Investigating the effects of prestige on the diffusion of linguistic variants

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Abstract

Language, arguably the cognitive capacity that distinguishes humans, is a dynamic complex adaptive system whose structure and evolution is influenced by a host of factors. This paper takes a population dynamics approach to investigate the diffusion of linguistic variants in populations, focusing on the effect of differential prestige of linguistic variants and of speakers. A novel method that combines computer simulation with mathematical modeling is applied to the specific aim of identifying factors that formally constitute selective pressures on variant diffusion. Of the factors studied, only the intrinsic prestige of variants is found to pose selective pressure, while speakers' prestige merely modulates variant spread.

Keywords: Language evolution, Price equation, Pólya urns, population dynamics.

Introduction

Language, arguably the cognitive capacity that defines humans, is a dynamic complex adaptive system (Beckner et al. 2009) whose structure and evolution is influenced by a host of factors. We apply the principles of population genetics (Fisher, 1930; Wright, 1984) to language, and focus on one aspect of language evolution, i.e., the changes in the proportions of linguistic variants in a linguistic community. Such changes are usually achieved via diffusion of various (phonetic, lexical, syntactic, etc.) variants. At the population level, linguistic diffusion (henceforth simply “diffusion”) can be viewed as the shift in the proportions of linguistic variants used by a population over time (Nakamura et al., 2007). Some well-documented examples of diffusion include the Great Vowel Shift in English occurring from the 14th to 16th century (e.g., Wolfe, 1972), other sound changes in modern languages (e.g. Shen, 1997; Labov, 2001), and lexical borrowing among languages (e.g., Bloomfield, 1933; Cheng, 1987).

Examining the mechanisms for diffusion can shed light on questions concerning the cognitive capacities for language and the effects of linguistic or socio-cultural constraints on language evolution (Wolfe, 1972; Pinker & Bloom, 1990; Croft, 2000; Hauser et al., 2002; Tomasello, 2008). Empirical studies from historical linguistics and sociolinguistics have revealed that linguistic, individual learning and socio-cultural factors could all affect diffusion (e.g., Labov, 1994, 2001; Shore, 1995; Fisiak, 1995; Croft, 2000), and recently, mathematical analysis and computer simulation have been used to quantitatively analyze the effects of these factors on diffusion. By quantifying the contact patterns and constraints within or across populations, mathematical analysis helps to predict the influence of these factors (e.g., Nowak et al., 2002; Abram & Strogatz, 2003; Wang et al., 2004; Dall’asta et al., 2006; Kalampokis et al., 2007; Minett & Wang, 2008); by simulating individual behaviors during linguistic interactions, computer modeling helps to trace how interactions among individuals spur the origin of a common set of form-meaning mappings (e.g., Steels, 1995; Ke et al., 2002), how processing constraints lead to linguistic regularities (e.g., Kirby, 2002; Gong et al., 2009), and how social connections affect diffusion within and across communities (e.g., Nettle, 1999; Ke et al., 2008).

Diffusion can be driven by chance factors; then the process is called drift and follows the neutral model of evolution (Kimura, 1968). It can also be driven by selection, in which case, a feature of the linguistic variants (e.g. ease of pronunciation, cognitive salience, social prestige) increases its fitness, i.e., makes it more likely to be used and learned, and therefore diffused among speakers, than alternative variants.

The present study focuses on three factors, namely variant prestige, model bias and transmission error, and seeks to establish whether each of them poses selective pressure on the evolution of linguistic variants. How these factors relate to linguistic behavior is illustrated next: First, linguistic variants possess feature values which may affect the probability with which the variants carrying them are adopted and used, in other words, they affect the variant’s prestige. A physical feature, such as the ease in perception, for instance, could confer high prestige to a certain variant (Labov, 1994), meaning that it will be more likely to be produced than other variants. Cheng (1987) describes lexical variants borrowed from other languages as having high prestige when they are more salient to hearers than the existing variants for the same meaning. Second, in human society, ordinary people preferentially copy from individuals (models) of higher social, political, or economic status (Labov, 1963; Johnstone, 2010); this is called
implementing this – when hearing a token used by the high-status individuals, hearers add more tokens of that type to their urns than if the token is produced by a low-status individual. Transmission error, or mutation, occurs when a token is returned with some token(s) of different type(s). The probability of mutation is a parameter in the model.

The Price Equation

The aim of the present study is to examine whether a number of factors constitute selection pressures on variant diffusion. A variant may come to dominate in a population for several reasons: it may have intrinsic properties that make it adaptive in its environment and it may therefore be selected for. Alternatively, the random dynamics of evolutionary drift may increase the frequency of the variant. The virtue of the Price equation (Eq. 1), a tool from evolutionary biology, is precisely that it splits change into two components: selection and transmission, allowing us to identify which one is causing evolutionary change.

\[ \Delta x = \text{Cov}(s_i / s, x_i) + E(\Delta x_i \times s_i / s) \]  

Here, \( x_i \) is the feature value of \( v_i \), \( s_i \) is the fitness of \( v_i \), \( s \) is the average fitness, \( \Delta x_i \) is the feature discrepancy of \( v_i \) between time steps, and \( \Delta x \) is the expectation of feature value change.

We apply the equation to trace change in the average value of a quantifiable feature in a population between two consecutive time steps in the computer model and calculate the two terms: 1) The covariance between the feature value \( x_i \) and the fitness ratio \( s_i / s \) measures selection, or evolution caused by fitness differences between different types of variants. Consistent non-zero covariance values over the course of a computer simulation indicates that feature \( x_i \) is under selective pressure. 2) The expectation of the product of the fitness ratio \( s_i / s \) and the feature discrepancy \( \Delta x_i \) measures evolution occurring at transmission, in other words differences between parents and offspring variants. Consistent non-zero expectation values indicate that feature \( x_i \) is undergoing transmission error such as mutation.

By quantifying a feature relevant for diffusion and analyzing the average values of the components in the Price equation over many simulation runs, we can identify the selective pressures on this feature.

Identifying Selective Pressures on Linguistic Diffusion

For the sake of simplicity, our models contain only two variants, each characterized by a quantifiable feature \( F = \{1, 2\} \). Example quantifiable features include vowel length, consonant voicing onset time or lexical item recall rate. A simulation has a 100-agent population and 2000 interactions among them (20 interactions per agent on average). We conducted 1,000 simulations in each of four conditions:

- Variant prestige with and without transmission error
- Model bias with and without variant prestige

The result of each simulation consists of a record of the proportions of variants of each type in each urn at each
timestep. On this data, we calculate the Covariance and the Expectation terms of the Price equation at 20 sampling points evenly distributed along 2000 interactions. To complement the Price equation, which traces changes, rather than proportions, of variant types, we also calculate Prop (see Equation 2) as the proportion of the majority variant type at each sampling point.

$$\text{Prop}(t) = \max_i (\text{proportion}(v_i, t))$$ (2)

By illustrating whether one type of variants gradually diffuses to the population, the average Prop of the 100 simulations helps to evaluate the conclusions drawn from the Price equation.

**Variant Prestige with and without Transmission Error**

Variant prestige encompasses intrinsic properties of the variant – and not of the individuals carrying the variant – that makes them more likely to be adopted by individuals. Henrich and Gil-White (2001)’s study of prestige in cultural transmission do not find an effect of variant prestige on diffusion, although admittedly their focus was on model bias, and variant prestige was implicitly subsumed within that focus. In our simulations, each interaction occurs between two randomly chosen agents. Differential variant prestige is introduced via \( p_i \). For conditions with variant prestige, \( P = \{1, 2\} \); for those without, \( P = \{1, 1\} \). If \( p = 2 \), two tokens of the same type (instead of one) are added to the listener’s urn, modeling the enhanced adoption of the high-prestige variant. Transmission error is introduced via mutation; \( c = 0.02 \) is the probability that an added token becomes a mutant (of the other type). Figure 1 shows the simulation results in these conditions.

![Covariance and Expectation graphs](image)

Figures 1(a) and 1(b) respectively show the covariance without transmission error and the expectation with transmission error. For covariance, with variant prestige, it becomes consistently positive; otherwise, it fluctuates around 0.0 (the proportions of the values above, below, and equal 0.0 are shown in the legend of Figure 1(a)). The gradual decrease in the absolute value of covariance is due to the increase in the total number of variants, which reduces the effect of a small number of changed variants in each interaction. The positivity of covariance clearly indicates that variant prestige is a selective pressure on diffusion. For expectation, with variant prestige, it becomes consistently negative; otherwise, it fluctuates around 0.0. This result suggests that transmission error can reduce the selective pressure of variant prestige. However, due to the low mutation rate, this effect is smaller than that of variant prestige.

Figure 1(c) shows the Prop in these conditions. With variant prestige, \( v_2 \), with the higher prestige value, becomes the majority type and its Prop gradually reaches a high level (above 0.8); without variant prestige, either type can become the majority type, but the small bias towards either type (due to random factors in early interactions) cannot be further amplified in later interactions, so Prop remains around 0.5. This result confirms the selective pressure of variant prestige, consistent with the conclusion drawn from the Price equation. Figure 1(c) also shows the Prop in the conditions with transmission error (the dotted lines). With variant prestige, the Prop with transmission error is lower than that without, showing that transmission error reduces the selective pressure of variant prestige; without variant prestige, the Prop with and without transmission error are similarly low, around 0.5, showing that transmission error alone has no significant effect on diffusion. This result also confirms the conclusion drawn from the Price equation.

The mathematical analyses based on the Price equation applied to the simulation results using the diffusion model formally show that variant prestige is indeed a selective pressure on diffusion and transmission error can reduce such pressure, but transmission error alone fails to consistently drive the diffusion.

The consistent positivity (or negativity) of the covariance based on variant feature identifies selective pressures on diffusion. In the following sections, therefore, we focus on covariance, and leave aside conditions without transmission.

**Model Bias with and without Variant Prestige**

Model bias reflects the phenomenon that members in a community tend to copy the variants, regardless of the actual forms, from certain individuals. It has been claimed that such bias could enhance the benefits of cultural transmission (Henrich & Gil-White, 2001). We analyze two types of model bias.

The first type involves a single high-status agent. Here, a single agent has a bias value of 2, and the other 99 agents’ bias value is 1. Variant prestige and model bias take effect jointly during interactions. Without variant prestige, when the high-status agent speaks, the heater adds 2 tokens of the

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1 Prop never reaches 100%, because the tokens of the other type are not removed.
produced type; when another agent speaks, the hearer adds 1 token of the produced type. With variant prestige, when the high-status agent produces a token of the prestigious type, the hearer adds 4 tokens of that type; when it produces a token of the other type, the hearer adds 2 tokens of that type; and when another agent speaks, the update is the same as in the condition with only variant prestige.

Figure 2 shows the results under this type of model bias. Without variant prestige, the Covariance fluctuates around 0.0; otherwise, it is consistently positive (see Figure 2(a)). These results show that the first type of model bias alone fails to exert a selective pressure; it has to take effect together with variant prestige. This conclusion can be confirmed by the Prop in Figure 2(b): without variant prestige, the Prop remains slightly higher than 0.5; otherwise, it approaches 1.0.

The second type of model bias concerns multiple individuals. The bias towards an individual is defined as the probability for this individual to participate in interactions, and all probabilities follow a normalized, power-law distribution (Newman, 2005). This implementation is inspired on empirical data (Newman, 2003), and has been adopted in previous work (e.g., Gong et al., 2008). In this paper, we only consider the power-law distributions whose \( \lambda \) values are 0.0, 1.0, 1.5, 2.0, 2.5, and 3.0.

Figure 3 shows the results under the second type of model bias. Similar to the first type, the second type of model bias alone fails to exert a selective pressure; it has to take effect together with variant prestige. This conclusion is shown by comparing the Covariance in Figures 3(a) and 3(b), and confirmed by the Prop in Figures 3(c) and 3(d). In addition, the Prop in the conditions with variant prestige seems correlated with the \( \lambda \) values (see Figure 3(d)). To illustrate such correlation, we define MaxRange (see Equation 3) as the maximum changing range of Prop:

\[
\text{MaxRange} = \max_{\lambda \in [0.0,3.0]} (\text{Prop}(x) - \text{Prop}(0)) 
\]

Figure 3(e) compares the MaxRange in the conditions with and without variant prestige. With variant prestige, the MaxRange increases along with the \( \lambda \). With the increase in \( \lambda \), some agents are more biased, and they can take part in more interactions than others. Due to variant prestige, the variant bias towards the prestigious variants in these biased agents will increase, quickly spread to others, and get further amplified after many interactions. However, without variant prestige, the variant bias in the biased agents remains small and cannot be amplified enough to increase substantially the proportion of one variant type. Therefore, the correlation between the MaxRange and the \( \lambda \) becomes less explicit.

The power-law distributed model bias reflects the omnipresent scaling law in social and cognitive domains (Kello et al., 2010). Our simulations show that in order for such a scaling characteristic to significantly affect diffusion, variant prestige is necessary. In addition, the correlation between the degree of diffusion and \( \lambda \) values in our study is different from that shown in other studies. For example, Gong et al. (2008) observe a threshold \( \lambda \) value (around 1.0), below or above which the spread of linguistic knowledge is less efficient – but our diffusion model differs from that of Gong et al. (2008) in that they explicitly modeled lexical and syntactic information. This different performance indicates that different types of linguistic knowledge may follow different diffusion trajectories in the population.

**Discussions, Conclusions and Future work**

Our study demonstrates that, of the factors studied, only variant prestige explicitly driving the spread of variants with higher prestige values in the population, whereas other individual learning or socio-cultural factors, such as transmission error or model bias, can take effect only if
variant prestige is involved. As shown in our study, transmission error simply introduces noise in the effect of variant prestige, and model bias does not pose a selection pressure. However, if variant prestige is also present, the strength of selection for the high-prestige variant can be modulated by the distribution of individual status in the population.

Our findings indicate that external, domain-general factors, such as individual status, must take effect via intrinsic, domain-specific factors, such as variant prestige. In linguistics, this finding also alerts us not to exaggerate the effect of language-external factors and inspires us to re-evaluate conclusions in previous studies (e.g., Henrich & Gil-White, 2001). Meanwhile, the Pólya urn dynamics is a general transmission framework not specific to linguistic communication, and the simulation results are less dependent on population size, variant number, or interaction number. Additionally, the Price equation provides a concise description of evolutionary processes that abstracts away from the specific properties of biological evolution (Jäger, 2008; Gardner, 2008). These aspects make this finding also instructive to other phenomena that involve socio-cultural transmission.

Computer simulation and mathematical analysis jointly establish a theoretical platform for linguistic research (Loreto & Steels, 2007). Our work exemplifies how these two approaches assist each other to explore the target question. The conclusions drawn from the Price equation are difficult to prove purely mathematically, but they are nicely assessed by the proportions of the majority variant type in the simulations. The simulations can further examine the complementary roles of individual learning and socio-cultural factors in diffusion. When variants have differential variant prestige, transmission error delays the diffusion process and helps to preserve the tokens of less prestigious type; model bias accelerates the diffusion by spreading and amplifying the bias towards prestigious variants, and there is a correlation between the degree of diffusion and that of model bias.

Finally, some aspects of this study can be modified in order to explore further questions on the diffusion of linguistic and other cultural variants. Among possible manipulations we find: changing the structure of the social network, the population structure over time – for instance adding generation turnover involving death of agents and birth of new agents or implementing frequency-dependent prestige. These modifications and others are easily feasible within the combination of computer simulation based on the Pólya urn model and mathematical analysis using the Price equation presented here.

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