Meaning, Evolution, and the Structure of Society

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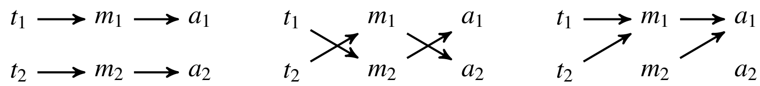
Abstract. Leading models of language evolution seek to explain key properties of language as emerging from repeated interactions of language-using agents. This paper will explore some of the consequences that integrating a more realistic social interaction structure into established models of language evolution in terms of evolutionary game theory has and reflects on prospective applications.

Leading models of language evolution seek to explain key properties of language as emerging from repeated goal-oriented interactions of language-using agents [26, 32, 4, 2, 31]. Models of meaning evolution delineate exact conditions under which semantic meaningfulness can emerge, by imitation of others or by rationally responding to the behavior of one's environment. It is obvious that the *psychology* of language users plays a pivotal role here: among other things, the particulars of agents' perception and memory, their disposition to adapt their behavior, including the extent to which they make rational choices will heavily influence the way linguistic behavior evolves over time. Consequently, there has been a lot of research into the impact of different agent-based learning dynamics [18, 17, 3, 21, 8, 13]. Moreover, the *sociology* of language-using populations plays a role in determining the time course and outcome of evolutionary processes. Many evolutionary models make explicit assumptions about the interaction patterns within a population of language users, such as who interacts with whom [25]. Different interaction structures may give different predictions about uniformity or diversity of language [37, 34, 23]: if everybody in a large population were to interact with everybody else equally, language uniformity is to be expected; but given a tendency to interact mostly with nearby kinsmen, we expect dialects and regional variations. Further obvious consequences of different social interaction structures are the readiness and speed with which new innovations may spread in a population [16, 6], or the social standing of the innovators [6, 24].

The aim of this paper is to highlight where and how psychological and sociological constraints interact and influence the outcome of evolutionary processes relevant for the evolution of meaning. Our goal is to communicate ideas, not mathematical detail. Section 1 introduces basic notions of evolutionary game theory and formal network theory. Section 2 demonstrates how restrictions on social interaction patterns influence the equilibrium outcomes for a simple game that has been used frequently in the literature to study *structural iconicity* in language [5]. We show that more realistic interaction structures make it more likely that iconic language use evolves. Section 3 recaps the conditions under which simple signaling game models of meaning evolution give rise to regional variability, and Section 4 zooms in on the *global* and *local* network properties that characterize, among others, language boundaries or origins of conventionalization.



(a) strategy profile s_1 (b) strategy profile s_2 (c) strategy profile s_3

Fig. 1. Different strategy profiles for a signaling game with 2 states/messages/actions.

1 Background: Evolutionary Games & Networks

Signaling Games. We will restrict our attention to *signaling games* [20]. A sender has private information which a receiver lacks. The sender sends a message, which has no pre-established meaning. The receiver then takes an action in response to observing the sender's message. If the receiver's action matches the sender's private information, the game is a success; if not, it's a failure. For illustration, we consider signaling games with a set of two states $T = \{t_1, t_2\}$, a set of two messages $M = \{m_1, m_2\}$ and a set of two receiver actions $A = \{a_1, a_2\}$. With probability p state t_1 occurs, and with probability $1 - p$ it is t_2. The utilities for sender and receiver of one round of play are given by functions $\mathrm{U}_{S,R} : T \times M \times A \to \mathbb{R}$ as follows:

$$\mathrm{U}_R(t_\mathrm{i}, m_\mathrm{j}, a_\mathrm{k}) = \begin{cases} 1 & \text{if } i = k \\ 0 & \text{otherwise} \end{cases} \qquad \mathrm{U}_S(t_\mathrm{i}, m_\mathrm{j}, a_\mathrm{k}) = \mathrm{U}_R(t_\mathrm{i}, m_\mathrm{j}, a_\mathrm{k}) - \epsilon_j$$

where $0 \leq \epsilon_1 \leq \epsilon_2 < 1$ are costs of sending messages m_1 and m_2 respectively. When the state probabilities are equal $p = .5$ and the message costs are zero $\epsilon_1 = \epsilon_2 = 0$, then we call the game a *Lewis game*. We also consider the case where $p > .5$ and $0 \leq \epsilon_1 < \epsilon_2$ and call it a *Horn game*. This case has been used frequently to study the *structural iconicity principle* a.k.a. *Horn's division of pragmatic labor* [11] from an evolutionary perspective, namely the observation that most often languages encode frequent or stereotypical meanings with short and economic forms [27, 19, 15, 7, 23].

A *pure sender strategy* is a function $s : T \to M$ from states to messages; a *pure receiver strategy* is a function $r : M \to A$ from messages to acts. A pair of pure strategies is a *pure strategy profile*. There are 4 pure sender and 4 pure receiver strategies for the signaling games we look at here and consequently 16 pure strategy profiles. Next to pure strategies, there are also *mixed strategies*. These are probability distributions over pure strategies. So, a mixed sender (receiver) strategy $\tilde{s}$ ($\tilde{r}$) is a function assigning a probability to each pure sender (receiver) strategy. In an evolutionary context, we interpret these as giving the frequency with which each pure strategy occurs in a population of agents. A *mixed strategy profile* is then a pair of mixed sender and receiver strategies that describes the current *population state*, i.e., the frequencies of pure sender and receiver strategies occurring in the population at a given time.

Static Solutions. For the Lewis game, the two pure strategy profiles s_1 and s_2 in Figure 1 are of particular interest. In each of these, all of the agents play the same strategy in either sender or receiver role. Lewis called profiles like these, where agents succeed to communicate perfectly, *signaling systems*. Although messages are initially meaningless, they become meaningful if a population of agents uses them in the way described by a signaling system. E.g., in strategy profile s_1 from Figure 1(a), message m_1 denotes state t_1. The population states in s_1 and s_2 are evolutionarily stable states (ESSs) [22, 35]. When, as we assume here, agents hold both a sender and receiver strategy independently, the ESSs of the game are just the strict Nash equilibria [30].

Dynamic Solutions. Knowing which population states are ESSs is important, but we may also wish to know whether and how a population which is not in an ESS develops if every agent adapts her behavior in some way or another. The most common evolutionary dynamic studied for that purpose is the *replicator dynamic* of [33]. The general idea behind the replicator dynamic is that the frequency $\tilde{s}_t(s)$ of pure sender strategy s at time t in the population changes proportional to how successful s fares against the averaged receiver behavior $\tilde{r}_t$ at time t. If s does better than the average over all pure sender strategies, then the frequency of s increases proportionally to how much better it does than average; if s does worse, then its frequency decreases proportionally to how much worse it does in comparison with other sender strategies. Similarly, for the receiver. A *fixed point* of the replicator dynamic is a population state that does not change under the replicator dynamic. An *attractor* is a fixed point such that population states close to it converge towards that fixed point. For each attractor, we call its *basin of attraction* the region of population states that converge to it. To simplify parlor, we restrict attention to *relevant attractors* that have a non-negligible basin of attraction.

The behavior of signaling games under the replicator dynamic is well-studied [12, 31, 13]. For populations where sender and receiver role are treated separately, we obtain the following picture. The two signaling systems s_1 and s_2 in Figure 1 are the only relevant attractors of the replicator dynamic for the Lewis game and have equally sized basins of attraction. For the Horn game, there are three relevant attractors (Figure 1): strategy s_1 is called the *Horn state* since it captures the *structural iconicity principle* mentioned above according to which the more efficient form is linked with the more frequent meaning; strategy s_2 is called the *Anti-Horn state*, since it operates exactly the other way around; and strategy s_3 is called the *Smolensky state* [11, 5, 19]. The Horn state is the more efficient way of using language than the Anti-Horn state, although both achieve perfect communication throughout. The Smolensky state is worse than Horn or Anti-Horn, as communication is achieved in only p times cases. This is reflected in the relative sizes of the basins of attraction. To estimate these by numerical simulations, we generated 1 million randomly chosen initial population states, ran the replicator dynamic for a Horn game ($p = .75$, $\epsilon_1 = 0$, $\epsilon_2 = .1$) and recorded the number of times the system converged to one of the three states. 54.5% or trials converged to the Horn state, 33.0% to the Anti-Horn state, and 11.9% to the Smolensky state.

The bigger size of the basin of attraction of the Horn state could be taken as a partial explanation for the relative prevalence of the structural iconicity principle. However, although Horn and Anti-Horn states support full communication, the Smolensky state is communicatively inefficient but still attracts almost 12% of initial population states for the chosen parameter values. Interestingly, this changes when we consider communication in structured populations, which is what we will work towards next.

Network Games. The replicator dynamic describes how the frequencies of various strategies in a population of agents develop over time. This is a *macro-level perspective*, because there is no mention in the formulation of the replicator dynamic of what each individual agent is doing. But we can also link the replicator dynamic to a *micro-level perspective*. It can be shown that the replicator dynamic describes the most likely path of strategy distributions in a virtually infinite and *homogeneous* population when every agent updates her behavior by *conditional imitation* [9, 29]. A population is *homogenous* if every agent repeatedly interacts with everybody else equally. An agent who updates her behavior by *conditional imitation* plays a constant pure strategy for a while, but, every now and then, checks how well all neighbors fare with the strategy that they play. If some set X of neighbors do better than the agent, he adopts the pure strategy of some $x \in X$, where x is chosen from X with a probability that is proportional to the relative success of x's strategy if compared with that of the other elements in X.

The conditional imitation rule adopts a *micro-level, agent-based perspective*. The micro-level perspective makes it possible to dispense with the assumption that the population is virtually infinite and homogeneous. Instead, we can fix an explicit *interaction structure* for a population by defining which agents can interact with one another. At the same time, we can also look at different *update rules*, i.e. different ways of changing behavior over time. We refer to a fixed interaction structure and a fixed update rule as a *network game*, when the interaction structure of the agents is given by a social network of relations. Such a network is formally represented as an undirected graph $G = \langle N, E \rangle$ where $N = \{1, \ldots, n\}$ is the set of nodes, representing the agents, and $E \subseteq N \times N$ is an irreflexive and symmetric ordering on N. Agents i and j interact if and only if $\langle i, j \rangle \in E$. In the following, we look at some relevant graph structures whose interaction with various update rules we will explore thereafter.

Network Types. The most trivial graph structure is a *completely connected network*: every agent interacts with everybody else equally; the population is homogeneous. In a *k-ring network* all of the agents are ordered and connected in a circular way to their k-nearest neighbors. In a *grid network* the agents are arranged on an $n \times m$ toroid structure, where every agent interacts with the 8 nearest neighbors. Rings and grids are easy to implement and facilitate proofs, but they are quite unrealistic models of human interaction patterns. We therefore also consider two more complicated graph types that are created with a random component. The first are so-called *β-graphs*. A β-graph is obtained by considering a k-ring network and subsequently, for each node, rewiring its $k/2$ left neighbors to a random vertex n with probability β [36]. β-graphs have so-called *small-world properties*: a *short characteristic-path length* and a *high clustering coefficient*, features that also show, for instance, in the analysis of human friendship networks [14]. Nodes in a β-graph almost all have the same number of connections, but it seems more realistic to assume that most agents interact with a smaller number of agents, but there are also agents who interact with many. If the frequency of agents with ever larger numbers of connections follows a power-law distribution, the network is said to be *scale-free*. We consider a special kind of *scale-free networks* here, which is both scale-free and has small-world properties [1]. These are constructed by a simple parameterized preferential attachement algorithm [10].

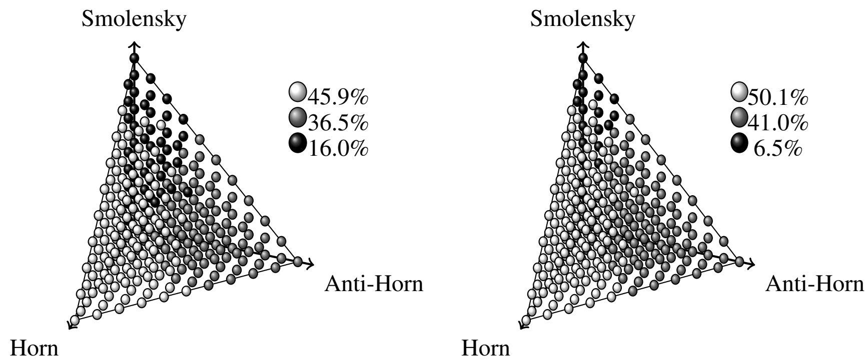
Update Rules. We will here only consider general classes of update rules, namely the *imitation class* and the *learning class*. The *imitation class* comprises update rules where agents would adopt other agents' behavior under certain conditions. The conditional imitation update rule that we linked to the replicator dynamic above is, of course, a first example. Moreover, we consider the *imitate-the-best* update rule used by [37] and [34]. This update rule is the special case of the conditional imitation where agents adopt the strategy of the neighbor who is doing best with probability 1 if this neighbor is doing better than the agent himself.

When imitation is conditional on success of neighboring strategies, imitation-based update rules are not as innocuous and resource efficient as they may seem at first. Payoff-dependent imitation requires keeping track of the neighbors' average success. It may be easier to keep track just of one's own. For that reason, we also look at two specimen from the *learning class* of update dynamics. Learning-based dynamics assume that agents try to optimize their behavior by keeping track of the past interactions that they were engaged in. Whereas imitation-based dynamics have agents change their entire pure strategy when they imitate, learning-based update rules often induce only local and gradual changes to the agents' *behavioral strategies*. A behavioral sender strategy σ is a function from T to probability distributions over M. Similarly, a behavioral receiver strategy ρ is a function from M to probability distributions over A.

Reinforcement learning (RL) is the most popular learning dynamic when it comes to signaling games [31]. Here, agents are more likely to repeat a certain choice the more successful is was in the past. This can be pictured as a process of updating *Pólya urns* [28]. An urn models a behavioral strategy, in the sense that the probability of making a particular decision is proportional to the number of balls in the urn that correspond to that action choice. By adding or removing balls from an urn after each encounter, an agent's behavior is gradually adjusted. For signaling games, the sender has an urn Ω_t for each state $t \in T$, which contains balls for different messages $m \in M$. The number of balls of type m in urn Ω_t is $m(\Omega_t)$, the overall number of balls in urn Ω_t is $|\Omega_t|$. If the sender is faced with a state t she draws a ball from urn Ω_t and sends message m, if the ball is of type m. The resulting behavioral strategy is: $\sigma(m|t) = {}^{m(\Omega_t)}/_{|\Omega_t|}$. (Similarly, for the receiver.) The learning dynamics are realized by changing the urn content dependent on the communicative success. If communication via t, m and a is successful, the number of balls in urn Ω_t is increased by $\alpha \in \mathbb{N}$ balls of type m and reduced by $\gamma \in \mathbb{N}$ balls of type $m' \neq m$. Similarly, for the receiver. In this way successful communicative behavior is more probable to reappear in subsequent rounds. In our experiments, all urns were initially filled with 100 balls and we set $\alpha = 10$ and $\gamma = 4$.

2 Network Structure Shifts the Basin of Attraction

We have seen above that there are three relevant attractor states for the replicator dynamic in the Horn game (Figure 1), with differently sized basins of attraction. Let's see what happens when we look at various network games instead. To isolate the impact of interaction structure, we look at a network game with the conditional imitation update rule. This is because, as explained above, for huge and completely connected networks, average behavior of conditional imitation imitates that of the replicator dynamic. Com-



(a) Homogeneous population (b) Heterogeneous population

Fig. 2. Comparing the basins of attraction for the conditional imitation rule by numerical simulation for different network topologies. Figure 2(a) shows the results for a completely connected network, while 2(b) shows the results for a small-world network, both for 100 agents.

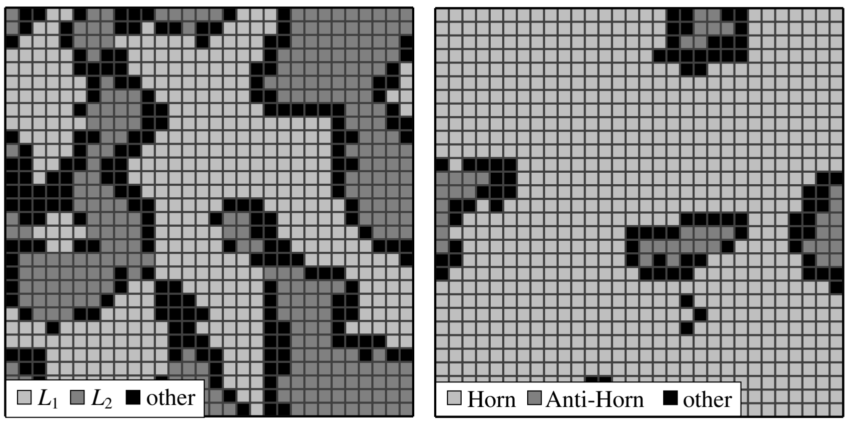
paring completely connected networks to other types of interaction structure, we get a good glimpse at the consequences of the assumption of homogeneity that is hidden in the elegant formulation of the replicator dynamic.

We fix a Horn game with $p = .75$, $\epsilon_1 = 0$ and $\epsilon_2 = .1$, as before, and compare, by numerical simulation, several trials on both homogeneous and heterogeneous populations. Figure 2 shows the averaged outcomes of several trials of a discrete traversal of the strategy space. Each dot in the graph corresponds to an initial state of the sender population. (The picture for the receiver would be largely parallel.) Since population states for this game are probability distributions over four strategies, it suffices to describe these states by three numbers, leaving implicit the frequency of strategies $\{t_1, t_2\} \rightarrow m_2$ and $\{m_1, m_2\} \rightarrow a_2$. The color of the dots represents the most frequent sender strategy to which the initial strategy eventually evolved. Depicted are trials over 100 runs. Figure 2(a) visualizes the basins of attraction for a homogeneous population of 100 agents with a completely connected network as interaction structure. Notice that these results are for a very small population only, but still meet the predictions of the replicator dynamic in 93.2% of the trials. Figure 2(b) shows the results for a heterogeneous population of 100 agents located on a β-graph ($k = 4$; $\beta = .1$) as the underlying interaction structure. The pictures in Figure 2 show clearly that conditional imitation on small-world networks leads to fewer Smolensky outcomes.

Table 1 compares basins of attraction (BoA), not only for complete and small-world networks, but also for scale-free network (with $m = 3$ and $p = .8$) and grid topologies. They all differ not only in this distribution, but also in the correspondence to the basin of attraction of the replicator dynamic (RD-correspondence). These results show clearly that social factors of interaction have non-trivial effects on the results of evolutionary processes of language games.

Table 1. Basins of attraction and replicator dynamic correspondence for different topologies

	BoA Horn	BoA Anti-Horn	BoA Smolensky	RD-corresp.
complete network	45.9%	36.5%	16.0%	93.2%
scale-free	49.7%	38.3%	10.5%	91.0%
β-graph	50.1%	41.0%	6.5%	89.1%
grid topology	50.1%	40.8%	6.7%	88.2%



(a) Lewis game (b) Horn game

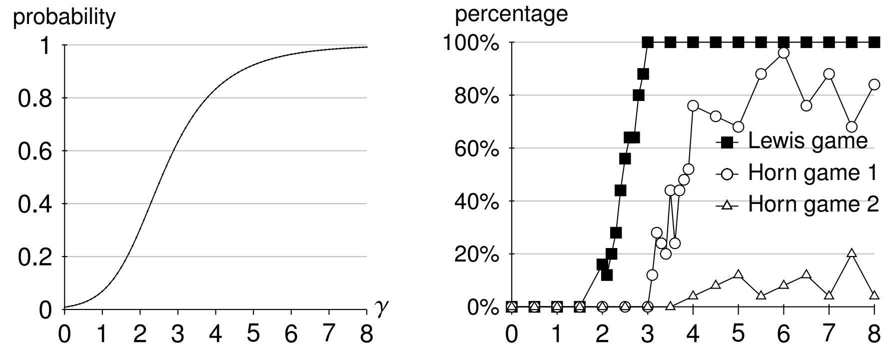
Fig. 3. Exemplary distribution of players with different strategies. Figure 3(a) shows the result of a Lewis game, Figure 3(b) of a Horn game with $p = .6$ and $\epsilon_1 = .1$, $\epsilon_2 = .2$.

3 Emergence of Regional Meaning

[37] analyzed the *Lewis game* played on 100×100 grid under the *imitate the best* rule. The main finding was that all agents learned a signaling system and that the population was divided in multiple *language regions*: regions of agents playing either the one or the other signaling system. In other words, heterogeneous interaction structures can lead to the *emergence of regional meaning*.

[23] applied *reinforcement learning* to a Horn-game, played on a 30×30 grid network. Multiple language regions emerged in ca. 80% of all simulation runs and, on average, the number of Anti-Horn players amounted to ca. 3% (30 agents) of all agents. Furthermore, language regions were always separated by border players, who never learned a language, but rather switched between different strategies continuously. Exemplary distributions for Lewis and Horn game are depicted in Figure 3.

[23] also extended the grid structure to a *social map* [25]: agents communicate not only with their immediate neighbors on the toroid structure, but with all agents of the population, whereby the probability of communicating with another agent was inversely proportional to the *Manhattan distance*. A parameter *degree of locality* γ determines the



(a) Prob. of neighborhood communication as a function of degree of locality γ

(b) Percentage of trials with multiple language regions as a function of degree of locality γ

Fig. 4. The probability of neighborhood communication increases with degree of locality γ (4(a)). The emergence of a society of multiple language regions is supported by high γ-values (4(b)).

relation between distance and probability. While for $\gamma = 0$ each agent in the network is chosen as interlocutor with the same probability, by increasing γ, the probability of choosing a close agent increases. Figure 4(a) depicts the probability to communicate with a direct neighbor dependent on γ for a 30×30 social map. By increasing γ the social map structure approximates neighborhood communication on a grid network. We can then examine how the emergence of multiple language regions depends on the degree of locality γ in three different games: the Lewis game, Horn game 1 ($p = .6$, $\epsilon_1 = .1$, $\epsilon_2 = .2$) and Horn game 2 ($p = .7$, $\epsilon_1 = .1$, $\epsilon_2 = .2$). Since for $\gamma = 0$ the social map corresponds to a complete network, in any trial for any game only one signaling system emerges, as expected. For $\gamma = 8$ the social map equals a grid structure and all trials of the Lewis game, ca. 80% of the trials of Horn game 1 and only ca. 10% of Horn game 2 result in a society of multiple language regions. Figure 4(b) depicts how the percentage increases with γ for $0 \leq \gamma \leq 8$.

In sum, the emergence of variability depends strongly on the network topology, especially the level of connectedness. Moreover, [34] showed for β-graphs that the number and kind of language regions depends on global network properties like *clustering coefficient* and *average path length*. In the next section we extend this line of research by looking at the evolution of signaling conventions, not only on β-graphs, but also scale-free networks. Adding to previous work, we investigate the network properties associated with regions of agents that have successfully learned a language.

4 Structure of Regional Meaning

Deepening our understanding of synthetic evolutionary processes in structured populations us useful for a more thorough understanding of the sociological factors of linguistic variability. Most previous work has focused on studying which network structures are conducive to innovation and its spread [16, 6], less has been done to investigate the structure of the sub-regions of agents that have successfully learned a language. Towards this goal, we modeled structured populations as β-graph and scale-free networks and created appropriate 10 networks of each type with 300 nodes. For each network, 20 simulation runs were conducted. Agents played the Lewis game with randomly chosen neighbors on the network, and each agent's behavior was updated via reinforcement learning, separately after each round of play. We recorded strategies of agents in suitably chosen regular intervals. Each trial ran until at least 90% of agents had acquired a language, or each network connection had been used 3000 times in either direction.

In order to determine which global network properties best characterize where, on average, learning would be most likely successful, we looked at what we will call *language regions*. A language region is a maximal subset of agents that have acquired the same language that forms a connected subgraph. Despite using reinforcemant learning instead of imitation dynamics, our data confirmed Wagner's [34] results that in small-world networks like ours the number of language regions is small while the size of language regions is relatively big. On β-graphs multiple language regions emerged for each simulation run, whereas on scale-free networks more than one language region emerged in ca. 90% of all runs. However, most of the time, only two big language regions formed on scale-free networks and β-graphs as well, one for each signaling convention.

To analyze the properties of language regions, we looked at relevant properties of (sub-)graphs: *density*, *average clustering* and *transitivity*.[1] Our simulation data show that each connected language region of a given type had always a higher *average clustering* value than the expected value for a random connected subgraph of the same size, whereas the *density* value didn't exhibit such a divergence (Figure 5). So, a regular local clique structure supports locally coherent language, but mere number of connections does not. For β-graphs this conclusion is also supported by the fact, that language regions always had a higher *transitivity* value than expected from random sampling. Interestingly this doesn't hold for scale-free networks. This divergence results from the nature of both network types: in a diffuse network like β-graphs transitivity and clustering roughly correspond to each other, whereas scale-free networks can have high individual clustering because of the cliquishness of sub-communities, but unions of those communities are connected by only few hubs and therefore the more global transitivity value stays low, or doesn't exceed the expected average value.

5 Conclusion & Outlook

We presented cursorily data from a number of studies that all support a very general conclusion: the social structure in a society matters to the evolution of conventional meaning. Not only can different interaction structures in network games lead to shifts in the basins of attraction of different strategies under identical dynamics, constraints on social interaction patterns can also lead to the emergence of regional variety. Using notions from formal network theory, this paper tried to dig deeper into the relation between social structure and evolutionary dynamics of meaning by investigation where languages are most likely situated in the population.

[1]For the formal definitions, we refer to [14].

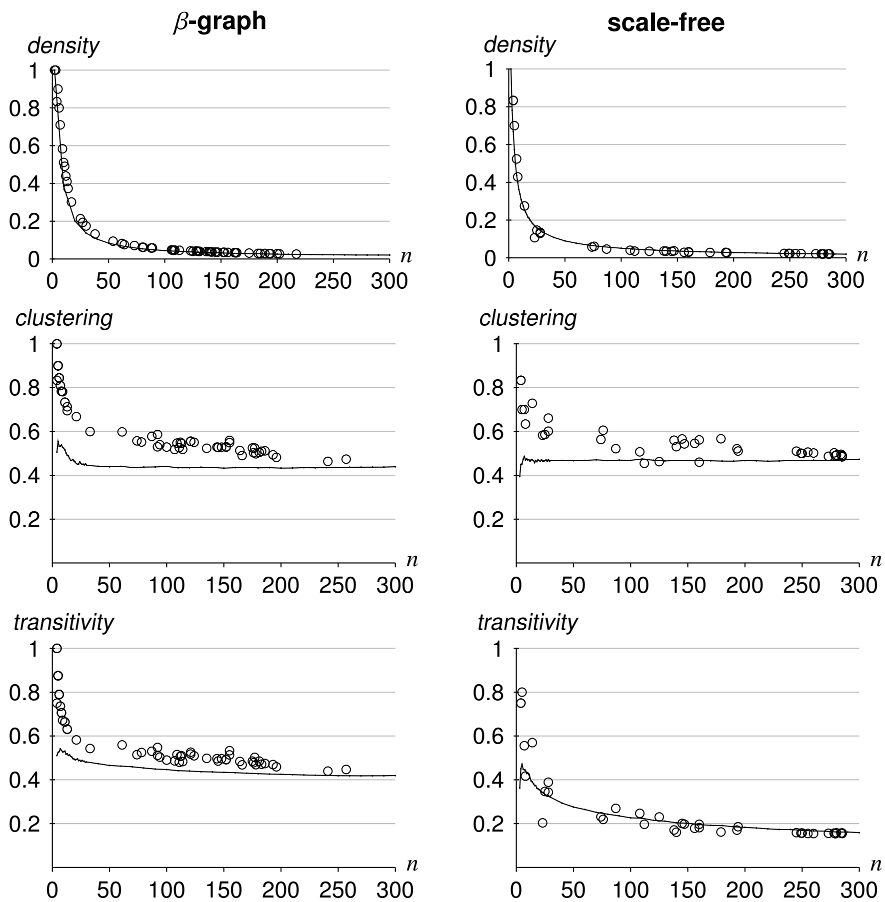


Fig. 5. Comparing observed density, clustering and transitivity of a language region (o) with expected values from randomly chosen subgraphs (solid lines, subgraph size *n* along the *x*-axis).

The models and results we presented explore the impact of social factors on language evolution on a very high level of abstraction. But it is nonetheless clear that this approach promises to lend itself to a number of concrete linguistic applications. We therefore consider the presented material here, as a first step into new terrain. The most obvious future applications of this line of work are language contact phenomena and the sociolinguistics of innovation and innovation-adoption. But also, for example, by looking at scale-free networks with a few super-agents connected to (almost) all other agents, the impact of modern media on language change can be formally studied. Moreover, once we move beyond static interaction structures and also take generational models of language evolution into account, it becomes possible to study the way changes in social interaction structures could have interacted with, i.e., causing and being caused by, language use.

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