Language Evolution and Social Networks

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Key Points

- Languages adapt to features of social network structure, such as population size, network connectivity and heterogeneity.
- Network structure influences linguistic variability, convergence and rate of change of languages.
- The structure, systematicity and transparency of linguistic systems is also impacted by social network properties.
- Observational, experimental and computational approaches offer important insights into the relationship of language evolution and social networks.

Abstract

Languages are complex adaptive systems that culturally evolve under different pressures and conditions. Social structure, and in particular population size, network connectivity, and heterogeneity, play an important role in shaping human language across multiple levels of analysis. These factors impact evolutionary and communicative dynamics such as the degree of variability versus uniformity in the linguistic community, and the rate at which innovations spread and languages change. They also influence the very structure of languages by shaping the degree of systematicity and transparency of grammars. Synthesizing observational, experimental, and computational approaches, we shed light on the complex relationship between language evolution and network structure.

Introduction

Languages are constantly changing. But why do languages change in the way that they do? Why do different languages end up having different sounds, different vocabularies, and different grammars? According to our current understanding, this is the result of languages evolving under different conditions—spanning from differences in individual usage patterns, to ecological niches, to social structures, to historical events. These cultural and environmental differences eventually lead to the formation (and ongoing change) of various kinds of phonological systems, lexicons, and grammatical structures. The underlying principle here is that languages are complex adaptive systems (Beckner et al., 2009), and as such are continuously shaped by social, cognitive, and environmental factors.

One thing that impacts the evolution of language is social structure—the fact that languages are used in diverse cultures and evolve within communities that vary in their social composition and communicative needs. This includes the size and structure of the community, specific patterns of interaction, the frequency and intensity of communication, the spatial distribution of speakers, the degree of heterogeneity in the population, the amount of contact with outsiders, and social dynamics such as the degree of common ground and familiarity between individuals, and their potential hierarchical relations. Indeed, observational studies, experimental research, and computational models all suggest that the structure and transmission patterns of languages are directly shaped by these social properties.

Traditionally, scholars distinguish between esoteric and exoteric communities (Meir et al., 2013; Lupyan & Dale, 2010; Wray & Grace, 2007): Esoteric communities are typically small, isolated, and tightly-knit communities with minimal contact with outsiders, while exoteric communities are larger and more socially and spatially diffused, with greater interaction with strangers and a higher presence of non-native speakers. Notably, research suggests that languages spoken in esoteric and exoteric communities have different features (Lupyan & Dale, 2010; Wray & Grace, 2007). For example, as members of esoteric communities are typically highly familiar with each other and share much common ground, this may lead to more alignment and uniformity in such communities, but also to higher chances of developing rich and non-transparent grammatical structures that rely heavily on context. On the other hand, members of exoteric communities are more likely to interact with outsiders and typically include more adult second-language learners that notoriously struggle with learning complex and opaque languages (DeKeyser, 2013), and as a result exoteric communities may be more likely to develop more transparent and systematic morphological rules.

Here, we focus on the three features of social network structure that classically differentiate esoteric and exoteric communities: population size, network connectivity, and heterogeneity (often reflecting the degree of contact with outsiders and, as a proxy, the proportion of non-native speakers in the community). Importantly, these three social features are often intertwined and confounded in real-world communities (e.g., small communities tend to be more densely connected, while larger communities tend to be more sparsely connected), which makes it difficult to determine their individual effects on language evolution and change. As such, research on this topic often focuses on disentangling which aspects of language use, structure, and transmission are influenced by which social factors, and in which way. Understanding the independent contribution of each factor is essential for explaining how languages adapt to social environments.

When looking at the influence of population size, network connectivity, and heterogeneity on linguistic systems, research has mainly revolved around two key areas:

1. **Variability, convergence, and rate of change**: How fast do innovations spread through the community until they become the new linguistic norm? How much variability exists between speakers of the same language, and to what degree do language users converge on the same, uniform system?
2. **Structure, systematicity, and transparency**: To what degree are languages' phonology, vocabulary, and morpho-syntactic structure affected by the social environment? Are different social structures associated with different degrees of complexity, regularity, and iconicity of linguistic systems?

In the past few decades, these two themes have been extensively investigated from three main perspectives: observational, experimental, and computational. Observational research mainly includes broad-scale typological comparisons that try to find correlations between social features and linguistic features across thousands of languages (Lupyan & Dale, 2010; Nettle, 2012; Bentz et al., 2015), as well as detailed historical and sociolinguistic analyses that analyze and document how specific linguistic innovations diffused in real-life languages (Milroy & Milroy, 1992; Meir et al., 2013; Trudgill, 2002). Experimental research tries to empirically test the influence of different properties of social structure on newly emerging communication systems in controlled settings, for example by manipulating properties such as group size, network connectivity, and the amount of non-native speakers, using communication games and iterated learning paradigms with participants in the lab or online (Centola & Baronchelli, 2015; Raviv et al., 2019, 2020; Smith, 2024). Computational modeling does the same by simulating communication in interacting populations of artificial agents, further manipulating variables such as cognitive capacities, learning biases, and long-term generational changes, which cannot be easily tested in experimental settings (Josserand et al., 2024; Lou-Magnuson & Onnis, 2018; Reali et al., 2018).

This overview synthesizes key findings from these three lines of research, demonstrating the complex effects of social structure (and specifically, population size, network connectivity, and heterogeneity) on patterns of language evolution and change.

Variability, Convergence, and Rate of Change

Across many cultural domains, smaller and tightly-knit communities are generally more homogeneous and less diverse, while larger and more sparsely connected communities are associated with more innovations and more variability (Allcott et al., 2007; Granovetter, 1983; Lev-Ari, 2018). With respect to language, tight and close connections often function as a conservative force, preserving and amplifying existing norms and resisting external pressures to change (Milroy & Milroy, 1992; Trudgill, 2002). As such, smaller, denser, and more isolated communities can exhibit a stricter maintenance of linguistic conventions, even when these norms are relatively irregular and harder to learn (Reali et al., 2018; Trudgill, 2002).

However, even though closed and tightly-knit communities tend to be more resilient to change, a common finding in computational modeling is that, once a change does occur, it is likely to spread more rapidly in a small and dense community compared to a large and sparse one. That is, there is more effective diffusion of innovations in smaller and denser networks (Fagyal et al., 2010; Ke et al., 2008; Segovia-Martín et al., 2020). This is because the propagation of variants is naturally faster when there are less individuals to propagate to. Moreover, people are more likely to copy the behavior of strong ties (i.e., close contacts with whom one interacts frequently) than that of weak ties (i.e., more distant or infrequent social connections) (Centola, 2010). However, in scale-free networks that follow a power-law distribution (whereby most individuals have few connections but some have very many), the presence of "hubs", or highly connected agents, can accelerate the spread of new forms even in a larger population (Fagyal et al., 2010; Zubek et al., 2017). Notably, computational models typically find that the time needed for new variants to spread in a population is proportional to its size, with convergence achieved faster in small populations compared to larger populations (Baronchelli et al., 2006; Centola, 2010; Vogt, 2007). Accordingly, these models predict that, given the same time, small communities should be more uniform than larger communities, and should converge fater than networks that are big and sparse.

Data from real-world languages does not always corroborate these computational results, though. For example, emerging sign languages often show the exact opposite pattern, with a seemingly inverse relationship between convergence time and population size. In newly emerging sign languages, small and homogenous communities are typically less conventionalized than big communities (Meir et al., 2013; Meir & Sandler, 2019; Tkachman &Hudson Kam, 2020). Specifically, sign languages that emerged in small, isolated, and tightly-knit villages feature significantly higher lexical variability across signers (i.e., with different individuals using different signs to refer to the same meaning), and are considerably less conventionalized compared to sign languages that emerged in larger, sparser, and more geographically spread communities within the same period of time. Moreover, new sign languages developed in bigger and more heterogeneous communities converged more quickly on a fixed word order. These findings echo experimental work with newly emerging artificial languages, where small groups of interacting participants typically showed greater variability compared to larger groups (Raviv et al., 2019), and further resonate with the fact that small groups appear to be more sensitive to random drift (Nettle, 2012; Spike, 2017).

Several things may explain these conflicting patterns of results. First, computational models often include simplified or unrealistic assumptions regarding the agents' cognitive abilities (e.g., having an unlimited memory capacity), or operationalize learning and interaction in different ways (e.g., updating agents' knowledge either by adding a new variant to the existing inventory, or by completely overriding all previous variants). These differences may dramatically impact the findings obtained from such models. For instance, the effect of group size on language change seems to vary depending on whether agents are set up to learn globally or locally within a network (Wichmann et al., 2008): when agents are assumed to copy from all other agents in their network, larger populations show slower rates of language change; yet when agents are assumed to copy more from their closest neighbors, community size has no effect. Second, for real-world languages, historical events and other external factors might confound the possible influence of population structure on language evolution (Bromham, 2025). Finally, the specific configurations of social networks might play a critical role in shaping transmission and conventionalization patterns. For example, if sparsely connected networks have small-world properties (with "strangers" being indirectly linked by a short chain of shared connections), the size of the population seems to have no effect on the speed of conventionalization (Spike, 2017). Underscoring this point, a recent computational model that carefully manipulated various global parameters associated with network structure suggests that connectivity by itself is not a precise enough measure, and that more fine-grained metrics such as path lengths and clustering coefficients are more crucial for predicting interindividual variation and convergence rates (Josserand et al., 2024). Their results help resolve previously and seemingly conflicting findings by showing that variation is more likely to occur in populations where individuals are not well-connected to each other, but also in small communities. Moreover, they highlight the importance of differentiating between the scenarios of language emergence versus language change, which differ in the degree of pre-existing conventions and consequently in the type of linguistic input learners are exposed to.

Structure, Systematicity, and Transparency

Beyond shaping communicative dynamics such as the degree of convergence and rate of change, community structure and size can also have a significant impact on the structure of languages themselves, shaping them across all levels of analysis: from phonology, to vocabulary, to grammar. This idea is captured by the *Linguistic Niche Hypothesis*, which suggests that socio-demographic features can influence the basic building blocks of language and lead to different types of languages emerging in different communities (Lupyan & Dale, 2010, 2016).

For example, community size can affect the sound systems of languages, with larger populations often having larger phonological inventories compared to smaller populations, i.e., using more diverse sounds (Hay & Bauer, 2007; Nettle, 2012). However, the mechanisms leading to differences in phonological inventories are still debated and not found across all studies (Moran et al., 2012). One reason why smaller populations would have smaller phonological inventories is because they are more likely to lose phonemes due to drift and founder effects, which occur when a small group of individuals separates from a larger ancestral population to establish a new, isolated population (Atkinson, 2011). In these cases, often only a subset of the variety of the original population is preserved, which may include rarer variants (Bromham, 2025; Fort & Pérez-Losada, 2016). That is, typologically rarer sounds are often found in the sound systems of smaller languages (although our notion of what constitutes a rare sound is based on well-documented Indo-European languages with big speech communities) (Cardoso et al., 2022).

Yet the most well-known and documented relationship between community structure and language structure is in the domain of morpho-syntax, where ample observational, experimental, and computational work repeatedly points to the same pattern: larger communities are typically associated with "simpler" linguistic structures, whereas smaller communities are typically associated with more "complex" linguistic structures. While the terms "simple" and "complex" are debated (Bisnath et al., 2025; Raviv et al., 2022), the main finding is that languages spoken in larger communities tend to have fewer and/or less elaborate morphological rules, fewer irregularities, and overall more transparent and compositional grammars. For example, in a seminal large-scale cross-linguistic study looking at over 2,000 languages worldwide, Lupyan and Dale (2010) reported an inverse correlation between population size and grammatical complexity, such that languages spoken by smaller populations tended to exhibit richer inflectional morphology and more irregular forms. Similarly, typological work has found that highly polysynthetic languages in which words are composed of many morphemes are more likely to be used in small and isolated populations (Bromham et al., 2025).

In line with these correlational findings, group communication experiments show a causal relationship between group size and language structure: in lab settings, larger microsocieties (8-people) create artificial languages that are more systematic and compositional compared to those created by smaller microsocieties (4-people), and systematic structures seem to evolve significantly faster and more consistently in larger groups (Raviv et al., 2019). These findings are attributed to the fact that members of larger groups are typically under a stronger pressure to create communication systems that are more transparent and easier to use, since this can in turn ease the communicative challenges associated with interacting with more people (i.e., exposure to more variability and more difficulty to reach conventionalization; see Section **Variability, Convergence, and Rate of Change** above). Computational models similarly find that larger populations create more compositional languages (Vogt, 2007) or are associated with less complex grammars (Reali et al., 2018), and further suggest that more sparsely connected networks tend to have more regular and systematic linguistic systems, whereas densely connected networks are more conducive to the preservation of linguistic complexity (Lou-Magnuson & Onnis, 2018). However, the effect of network connectivity has so far not been replicated experimentally (Raviv et al., 2020).

In addition to size and types of connectivity, many theoretical accounts of language diversity suggest that linguistic structure is directly affected by the degree of language contact and the proportion of non-native speakers in the population (McWhorter, 2007; Trudgill, 2002; Wray & Grace, 2007). Specifically, since larger populations typically have more interactions with strangers (who share less common ground) and include more adult second-language (L2) learners (who have difficulties learning complex grammatical rules), they should favor more transparent and easier-to-learn structures that could facilitate successful communication. This idea is supported by two lines of evidence.

First, communication systems originating in larger communities are easier to learn by naive individuals, and show more iconic structures. For example, people are more accurate in guessing the meaning of words for "big" and "small" when they come from languages spoken in larger communities (Lev-Ari et al., 2021), and drawings created by larger groups are better understood by naive participants compared to drawings created by dyads (Fay & Ellison, 2013). This is thanks to greater auditory or visual similarity between form and meaning in signals coming from larger groups, which make them more "guessable". Similarly, artificial languages developed by larger groups are learned better and faster by both humans and neural networks (Galke et al., 2024; Raviv et al., 2021).

Second, more non-native speakers have been found to promote simpler and more systematic grammatical structures. For instance, in small populations of simulated computer agents, having only "child" learners with a bias to imitate significantly increases the chances that the language will develop complex morphology, while inflectional morphology drops or even disappears in slightly bigger populations of agents with more "adult" learners with a bias against such systems (Dale & Lupyan, 2012). In addition, iterated learning experiments show that the presence of non-native learners leads to morphological simplifications such as a reduction in case markings (Berdicevskis & Semenuks, 2022; Smith, 2024; Atkinson et al., 2018). However, follow-up typological studies that tested this link directly show mixed results: while some find that the proportion of L2 speakers affects language structure (Bentz & Winter 2013; Nettle, 2012; Sinnemäki & Di Garbo, 2018), others find no such correlation (Koplenig, 2019; Shcherbakova et al., 2023)

Conclusion and Outlook

There is a complex interplay between language evolution and social networks. Synthesizing observational, experimental, and computational approaches shows that factors such as population size, network connectivity, and heterogeneity (often reflected in the proportion of non-native speakers in the population) can significantly impact languages in terms of their variability, convergence, and rate of change, as well as their linguistic structure, systematicity, and transparency.

Crucially, social factors drive not only the evolution of human languages, but also the evolution of other animals' communication systems. There are striking parallels between the work reviewed here and research done on non-human animals, with comparative work showing that, across an array of different species, animals with more complex social structures tend to exhibit more complex and flexible vocal repertoires (e.g., Freeberg et al., 2012). However, for comparisons with animal communication systems to be fruitful, it is necessary to find a shared theoretical framework and clarify the levels of analysis and subcomponents that underlie terms such as "simple" and "complex" (Raviv et al., 2022).

One of the main challenges in this area of research is resolving seemingly conflicting findings, for instance when the results of computational models are at odds with typological data. As Josserand et al. (2024) suggests, two important elements may help reconcile such patterns: (a) differentiating between language emergence and language change scenarios, as these are often associated with different pressures and starting conditions; and (b) clearly identifying the causally relevant parameters of computational models, which are often not sufficiently acknowledged or discussed. Future work would greatly benefit from more multidisciplinary, multi-method work with a stronger integration of computational and experimental approaches, which can together help test the causal mechanisms shaping languages (Smith, 2025). Furthermore, careful application of methods and techniques from evolutionary biology can highlight relevant analogies between language evolution and biological evolution, and may uncover crucial parallels between the role of e.g., population size in shaping the evolution of languages and species (Bromham, 2025).

Ultimately, understanding how languages adapt to their social environment will not only advance theories of language evolution, but also inform broader questions about the evolution of communication, cognition, and culture.

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