An Agent-Based Computational Interpretation of the Transmission and Diffusion of Vowel Chain Shifts across Large Communities

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ABSTRACT

The value of computational modeling of language variation and change has been demonstrated by Baxter et al. [2009, Language Variation and Change 21:257-96] and Fagyal et al. [2010, Lingua 120:2061-79]. Following such work, we develop an agent-based model of vowel chain shifts across large communities. Our model provides an economical interpretation of Labov’s notions of transmission, diffusion, and incrementation [2007, Language 83:344-87], and Nerbonne’s (2010) large-scale patterns of diffusion.

Labov (2007) determines that parent-to-child transmission faithfully reproduces structural patterns like the Northern Cities Shift (NCS), but adult-to-adult diffusion does not. NCS is transmitted faithfully to new generations of U.S. Inland North children, and then progressively incremented. But St. Louis speakers, depending only on adult-adult contact, only attain an incomplete, unsystematic version. Labov attributes the difference to children’s superior language-learning ability; transmission and diffusion are therefore categorically different processes. We suggest that simple density of interactions among different cities may be more important as an underlying principle. Our model does not require different categories of learning abilities for children and adults, nor a dichotomy between transmission and diffusion. Instead, simple density of interactions and a simple exemplar-based approach to learning are sufficient to model the effects of transmission, diffusion, and incrementation found in Labov (2007) as well as the large-scale patterns of diffusion in Nerbonne (2010). The unified results of this economical model suggest that similar principles may underlie these processes in the real world as well.

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Computational modeling is a valuable modern tool for understanding language variation and change. Baxter, Blythe, Croft & McKane’s (2009) computational model of New Zealand English exemplifies the growing importance of such approaches in variationist sociolinguistics. Likewise, Fagyal et al. (2010) show how “agent-based modeling” can be used to test the role of social networks from a variationist perspective. Following such work, we use agent-based modeling to provide a computational interpretation of Labov’s (2007) notions of transmission, diffusion, and incrementation in the context of vowel chain shifts across large communities, as well as the related large-scale diffusion patterns in Nerbonne (2010).

In agent-based modeling (ABM), simple interactions between individual “agents” can lead to the emergence of complex patterns (Fagyal et al. 2010; Beckner et al. 2009; Blythe & Croft 2009; Harrison et al. 2002; Epstein & Axtell 1996; Steels & McIntyre 1999 inter alia). In such models, individual agents interact with each other in a virtual world with simple initial parameters, such as a world where agents are required to move randomly around a “hometown” location, interact with other agents, and then return to the hometown after a certain amount of time. The behavioral patterns that emerge from “face-to-face” interactions among agents can be used to make predictions about real-world situations.

For this reason, ABM is being used across the social sciences, biology, economics, public policy, and many other fields of study (Heath et al. 2009). Medical researchers, for example, use ABM to determine which treatments may be most effective in the real world (Folcik et al. 2011; Wang et al. 2007). Within linguistics, ABM research has informed historical linguistics, language contact, and language evolution (e.g., Harrison et al. 2002; Kirby 1999; Oudeyer & Kaplan 2007; Satterfield 2001; Abrams & Strogatz 2003; Schulze et al. 2008; Minett & Wang 2008; Niyogi & Berwick 2009). The growing influence of exemplar models of language (Bybee 1994, 2001; Pierrehumbert 2001 inter alia) and related conceptualizations of language as a complex adaptive system (e.g., Beckner et al. 2009; Blythe & Croft 2009; Kretzchmar 2009; Nowak et al. 2002) all fit naturally with the goals and methods of ABM.

Unfortunately, however, ABM has been underutilized in variationist sociolinguistics, even though it
offers very strong explanatory power. In many ways, ABM is an ideal tool since it can probe the individual effects of face-to-face interactions while also showing how those interactions lead to large-scale sociolinguistic patterns. Through ABM, it becomes possible to clearly see how large-scale patterns, such as dialect diffusion and speech communities, emerge from thousands of small-scale, individual interactions between speakers.

Bloomfield (1933) highlights the importance of individual interactions in his “principle of density,” which predicts that speakers will become more like those around them, all things being equal: “Every speaker is constantly adapting his speech habits to those of his interlocutors” (1933:476, quoted in Labov 2001:19; cf. Trudgill 2004, 2008, 2010:187-90). Moreover, Fagyal et al. (2010) point out that Bloomfield long ago envisioned an experiment where a vast number of personal interactions could be tracked in order to follow the progress of language variation and change (1933). With the rise of computational methods, it is now possible to use agent-based approaches to model something similar to Bloomfield’s original idea.

Goals of the present study

This study creates an agent-based model of “Chicago” and “St. Louis.” We trigger a vowel chain shift in “Chicago” in order to explore Labov’s (2007) notions of (1) transmission, (2) diffusion, and (3) incrementation, as well as (4) the large-scale diffusion patterns that are found in Nerbonne (2010) and in related work. Our goal is to determine whether a minimal set of assumptions can generate these effects in an agent-based world. On that basis, we can then suggest that similar underlying principles may be operating in the real world.

1. Transmission: Labov (2007) defines transmission as the “unbroken sequence of native-language acquisition by children” (p. 346). Transmission occurs from parent to child, and it faithfully reproduces structural patterns. For example, Labov notes that the U.S. Northern Cities Shift (NCS) is being faithfully transmitted across generations in the U.S. Great Lakes region.
2. Diffusion: By contrast, *diffusion* occurs when adult speakers come into contact with other adult speakers. Diffusion does not faithfully reproduce structural patterns. Labov states that the process of diffusion has a “very different character” than transmission (2007:347), and the difference between transmission and diffusion is attributed to the weaker language-learning abilities of adults in comparison to children. Diffusion produces only an incomplete transfer of linguistic features because “adult learning…loses much of the fine structure of the linguistic system” (p. 380). For example, NCS parents in cities like Chicago transmit their vowel systems to their children, but the NCS vowels are diffused to St. Louis through adult-adult contact. As a result, adults in St. Louis show evidence of the influence of NCS vowels, but they do not have the full structure and systematicity of the NCS. St. Louis speakers only acquire phonetic variants, not a faithful reproduction of the system itself (Labov 2007:379). Labov also discusses the New York City short-\(a\) pattern as another example of these principles of transmission and diffusion. In our study, we chose to model the NCS since the notion of a chain shift can be more effectively modeled as a system in our computational world of agents.

Using evidence from the NCS and from the New York short-\(a\) pattern, Labov concludes that there is a “clear dichotomy between transmission and diffusion” (p. 347). He determines that transmission and diffusion represent “two different kinds of language learning” (p. 349), i.e., adults and children. This is an elegant and insightful analysis of the data, but we wonder about the role of density of interactions among speakers in the different cities. For example, it is certainly the case that most St. Louis speakers typically have less contact with Chicago speakers than they do with other St. Louis speakers. Could the incompleteness and “irregularity” (Labov 2007:378) of St. Louis adults’ acquisition of NCS be largely due to the limited number of interactions they have with NCS speakers -- rather than primarily due to inherent language-learning differences between adults and children? There may well be inherent differences between child language-learning abilities and adult abilities, but our model suggests that the L1 dialect acquisition observations in Labov (2007) may be modeled economically as a matter of simple density of interactions.
3. Incrementation: In incrementation, children advance a sound change beyond the level of the previous generation. That is, “successive cohorts and generations of children advance the change beyond the level of their caretakers and role models, in the same direction over many generations” (Labov 2007:346).

4. Large-scale patterns of diffusion: Since we are testing points 1-3 above with a model that uses large-scale populations, we also naturally encounter a related pattern, namely, “Seguy’s Curve.” Many quantitative analyses of large-scale dialect diffusion (e.g., Seguy 1971; Nerbonne 2010; Kretzschmar et al. 2010) have reported a sub-linear relationship between dialect differences and geographic distance, which has been called Seguy’s Curve (Nerbonne 2010; Kretzschmar et al. 2010). As with points 1-3 above, Seguy’s Curve is a real-world observation that can be economically generated through the simple face-to-face interactions of individual agents in our model.

*Hypothesis*

Our agent-based model tests the following hypothesis:

Simple density of interactions among agents, combined with simple exemplar-based learning, can economically model four phenomena observed in real-world dialect studies: (1) transmission, (2) diffusion, (3) incrementation (Labov 2007), and (4) large-scale patterns of diffusion (Seguy’s Curve in Nerbonne 2010).

If this hypothesis is found to be true in our model world, it will provide additional support for Labov’s (2007) observations in the real world, while also suggesting a parsimonious explanation for those observations. In particular, Labov’s perspective requires the assumption that there is a dichotomy between transmission and diffusion: “two different kinds of language learning” (p. 349). By contrast, in our model, children and adults all have the same, simple, exemplar-based learning mechanism. Our model can therefore test whether the phenomena of transmission, diffusion, incrementation, and Seguy’s Curve all naturally emerge in a unified, economical way through simple density of interactions as agents move around in different cities in the model world.
THE NORTHERN CITIES CHAIN SHIFT AND THE ST. LOUIS CORRIDOR

The Northern Cities Chain Shift (NCS) involves vast populations across the Great Lakes region of the United States, and it has been a topic of extensive fieldwork and theoretical analysis (Labov et al. 1972; Eckert 1988, 1999; Labov et al. 2006; Gordon 2001; cited in Labov 2007). The shift is typically envisioned with the following stages.

Stage 1 (trigger): Tensing and raising of /æ/ in words like cat.
Stage 2: Fronting of /a/ in words like cot, and lowering of /ɛ/ in words like bet.
Stage 3: Lowering and fronting of /ʌ/ in words like caught.
Stage 4: Backing of /ɛ/ in words like bet toward /ɑ/ in but, or lowering/backing of /ɛ/ toward /æ/ in cat.
Stage 5: Backing of /ɑ/ in words like but.
Stage 6: Lowering and backing of /u/ in words like bit.

The NCS is illustrated in Figure 1 (Roeder 2006).

![Diagram of the Northern Cities Chain Shift](image_url)

Figure 1. The Northern Cities Shift (Roeder 2006). [We will ask for permission to reprint this figure.]

Labov defines the NCS in terms of five vowel measures (2007:379), and Figure 2 illustrates one of those measures with respect to St. Louis. Diffusion of the NCS to St. Louis is evidenced in empirical results for speakers in the St. Louis Corridor (i.e., St. Louis and locations along Interstate 55 approaching St. Louis). Labov observes that the St. Louis Corridor speakers have received some influence from NCS vowels, but only one of the nine speakers in the St. Louis Corridor has all five criteria of the NCS (p. 377). Since the NCS vowels are a system, the spread or lack of spread of this system to other speakers can be described in terms of transmission and diffusion. Labov finds that “…the St. Louis corridor produces a more irregular result, indicating that individual sound changes are diffusing individually, rather than as a
system” (2007:383), and “It is proposed that this is the result of the difference between the learning abilities of children and adults” (p. 344).

Figure 2. NCS and the St. Louis Corridor in terms of the “ED criterion” (Labov 2007:374). Dark symbols indicate that F2 of the bet vowel minus F2 of the hot vowel is less than 375 Hz. [We will ask for permission to reprint this figure.]

METHODS

A minimalist perspective

Agent-based worlds can be built using a wide range of different modeling approaches, from simple abstract worlds to highly complex simulations involving rich details of human social life and complex interpersonal behavior and motivations (cf. Epstein & Axtell 1996). In the present study, we take a minimalist approach in order to uncover underlying principles. Using an Occam’s Razor perspective, we focus on the minimal assumptions needed to generate the observed real-world patterns of transmission, diffusion, and incrementation. In this sense, we follow Labov’s suggestion that “it is good practice to consider first the simpler and more mechanical view…” (2001:506; cf. Trudgill 2008:251, 2010:187-90, 2004). After all, if simple “mechanical” interactions between agents in a model world can successfully produce the effects observed in the real world, then this potentially suggests that both the model world and the real world have similar underlying principles in this respect. Such reasoning has been valuable in modeling cancer
treatments in medical research (Wang et al. 2007), for example. Likewise, computational models of the Earth’s atmosphere also try to isolate crucial principles that may underlie weather patterns in the real world (Warner 2011).

Simplification is therefore one of the strengths of computational modeling in a sociolinguistic context. Real-world human communities have complex sociocultural histories and other innumerable idiosyncratic factors that are difficult to account for. But in a model world we can put the spotlight on the few key parameters that appear to underlie major behavioral patterns. Moreover, unlike the real world, we can easily rerun the model multiple times, testing different possible conditions across many generations and configurations.

Of course, various additional social factors may be relevant for certain research questions. For example, Fagyal et al. (2010) model social networks and the role of prestige in the spreading of dialect features, and these are clearly very important aspects of language variation and change (cf. Bloomfield 1933:345, quoted in Fagyal et al. 2010:2063). For our study, however, we have a different goal: To uncover the minimal assumptions needed to generate dialect transmission, diffusion, and incrementation, and large-scale diffusion patterns. Can simple “mindless” interactions among agents generate these basic phenomena as found in the real world?

Chicago and St. Louis

The computer program was developed by the second author using Java with Swarm (www.swarm.org), which is a publicly available software package for agent-based modeling. Our model world was designed to have two distinct “cities” of agents: “Chicago” and “St. Louis.” The number of agents in each of these cities is based on a ratio of approximately 1,500 humans to 1 agent (calculated from city populations in the 2009 US Census\(^1\)). In our world, “Chicago” has a population of about 1,850 agents, and “St. Louis”

\(^1\) http://factfinder.census.gov/home/en/official_estimates_2009.html
has a population of about 250 agents (the exact number of agents may vary depending on birth and death at a given moment). Figure 3 shows a screenshot of Chicago and St. Louis agents interacting. The large circle represents the “city limits” of Chicago, and the smaller circle represents the city limits of St. Louis.

Figure 3. A screenshot of the agents in action: Chicago agents (gray dots) and St. Louis agents (white dots).

The distance between the cities was designed to create a realistic amount of interactions. If the cities are placed too close together, agents constantly interact and the notion of two separate cities is lost. On the
other hand, if the cities are too far apart, little or no interaction occurs. We chose a balanced placement that produced a reasonably lifelike pattern of interaction. We give the agents a “homing instinct” which causes them to occasionally return to the city limits of their respective home cities. Without such a homing parameter, the agents simply become more and more diffused throughout the world, and the cities completely dissolve. Since we are trying to model effects in human society, we selected this parameter as a straightforward way to get the desired effect: Agents are free to move around in the world, yet they are given a general tendency to remain rooted in one city.

Time in the model is measured in terms of “time-periods.” During each time-period, each agent moves 1,000 times. A move consists of a random choice between 9 different options: the 8 compass directions plus an option to remain stationary. As a result of the homing parameter, every agent returns to the home city at randomly selected intervals of 1-4 time-periods.\(^2\)

To generate “traffic flow” between the cities in our model, we designed a travel parameter that causes agents to occasionally travel to the other city. This is the model equivalent of the effect of Interstate 55 in real-world Illinois, as described above (Figure 2). With or without this traffic flow parameter, our Chicago and St. Louis agents can interact with each other to some extent. However, the traffic flow parameter helps to model Interstate 55’s role of promoting contact between these two cities in the real world. In our model, approximately 75-80 agents in each of the two cities are traveling at any given time. These agents are randomly selected to travel to the opposite city, spend a random number of time-periods in the other city, and then return home.

*Distance in the model world*

In many agent-based models (Epstein & Axtell 1996), agents’ movements have a slightly different geometry than the real world. In such models, each move in the grid costs 1 unit, regardless of whether the move is diagonal or orthogonal. In the real physical world, a move from one grid point diagonally to

\(^2\) The random range of 1-4 time-periods prevents an unnatural situation where all agents would always return to their cities at exactly the same time.
another grid point would actually be the square root of 2 times the distance of an orthogonal move (1 unit x 1.41421), following the Pythagorean Theorem. Since we would like our model to be easily interpretable in terms of physical patterns of real-world dialect diffusion, we need to have a geometry that matches the real world. In our model, we define diagonal grid points as having a distance of 1.41421 units, as in the real world. Agents move 1 unit at a time. Therefore, when an agent chooses to move in a diagonal direction, it moves just 1 unit in that direction. It does not immediately reach the nearest diagonal grid point since that point is 1.41421 units away. At that moment, the agent will not be located at a specific grid point that can be plotted (the Swarm software plots the agents using 1-unit grid points). We simply tell the computer to plot the agent at the closest possible grid point, while the actual location is stored in memory after each move. In this way, agent movements are always computed in a manner that matches real-world geometry, and all calculations and analyses are handled according to these movements. The computer plots the agents graphically at the closest possible grid points corresponding to their actual locations after each move.

The vowel system

In our model, vowel systems emerge through language use as agents encounter each other in face-to-face interactions, following prevalent, usage-based, exemplar theories of language (e.g., Bybee 1994, 2001; Bybee & Hopper 2001; Johnson 1997, 2006; Pierrehumbert 2001, 2003 inter alia (cited in Mendoza-Denton 2008:213); Wedel 2006). Prior work (e.g., De Boer 2000, 2001) shows that vowel spaces of different types can be computationally modeled as emergent systems, i.e., complex adaptative systems (e.g., Beckner et al. 2009 inter alia). De Boer uses an algorithm of “language games” where two agents communicate with different vowel values (cf. De Boer & Zuidema 2010). The end result is a human-like vowel space. As for vowel chain shifts, Ettlinger (2007) develops an agent-based model of a two-vowel system where vowels affect each other as two agents interact. In the present study, we place such an emergent vowel system into a world where thousands of agents interact with each other throughout a
geographic space divided into two major population centers (Chicago and St. Louis). We use a three-vowel system in order to see both the initial stage of a chain shift (raised vowel A affects vowel B) as well as more advanced stages (raised vowel A affects vowel B which then affects vowel C).

We follow the basic notions of vowel dispersion in Schwartz et al. (1997) and De Boer (2000, 2001 inter alia) and Ettlinger’s (2007) agent-based approach to vowel chain shifts (cf. Lakkaraju et al. 2009). Our vowel system is modeled with an abstract set of vowel “frequencies,” such as Vowel A=5.0 units and Vowel B=15.0 units, etc. As agents interact, they affect each other’s vowels.

When any two agents are adjacent to each other during a given moment in the model, they each “speak” each one of their vowels. After the interaction is over, they may store each other’s vowel values as exemplars, and draw upon those exemplars in subsequent interactions. Each agent therefore builds up a set of exemplars for each vowel, i.e., a “bag of balls” (Baxter et al. 2006, cited in Blythe & Croft 2009) that the agent can draw from each time it speaks a vowel to another agent. Following Labov (2010a:142-4), we assume that speakers have a “cloud” of exemplars which affect their production and perception of vowels. Figure 4 illustrates a speaker’s exemplar sets for two vowels, Vowel A and Vowel B. As particular tokens of these vowels encroach on another exemplar set, shifts can occur. In Figure 4, a token of Vowel B is produced within the range of the exemplar set for Vowel A. Such instances can gradually change the speaker’s vowel production.

![Figure 4. Exemplar “clouds” of two different vowels. Reprinted from Labov (2010a:142-4) [We will ask for permission before printing this figure.]](image-url)
Our model uses the same overall approach, although we simplify to one dimension of vowel space (following Ettlinger 2007). Two-dimensional vowel spaces are not needed to accomplish the purposes of our study, so we choose the simplest possible parameters. Future studies may choose to add more realism by using a two-dimensional vowel space, but this will raise additional issues, including the relative importance of F1 and F2 dimensions in different vowels, etc. As discussed earlier, for this study we use a “minimalist” approach of finding the minimal parameters necessary to produce the effects being tested.

For our model, each agent has an exemplar set for each of the three vowels: Vowel A, Vowel B, and Vowel C. When two agents are within 1 grid unit of each other, each agent “speaks” 3 vowels, such as “10.0, 15.2, 19.5”. The specific values are randomly selected from a normal distribution around the average of the exemplar set for the given vowel for that agent. Each agent then “listens” to the vowels produced by the other agent. If the given vowel value is close to the agent’s own exemplar set for that vowel, there is a likelihood that the agent will add that value into its exemplar set. This “likelihood” is not based on any hard-coded probability. Rather, it is an emergent likelihood that changes according to the exemplar sets: An agent will perceive a token of Vowel A to actually be Vowel A if and only if the token is close enough to the agent’s own Vowel A exemplar such that it is distinguished from its exemplar sets for Vowels B and C. Examples 1 and 2 illustrate this process.

Example 1: Vowel token accepted as an exemplar

Suppose that Agent 1 and Agent 2 come into contact in the grid, and Agent 1 speaks “11.5” as a token of Vowel A. Suppose Agent 2’s exemplar set for Vowel A currently contains: {9, 9, 10, 10.5, 11}. Since the “11.5” token spoken by Agent 1 is close to the range of Agent 2’s exemplar set for Vowel A, Agent 2 is likely to add it to the exemplar set. Agent 2’s exemplar set for Vowel A then becomes {9, 9, 10, 10.5, 11, 11.5}. As a result, in future interactions, Agent 2 is now likely to produce a slightly higher Vowel A on average.

Example 2: Vowel token not accepted

Suppose that Agent 2 and Agent 3 come into contact in the grid, and Agent 3 speaks “16” as a token for Vowel A. Suppose Agent 2’s exemplar set for Vowel A currently contains: {9, 9, 10, 10.5, 11, 11.5}. The “16” token is not close to Agent 2’s exemplar set for Vowel A, so Agent 2 does not “perceive” it to be a token of Vowel A. The token is not correctly perceived as being a token of Vowel A, so no changes occur in Agent 2’s exemplar set for this vowel.
Triggering a chain shift

The very first (and only the very first) generation of agents is initialized with 50 exemplars for each vowel for each agent. Subsequent generations of agents are born into the world with a “blank slate” of zero exemplars. The values we select at the time of initialization determine whether or not a chain shift will be triggered in the world. We can “trigger” a chain shift by initializing two vowels close together for that first generation of agents. For example, when the vowels are initialized at a distance of 10 units, no chain shift effects are observed (Figure 5).

Vowel C = 25 units

\[\text{Separated by a large distance: No chain shift is triggered.}\]

Vowel B = 15 units

\[\text{Separated by a large distance: No chain shift is triggered.}\]

Vowel A = 5 units

Figure 5. Vowel space with intervals of 10 units.

We find that chain shifts are triggered when two vowels are initialized close together (Figure 6).

Vowel C = 25 units

Vowel B = 15 units
Vowel A = 14 units

\[\text{Close together: Triggers a chain shift}\]

Figure 6. Chain shift triggered due to close proximity of Vowel A and Vowel B.
When the world is initialized with the values in Figure 6, Vowel B begins to raise since it is too close to Vowel A. Then Vowel C also begins to raise as Vowel B becomes too close to Vowel C. In our model, we use a triggering distance of 1 unit in order to produce the clearest effects. Gradual chain shifts also slowly emerge when we use larger triggering distances, but we prefer a relatively fast (i.e., close) trigger for this model. Crucially, as discussed below, chain shifts do not occur when vowels are separated by approximately 10 units or more.

The initial conditions in Figure 6 produce a chain shift only if the trigger vowel (Vowel A) has a “fixed” value. In that case, Vowel B raises and then Vowel C raises as well, resulting in a chain shift. But if Vowel A is allowed to freely move like Vowel B and C, the chain shift does not emerge. Instead, the vowel system self-organizes into a more symmetrical form: Under pressure from Vowel B, Vowel A simply moves downward until there is adequate space again (cf. Preston 2008; Dinkin 2011). Since we need to generate a chain shift to test our hypothesis, we fix Vowel A at 14 units for the population of agents where we want a chain shift to be triggered. In this way, our model follows Labov’s (2010a) notion of the “unidirectional character of linguistic change” (p. 195), citing Lieberson’s (2000) “ratchet principle” of sociology: When a sociological change occurs, subsequent changes tend to move in a unidirectional manner. This appears to be a fundamental requirement for a chain shift to occur.

When all three vowels are separated by 10 units (Figure 5), the three vowels maintain a stable distance of approximately 10 units throughout the run. There are no chain shift effects, and the vowels do not raise. If anything, the vowel system lowers slightly under those conditions; the three vowels typically migrate downward slightly while maintaining the stable distance between them. Therefore, with the model parameterized in this way, we ensure that any vowel-raising that emerges as a result of the other condition (Figure 6) can be attributed to the chain shift effects being explored in the study, not to other model effects.
Birth and death

Since our research question includes generational effects (transmission and incrementation), we designed the computer program to periodically cause “child” agents to be “born” into the world. The rate of child-birth is balanced with the rate of death so that the world population is stable. To model the influence of child-rearing in early language development, each child agent is required to stay within a few grid points of a “parent” agent during the child agent’s first 6 time-periods of life. In future work, it might be valuable to explore more nuanced parameters of child dialect acquisition in an agent-based model, i.e., parent influence versus peer influence (Labov 1991:304; Stanford 2008; Kerswill & Williams 2000:68). For the purposes of the present study, we use the simplest parent-child relationship that reasonably reflects the real world: parent and child stay nearby each other until the child reaches adulthood (at the age of 6 time-periods). An even simpler approach would allow children to wander freely around the world immediately after birth, just like adults. This alternate approach would not produce noticeably different results in this dialect study (since newborn agents are naturally surrounded by many speakers of their dialect), but it would diverge rather drastically from the patterns of socialization and child-rearing seen in the real world. Therefore, we require the child agents to stay near a parent during the first 6 time-periods of the child’s life.

To maintain a stable overall population count in the world, we designed the model so that agents “die” at the age of 25 time-periods. At the end of each time-period, all agents who have reached the age of 25 time-periods are permanently removed from the world.

Child dialect acquisition

The world is initialized by randomly placing agents throughout Chicago and St. Louis, and each of these initial agents is given 50 exemplars for each of the three vowels. Once the world is initialized with these starting values for the very first generation of agents, the subsequent processes of dialect variation, change, and acquisition are emergent, including child dialect acquisition. Whenever a new agent is “born”
into the world, it arrives with a “blank slate” of vowel values, i.e., zero exemplars. In other words, children acquire their vowel systems through interactions with other agents in the world. This approach to dialect acquisition follows exemplar models of language discussed above (Bybee 1994; Wedel 2006 inter alia) and related understanding of L1 acquisition (e.g., Tomasello 2003; Tomasello 2009; Nowak et al. 2002; Niyogi & Berwick 2009; Clark 2009; Lust & Foley 2004 inter alia).

**Age cohorts**

In order to have an analysis that is comparable to real-world studies where researchers take a sample from different age groups at a particular moment in time, our analysis focuses on two contrastive age groups. Both of these age cohorts have an age range of 6 time-periods. The younger group (henceforth “children”) are defined as those agents aged 0-5 time-periods at the time of the sample. The older group (henceforth “adults”) are middle-aged adults who are aged 13-18 time-periods. Since the lifespan is 25 time-periods in the model, an agent’s full adulthood is the age range of 6-25 time-periods. The middle 6 time-periods of adulthood (middle age) is therefore the age range of 13-18 time-periods. Of course, future research could examine more age ranges or narrower/broader age ranges, but the two age ranges we have selected are sufficient to test our hypothesis.

**RESULTS FOR TRANSMISSION, DIFFUSION, AND INCREMENTATION**

The model correctly produced the phenomena of transmission, diffusion, and incrementation found in real-world Chicago and St. Louis: Child agents acquired shifted vowels from native “Chicago” adults (transmission) and began advancing it farther than the adults (incrementation). The non-shifted “St. Louis” adults in contact with Chicago adults only learned an unsystematic, incomplete set of “phonetic variants” (diffusion). The St. Louis agents’ vowels were influenced by the Chicago vowel values, but they were not incorporating the full, systematic chain shift. These outcomes therefore support our hypothesis (INTRODUCTION section). The detailed results are given in the following.

We sampled the vowel values of agents in the world after 40 time-periods. Other similar lengths of
time show similar results, but we found the clearest examples of the targeted phenomena after 40 time-periods. Naturally, since Chicago is considerably larger than St. Louis, if we ran the model indefinitely then the Chicago vowel system -- and its systematic chain shift effects -- would eventually take control of St. Louis. This is not what has happened in the real world to date, as Labov (2007) observes. Therefore, we look for points of time in the model (e.g., 40 time-periods) that best test our hypothesis and best fit Labov’s empirical findings. As with any model world, the passage of time in our model is only abstractly related to the passage of time in human interactions. In a more detailed simulation, we could add complex behavioral patterns that correspond to detailed daily human behavior or social milestones in a human lifespan. For the present study, however, we take the minimalist approach of limiting the model to parameters that are needed for our specific research questions.

Table 1 lists the starting values for vowels in the two different cities. As explained above, the initial agents in Chicago start with 50 exemplars of each vowel, using values that trigger a chain shift. The initial agents in St. Louis start with 50 exemplars of each vowel, using values that do not trigger a chain shift (all three vowels separated by a large distance: 10 units). Subsequent agents born into the world arrive with zero exemplars.

Table 1. Initialization of the model

<table>
<thead>
<tr>
<th></th>
<th>Vowel A</th>
<th>Vowel B</th>
<th>Vowel C</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chicago</td>
<td>14.0 (fixed)</td>
<td>15.0</td>
<td>25.0</td>
</tr>
<tr>
<td>St. Louis</td>
<td>5.0</td>
<td>15.0</td>
<td>25.0</td>
</tr>
</tbody>
</table>

Graphical evidence of transmission, incrementation, and diffusion

1. Transmission and incrementation

Figure 7 provides a graphical view of the results for Chicago after 40 time-periods. Each black triangle represents the average value of Vowels A, B and C for a Chicago adult. Each gray circle represents the average vowel value for a Chicago child for the same vowels. “Chicago adults” are agents who were aged 13-18 time-periods at the moment of sampling, and who were originally born in Chicago. “Chicago children” are those agents who are aged 0-5 time-periods and who were originally born in Chicago. At the
time of the sample, there were 511 such Chicago adults and 451 Chicago children.

![Graph showing vowel frequency over time for Chicago adults and children.]

**Figure 7.** Plot of the Chicago adults (black triangles) and the Chicago children (gray circles) after 40 time-periods.

First, for both age groups, Vowel B raised significantly above its initialized value of 15. This raising of Vowel B is the first stage in the chain shift. In addition, observe that Vowel C also raised above its initialized value of 25 units. This shows evidence of the second stage of the chain shift. In each case, the children had acquired the adults’ vowel system, so transmission has occurred. The children started with zero exemplars, and the adults’ vowel values were transmitted to them. This transmission included the full, systematic chain shift. Finally, notice that on average the children’s Vowel B and Vowel C values were slightly higher than the adults’ Vowel B and Vowel C. This is evidence of incrementation: On average,
the children had advanced the vowel-raising beyond the adults’ level. Numerical and statistical evidence for these observations are given below (Statistical evidence section).

2. Diffusion

Figure 8 compares the Chicago adults (black triangles) versus the St. Louis adults (gray circles).

Figure 8. Chicago adults (black triangles) plotted with St. Louis adults (gray circles) after 40 time-periods.

As before, our analysis focuses on “children” (ages 0-5 time-periods) and middle-aged “adults” (ages 13-18 time-periods). Our model world’s St. Louis population is smaller than Chicago, so there are fewer St. Louis adults than Chicago adults in this sample taken at 40 time-periods: 49 St. Louis adults and 511 Chicago adults. Therefore, to keep the sample sizes balanced for statistical analysis, 49 adult agents were
randomly selected from the Chicago sample (speakers #1-49) for analysis, rather than the full set of 511 agents.

In Figure 8, first note that the Chicago adults raised Vowel B above its initial value of 15, and they also raised Vowel C above its initial value of 25: A chain shift is in progress in Chicago. Now consider the St. Louis adults in the figure. The results show diffusion, not transmission. For St. Louis adults, Vowel B was just slightly higher on average than its start value of 15, and Vowel C was just slightly higher on average than its start value of 25. In this way, St. Louis Vowels B and C were influenced by the Chicago vowels to some extent, but they lag quite far behind. Crucially, Vowel B and Vowel C were not involved in a chain shift for St. Louis speakers as they were for Chicago speakers. St. Louis speakers’ Vowels B and C are separated by an average of 10 units (numerical results are given below), which we have shown to be beyond the range where a chain shift can occur. The St. Louis adults acquired some “phonetic variants” of the Chicago vowels but not the systematic, structural effect of the chain shift. Likewise, St. Louis adults’ average Vowel A is considerably higher on average than its original start value of 5 units, but it is too far from the average of Vowel B to be involved in a chain shift (recall Figures 5-6).

Therefore, we conclude that our St. Louis adults acquired some phonetic variants (slightly raised vowels) from Chicago, but the great majority of the St. Louis adults did not acquire the chain shift itself. Our St. Louis adults only acquired an “irregular” version of the Chicago vowels (Labov 2007:378-9). As Labov observes in the real world, contact from Chicago to St. Louis results in phonetic influence on the St. Louis vowels, but not acquisition of the systematicity of a chain shift.

Note that there are a few “outliers” among the Vowel A values for the St. Louis adults (4-5 data points considerably higher than the other Vowel A data points). These data points represent agents who traveled to Chicago due to the “traffic flow” parameter (see METHODS section). These particular speakers appear to be participating in a chain shift; their respective Vowels B and C are raised in a way that reflects the chain shift being experienced by the Chicago agents. This small handful of St. Louis speakers exemplifies how a high density of interactions influences a speaker’s vowel space: Because these particular St. Louis
speakers came into direct contact with Chicago (due to the traffic flow parameter), they acquired the systematicity of the chain shift, unlike other St. Louis agents. In other words, this is the exception that proves the rule. St. Louis adults who remained closer to St. Louis (the majority in Figure 8) did not acquire the chain shift; they only acquired some minor “phonetic” influences from Chicago. However, the particular St. Louis adults who happened to be selected by the traffic flow parameter spent some time within the city limits of Chicago itself. As a result, they acquired considerably more of the Chicago vowel pattern, including the systematicity of the shift. Yet in Labov (2007), adult speakers are limited to incomplete, unsystematic learning (diffusion). Our results suggest that this assumption of a dichotomy between transmission and diffusion is not necessary. Moreover, Labov reports that one of the real-world St. Louis adult speakers actually did have a fully developed NCS vowel system (2007:378-9, Table 2), much like the small handful of St. Louis adult agents who acquired the chain shift in our model.

Statistical evidence

Table 2 provides the specific numerical results for each group and each vowel after 40 time-periods, i.e., the statistical results corresponding to the graphical data in Figures 7-8. In Table 2, “Avg” indicates the average vowel value for that group of speakers after 40 time-periods. In the “Sig.” column, a check mark √ indicates a significant difference for the given pair (p<0.05, t-test), while “n.s.” indicates it is not significant. The “S.D.” column provides standard deviations. Note that the values are slightly different when comparing to the St. Louis group; there are less agents in St. Louis, so a similar-sized subset was sampled from Chicago. The specific sample sizes are listed in the “N” column.
Table 2. Results after 40 time-periods for each vowel in each group.

<table>
<thead>
<tr>
<th></th>
<th>Vowel A</th>
<th></th>
<th>Vowel B</th>
<th></th>
<th>Vowel C</th>
<th></th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Avg.</td>
<td>Sig.</td>
<td>S.D.</td>
<td>Avg.</td>
<td>Sig.</td>
<td>S.D.</td>
<td>Avg.</td>
</tr>
<tr>
<td>Chicago adults</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>versus Chicago children</td>
<td>14.0</td>
<td>n.s.</td>
<td>0.0</td>
<td>17.526</td>
<td>✓</td>
<td>0.280</td>
<td>26.488</td>
</tr>
<tr>
<td>St. Louis adults</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>versus St. Louis children</td>
<td>14.0</td>
<td>✓</td>
<td>0.0</td>
<td>17.588</td>
<td>✓</td>
<td>0.290</td>
<td>26.524</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
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</tr>
<tr>
<td>Chicago adults</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>versus St. Louis adults</td>
<td>5.532</td>
<td>n.s.</td>
<td>1.422</td>
<td>15.263</td>
<td>n.s.</td>
<td>0.700</td>
<td>25.314</td>
</tr>
<tr>
<td>St. Louis adults</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>versus St. Louis children</td>
<td>5.532</td>
<td>n.s.</td>
<td>1.422</td>
<td>15.263</td>
<td>n.s.</td>
<td>0.700</td>
<td>25.314</td>
</tr>
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</tbody>
</table>

*The three other possible combinations are not included here since they are not relevant to the research questions in the study: Chicago adults versus St. Louis children, St. Louis adults versus Chicago children, and St. Louis children versus Chicago children.

The results in Table 2 support our graphical analysis of Figures 7-8. The Chicago children acquired the Chicago adults’ vowel chain shift (transmission). Secondly, for both Vowel B and Vowel C, the Chicago children advanced the shift significantly higher than the Chicago adults (incrementation). Finally, as for diffusion, Table 2 shows that the vowels of St. Louis speakers were influenced by the higher values of the Chicago vowels, but only as minor “phonetic variants”. This is a case of diffusion, rather than full acquisition of the Chicago chain shift system: St. Louis speakers’ vowels were significantly lower than the Chicago vowels, and the St. Louis vowels were too far apart to be undergoing a chain shift (recall Figures 5-6). Further, there was no significant difference between the vowels of St. Louis children and St. Louis adults. This is further evidence that the chain shift had not taken hold in St. Louis. If it a chain shift were in progress, we would expect that the St. Louis children would be raising their vowels faster than the adults in their community (incrementation) as observed in our Chicago results. But this is not the case in St. Louis. In Labov’s analysis of the real world, age was a significant factor in Chicago but not in St. Louis (2007:378), thus suggesting that younger generations were incrementing the NCS in Chicago but not in St. Louis. In our model, we find a comparable result: Chicago children were significantly more advanced in the chain shift than Chicago adults. In St. Louis, we find no significant difference between children and adults.

Finally, we can confirm that St. Louis speakers raised their vowels significantly from the St. Louis initialization values: For each of the vowels, there was a statistically significant amount of raising com-
pared to the initialized St. Louis values (5.0, 15.0, 25.0), both for St. Louis adults and St. Louis children (p≤0.05, t-test). This raising is due to the influence of Chicago. By contrast, when we observe the St. Louis agents in an isolated world without Chicago, there is no raising. Likewise, we confirm that the Chicago speakers had raised their Vowels B and C statistically significantly higher than their respective 15.0 and 25.0 initialized values (p≤0.05, t-test).

To ensure that these results were not artifacts of any particular run, we ran the model four more times. The outcome was very similar each time, thus confirming the results of the individual run examined in detail above. Table 3 shows the averages for each vowel over the four runs, and the Appendix lists the results of each of these runs individually.

Table 3. Values after 40 time-periods averaged over four different runs.

<table>
<thead>
<tr>
<th></th>
<th>Vowel A</th>
<th>Vowel B</th>
<th>Vowel C</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Average</td>
<td>Std. Dev.</td>
<td>Average</td>
</tr>
<tr>
<td>Chicago Adults</td>
<td>14.0</td>
<td>0.0</td>
<td>17.543</td>
</tr>
<tr>
<td>Chicago Children</td>
<td>14.0</td>
<td>0.0</td>
<td>17.860</td>
</tr>
<tr>
<td>St. Louis Adults</td>
<td>5.373</td>
<td>0.188</td>
<td>15.168</td>
</tr>
<tr>
<td>St. Louis Children</td>
<td>5.853</td>
<td>0.285</td>
<td>15.180</td>
</tr>
</tbody>
</table>

Summary of results for transmission, diffusion, and incrementation

Using a set of simple assumptions, our agent-based model effectively produces transmission, diffusion, and incrementation. The shift is passed down faithfully (transmission) from Chicago adults to Chicago children due to their close proximity within the dense Chicago population. St. Louis speakers receive only an incomplete and unsystematic version (diffusion) due to the fact that St. Louis speakers have less contact with distant Chicago. As for incrementation, children advance the shift beyond the adult generation for a simple reason: Children have less exemplars to begin with (zero exemplars), so they always have fewer conservative exemplars to resist change.
LARGE-SCALE DIFFUSION PATTERNS

Now that we have examined transmission, diffusion, and incrementation, we can use the model to examine the related issue of the fourth component of our hypothesis: The large-scale diffusion pattern known as Seguy’s Curve. This pattern naturally emerges in our large-scale diffusion modeling.

_Seguy's Curve_

A common finding of dialectology is that there is a sub-linear relationship between geographic distance and dialect differences (Nerbonne 2010; Kretzschmar et al. 2010; Heeringa & Nerbonne 2001). Real-world dialectometry in Germany, Norway, U.S., and many other locations consistently uncovers this logarithmic relationship between geographic distance and dialect differences (Kretzschmar et al. 2010; Heeringa & Nerbonne 2001; Nerbonne 2010). As geographic distance increases, dialect differences increase. For example, Figure 9 shows a map from Heeringa & Nerbonne’s (2001) study of 27 Dutch locations. Figure 10 shows the result when all of the locations are plotted against Schiemda, a location in the northeast corner of the Netherlands. In addition, a logarithmic curve also appears when all locations are plotted pairwise against each other, and Nerbonne (2010:3825) provides such plots of German, Norwegian, English, and other languages. In each case, there is strong correlation between dialect differences and geographic distances (16-38%), and the best fit is usually obtained with a logarithmic curve. This curve is called Seguy’s Curve since Seguy (1971) first noted this sub-linear relationship (Nerbonne 2010:3823).
Figure 9. Map from Heeringa & Nerbonne’s (2001) study of Dutch. [We will ask for publisher permission before reprinting this figure.]

Figure 10. Real-world results from Heeringa & Nerbonne (2001) (reprinted). Dialect differences (y-axis) versus geographic distance (x-axis) from a single location, Scheemda. [We will ask for publisher permission.]

Our large-scale diffusion model

For this aspect of the study, we can further reduce the assumptions needed in the model. Since the goal of
this section is to examine large-scale diffusion patterns, we reduce the model to a simple “dialect index” rather than vowel chain shift effects. 1,000 agents are initialized randomly throughout a grid (Figure 11). Each agent has a “dialect index” initially set to zero, except for a group of agents in a dense “city” in the center with a fixed dialect index of 100 (the white circle in the center of Figure 11). Agents move randomly for “time-periods” of 120 movements each. At the end of each time-period, each agent returns to its original starting location. At that moment, each agent’s dialect index is recalculated by averaging it with the dialect indexes of the other agents it had encountered during the preceding time-period.

Figure 11. Large-scale diffusion test using a “central city.”

For example, suppose that Agent 1 has a dialect index of 20 at the beginning of a given time-period. During the time-period, suppose that Agent 1’s movements cause it to be adjacent to 4 different agents who had dialect indexes of 3, 17, 44 and 6. At the end of the time-period, Agent 1’s new dialect index is computed as \( \frac{20+3+17+44+6}{5} = 15 \). Of course, this is a highly simplistic approach to dialect
acquisition – but that is exactly the point. We would like to see whether the large-scale diffusion patterns seen in real-world studies will emerge in a simple agent-based model with no factors of social identity and where agents mindlessly influence each others’ dialect index. In the real world there are countless influences of social identity, culture and politics, and speakers make individual choices to linguistically construct personae along various social dimensions (e.g., Eckert 1999, 2005; Mendoza-Denton 2002; Coupland 2001; Siegel 2010). However, as before, we “consider first the simpler and more mechanical view…” (Labov 2001:506; cf. Trudgill 2008:251). It turns out that the simple model works quite well.

Results of the large-scale diffusion model

After 1,000 time-periods, we plotted each agent’s dialect index versus its distance from the grid center (Figure 12). The result was a logarithmic curve (p<0.0000001), i.e., Seguy’s Curve, just as expected from the real-world results. Compare Figure 12 with Figure 10. This shows that the model can simulate this fundamental pattern of diffusion predicted by real-world dialectometry, and the basic pattern emerges from simple density of agents in mindless interactions, not anything specific to human language.

Figure 12. Results of our large-scale diffusion model.
This paper has used agent-based modeling to explore Labov’s (2007) notions of transmission, diffusion, and incrementation, and the large-scale diffusion patterns in Nerbonne (2010). We hypothesized that all of these real-world processes could be modeled with two basic assumptions: simple density of interactions among agents and a simple exemplar-based approach to learning. The results strongly confirmed the hypothesis: Using an exemplar-based approach, we triggered a vowel chain shift in a virtual “Chicago.” Chicago children accurately acquired the Chicago adults’ vowel system (transmission), and they advanced the chain shift significantly farther than the adults (incrementation). St. Louis agents achieved only an incomplete, non-systematic version of the Chicago vowels (diffusion), rather than the full chain shift.

In this way, our model supports Labov’s (2007) real-world observations while using a more economical set of assumptions. Labov’s approach requires the assumption that transmission and diffusion are two categorically different processes that depend on inherent differences in the language-learning ability of adults and children. In this view, there is a dichotomy between transmission and diffusion: “…structural patterns are not as likely to be diffused because adults do not learn and reproduce linguistic forms, rules, and constraints with the accuracy and speed that children display” (Labov 2007:349). By contrast, the results of our model suggest that transmission and diffusion effects may be explained more parsimoniously in terms of simple density of interactions of agents and exemplar-based learning. Of course, the differential learning abilities of adults and children are key issues to examine in various other aspects of L1 and L2. But for our model of L1 vowel chain shifts at least, we find that the effects of transmission and diffusion can be generated and explained without any added assumptions about differential language-learning abilities. The simplicity and explanatory power of this model world suggests that similar principles may underlie real-world processes as well. After all, the limited number social parameters in our model are all basic necessities of any model of a human society in geographic space and time (birth, death, movement parameters, etc.). The details of these parameters may be configured differently in various models of human society, but the basic necessary functions are the same (cf. Epstein & Axtell).
1996). Likewise, our vowel systems emerge from the minimal parameters necessary for a chain shift in an exemplar-based approach.

Moreover, incrementation can be naturally explained under the same assumptions as well: Children simply have less exemplars than adults (children start with zero exemplars). Therefore, in our model, when children acquire a chain shift, they are more likely to advance the vowels farther than the adults simply because the adults have more prior exemplars to resist additional shifting. In the real world, of course, various additional factors of social identity, individuals’ choices, and many other factors may have a role in increasing or decreasing the amount of incrementation. However, our model shows that the basic process of incrementation does not require any such factors.

As for large-scale dialect diffusion, our model generates Seguy’s Curve through simple density of interactions between individual agents, suggesting that such diffusion patterns are not dependent on particulars of human language or human society. Large-scale uniformity emerges inexorably from small-scale, face-to-face interactions of agents.

The uniformity of the Northern Cities Shift

We close the discussion by commenting on a related issue: the uniformity of the NCS. Labov (2008) observes that the NCS maintains a remarkable level of uniformity (“the mysterious uniformity of the NCS”) among millions of speakers across thousands of miles in the U.S. Inland North. How can millions of people be undergoing the same sound change across large distances, even though they do not know each other and even though the sound change is almost completely below the level of consciousness? Our large-scale diffusion model in Figure 11 may help to provide perspective on this question.

In our model world and in the real world NCS of the U.S. Great Lakes region, large populations can be quickly and uniformly permeated by the same linguistic change across large distances, despite the fact that individual agents may not personally come into contact with distant agents. An agent near the center of Figure 11 is unlikely to come into direct contact with an agent on the periphery of that world. Nonetheless, as agents interact in face-to-face encounters, this multitude of small-scale interactions can lead to a
uniform spread across vast distances and vast populations, even though each agent has only a limited scope of personal interactions and a limited range of movement. Thousands of small-scale interactions can easily create an emergent set of shared norms across large distances. Our results therefore support Labov’s (2010b) notion of the primacy of the speech community: Through a multitude of individual, face-to-face interactions, the agents can collectively (and unconsciously) construct a speech community which has a high level of uniformity, and it is able to span vast spaces and vast populations.

In conclusion, for all four topics that we have examined in this study (transmission, diffusion, incrementation, and large-scale diffusion), we find that agent-based modeling provides valuable explanatory power. All of these large-scale sociolinguistic patterns can emerge naturally from small-scale, face-to-face interactions as agents come into contact with other nearby agents. In this respect, the results of our agent-based model are consistent with the large body of social constructionist literature that views language and society from a practice-based, emergent perspective (e.g., Giddens 1979; Gergen 1994; Berger & Luckmann 1967[1966]; Ricoeur 1978:114-16; Eckert 2005:16; Johnstone 2004; Coupland 2001:198-99; Bucholtz 1999:209). At the same time, our results also clearly support Labov’s (2010b) emphasis on the speech community and other large-scale, generalizable sociolinguistic patterns (Labov 1991, 2001, 2010a). In our model, stable speech communities emerge as systems of shared norms among agents interacting in space and time. For artificial agents as well as real humans, the simple, localized encounters of daily life have far-reaching effects.
APPENDIX

Average vowel frequencies over 4 runs (measured after 40 time-periods in each case):

<table>
<thead>
<tr>
<th>Run</th>
<th>Vowel A</th>
<th>Vowel B</th>
<th>Vowel C</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Chicago Adults</td>
<td>14.0</td>
<td>17.58</td>
</tr>
<tr>
<td></td>
<td>Chicago Children</td>
<td>14.0</td>
<td>17.93</td>
</tr>
<tr>
<td></td>
<td>St. Louis Adults</td>
<td>5.34</td>
<td>15.23</td>
</tr>
<tr>
<td></td>
<td>St. Louis Children</td>
<td>5.80</td>
<td>15.27</td>
</tr>
<tr>
<td>2</td>
<td>Chicago Adults</td>
<td>14.0</td>
<td>17.57</td>
</tr>
<tr>
<td></td>
<td>Chicago Children</td>
<td>14.0</td>
<td>17.79</td>
</tr>
<tr>
<td></td>
<td>St. Louis Adults</td>
<td>5.53</td>
<td>15.29</td>
</tr>
<tr>
<td></td>
<td>St. Louis Children</td>
<td>6.05</td>
<td>15.27</td>
</tr>
<tr>
<td>3</td>
<td>Chicago Adults</td>
<td>14.0</td>
<td>17.49</td>
</tr>
<tr>
<td></td>
<td>Chicago Children</td>
<td>14.0</td>
<td>17.82</td>
</tr>
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<td></td>
<td>St. Louis Adults</td>
<td>5.12</td>
<td>14.96</td>
</tr>
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<td></td>
<td>St. Louis Children</td>
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<td>14.75</td>
</tr>
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<td>Chicago Adults</td>
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</tr>
<tr>
<td></td>
<td>Chicago Children</td>
<td>14.0</td>
<td>17.90</td>
</tr>
<tr>
<td></td>
<td>St. Louis Adults</td>
<td>5.50</td>
<td>15.19</td>
</tr>
<tr>
<td></td>
<td>St. Louis Children</td>
<td>6.09</td>
<td>15.43</td>
</tr>
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</table>

REFERENCES


