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Coevolution with weights of names in structured language games

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ABSTRACT

We propose a coevolutionary version to investigate the naming game, a model recently introduced to describe how shared vocabulary can emerge and persist spontaneously in communication systems. We base our model on the fact that more popular names have more opportunities to be selected by agents and then spread in the population. A name's popularity is concerned with its communication frequency, characterized by its weight coevolving with the name. A tunable parameter governs the influence of name weight. We implement this modified version on both scale-free networks and small-world networks, in which interactions proceed between paired agents by means of the reverse naming game. It is found that there exists an optimal value of the parameter that induces the fastest convergence of the population. This illustration indicates that a moderately strong influence of evolving name weight favors the rapid achievement of final consensus, but very strong influences inhibit the convergence process. The rank-distribution of the final accumulated weights of names qualitatively explains this nontrivial phenomenon. Investigations of some pertinent quantities are also provided, including the time evolution of the number of different names and the success rate, as well as the total memory of agents for different parameter values, which are helpful for better understanding the coevolutionary dynamics. Finally, we explore the scaling behavior in the convergence time and conclude a smaller scaling parameter compared to the previous naming game models.

1. Introduction

Language dynamics, as a typical example of social dynamics, have been widely explored in the past few years. Understanding the origin and evolution of language remains a fascinating challenge for the interdisciplinary scientific community [1–3]. Based on the definition of the language game, a complex adaptive system, in which simple local interactions coupling with a self-organized process [4] lead to a global convergence, is constructed [5,6]. Various contributions have attempted to shed light on the dynamics of opinion formation [7–10]. In these studies, the organization of language is treated at a purely semiotic level, i.e., neglecting semantic relations between symbols and meanings, and linguistic conventions just evolve over time in a communication system. Recently, in the physics field, the naming game, inspired by global coordination problems in artificial intelligence and peer-to-peer communication models, has become an important approach to characterize the evolution of language [11]. In the naming game, interacting agents try to agree on the names of objects through self-organization of local pairwise interactions and without global supervision or a priori common knowledge [12–14], the process of which can be analyzed well via statistical physics [15–18]. A prototypical example of naming games is the so-called Talking Heads experiment [19], in which embodied software robots assign

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names to objects observed through digital cameras and communicate these names with each other in order to reach a final consensus.

More recently, models of semiotic dynamics have promised practical application in the study of newly developed web tools, such as del.icio.us or www.flickr.com, which enable network users to share classification of information by tagging items [20,21]. A minimal naming game model, proposed by Baronchelli et al. [22], can reproduce the same experimental results as the Talking Heads experiment, where all agents can reach a global consensus on fully connected networks. Based on the previous work, Baronchelli et al. further investigated the effect of a low-dimensional lattice on the agreement dynamics [23] and found that the consensus is reached through a coarsening process of clusters. The rapid development of complex networks theory, such as small-world networks [24,25] and scale-free networks [26,27], which can more realistically describe the population structures, drives researchers to introduce this minimal model into various topology structures. Dall'Asta et al. [28,29] probed the effects of the degree heterogeneity, the clustering coefficient and the hierarchical structures on naming dynamics and found that hubs play a positive role in favoring the final consensus if they act as speakers with high probabilities, and a higher clustering coefficient leads to the fast arrival of local consensus but inhibits global convergence in the long run.

Following Baronchelli's model, various reasonable modified versions of naming games have been proposed to study the evolution and scaling properties of agreement dynamics in self-organized communication systems. Tang et al. [30] introduced a word weight characterized by the power function of the speaker's connectivity into the naming game, and demonstrated that a moderate value of power can lead to the shortest convergence time. Wang's finite-memory naming game model [31] found that small memory length does harm to the convergence efficiency, but an optimal average degree of the networks results in the fastest convergence. In addition, many other modifications have been presented, such as the effects of asymmetric negotiation strategy [32], of reputation [33] and of geographical distance of small-world networks [34] on the dynamics behavior, to name but a few.

However, previous works mostly ignore the impact of the role of names' popularity. In these studies, names tend to be selected by speakers from their inventories with equal probability when communication occurs, which is not always in line with a realistic situation. Because of social diversity [35], it is natural to consider that the influences of different names or individuals are different. To incorporate diversity into naming games, we assume that a particular individual chooses a name with a probability related to the communication frequencies of names in their memory. This is reasonable because popular and sophisticated names can be more easily widely disseminated in self-organized communication systems, whereas strange and rarely used names are less implemented in communication, leading to their extinction by the more popular names. In this paper, to address the dynamic behavior of naming games in a quantitative manner, we introduce the weights of names according to their communication frequencies, which are also subject to change in the evolutionary process. Note that our model is different from previous weight versions of naming games [30,36]. In these two studies, the weights of names are determined by the speakers' connectivity and by the success rate in negotiations, respectively. The weight involved in our model is correlated with the name's communication frequency and alters over time. Specifically, each name spreads in the system together with its weight, which increases if the name is selected to transmit. A tunable parameter is introduced to accurately control the heterogeneity level of names' weights. By numerical analysis, we found that there exists an optimal parameter value leading to the highest convergence efficiency. To better understand how this nontrivial phenomenon emerges, investigations of some associated quantities, including the time evolution of the number of different names, the success rate and the total memory of agents, would also be provided.

2. Model

We first construct scale-free and small-world networks, by using Barabási–Albert (BA) [26] and Newman–Watts (NW) [25] models, respectively. Each node represents a specific agent. For BA networks, at each time step, a new node is added, with m links being preferentially attached to different nodes in the existing network. We repeat this process until there are N nodes in the network. The average degree is approximately $\langle k\rangle = 2m$. For NW networks, a parameter p controls the fraction of edges randomly added to the one-dimensional lattice for nearest and next-nearest interactions with periodic boundary conditions, and duplicate connections are prohibited. The relationship between the average degree $\langle k\rangle$ and the parameter p is $\langle k\rangle = 4(1+p)$ [25,37].

In the minimal naming game [22,23], N identical agents observe an unknown object and try to communicate the object's name with others. Each agent is endowed with an intrinsic memory (inventory) to store an unlimited number of different names. Initially, each agent has an empty memory and the system evolves as follows:

(i) At each time step, a hearer j, chosen at random from the population, picks randomly one of his neighbors i as the speaker. In this so-called reverse naming game [28], hub nodes have higher probabilities to act as speakers.

(ii) If the speaker i's memory is empty, he invents a new name and records it, assigning an initial weight $w = 0$ to this name, where w is a direct reflection of the communication frequency of the name. Otherwise, if i has already stored one or more names for the object, the probability of a name x being chosen is proportional to the influence of its weight, i.e.,

$$p_x = \frac{w_x^{\alpha}}{\sum_l w_l^{\alpha}},$$

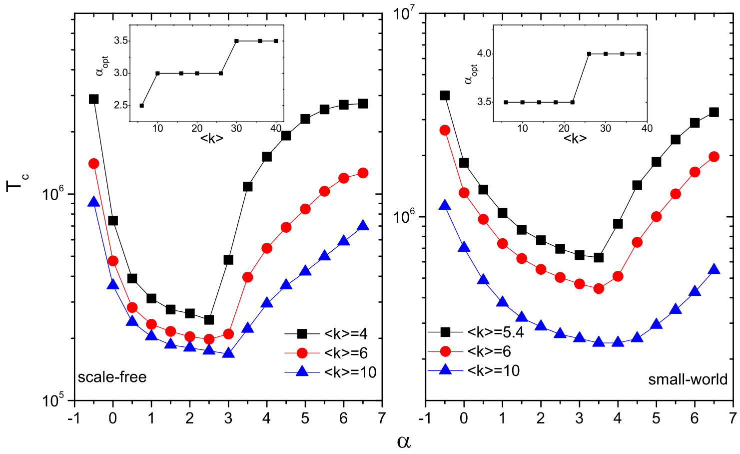

Fig. 1. Convergence time T_c as a function of α on scale-free networks and small-world networks for different average degrees $\langle k\rangle$, both with $N = 6000$. For NW networks in the right panel: the average degrees of the networks, $\langle k\rangle = 5.4,\ 6,\ 10$, are obtained by parameter $p = 0.35,\ 0.5,\ 1.5$, respectively. The insets illustrate the optimal values α_{opt} corresponding to the minimum T_c for different $\langle k\rangle$. Each data point is obtained by averaging over 500 independent realizations.

where α is a tunable parameter and the sum is over all names of i's memory. Correspondingly, the weight of the invented or selected name increases by one in i's memory and then the name, together with its weight (communication frequency), is transmitted to the hearer.

(iii) If this transmitted name already exists in the hearer j's memory, then the negotiation is successful. Both agents preserve this agreed name and its maximum communication frequency, which is equivalent to the larger weight of the agreed name between the speaker and the hearer. Meanwhile, both cancel all other terms in their memory. Otherwise, the negotiation fails, then the new name together with its weight is added to the hearer j's memory without any cancellation. We repeat the above process until the system achieves a global consensus or the preassigned time step is arrived.

Our simple assumption reflects the conformity behavior which is omnipresent in the real world. For $\alpha > 0$, the names with higher weights (popular ones) are more likely selected to spread. For $\alpha = 0$, the modified model recovers to the classical version of naming games [22], in which each name is selected equiprobably by agents to disseminate in the communication systems. For $\alpha < 0$, the opposite happens, but seems to be divergent from real-world observations, and we shall pay less attention to this situation. Therefore, the power function captures the effect of names' diversity well, i.e., the parameter α precisely quantifies the influence strength of the name weight.

3. Simulations and discussions

The convergence time T_c, as the most important quantity, is studied first, and is defined as the time for the population to reach a global consensus. Fig. 1 reports T_c as a function of parameter α for different $\langle k\rangle$ on both BA scale-free networks and NW small-world networks. It is observed that T_c shows a nonmonotonic behavior in the range of α, with an optimal value resulting in the fastest convergence. Moreover, the optimal value of α slowly increases with increasing $\langle k\rangle$ on both types of networks, as shown in the insets of Fig. 1. In fact, the optimal values of α are above 0 for all studied cases, which is consistent with the behavior observed in reality. Namely, the mechanism of weighting a name according to its popularity reflects the potential scenario of social behavior well, with the influence of positive weights leading to the faster convergence of the system. However, a very strong influence of weights plays a negative role on the convergence efficiency, and is even worse than the case without weights, i.e., too large a value of α damages the achievement of the final consensus. Later, we shall examine the fundamentals underlying this nontrivial phenomenon. A careful inspection of the results for both networks reveals that the optimal value of α on small-world networks is slightly larger than that on scale-free networks. This phenomenon can be interpreted by considering the difference in the topological structure of the networks. The degree distribution of scale-free networks is highly heterogeneous, but their clustering coefficient [25,38] is very close to zero. However, homogeneous small-world networks have a considerably higher clustering coefficient, i.e., in topological terms, there is a heightened density of loops of length three in the networks [38]. In self-organized communication systems, network clusters to a large extent contribute to maintaining the current opinions of agents instead of being freely changed. From this perspective, the optimal value of α on scale-free networks cannot provide enough influence to impose the names (opinions) of the clusters of triangle formation in the case of small-world networks. Thus a higher value of α is required for the fastest convergence on small-world networks.

In order to better understand the effect of name weight on the coevolutionary dynamics for achieving convergence, investigations of some affinitive quantities would be indispensable. In view of the above illustration, we know generally

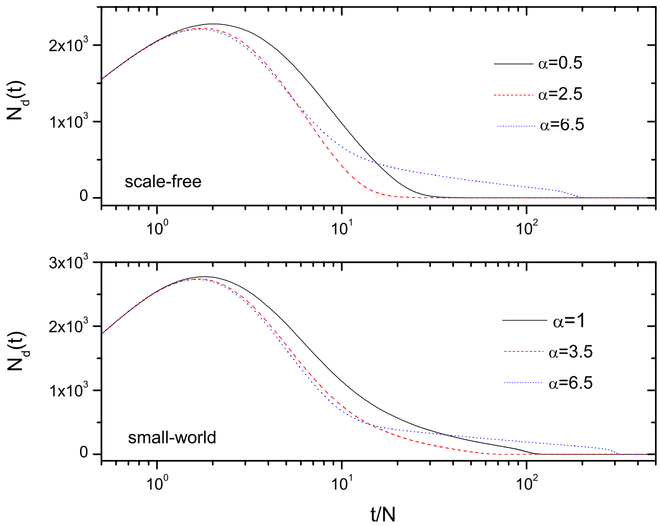

Fig. 2. Time evolution of the number of different names $N_d(t)$ versus rescaled time t/N, for different values of α with fixed average degree $\langle k\rangle = 6$ and network size $N = 6000$, on scale-free networks and small-world networks, respectively. Data points are obtained by averaging over 100 independent realizations.

that α plays an important role in the process of evolution. In the following, we mainly focus on why higher values of α inhibit the progress of global consensus. First, we report the evolution of the number of different names N_d in Fig. 2. At the early stage of coevolution, there exists a negligible behavior difference for different values of α. Initially distinct names are invented and directly transmitted, the number of which rapidly grows and reaches a maximum scaling synchronously as N for different values of α. As the coevolution proceeds to the middle stage, the decrease in N_d for higher α is slightly faster than that for smaller α, i.e., higher α is more likely to expel the names with lower weights through successful negotiations. Along with name spreading, the agreement dynamics induces the establishment of local consensus (i.e., the formation of name clusters [23]), in each of which agents share a common unique name. Moreover, a higher α leads to more clusters being constructed during the coevolution. Nevertheless, it takes a long time for competition between different name clusters and for a strong cluster to successfully invade the other clusters and finally dominate the system with a global consensus. Therefore, higher α precludes fast convergence and spends a longer time in an asymptotic absorbing state until reaching the final consensus.

To support the above discussion on N_d, we report the final accumulated weights (F_w) of names, defined as follows, versus the rank-size distribution in Fig. 3,

$$F_w = \frac{\sum_l w_{del}}{T_c/N},$$

where w_{del} is the weight of a certain name being deleted by success negotiation and the sum is over all the times when this name is cancelled. To some extent, F_w implies the survival time of a name in the system, i.e., generally speaking, the lower the value of F_w, the earlier the name vanishes from the system. The larger number in rank, the lower its corresponding rank. In particular, the name of rank 1 stands for the one surviving in the final consensus. As one can see that, for lower rank names, F_w induced by a larger α is smaller than that induced by a smaller α. This phenomenon indicates that a larger α has a stronger ability to expel distinct names compared to a smaller α, which is consistent with the middle stage of coevolution in Fig. 2. For instance, there are three names in one's memory, the weights of which are 1, 1, 2, respectively. Then the name of weight 2 is chosen with larger probability for $\alpha = 6.5$, compared to that for $\alpha = 0.5$ or 2.5, and propagates locally, quickly leading to other names vanishing with smaller weights. On the other hand, for higher α, the growth of name clusters by coarsening in different areas leads to the homogeneous formation of tribes. With these coevolutionary dynamics process, the weights of names increase continuously both within the cluster and across clusters. The extra-cluster interaction means an active contention between different clusters of agents. Nevertheless, these large homogeneous clusters of higher α are so strong and persistent that invasion is very difficult, which also results in the weights of names of different clusters intensively growing through intra-cluster interaction. In contrast, moderate values of α, such as $\alpha = 2.5$ on BA networks and $\alpha = 3.5$ on NW networks, produces relatively heterogeneous clusters, which benefits names diffusing across different clusters. As we can see in Fig. 3, for higher rank, there is a slowly decreasing velocity in rank of names vanishing finally for larger α. Intuitively, the competition of these approximately identical ranks of names needs a longer time for the consensus state compared to the case where the rank difference is relatively large. Here, it should be pointed out that smaller α can not provide enough strength to invade name clusters, thus it also produces a slightly slower decreasing tendency in rank

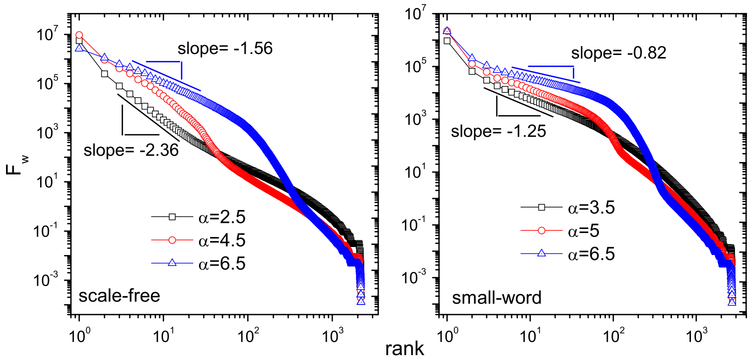

Fig. 3. Log–log plot of rank-size distribution, i.e., the rank versus the final total weights (F_w) of names on scale-free networks and small-world networks, respectively. The size of both networks is $N = 6000$ with fixed average degree $\langle k\rangle = 6$.

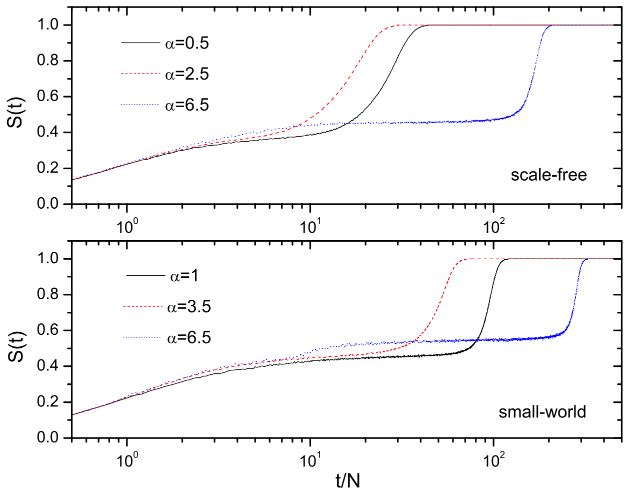

Fig. 4. Time evolution of the success rate $S(t)$ versus rescaled time t/N for different values of α with fixed average degree $\langle k\rangle = 6$ on scale-free networks and small-world networks. Here, $N = 6000$. Data points are obtained by averaging over 100 independent realizations.

compared to the optimal value of α. Therefore, these phenomena correspond well to the converging velocity at the late stage of coevolution in Fig. 2.

We report another relevant quantity, the time evolution of the average success rate $S(t)$ in negotiation, in Fig. 4. Similar to previous studies, after a rapid increase, $S(t)$ reaches a plateau with a slowly increasing rate. Subsequently, $S(t)$ rises to 1 over very short periods. In the early stage, different values of α have a negligible effect on $S(t)$. Once the formation of a name cluster emerges in the middle stage, α plays an important role in deciding the success rate. The intra-cluster interaction enhances the success rate, thus $S(t)$ for larger α first reaches a plateau which is higher than that for smaller α on both networks. On the other hand, the powerful competition between different clusters causes $S(t)$ to become almost stable for long periods of time. Nevertheless, for the relatively heterogeneous name clusters of moderate α, the diffusion and free invasion of names favor the coarsening of a strong cluster, which leads to an earlier fast increase of $S(t)$ towards 1, so that the convergence of global consensus is accelerated.

It is interesting to explore the evolutionary behavior of the total memory $N_w(t)$ used by all agents in the system. To our best knowledge, the size of the total memory means the quantity of occupying resources in communication systems. If agents observe a set of different objects for naming games or opinion formation models in reality, the required memory would be of more practical importance. Here, we also neglect the semantic correlation among objects and just consider a single one in our study. We report $N_w(t)$ for different values of α on scale-free and small-world networks in Fig. 5. It is observed that there exists a maximum value of the total memory, $N_w^{\max}$, for each α. Moreover, the higher the value of α, the smaller the size of $N_w^{\max}$, especially on BA networks. This is because in the middle state of evolution, a higher success rate results in a faster name elimination in the memories of agents for higher α, and vice versa. This phenomenon indicates that both larger and smaller maximum total memory used by agents are unable to induce the fastest convergence. Similar to the results reported in Ref. [32], some trade-off between the total memory and the convergence efficiency is required, i.e., to converge faster, more total memory is used by agents, which can be optimally reproduced by moderate α. In the late stage, the rapid increment of success rate towards 1 induces a decrease in N_w most quickly for moderate α, while the long plateau of $S(t)$ makes N_w have a similar behavior for higher α.

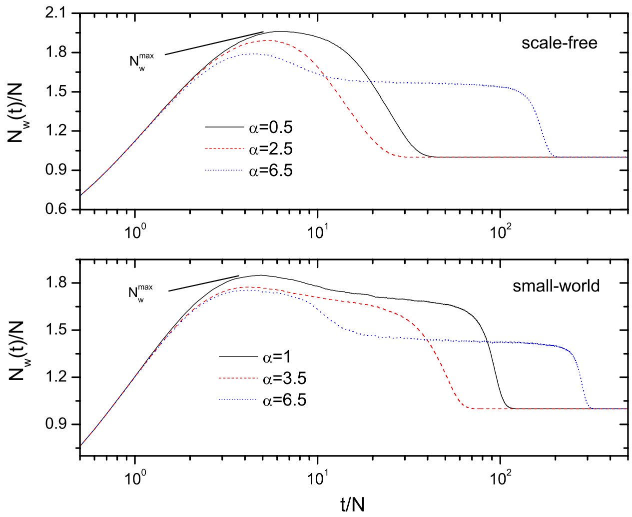

Fig. 5. Time evolution of the average memory per agent $N_w(t)/N$ versus rescaled time t/N for different values of α on scale-free networks and small-world networks. Both networks have fixed average degree $\langle k\rangle = 6$ and size $N = 6000$. Data points are obtained by averaging over 100 independent realizations.

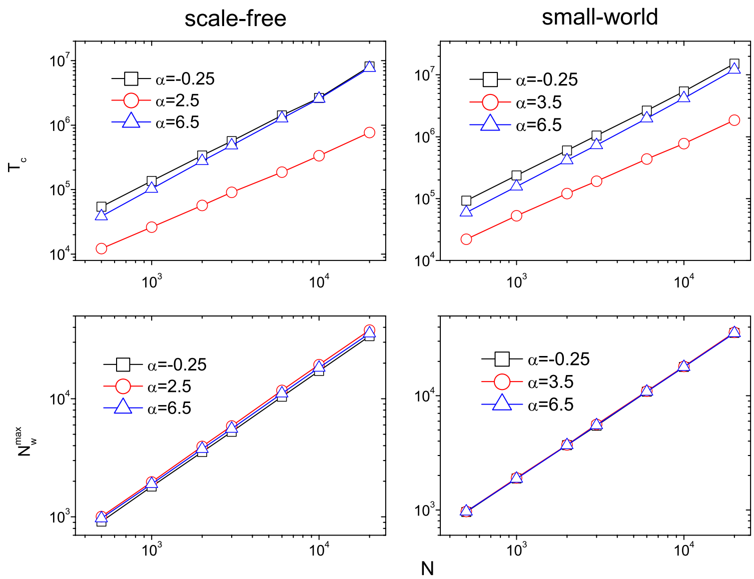

Fig. 6. Convergence time T_c and maximum total memory N_w^{max} as functions of the network size N for different values of α on scale-free networks (left two panels) and small-world networks (right two panels). Both networks have fixed average degree $\langle k\rangle = 6$. T_c scales as N^β on both networks. Explicitly on BA networks, the scaling parameters β of $\alpha = -0.25,\ 2.5,\ 6.5$ are 1.52, 1.17 and 1.53 respectively. For NW networks, β from top to bottom is 1.46, 1.51 and 1.22. Each data point is obtained by averaging over 500 independent realizations.

Finally, we investigate the scaling property of the convergence time and the maximum total memory of agents on BA and NW networks, respectively. For both networks, as shown in Fig. 6, T_c scales as N^β, with β being an estimated parameter and slightly depending on the value of α. In particular, for the optimal value of α on both networks, 2.5 and 3.5, T_c scale as $N^{1.17}$ and $N^{1.22}$, respectively, which are both smaller than the previous models (for instance, both scaling parameters are 1.4 in the original minimal naming game [28], and in the asymmetric negotiation naming game [32] are 1.18 and 1.35, respectively). Similar to the original naming game, N_w^{max} scales linearly with the size of the network, and presents a universal robust feature in our coevolutionary naming game.

4. Conclusions

In this paper, we have studied a modified minimal naming game, in which names coevolve with their weights on both BA scale-free networks and NW small-world networks. Among the diverse names, agents are more inclined to select more popular ones to communicate with others. Thus it is reasonable to associate the popularity of names with their communication frequencies. Interestingly, it is found that there exists an optimal value of parameter α leading to the fastest convergence of the population, i.e., diversity induced by name weight can promote convergence efficiency, but too much diversity is not desirable for fast convergence. Through plotting the rank distribution of the total weights of the canceled names, this nonmonotonous behavior can be explained qualitatively in that a very strong influence of name weight (i.e., higher α) produces many local name clusters easily, but inhibits the progress of global consensus to a greater extent. We have also investigated some relevant statistical quantities to characterize the dynamical behaviors, including the number of different names, the success rate in negotiation and the total memory of agents. All results obtained demonstrate that the influence of name weight plays an important role in the evolutionary process of self-organized communication systems. We further investigate how the convergence time and the maximum total number of names depend on the network size. It is found that the scaling parameter is smaller than that in the previous models in the convergence time for the optimal α, while the robust property of the maximum total memory, scaling linearly with the network size, shows a similar dynamical behavior. We hope that our work can offer some insight into the investigation of intricate consensus dynamics in language games.

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