Linguistic Convergence in Societies with Asymmetrically Distributed Reputation

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Abstract. Following the line of research introduced by (Baronchelli *et al.*, 2006) and developed by (Brigatti, 2008), this paper explores the impact of reputation in the process on linguistic convergence. To do that, we consider societies with two groups of asymmetrically distributed reputation, and simulate processes of language change under several configurations of the society and values of reputation.

1 Introduction

To fully understand the dynamics of language change and evolution simple computational models are needed. These models can help to simulate processes that cannot be completely explained only by using learning parameters in each generation of speakers. The mechanisms underlying language change act not only across generations, but in the every day utterances, and, because of this, language change is very fast. Furthermore, it is also remarkable that speakers are not usually aware of most of the changes in their grammar and phonological systems.

The emergence of cognitive capacities that allow human beings to talk, as well as syntax and semantics, have been approached by several models that explain the arising of compositionality and the building of a common linguistic knowledge in a society (Smith *et al.*, 2003).

Language change and interaction, as well as approaches to language convergence and splitting, can take advantage of these simple models launched to account for language evolution and emergence.

Among the proposals that have been introduced, one of the simplest experiments to understand language convergence is the one by Baronchelli 2006. Baronchelli's model is based in a variant of the naming game (Steels, 1997) strengthening the feature of simplicity. In Baronchellis model, a number of agents have to agree in naming an object with no pre-established protocol. Two chief features of the model are that : a) the agents have nothing in the beginning, and b) they delete every word they have stored for an object when they agree with another individual. Mathematical and physical results obtained by this model show how there is strong correlation between the parameters of the simulation (Baronchelli *et al.*, 2006).

After Baronchelli's work, Brigatti introduced the concept of reputation in the process of linguistic convergence, pointing out the possibility of analyzing the influence of such parameter in language evolution. This is where the present paper is placed. The main goal of this work is to pay some attention to the impact that different distributions of reputation in a society can have to the final result of the process of linguistic convergence.

The method that has been used in the paper relates to complex adaptive systems (Holand, 2006) and complex network theory (Strogatz, 2001). After defining some agents, they have to interact until they are able to create a society with a linguistic code. Social networks (Wellman & Berkowitz, 1988) and social impact theory (Nettle, 1998) can help to understand the dynamics of these societies, and their input and output configuration. In other words, we claim that language and linguistic interaction can change the configuration of the society and, to demonstrate that, we suggest the use of computational simulations and the mathematical support that complex network theory provides.

To develop the topic, in Section 2 we introduce Baronchelli's model with the parameter of reputation, slightly different from the one offered by Brigatti. In Section 3, we study the main results of the model, offering a discussion in Section 4.

2 Convergence Model with Reputation

Brigatti introduces the concept of reputation in the simple Baronchelli's scheme. The idea is very interesting because it highlights the relevance of social position in language change. In (Brigatti, 2008) the main results of the model are explained. One of the suggestions of this author is the study of the impact of reputation in a society with individuals gathered in two groups of different status.

This paper deals with the process of linguistic convergence in societies with two different social groups, named H (High reputation) and L (Low reputation), each one with a given reputation (R_H and R_L). The difference of reputation between H and L ($R_H - R_L$) is denoted by δ. Following Brigatti's assumption, communication between two agents Speaker (S) and Hearer (E) is allowed even if they have two different values of Reputation (R). If the communication is successful - if S and H share the word they exchange - the parameter of reputation does not play any role, but if communication fails because a word W sent by S in not known by E, then reputation becomes a key parameter in the development of the linguistic evolution of the society.

Establishing a rough parallelism between populations of agents and societies, we can say that we want to test the behaviour of societies with two clearly different social groups, one of them (H) being more powerful (in a degree δ) than the other (L). In such society everybody is allowed to communicate with everybody if they share the same linguistic items, but individuals of L are not able to extend their words to individuals in H, or, in other words, people from H do not learn any word from L. Our hypothesis is that, in such societies, linguistic confluence is always reached, but the time and memory needed by the process varies depending on both the size of complementary groups H/L and δ.

When the evolution starts, every agent has an empty store and not predefined protocols are established. The algorithm for communication is based in the one in (Brigatti, 2008) but it includes some modifications. It is the following :

- Speaker (S) and Hearer (E) are randomly selected.
- If H has words stored, it selects one. If not, it invents one.
- The speaker transmits the selected word to the hearer, characterized by the reputation R_E
- If the hearer's inventory contains such a word, the communication is a success. The two agents update their inventories so as to keep only the word involved in the interaction. The speaker's reputation increases by one.
- Otherwise, if $R_S > R_E$, the hearer adds the new word to its inventory and the speaker does nothing. The speaker's reputation decreases by one.
- If hearer's inventory does not contain such a word and $R_S < R_E$, the communication is a failure. The speaker's reputation decreases by one.

In this model, success is not quantified, since this measure is not relevant for the study we are carrying out here.

The main aspects that will be investigated in this paper, are the following :

1. The influence of δ in the convergence process.
2. The influence of the distribution of H and L in the convergence process.
3. The evolution of R during the computation.

To do that, we study by means of computational simulations, the following general parameters :

- t_{conv}, the total time the system takes to reach convergence
- W_{max}, the maximum number of words the system reaches at time t_{max}
- W_{dif}, the maximum number of different words
- t_{max}, the time where the system gets W_{max}
- Variation of R_H and R_L

3 Results

The results analyzed here are obtained with small populations of only 100 agents, averaged after 100 runs of the program.

The first value to analyze is t_{conv}, showing the results summarized in Figure 1. There are several aspects worth to highlight :

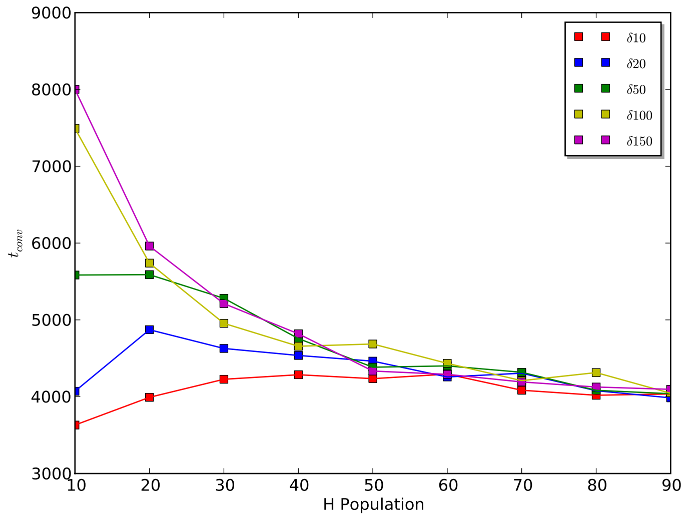

FIGURE 1 – Results of t_{conv} with different values of δ

- δ is important in societies where $H < 50\%$ and very important when $H < 30\%$. With $L \geq 50$, it can be said that the smaller H is, the greater is the impact of δ.
- In groups where $H > 50\%$, the impact of δ is negligible.
- For societies with $\delta \leq 10$, $H = 10\%$ presents a more efficient behaviour than $H = 90\%$. With other values of δ, the configuration with $H = 90\%$ is clearly the fastest to achieve convergence. The difference in the results with $H = 10\%$ and $H = 90\%$ increases proportionally to δ.
- Whereas the results obtained in societies with $H \leq 40\%$ are clearly dependent on δ, the results with social distributions where $H \geq 60\%$ are only slightly dependent on δ, and with $H = 90\%$ the results are independent on δ, this is, there is no influence of δ in the time these societies need to reach convergence.

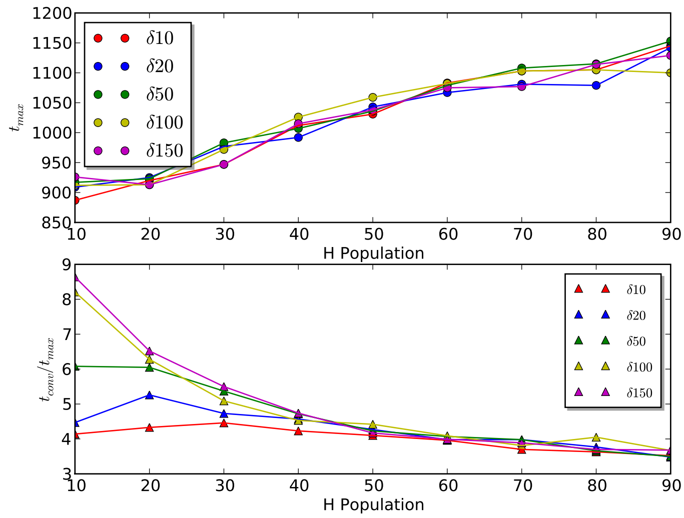

FIGURE 2 – Up : results of t_{max} with different values of δ and H. Down : t_{conv}/t_{max}

Concerning these results, Brigatti, who tested a very similar program using only $\delta10$, remarks that the consensus is easier in authoritarian communities with a few individuals with high reputation. In our program, this could be said looking also to the outcome with $\delta10$. But with higher values of δ the interpretation is completely different. These communities get worst results, showing that, finally, the totally reverse distribution, with $H = 90$ is more efficient for convergence, attending only to t_{conv}.

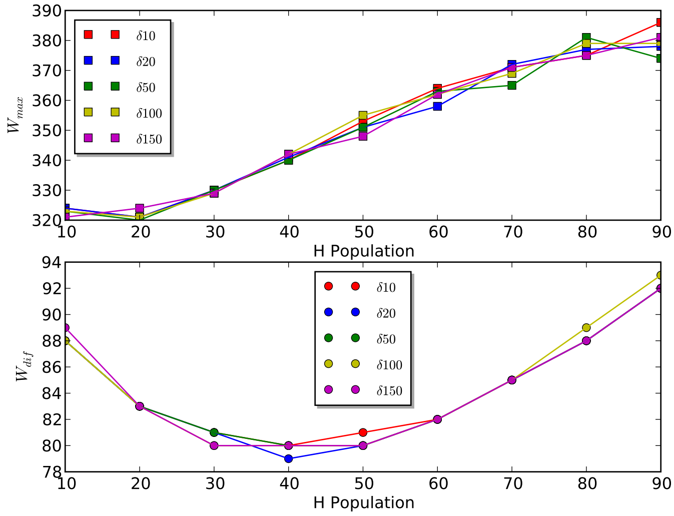

FIGURE 3 – W_{max}, W_{dif} with different values of δ and H

The behaviour of t_{max}, can be seen in Figure 2 (top). On the contrary than the values for t_{conv}, the parameter δ does not seem to have any influence in the final result, that shows a progressive increasing of the value with the higher H. Since t_{max} is a parameter that is linked to W_{max}, the relationship if the value with H can be explained in the following way. In the system, agents belonging to both groups, H and L are allowed to produce new words, but H always have the final winning word, in a way that, being H smaller means having less competence, and this implies generating a smaller amount of words. However, the comparison between t_{conv} and t_{max} refers to another phenomenon. If populations with $H = 10$ reach soon t_{max} and get the worst results for t_{conv}, this means that there is a hard "fight" to decide the final winning word among a small number of them, and spread it in the large population L. This can be seen in Figure 2 (bottom), that explains the relationship between t_{conv} and t_{max}, and shows how systems with $H \geq 50$ are more balanced in transitions t_0 to t_{max} and t_{max} to t_{conv}.

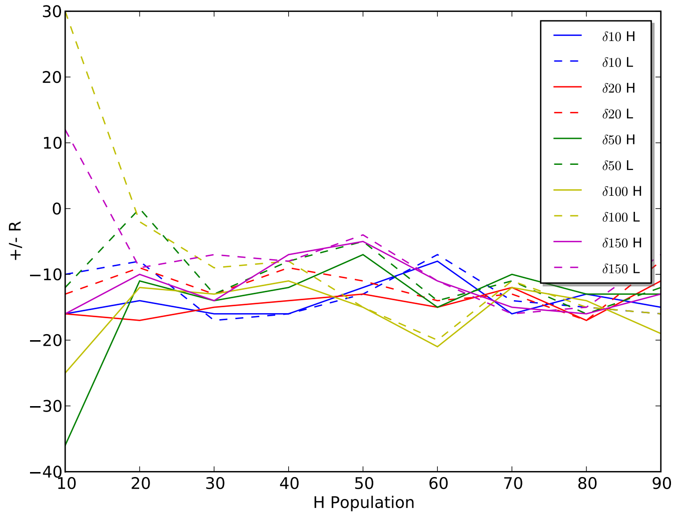

FIGURE 4 – Variation of reputation in systems with asymmetrically distributed populations

Whereas values t_{conv} and t_{max} refer to the speed of the system (society) to converge, W_{max} and W_{dif} establish the memory the system needs to perform the operations to reach the convergence. Figure 3 shows the outcome of the simulation for different values of δ.

The parameter W_{max} has extremely similar results with every δ, with small variation depending on H/L. The value increases from $H = 10\%$ to $H = 90\%$ with almost the same results in any case. An exception to this rule is found with $H = 20\%$, whose results are always lower than the ones with $H = 10\%$. This confirms, again, the difficulty the system finds to converge with a distribution of the $H = 10\%$ with high values of δ.

W_{dif} follows a convex distribution. Like in W_{max}, δ does not seem to have a great impact in the final result. In all cases, the initial left end is 88/89 and the right end is 92/93. The peak is achieved at $H = 40\%$ for $\delta 10$ and $\delta 20$, in $H = 40\%, 50\%$ for $\delta 50$ and in the segment $H = 30\% - 50\%$ for $\delta 100, \delta 150$.

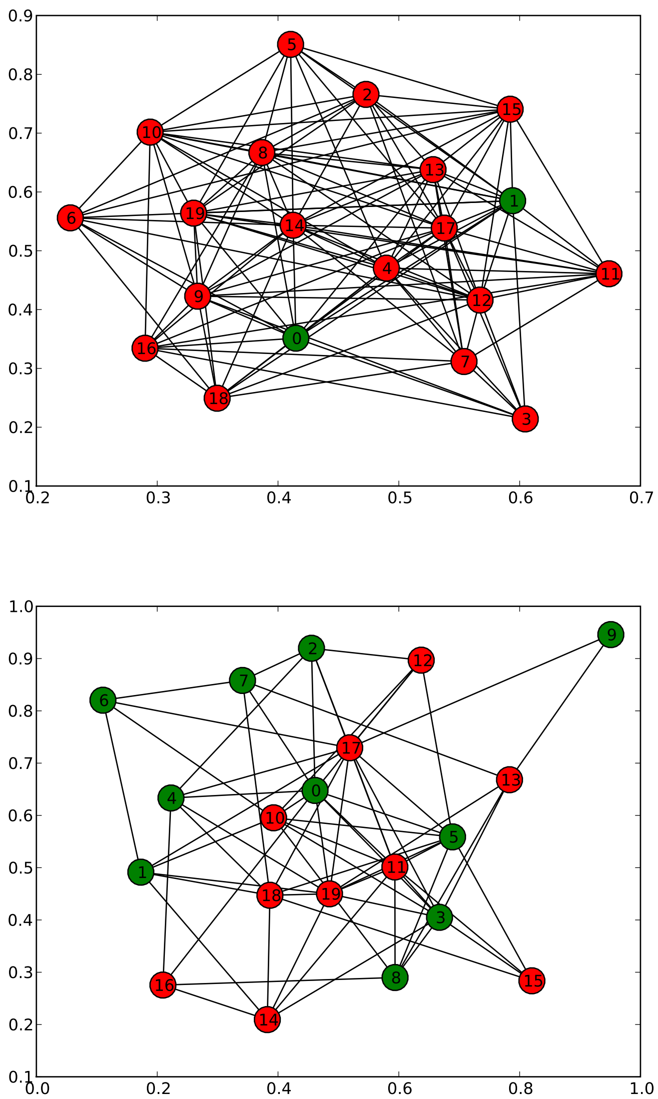

FIGURE 5 – Social dynamics established to reach the consensus in two societies with different distribution of Reputation and social groups. Top $\delta 50$, 50/10. Bottom $\delta 50$, 50/50

The last aspect that we are approaching in this article is the variation of R along the computation. To do that, we check the average difference between the initial and the final reputation in H and L, as it can be seen in Figure 4. As a general tendency, the whole population looses reputation, but the group H looses more than L, like following a rule "if you have more, you lose more". Even though, in general, there is not a relationship between the initial R and the reputation an agent loses. Moreover, there is another unexpected fact, again with populations with $H \leq 10$. In these populations, with high values of δ, the group L strikingly increases the values of R while H decreases such values in the same way.

From here, a prediction can be inferred and should be tested in the future : running different processes of linguistic confluence in societies with asymmetrically distributed R and inheritance of R would give rise to equal R populations.

The social dynamics of the game has been also studied, as can be seen Figure 5. This work is based in the hypothesis that creating language has to do with social interaction, and that while language is in process of convergence, the structure of the society is transforming or emerging. If the society is represented by a dynamic graph, the evolution of the network can show the dynamics of the society. In our simulation, we are using only 20 agents for the sake of clarity. This small sample reproduces in a reduced scale what happens in large societies. At the beginning the agents do not have any connection. For every successful linguistic interaction, an edge is created between S and E. For every unsuccessful interaction between two nodes, if they are joint by an edge, this is removed. The first picture of Figure 5 represents the final state of a very small society with a difference of reputation $\delta 50$ and only the 10% with the highest degree. The picture at the bottom shows how the society with the same value of δ and two different social groups H and L of the same size, reaches a consensus with a considerable faster social negotiation. Therefore, following the model, it can be stated that taking decisions is way more difficult with a small group with higher power.

4 Discussion

This paper highlights the role of reputation in language change, starting from a very simple model (Baronchelli *et al.*, 2006) without pre-established protocols in the agents. The work shows that there are two different parameters, the distribution of reputation in a society and the difference between both groups, that have an influence on the evolution of language.

Considering the efficiency of the systems, the ones using less time and memory in their operations, the conclusions we can extract from these simulations, are the following :

– In terms of time, with values of $\delta > 10$, systems converge faster with configurations where H is 90%.
– In terms of memory, the best configurations are achieved with $H \leq 40$ for W_{max} and $H = 40$ for W_{dif}.
– Considering time/space categories, an optimal configuration of society for fast and efficient convergence would be one with $H = 10/20$ and $\delta \leq 10$. But looking at general conditions, it can be said that systems with $H/L \approx 1$ assure a fast convergence with almost every value of δ.

As for the variation of reputation, the results suggest that after a number of processes the whole population would have similar levels of R, in a way that $\delta \to 0$. A question for the future would be demonstrating this rule by applying simulations many times in the same population with inheritance of R.

For the future, it could be interesting to explore if some other models of language learning and transmission that seem to be more realistic allow the application of reputation in their formalization. The final result of this research can be to remark the importance of social structures in language evolution and change.

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