COMPUTATIONAL SIMULATION OF LINGUISTIC CHANGE:

AN AGENT-BASED MODEL

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DEDICATION

To VRATUS.
I never am really satisfied that I understand anything; because, understand it well as I may, my comprehension can only be an infinitesimal fraction of all I want to understand about the many connections and relations which occur to me, how the matter in question was first thought of or arrived at, etc., etc.

—Ada Lovelace
ABSTRACT OF THE THESIS

Computational Simulation of Linguistic Change: An Agent-Based Model
by
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This study takes an individual-based approach on the role of social space and social network structure on the diffusion of linguistic innovation, a process that facilitates language change and variation. An agent-based model (ABM) that generates random graphs of interconnected collectives was devised to evaluate the effects of individual and collective variables on innovation adoption time. Significant findings include the phenomenon that individuals with relatively low degree ties (first through fourth) to the source of an innovation tend to adopt innovations much more quickly when they have a larger amount of weak ties. This supports a notion of a speaker-innovator who is a fringe member of a collective, characterized by a relatively large number of weak ties. This definition of the speaker-innovator is congruent with the “strength of weak ties” theory, which asserts that it is through weak ties that innovations travel beyond the innovator’s local network to external networks. However, the model is not without weakness and several ways in which the model may be improved and extended are provided.
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CHAPTER 1

INTRODUCTION

1.1 THE SCIENTIFIC INVESTIGATION OF LANGUAGE

The field of linguistics is often misinterpreted by non-linguists. The linguist, often mistaken for a polyglot (true as it may be for some of us, it is by no means a prerequisite for linguist-hood), is, like any other breed of scientist, concerned with investigating worldly phenomena in a systematic and empirical fashion. The linguist specifically does so within the vast, interdisciplinary realm of language. Outsiders to this realm of investigation might wonder what is so fascinating about language—after all, we all, as human beings, acquire and use language on a daily basis. In this light, language seems common and mundane. But there is a certain intellectual danger harbored by remaining satisfied with the explanation that something so commonplace such as language just is.

Such an approach is illustrated by the Bible’s story of the Tower of Babel:

Now the whole world had one language and a common speech. As people moved eastward, they found a plain in Shinar and settled there. They said to each other, ‘Come, let’s make bricks and bake them thoroughly.’ They used brick instead of stone, and tar for mortar. Then they said, ‘Come, let us build ourselves a city, with a tower that reaches to the heavens, so that we may make a name for ourselves; otherwise we will be scattered over the face of the whole earth.’ But the Lord came down to see the city and the tower the people were building. The Lord said, ‘If as one people speaking the same language they have begun to do this, then nothing they plan to do will be impossible for them. Come, let us go down and confuse their language so they will not understand each other.’ So the Lord scattered them from there over all the earth, and they stopped building the city. That is why it was called Babel—because there the Lord confused the language of the whole world. From there the Lord scattered them over the face of the whole earth. (Genesis 11:1-9, New International Version)

This approach attributes the existence of language variety to an act of God—we all once spoke one language and lived in one land but then God split us up and made all of our languages different. The “act of God” explanation is easy to apply to most worldly observations but it does not offer an objective understanding of the world. Accepting such an explanation without question contributes to the stifling of human curiosity and the stagnation
of the conquest for knowledge and discovery. Isaac Asimov (1984) notes science’s indispensable role in maintaining humanity’s intellectual inertia against such mindless acceptance: “There are many aspects of the universe that still cannot be explained satisfactorily by science; but ignorance only implies ignorance that may someday be conquered. To surrender to ignorance and call it God has always been premature, and it remains premature today” (p. 183).

While science is more readily associated by the general public with domains such as biology or astronomy, there is the same fundamental significance in the scientific investigation of language—that it contributes to the demystification of who we are and how we work, for language is an evolved behavior unique to our species. The Tower of Babel story offers an anecdotal explanation of the existence of the diversity of language that, not only abandons factual evidence, but ignores the fact that language change—a major contributor to language variety—is not an isolated event but a continuous one persisting throughout time; this thesis investigates the underlying factors that drive linguistic change. Though this domain is rather specific, by acknowledging language as a behavior, this investigation is able to contribute to and to draw upon a more general collection of knowledge pertaining to the spread of information and behavioral innovations throughout a population. If we exhibit that the spread of linguistic innovation is consistent with the spread of other behaviors, we not only gain support from the evidence of extant research in interdisciplinary fields, but we in turn provide additional support to that growing body of research.

1.2 Linguistic Diffusion

As we will see, language change does not simply occur through the act of one speaker. Instead, language change is brought about through the interaction of many speakers so that a new linguistic phenomenon or innovation (discussed further in 1.3.2) can spread through space—a process known as linguistic diffusion (J. Milroy, 1992). This may seem like a straightforward albeit simplistic definition, however, we can mean a few things when we speak of the notion of space.
1.2.1 Diffusion and Space

Britain (2002) argues that there are three equally important but not equally objective notions of space relevant to linguistic diffusion—Euclidean space, social space, and perceived space. Euclidean space, the objective notion of space, is free of social interpretation or perspective. Social space is an effect of human existence—it is how we as individuals and communities have shaped the physical environment in which we live. Perceived space is an entirely subjective concept of space; it is how we perceive our surroundings and other environments that we are aware of. Though conceptually different, these three notions of space are dependent on one another. Euclidean space is immediately made social as soon as humans are added to any space. Humans, as perceptive beings, do not have a purely objective notion of space so any Euclidean space that is made social with the addition of humans is inherently perceptive space as well. These three concepts of space may be thought of as separate dimensions embodying the same space (Britain, 2002).

Addressing the existence of these three qualities of space is important when evaluating and understanding any model of linguistic diffusion. A model that relies wholly on Euclidean or geographic space is arguably too simplistic since language is intrinsically a social behavior which itself involves human perception and evaluation. Two of the perhaps most cited theories of linguistic in an attempt to argue whether the patterns of diffusion are either continuous or discontinuous, rely heavily on the notion of geographic space. These are the Wave Model and the Gravity Model.

1.2.2 Theories of Diffusion

Arguing that linguistic innovations diffuse continuously over geographic space, the Wave Model postulates that linguistic innovations spread like waves in all directions (Britain, 2002). A more specific variation of the Wave Model stipulates that these waves travel down immigration routes or transportation lines (Chambers & Trudgill, 2004, p. 166). In either case, the waves of innovation are proposed to become weaker the farther they travel from their source, resulting in the phenomenon that the communities closest to the source will be more linguistically similar than communities farther from the source. Today, the Wave Model is usually disregarded as an accurate analogy for linguistic diffusion in favor of models consistent with a discontinuous notion of diffusion (Chambers & Trudgill, 2004,
p. 166); however, some recent publications have claimed to support a continuous pattern of linguistic diffusion.

In one such publication, Nerbonne (2010) devises a simulation that replicates Seguy’s Curve—a sub-linear curve that expresses a continuous relationship between geographic distance and aggregate linguistic difference. Nerbonne’s simulation applies a dialectical approach by measuring aggregate linguistic differences through a process of sampling large amounts of data consisting of a large variety of linguistic features at discrete distance steps uniformly across an area of interest (Heeringa & Nerbonne, 2001). Nerbonne’s sample sites are represented by elements in an array of \( n \) length and each site’s geographical distance from the source of innovation is proportional to its index in the array. The source site is always the first element in the array, since its geographical distance from the source will always be calculated as zero. Each site has an array of binary value integers, which, initially, are all set to 1’s. As the simulation runs, sites farther from the source site are given more chances to vary their linguistic inventories by changing values from 1’s to 0’s. The aggregate linguistic differences are then calculated by adding up the elements of each site’s linguistic inventory and subtracting the sum from the source site’s linguistic inventory total. While the results support the Wave Model of diffusion, this approach does not reveal the ordered process by which innovations reach (or, more fundamentally, get accepted by) each speech community.

Discontinuous models of linguistic diffusion include the Cascade or Gravity model of diffusion. The Cascade Model contrasts with the Wave Model in that the “waves” of diffusion reach more populated communities before smaller, closer communities. In this sense, language change cascades from one level of population to the next (Labov, 2003). Trudgill’s (1974) Gravity Model extends the Cascade Model, drawing an analogy between linguistic influence and gravitational force:

\[
I_{ij} \propto s \cdot \frac{P_i P_j}{(|d_{ij}|)^2}
\]

The Gravity Model suggests that the influence \( I \) of a site \( i \) on another site \( j \) is directly proportional to the product of the two sites’ populations—\( P_i \) and \( P_j \), respectively—and inversely proportional to the square of the geographic distance between them. Like the Wave Model, the Gravity Model focuses on the influence of one aggregate mass (e.g. a city) upon
another. To establish an individual-based model of linguistic diffusion, we turn to extant theories of social learning and collective behavior.

1.3 LANGUAGE AS A SOCIAL BEHAVIOR

The theories discussed in Section 1.2 evoke an image of a signal being transmitted across physical space with little attention towards the individuals that produce and perceive it. While it may be a helpful analogy to treat language as its own autonomous entity because it is subject to several processes inherent to living organisms—birth, death, change, and variation—it is important to note that this is merely an abstraction taken from the interactions between speakers (J. Milroy, 1992, p. 6). Language does not have a self-contained existence; language does not exist independently of its speakers. It is through the social interactions of these speakers through which language emerges, changes, and varies. Furthermore, only languages without speakers—dead languages—do not change (J. Milroy, 1992, p. 4). This critical difference between language systems and its speakers should be addressed and considered in any attempt to explore and explain linguistic phenomena.

The inseparability of the speaker from language suggests that language is a social behavior, which is best studied in its social context (J. Milroy, 1992, p. 4). This is not to say that other, oftentimes more economically feasible methods of inquiry, such as relying wholly on written language or decontextualized narrowly transcribed data, are useless. In fact, these alternative methods may provide a preliminary basis for future research. Moreover, in the case of extinct languages, studying language in a social context simply is not an option. It is critical, however, to bear in mind that any research design that relies solely on intralinguistic analysis and that does not involve language taken from its social context suffers from this as a limitation and a weakness.

1.3.1 Innovators and Adopters

Linguistic change must first begin with an innovation—a novel occurrence in the grammar, lexicon, or pronunciation in the language produced by a speaker. The speaker or speakers who initiate an innovation are called innovators. This is not an idea limited to the field of linguistics, but is a relevant concept to other fields such as sociology. In Section 1.2, we reviewed theories that attempted to explain how innovations diffused through geographic
space, a specific and perhaps incomplete notion of diffusion also referred to as *geolinguistic diffusion* (Boberg, 2000). An alternative theory, relevant to Britain’s (2002) notion of social and perceptual space, explores how innovation might diffuse throughout a social network.

In his 2003 edition of *The Diffusion of Innovations*, Rogers outlines four adopter categories in addition to innovators—early adopters, the early majority, the late majority, and laggards. The idea is that, while innovators introduce the innovation, *early adopters* are the first to copy the innovators’ behavior, followed sequentially by the *early majority*, the *late majority*, and *laggards*. These categories reflect degrees of *innovativeness* or the time it takes for an individual to adopt an innovation relative to the mean time of adoption. According to Rogers (2003, p. 281), the frequency of these categories are normally distributed across the population as a function of time (see Figure 1.1) such that the population is comprised of 2.5% innovators, 13.5% early adopters, 24% early majority, 34% late majority, and 16% laggards.

![Figure 1.1. Frequency distribution of adopter categories over time.](image-url)
Further, when the number or percentage of cumulative adopters is graphed as a function of time, a normal *sigmoid* (S-shaped) diffusion curve emerges (as shown in Figure 1.2), reflecting an initial long period of slow adoption rates, followed by a sharp increase in adoption rates, and ending in another period of slow adoption rates. This method of plotting the cumulative proportion (or number) in an attempt to fit it to a mathematical curve is an extant method of social learning detection called *Diffusion Curve Analysis* (Franz & Nunn, 2009, p. 1829). DCA is used to distinguish social from asocial learning as the method of innovative behavior diffusion. The S-shaped curve is assumed to be produced by social learning (Franz & Nunn, 2009, p. 1830).

![Diagram](image)

**Figure 1.2. Cumulative percentage of adopters of an innovation over time.**

This method of categorization attempts to measure a continuous variable, innovativeness, in a simplified and discrete fashion. Although operationalizing a continuous variable into a discrete one results in information loss, it is a helpful method of conceptualizing and understanding human behavior (Rogers, 2003, p. 280).
1.3.2 The Threshold Model of Collective Behavior

Rogers’ categorization of adopters, whether it is to explain the consumption of goods or the adoption of a new linguistic form, is complementary to Granovetter’s (1978) Threshold Model of Collective Behavior, which claims that individuals have distinct thresholds that must be reached in order for a *socially learned behavior*—a behavior learned by observation or direct instruction—to be accepted and copied. These thresholds are met when a certain percentage of the population exhibits the new behavior. Although the nature of the distribution of these threshold levels lacks sufficient investigation, a common trend in extant literature is to assume threshold levels are normally distributed as many naturally occurring characteristics are (Rogers, 2003, p. 355). Following this claim, we can assume that the threshold level for each of the five categories of adopters is simply the proportion of the population that fit into categories that occur earlier in the chain of adoption. For example, the threshold level for an *early adopter* is 2.5% since any individual that adopts an innovation earlier than when the innovation is adopted by 2.5% of the population would be considered an *innovator*. Table 1.1 exhibits a complete list of threshold levels. Note that the threshold level for an innovator is 0%, since the behavior need not have been adopted by anyone in order to trigger an innovator’s willingness to adopt an innovation. This willingness makes it possible for innovations to both emerge and to diffuse beyond a single individual.

<table>
<thead>
<tr>
<th>Adoption Categories</th>
<th>Threshold Levels</th>
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<tbody>
<tr>
<td>Innovators</td>
<td>0%</td>
</tr>
<tr>
<td>Early Adopters</td>
<td>2.5%</td>
</tr>
<tr>
<td>Early Majority</td>
<td>16%</td>
</tr>
<tr>
<td>Late Majority</td>
<td>50%</td>
</tr>
<tr>
<td>Laggards</td>
<td>84%</td>
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</table>

Table 1.1. Threshold Levels of Each Adopter Category
As previously mentioned, these five discrete categories are a simplification of a continuous variable. Now we must also consider another possible oversight of applying qualitative labels to individuals in a population. Do individuals generally maintain the same thresholds across all possible adoption scenarios? If we assume this is so, we would expect that all innovations have a fairly good chance at diffusing across a social system. In this case, the diffusion of linguistic innovations would always have a high likelihood of diffusing and the aftermath would be a quite uniform distribution of the previously innovative feature. This is, however, contrary to scientific observation of linguistic variation, which is brought about by non-uniform acceptance of innovations across speech communities.

In fact, predicting when and where an innovation will be accepted—the actuation problem (Weinreich, Labov, & Herzog, 1968, p. 186)—is regarded as the most intractable problem in language change theory (J. Milroy, 1992, p. 164). An innovation usually goes undetected by researchers until it is well in the transition (Weinreich et al., 1968, p. 184) of becoming accepted as a normative variant, reaching a level of adoption among speakers that ensures that a behavior will be copied by the rest of the community’s population (Granovetter, 1978). Rogers (2003) suggests that this level, which he refers to as critical mass (pp. 343, 349-352), is reached when innovators and early adopters—16% of the population—have adopted the innovation. As previously mentioned, however, this does not always occur.

L. Milroy and Milroy (1992, pp. 347-348) explain three potential outcomes of a linguistic innovation. The most successful outcome is that the innovation diffuses both locally—from speaker to speaker within a single community—and globally—from a speaker in one community to a speaker in an ancillary community, who then is successful in spreading it within their own community and possibly to speakers in other communities. In fact, this outcome has infinite permutations within itself due to recursion. When this process reaches the level of recursion such that a speech community linguistically influences another on the other side of the globe, the result is called globalization (Meyerhoff & Niedzielski, 2003, p. 539).

An intermediate success occurs when the innovation diffuses locally and stays within the speech community in which it originated, while the ultimate failure occurs when the innovation fails to spread among the community of origin, stagnating and dying. The
existence of these possibilities is evidence that individuals are driven by more than their theoretical thresholds for adopting innovative behaviors. Granovetter (1978, p. 1429) suggests that there must be some effect of social structure upon spatial and temporal dispersion of behavior. The Threshold Model alone assumes complete connectedness—that all people within a social network have connections with every other person—and the actions of any one person directly affect the behavior of all other people. This is an unrealistic depiction of real-world social networks, which vary in terms of connectivity and how much influence a particular connection has on an individual.

1.3.3 Social Networks and Structure

The social network of any given individual is defined as the aggregate of that individual’s connections or relationships with other individuals (L. Milroy, 2002, p. 549). Social networks can be structurally defined in terms of density, multiplexity, and locality. Consider the small group of five individuals in Figure 1.3.

![Figure 1.3. Five individuals in a hypothetical network.](image)

With a finite number of individuals, there are a maximum number of possible bidirectional connections in any such social network. We will use the individuals in Figure 1.3 to illustrate how to determine the number of possible connections ($M$) in a network. The general equation, such that $n$ represents the number of individuals, is:

$$M = \frac{n \times (n - 1)}{2}$$
Using this general equation, we can determine that the number of possible connections in our hypothetical network is 10:

\[ M = \frac{5 \times (4)}{2} = 10 \]

Now let us assume that the five individuals are connected as represented in Figure 1.4.

![Figure 1.4](image)

**Figure 1.4. Potential configuration of a five-individual network.**

Although the number of possible connections in a five-individual network is 10, our hypothetical network in Figure 1.3 only has 4. We can use this information to calculate the network density. The general equation to calculate network density \( D \), such that \( c \) is the number of actual connections in the network, is:

\[ D = \frac{c}{M} \]

For the network in Figure 1.3, the network density is 0.4:

\[ D = \frac{4}{10} = 0.4 \]

The network density value will always be such that \( 0 \leq D \leq 1 \) since a network with no connections has a density of 0:

\[ D = \frac{0}{M} = 0 \]
Conversely, a network that has the maximum number of connections has a density of 1 since $c$ and $M$ are equivalent.

**Multiplexity** supports the notion that any set of two individuals might be tied together by different social role types, e.g., kin, neighbor, or co-worker (Verbrugge, 1979, p. 1286). Rather than focusing on the social role of each tie, Granovetter’s (1973, 1982) categorizes the ties between individuals by their *strength*, focusing on a simple *strong* or *weak* dichotomy (similar models include a third category—*absent*—to correspond to non-existent ties). The strength of ties approach does not necessarily compete with the social role approach, since Verbrugge (1979, p. 1286) shows that relationships of increasing multiplexity increases social contact, which correlates positively with strong tie relationships (Granovetter, 1982, p. 106). Conversely, uniplex ties correspond to weak ties.

Social network ties may also vary in terms of *locality*. In terms relative to the subject of this research, local ties are formed between two individuals that reside in the same speech community. Conversely, non-local ties are ties formed between two individuals residing in different speech communities. In this sense, there is a global network comprised of smaller, local networks. Inevitably, locality will also contribute to the amount of social contact individuals with their ties, affecting tie strength.

Until relatively recently, strong-tie relationships have been viewed as more important than weak-tie relationships in the diffusion of innovations. In fact, with regards to language change, Labov (1980, p. 261) describes his notion of a *speaker-innovator*—a speech community member who is a leader in spreading innovation—as a person with both local and global prestige. Labov (2001, p. 360) specifies that this prestige is classified by a large number of local and global intimate ties, which suggests that Labov’s notion of a speaker-innovator is someone who has both a large number of strong local ties and a large number of strong outside ties. A critique of this definition of the speaker-innovator is that these two types of prestige are difficult to simultaneously maintain as they are often in conflict (J. Milroy, 1992, p. 173). Secondly, borrowing from Granovetter (1973, 1982), it is argued that only weak ties—not strong ties—function as bridges for innovation across one local group to another (J. Milroy, 1992, p. 178). In fact, it is suggested that networks highly connected with strong ties, such as those found in the highest and lowest socioeconomic strata, contribute to innovation resistance (J. Milroy, 1992, p. 181).
This does not discount the role of strong tie multiplex relationships in the process of language change. Innovations may diffuse locally within a close-knit network of individuals via these strong ties, but, to spread beyond that local network, the presence of uniplex weak-tie relationships that extend beyond the local network is instrumental, especially when we consider the likelihood that individuals are able to maintain a larger number of weak tie low-investment relationships than higher investment strong tie relationships (J. Milroy, 1992, p. 179). Without these weak tie bridges to and from other networks, regional varieties would become much more pronounced as any language change would be strictly network internal.

Contrary to Labov’s (1980) definition of a speaker-innovator, Rogers and Shoemaker (1970; as cited in J. Milroy, 1992), suggest that a typical speaker-innovator is a marginal or peripheral member of a relatively close-tie network, serving as a bridge between networks. It is important to note that any individual of a network can feasibly produce an innovation, however, the description offered by Rogers and Shoemaker may describe the type of individual (which they define as the deviant underconformist) that allows an innovation to travel beyond its network of origin. J. Milroy (1992, p. 181) suggests that densely knit norm-conforming networks that might have a lack of such fringe members may still adopt an outside innovation if many network members are exposed to the innovation while it is in the early stages of change from the outside network.
CHAPTER 2

THE MODEL: OBJECTIVE AND OVERVIEW

As model-based inquiries shift away from traditional analytical models, which can be represented by a clear set of equations, towards the more structurally complex agent-based models (ABM) of simulation, Grimm et al. (2006) recognizes a need for a standard protocol to communicate the details necessary for ABM replication by peers. Grimm et al. (2006) formulated and later revised (Grimm et al., 2010) the ODD protocol, an acronym of its three components—overview, design concepts, and details, each of which are broken down into smaller sections, as outlined in Figure 2.1.

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<tr>
<th>Elements of the ODD Protocol</th>
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<td><strong>Overview</strong></td>
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<td>3. Process overview and scheduling</td>
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Figure 2.1. Outline of the ODD protocol for describing an ABM.
The overview component of the ODD protocol is meant to give a succinct idea of the simulation—its purpose, the state variables and scales used, and the scheduling of the general processes. The design concepts component does not describe the model itself but instead focuses on the underlying concepts on which it is based. Finally, the details component provides a specific and complete description of how the model works. This component fills in the details left out in the overview component. The ODD description of the simulation devised for this thesis is detailed in this chapter.

2.1 Purpose

In the real world, it is difficult to identify the exact origin of an innovation as it may only be identified once it has already become well established as a variant in the process of becoming a change. A benefit of computer simulation is that it enables us to evaluate hypotheses that might otherwise be difficult or impossible to test in the real world due to a scarcity of data (Railsback & Grimm, 2012, p. 4).

The purpose of this ABM is not so bold as to solve the rather intractable problem of actuation. The model, in its current state, does not address factors that result in innovation failure; because individuals base their adoption decisions purely on threshold levels suggested by the Collective Behavior Model (Granovetter, 1978), all individuals will eventually adopt a given innovation. The goal of this model is to examine the role of social space (e.g. the shortest path between an individual and the innovator) and structure (e.g. network density) on the relative order of innovation adoption at an individual and collective-wide level.

Using NetLogo, a programmable modeling environment developed by Wilensky (1999), we represent the world with randomly generated graphs of artificial collectives (speech communities) of individuals or agents (speakers), each of which are connected via preferential attachment through a social network, both locally—with speakers in their home collectives—and globally with speakers across all other collectives. We are limited by the representativeness of our model to the real world. Therefore, the results of our model may only reveal possibilities rather than solid explanation. However, these possibilities may be explored further in future research and may have some implications for extending the model to include factors that contribute to innovation failure.
2.2 Entities, State Variables, and Scales

The model’s world has four kinds of entities: square patches of land, speakers, links between speakers, and collectives.

2.2.1 Patches

The artificial world used for this simulation is an 81 x 81 grid; however, because the role of Euclidean space is not explored by the present model, position of collectives and their relative distances from one another are not reported nor analyzed. In addition to this, there is no specific time scale imposed as we are concerned with the order in which language diffusion occurs rather than the length of time it takes to manifest. Therefore, all times remain measured in ticks.

2.2.2 Speakers

Speakers have five state variables—strong-tie-count, weak-tie-count, innovation?, threshold, and shortest-path. As one might expect, strong-tie-count is simply the sum of strong ties a speaker has, while weak-tie-count is the sum of weak-ties a speaker has. The Boolean state variable innovation? represents whether or not a speaker has adopted the linguistic innovation (a True value indicates that the speaker has adopted the innovation while a False value indicates that the speaker has not adopted the innovation). A speaker’s threshold value, adapted from Granovetter’s (1978) Collective Behavior Model and Rogers’ (2003) adopter categories, reflects the speaker’s willingness to adopt an innovation. The threshold value is equivalent to the requisite proportion of the speaker’s collective that must adopt an innovation before the speaker will adopt it (recall that these values were previously displayed in Table 1.1). The variable shortest-path is the lowest number of ties found in a breadth-first search of the network between the selected speaker and the speaker-innovator.

2.2.3 Links

There are two breeds of links—weak-ties and strong-ties. Both breeds encode which two speakers are on either end of the link. Strong-ties are only formed locally between speakers who inhabit the same collective, reasoning that proximity and collectivity
contribute to frequency and duration of contact, which have been found to be positively correlated with tie strength (Marsden & Campbell, 1984). **Weak-ties** are formed globally.

### 2.2.4 Collectives

Collectives each have a **population** state variable determined stochastically during initialization (Section 2.5). The population values are used during the generation of speakers at each collective. Collectives also have a **network-density** state, a value computed as the proportion of actual ties present within the local network of speakers to the number of possible ties present within the local network of speakers. The number of possible ties is calculated as: \( N * \frac{(N-1)}{2} \), where \( N \) represents the number of nodes (speakers) in the network.

Collectives also encode the **average-shortest-path** between their speaker members and the speaker-innovator, the **maximum-number-of-strong-ties** found among its speakers, and the **maximum-number-of-weak-ties** found among its speakers.

### 2.3 Process Overview and Scheduling

The pseudocode in Figure 2.2 provides only a succinct overview and scheduling of the simulation (Kazemi, 2014) in order to serve as an outline of the more detailed description to follow in Sections 2.5 and 2.7.

```
INITIALIZE-WORLD
create collectives
for all collectives:
    set population
    create population speakers
for all speakers:
    create weak-ties
    set weak-tie-count = number of weak-ties
    create strong-ties
    set strong-tie-count = number of strong-ties

INNOVATE
choose one random speaker to set innovation? = True
for all speakers:
    calculate shortest-path to innovator
for all collectives:
    calculate average-shortest-path of speakers to innovator
for all speakers in world with innovation? = True:
    COMMUNICATE
        select all strong-tie speakers with innovation? = False
        select one weak-tie speaker with innovation? = False
        for all speakers selected:
            EVALUATE
                if percent collective’s adopters >= threshold:
                    ADOPT
                    set innovation? = True
```

Figure 2.2. Overview of the simulation scheduling.
2.4 Design Concepts

The following section describes the underlying concepts on which the model is based. It describes how certain theoretical concepts are operationalized and measured.

2.4.1 Basic Principles

This model relies on several basic principles spanning several fields of study. Many real-world phenomena have been found to have distributions that follow a power law distribution such that one quantity varies as a power of another (Durrett, 2007, p. 90). Jiang and Jia (2011) found that the population distribution of natural cities within the United States was predicted by Zipf’s Law, an inverse power law extensively studied by Zipf (1949). Similarly, inverse power law distributions have been consistently observed when measuring degree distributions among people in a social network (Durrett, 2007, p. 12).

In order to create random worlds that maintain realistic population distributions, we create each world as a scale-free random graph by utilizing the Barabási and Albert (1999) Model of Preferential Attachment. The stochastic process of preferential attachment yields a distribution that follows an inverse power law; therefore, we get a graph of nodes (our collectives) such that very few have a large number of connections and the majority has a very small number of connections. If we let the number of connections belonging to each collective be proportional to the number of individuals within that collective (its population), we achieve a population distribution that is comparable to real-world observations.

The same process of preferential attachment is followed to create weak-tie relationships between individuals across the global network. The presence of weak-tie relationships is fundamental since this model relies on Granovetter’s (1973, 1982) notion of the strength of weak ties, which asserts that weak ties rather than strong ties are fundamental in the exchange of information or innovation to and from one local network to another. No upper-limit on the number of weak-ties is supplied since they require significantly less investment than strong-tie relationships. However, the model accounts for the distribution of popularity or Labov’s (1980) prestige by creating weak-tie relationships via preferential attachment. In addition to this, Granovetter’s (1978) Model of Collective Behavior is applied to Rogers’ (2003) five adoption categories in order to determine individual adoption threshold levels.
2.4.2 Interaction
Speakers interact by communicating with other speakers with whom they have ties; however, speakers interact more often with their strong ties (at every tick) than with their weak ties (one random weak tie selected at every tick).

2.4.3 Sense
Speakers have access to their internal state values and are also aware of how many of their local collective have adopted the innovation.

2.4.4 Adaptive Behavior
Speakers adapt to their environment through external and internal evaluation. When exposed to an innovative linguistic feature, a speaker will evaluate whether or not it should be adopted based on a randomly assigned adoption threshold level. A given speaker will only adopt the innovation if the percentage of local collective speakers that have already adopted the innovation is equivalent or greater than the speaker’s internal adoption threshold.

2.4.5 Emergence
If the widespread adoption of a linguistic innovation occurs among a population, a new linguistic feature officially emerges as a product of linguistic change. Because of the stochastically-based and goal-oriented adoption decisions that the speakers make are nondeterministic, differential patterns of individual adoption and language change (i.e., majority collective adoption) should emerge.

2.4.6 Stochasticity
By the nature of NetLogo, all entities (sites, speakers, links, and patches) are generated in pseudorandom order. In addition to the native stochasticity of NetLogo, the population of each collective is assigned randomly from a distribution that follows an inverse power law, created through the process of preferential attachment. As individual speakers are generated to fulfill each collective’s population value, this same process is used produce global weak-ties between speakers. Strong-ties are generated randomly between local neighbors in each site, each speaker being limited to a random number of strong-ties drawn
from a Poisson distribution with a mean of two. Lastly, each speaker’s threshold level (refer back to Table 1.1 for values) is assigned randomly from a normal distribution.

2.4.7 Goal

The goal of the innovators is to facilitate change by either innovating or adopting innovations. All other individuals will want to preserve their current linguistic inventory unless their internal adoption thresholds are reached or surpassed by the percentage of the local population’s adoption of the innovation.

2.4.8 Prediction

Speakers do not use prediction in this model.

2.4.9 Observation

To facilitate the observation of the patterns of language change, which occur out of individual interactions, the simulation outputs data pertaining to two dependent variables—the tick during which each individual adopted the innovation and the tick during which the majority (>50% of the population) of a collective adopted the innovation. Speaker adoption time will be analyzed to find possible effects of speaker adoption categories (categorized by threshold level), the number of weak ties a speaker has (categorized into discrete ranges), the number of strong ties a speaker has (categorized into discrete ranges), and the shortest path from the speaker to innovator (categorized into discrete ranges). Collective majority adoption times will be similarly analyzed to find possible effects of network density, the maximum number of weak ties, the maximum number of strong ties, and the average shortest path from the collective’s speakers to the innovator. Output is generated over 300 total simulation runs—100 runs each of worlds with 30, 60, and 90 collectives.

2.5 Initialization

Figure 2.3 illustrates a possible world initialized by the simulation. The target symbols, sized based on population, represent collectives, with the dots surrounding each collective being the individuals that comprise each collective. Colors are randomly applied to collectives (which carry over to individuals) in order to facilitate visual differentiation. The
grey and white lines are ties linking one individual to another. Grey lines indicate weak ties while white lines indicate strong ties.

The simulation is initialized by generating a random graph of a user-provided number of collectives on an 81 x 81 grid. Collectives are created pseudorandomly (i.e., Collective 0 need not be the first collective created and need not be followed by Collective 1 during the creation process). To attain a realistic map of collectives with a population distribution that is consistent with an inverse power-law, the process of preferential attachment is employed such that, with the exception of the first collective generated, each new collective created is linked to a pre-existing collective, with a preference for collectives that have a larger number of pre-existing links. The degree of connections of each collective are then used to determine the **population** count of each collective, resulting in a high number of low-population collectives and very few high-population collectives. After each collective **population** value is determined, the links between all collectives are cleared as they are not used for any purpose beyond establishing population values.
The **population** values of each collective are then used to generate speakers at each collective and the speakers encode which collective they belong to. Each speaker starts out with their Boolean **innovation?** variable set to **false**. Each speaker is randomly assigned a **threshold-level** value (refer back to Table 1.1 for values) from a normal distribution. As speakers are generated, they form weak ties with other speakers through preferential attachment. This results in weak ties both within and across local networks. Strong ties between speakers are generated randomly within local networks, each speaker being limited a random number of strong ties drawn from a Poisson distribution with a mean of two. The **network-density** of each collective is then computed. Finally, one random speaker is chosen to create a linguistic innovation, and that speaker’s **innovation?** value is set to **true**.

### 2.6 Input Data

The number of collectives generated during initialization may be controlled before a single run by the slider labeled **num-sites** in Figure 2.4.

![Figure 2.4. Varying parameters over multiple iterations using NetLogo’s BehaviorSpace.](image)
The range of collectives generated is 10-100. Alternatively, the BehaviorSpace component of NetLogo may be used in order to run several simulations with varied parameters. Figure 2.4 shows that we want to vary \texttt{NUM\textunderscore SITES} over the values 30, 60, and 90 and that we want to run 100 simulations over each of these values, producing a total of 300 runs.

\textbf{2.7 SUBMODELS}

This section describes exactly what happens at each stage of the simulation in order to promote reproducibility.

\textbf{2.7.1 Communication}

On every tick, all individuals that have adopted the innovation are allowed to communicate with all of their local strong ties who have yet to adopt the innovation and one randomly selected weak-tie who has yet to adopt the innovation. This is modeled by creating a list of these individuals, which are then subjected to the evaluation phase.

\textbf{2.7.2 Evaluation}

All individuals selected in the communication phase must evaluate whether or not they should adopt the innovation. The 2.5\% of each collective population that are innovators will adopt any innovation encountered, while the remaining individuals will evaluate whether or not their adoption thresholds have been reached or surpassed by comparing the value to the percentage of local individuals who have already adopted the innovation. If this condition is satisfied, the innovation is adopted.

\textbf{2.7.3 Adoption}

If the result of the speaker’s evaluation process is to adopt the innovation, that speaker’s \texttt{INNOVATION?} value is set to \texttt{True}. 
CHAPTER 3

RESULTS

3.1 ANALYSIS OF SPEAKER VARIABLES

A frequency analysis of the number of speakers ($N = 441,886$) as a function of the time the innovation was adopted (ranging over 1-33 ticks) yielded a unimodal curve ($M = 17.08$ ticks, $SD = 4.63$), slightly skewed to the right with a skewedness of .02 ($SE < .01$). These results, shown in Figure 3.1, form an approximately normal frequency distribution, consistent with Rogers’ (2003) normally distributed adoption categories, confirming that these categories were adequately modeled by the simulation.

Figure 3.1. Frequency distribution of speakers as a function of time adopted.
Viewing this frequency data in terms of the cumulative percentage of speakers adopting an innovation over time (Figure 3.2), an S-curve of diffusion indicative of diffusion by social learning emerges.

![Cumulative percentage of speakers as a function of time adopted.](image)

**Figure 3.2.** Cumulative percentage of speakers as a function of time adopted.

A univariate four-way analysis of variance (ANOVA) was performed to determine the effect of the following speaker variables on adoption time: number of weak ties, number of strong ties, adoption category, and shortest path length to the innovator. The ANOVA revealed main effects of the number of weak ties, $F(2, 441,886) = 4.78, p = .03$; adoption category $F(4, 441,886) = 192.69, p < .001$; and shortest path $F(8, 441886) = 45.91, p < .001$. However, there was no significant effect of the number of strong ties, $F(4, 441,886) = 1.76, ns$. Interactions were also found between the number of weak ties and shortest path, $F(2, 441,886) = 6.73, p = .001$; shortest path and adoption category, $F(8, 441,886) = 7.51, p < .001$; and adoption category and number of weak ties, $F(4, 441,886) = 40.46, p < .001$. 
3.1.1 Weak Ties and Shortest Path to Innovator

We first explore the interaction found between the number of weak ties a speaker has and the length of their shortest path to the innovator, illustrated in Figure 3.3.

Figure 3.3. Interaction between number of ties and shortest path to innovator on adoption time.

Further between-subjects analysis revealed that speakers with first and second degree ties with the innovator tended to adopt the innovation significantly sooner if they had 21 or more weak ties ($M = 11.58$ ticks, $SD = 6.47$) in comparison to 1-20 weak ties ($M = 13.90$ ticks, $SD = 6.77$), $t(5,233) = 4.66, p < .001$. Similarly, speakers with third and fourth degree ties to the innovator adopted the innovation significantly sooner if they had 21 or more weak ties ($M = 13.6$ ticks, $SD = 5.2$) rather than 1-20 weak ties ($M = 16.38$ ticks, $SD = 4.77$), $t(155,316) = 23.47, p < .001$. However, among speakers with fifth or higher degree ties with the innovator, the time of innovation adoption was not significantly different between
speakers with 21 or more weak ties ($M = 17.11$ ticks, $SD = 5.06$) and speakers with 1-20 weak ties ($M = 17.56$ ticks, $SD = 4.45$), $t(281,331) = 1.52$, $ns$.

3.1.2 Adoption Categories and Shortest Path to Innovator

Next we explore the interaction found between a speaker’s adoption category and the length of their shortest path to the innovator, illustrated in Figure 3.4. When discussing the innovator category of speakers, this differs what we refer to as the innovator, which is the speaker (of any adoption category) who is responsible for creating a novel linguistic feature. The innovator class of speakers refers to the speakers with an adoption threshold of 0%.

Among the innovator class of speakers, speakers with lower degree ties (shorter paths) with the innovator, tended to adopt the innovation sooner. Speakers with first and
second degree ties ($M = 8.05$ ticks, $SD = 7.03$) tended to adopt sooner than speakers with third and fourth degree ties ($M = 14.68$ ticks, $SD = 5.14$), $t(4,722) = -17.04, p < .001$ and speakers with fifth or higher degree ties ($M = 16.61$, $SD = 4.56$), $t(10,488) = -25.19, p < .001$. Speakers with third and fourth degree ties also adopted significantly sooner than fifth and higher degree ties, $t(14,836) = -22.80, p < .001$. This trend continues to be statistically significant throughout all adoption categories, though the differences become much less pronounced within the late majority and laggard categories.

Among early adopters, speakers with first and second degree ties ($M = 10.01$ ticks, $SD = 7.26$) tended to adopt sooner than speakers with third and fourth degree ties ($M = 14.75$ ticks, $SD = 5.05$), $t(21,828) = -24.67, p < .001$ and speakers with fifth or higher degree ties ($M = 16.37$, $SD = 4.53$), $t(37,890) = -37.34, p < .001$. Speakers with third and fourth degree ties also adopted significantly sooner than fifth and higher degree ties, $t(58,232) = -39.90, p < .001$.

Continuing the trend among the early majority, speakers with lower degree ties (shorter paths) with the innovator, tended to adopt the innovation sooner. Speakers with first and second degree ties ($M = 12.29$ ticks, $SD = 6.76$) tended to adopt sooner than speakers with third and fourth degree ties ($M = 15.34$ ticks, $SD = 4.74$), $t(58,722) = -27.42, p < .001$ and speakers with fifth or higher degree ties ($M = 16.71$, $SD = 4.43$), $t(104,345) = -43.01, p < .001$. Speakers with third and fourth degree ties also adopted significantly sooner than fifth and higher degree ties, $t(159,191) = -57.65, p < .001$.

As aforementioned, the trend of lower degree ties adopting significantly sooner continues among late majority, but the differences in adoption times are markedly reduced. Speakers with first and second degree ties ($M = 16.22$ ticks, $SD = 5.18$) tended to adopt sooner than speakers with third and fourth degree ties ($M = 17.34$ ticks, $SD = 4.27$), $t(59,904) = -11.14, p < .001$ and speakers with fifth or higher degree ties ($M = 18.33$, $SD = 4.13$), $t(106,682) = -21.90, p < .001$. Speakers with third and fourth degree ties also adopted significantly sooner than fifth and higher degree ties, $t(162,798) = -45.55, p < .001$.

The trend continues to a weaker extent among laggards, but fails to be statistically significant in some cases. Speakers with first and second degree ties ($M = 18.78$ ticks, $SD = 4.14$) did not adopt the innovation significantly sooner than speakers with third and fourth degree ties ($M = 19.11$ ticks, $SD = 4.22$), $t(15,367) = -1.69, ns$, but they did adopt
significantly sooner than speakers with fifth or higher degree ties ($M = 19.88$, $SD = 4.12$), $t(27,153) = -5.76$, $p < .001$. Speakers with third and fourth degree ties also adopted significantly sooner than fifth and higher degree ties, $t(41,584) = -18.18$, $p < .001$.

### 3.1.3 Adoption Categories and Number of Weak Ties

Finally, we explore the interaction found between a speaker’s adoption category and the number of weak ties a speaker has, illustrated in Figure 3.5.

![Figure 3.5](image)

**Figure 3.5.** Interaction between adoption category and number of weak ties on adoption time.

The innovator class of speakers tended to adopt the innovation significantly sooner if they had 21 or more weak ties ($M = 8.85$ ticks, $SD = 4.90$) rather than 1-20 weak ties ($M = 16.05$ ticks, $SD = 4.85$), $t(15,024) = 24.35$, $p < .001$. Similarly, early adopters adopted the innovation significantly sooner if they had 21 or more weak ties ($M = 10.53$ ticks, $SD = 4.21$) rather than 1-20 weak ties ($M = 15.76$ ticks, $SD = 4.85$), $t(58,976) = 25.46$, $p < .001$. 

The innovator class of speakers tended to adopt the innovation significantly sooner if they had 21 or more weak ties ($M = 8.85$ ticks, $SD = 4.90$) rather than 1-20 weak ties ($M = 16.05$ ticks, $SD = 4.85$), $t(15,024) = 24.35$, $p < .001$. Similarly, early adopters adopted the innovation significantly sooner if they had 21 or more weak ties ($M = 10.53$ ticks, $SD = 4.21$) rather than 1-20 weak ties ($M = 15.76$ ticks, $SD = 4.85$), $t(58,976) = 25.46$, $p < .001$. 

...
This phenomenon continued within the early majority, with adoption times of speakers with 21 or more weak ties ($M = 14.87$ ticks, $SD = 3.91$) being significantly sooner than the adoption times of speakers with 1-20 weak ties ($M = 16.18$ ticks, $SD = 4.64$), $t(161,130) = 7.53, p < .001$. However, within the late majority, speakers with 21 or more weak ties ($M = 18.73$ ticks, $SD = 3.91$) adopted the innovation significantly later than speakers with 1-20 weak ties ($M = 17.96$ ticks, $SD = 4.22$), $t(164,693) = -3.59, p < .001$. This reversal continued among laggards—speakers with 21 or more weak ties ($M = 20.67$ ticks, $SD = 3.87$) adopted significantly later than speakers with 1-20 weak ties ($M = 19.59$ ticks, $SD = 4.17$), $t(42,053) = -2.04, p = .04$.

### 3.2 Analysis of Collective Variables

A univariate four-way ANOVA was performed to determine the effect of the following collective variables on the time the majority of a collective adopts the innovation: network density, the maximum number of strong ties, the maximum number of weak ties, and the average shortest path length to the innovator. This yielded no significant effects of network density, $F(285, 2) = .42, ns$; the maximum number of strong ties, $F(285, 1) p < .01, ns$; the maximum number of weak ties, $F(285, 1) = .01, ns$, and the average shortest path, $F(285, 1) = 2.04, ns$. However, there was significant interaction between the average shortest path and network density was revealed, $F(285, 2) = 3.24, p = .04$ (Figure 3.6).

Further between-subjects analysis revealed that collectives with a network density of less than .05 tended to reach majority adoption significantly sooner if the average shortest path to the innovator had a 4-5 tie length ($M = 14.85, SD = 2.31$) rather than an average shortest path that was greater than five ties ($M = 18.56, SD = 4.01$), $t(117) = -3.26, p = .001$. However, in denser networks, this phenomenon is not present. Collectives with a network density between .05 and .08 did not reach majority significantly sooner if the average shortest path to the innovator had a 4-5 tie length ($M = 16.04, SD = 3.12$) rather than an average shortest path length of greater than five ($M = 17.00, SD = 4.55$), $t(117) = -.98, ns$. Similarly, collectives with a network density of greater than .08 did not reach majority significantly sooner if the average shortest path to the innovator had a 4-5 tie length ($M = 15.70, SD = 3.72$) when compared to an average path length of greater than five ($M = 14.25, SD = .96$), $t(45) = .78, ns$. 

$p < .001$.
Figure 3.6. Interaction between network density and average shortest path on time majority of collective adopts.
CHAPTER 4

DISCUSSION

4.1 IMPLICATIONS OF RESULTS

Granovetter’s (1973, 1982) notion that weak ties bear a significant role in the spread of innovation was supported by the data insofar that, on an individual basis, speakers with more weak ties tended to adopt an innovation significantly sooner than their counterparts with less weak ties. However, this result only emerged among speakers that were a first through fourth degree tie with the source of the innovation. Weak tie count did not matter when speakers had fifth or higher degree ties with the source. Furthermore, weak tie count seemed only to matter among more innovative members of the collective. According to Rogers (2003), innovators and early adopters comprise the first 16% of people who will adopt an innovation. According to the data, it was among these initial 16% that a larger weak tie count significantly decreased the time it takes to adopt an innovation. However, among the remaining 84% that comprise Rogers’ latter three adoption categories, a larger weak tie count did not significantly alter the time of adoption.

J. Milroy’s (1992) proposal that lower density networks are more susceptible to change was not clearly supported by the results; there was no effect of network density on collectives reaching majority levels of adoption. However, the results did indicate network density did contribute to a significant interaction. It was only in the lowest density networks—those with a density of less than .05—that collectives with shorter average path lengths reached majority adoption levels significantly faster. Higher density networks did not reach majority significantly faster if they had shorter average path lengths.

4.2 WEAKNESSES TO ADDRESS

The model suffers from an obvious simplification—the way in which it operationalizes strong and weak ties. First, strong ties are equated to ties that allow speakers to communicate much more often than weak ties. However, frequency of contact is just one possible predictor of the strength of a tie; Marsden and Campbell (1984) have found other significant predictors of ties strength such as contact duration. Second, strong and weak ties
are represented as permanent discrete states when they are in actuality continuous and dynamic. A more realistic model would allow ties to emerge and dissipate dynamically through the scoring of individual interactions (e.g. contact frequency and duration of contact).

Another major weakness of this simulation is that it relies on a hardcoded normal distribution of threshold levels associated with Rogers’ adoption categories. It is not unimaginable that such levels may be distributed differentially, depending on individual and group dynamics. In addition to this, other social learning strategies should be investigated and modeled. Hoppitt and Laland (2013) provide a categorization of possible social learning strategies that could bias individuals towards adoption or rejection of certain innovations (adapted into Figure 4.1).

Figure 4.1. A categorization of social learning strategies.
The present model is only representative of one of many potential social learning strategies, a context dependent and frequency dependent strategy Hoppitt and Laland (2013, p. 201) refer to as a strategy based on the number of demonstrators. As extant literature suggests, this is not the only social learning strategy that biases the adoption of innovative linguistic features. For example, Eckert (2000, 2002) has investigated the extent to which the preservation of social identity—based on gender and social category (jock or burnout)—of Detroit adolescents contributes to linguistic variation. If two social categories are in conflict, it suffices to say that an innovative feature produced by one type (e.g. a jock) would produce a bias in the other type (a burnout) to reject that innovation, regardless of threshold level and the number of overall demonstrators (i.e., the people in the population who have adopted the innovation). In order to account for this, an improved extension of the present model must consider the source collective of the innovation as well as which collectives have already reached majority adoption. An innovation may spread quickly within a network only insofar as the innovation had been internally generated. As noted by J. Milroy (1992), it is likely that, a network resistant to external change will only adopt an external innovation if it is sufficiently exposed to the innovation before the innovation has saturated the source network. Once the innovation is actively associated with an external network, the individuals of a highly resistant network are unlikely to adopt it to preserve social identity and to maintain distinction from opposing social categories.
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