other outliers) are neither innovative nor conservative, per se. In our model their action of holding on to existing linguistic variants longer than the rest of the population was due to the way in which they relate to the rest of the agents in the network: loners were not subjected to others' influence, but a few agents were influenced by them. And yet the very few incoming links of these agents were sufficient for their influence to travel through the network to all other agents, and eventually exert a decisive impact on newly emerging linguistic conventions (or norms) over time. This indirect influence, or "reach," of loners extending over the rest of the network is due to the structure of the heterogeneous social network, in particular the three properties described in Section 3.

The simulations showed that community-wide adoption of an innovative variant as a novel norm only takes place when all agents conform to a shared social convention: select a linguistic variant held by those who enjoy the highest relative prestige in the local community (Figure 3). The relative prestige of social groups might, therefore, be better understood as both network structural characteristics and shared individual preference for what is socially desirable to imitate in others' language use.

One of the main advantages of computational models is that they make all the underlying assumptions explicit. Building a minimal model, as we have done, allows us to lay out clearly our assumptions of the structure of the network and the dynamics of language diffusion. At a minimum, this will lead to a clearer dialogue, since these assumptions can now be systematically modified and tested. Understanding the dynamics of a simple model will also allow the rigorous development of more complex models; for example, ones that have a more detailed language model that would allow modeling interactions between grammar and diffusion.

In general, computational models can be built for multiple reasons (Epstein 2008), including explanation and prediction. Here, we have tried to shed more light on the role of network positions, and to illuminate the core dynamics of a particular model of linguistic diffusion on a realistic social network. There are many possible extensions of this model, such as deriving the social network for a particular region from demographic and survey data for that region (cf. Sankoff 2008), and making a model of network dynamics (how people change whom they interact with over time) in relation to the language dynamics. Computational modeling and sociolinguistics could also work synergistically, where the model guides data collection, and the data guide model-building.

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