



A fast no-rejection algorithm for the Category Game

Francesca Tria^{a,*}, Animesh Mukherjee^a, Andrea Baronchelli^b, Andrea Puglisi^{c,d}, Vittorio Loreto^{c,a,d}

^a Institute for Scientific Interchange (ISI), Viale Settimio Severo 65, 10133 Torino, Italy

^b Departament de Física i Enginyeria Nuclear, Universitat Politècnica de Catalunya, Campus Nord B4, 08034 Barcelona, Spain

^c Dipartimento di Fisica, Sapienza Università di Roma, Piazzale Aldo Moro 5, 00185 Roma, Italy

^d CNR-ISC Piazzale Aldo Moro 5, 00185 Roma, Italy

ARTICLE INFO

Article history:

Received 21 December 2010

Received in revised form

20 September 2011

Accepted 3 October 2011

Available online 12 October 2011

Keywords:

Category game

Metastable states

No-rejection algorithms

Agent-based simulation

ABSTRACT

The Category Game is a multi-agent model that accounts for the emergence of shared categorization patterns in a population of interacting individuals. In the framework of the model, linguistic categories appear as long lived consensus states that are constantly reshaped and re-negotiated by the communicating individuals. It is therefore crucial to investigate the long time behavior to gain a clear understanding of the dynamics. However, it turns out that the evolution of the emerging category system is so slow, already for small populations, that such an analysis has remained so far impossible. Here, we introduce a fast no-rejection algorithm for the Category Game that disentangles the physical simulation time from the CPU time, thus opening the way for thorough analysis of the model. We verify that the new algorithm is equivalent to the old one in terms of the emerging phenomenology and we quantify the CPU performances of the two algorithms, pointing out the neat advantages offered by the no-rejection one. This technical advance has already opened the way to new investigations of the model, thus helping to shed light on the fundamental issue of categorization.

© 2011 Elsevier B.V. All rights reserved.

1. Introduction

The Category Game (CG) is a computational model in which a population of individuals co-evolve their own system of symbols and meanings by playing elementary language games [1]. It has been introduced to investigate how categorization can emerge from scratch in a group of individuals who interact in a pairwise way without any central coordination. The reference problem is color categorization, which is a central issue both in linguistics [2] and in cognitive science [3–5]. Color naming represents in fact a fundamental access point to human cognition, and at the same time provides important clues on language evolution. The evolution of English color categories constitutes an excellent example. English color terms exhibited a gradual semantic shift from largely brightness color concepts (Old English) to almost exclusively hue concepts (Middle English) [6]. The World Color Survey, moreover, showed that color systems across language are not random [7,8], but rather exhibit certain statistical regularities, thus opening the way to a revolution in cognitive science [5,9].

The main point of interest of the CG is that it is able to reproduce qualitatively and, most remarkably, quantitatively the empirical data gathered in the World Color Survey [10]. Kay and Berlin [7] ran a first survey on 20 languages in 1969. From

1976 to 1980, this unique and extensively studied database was enlarged by the same researchers along with W. Merrifield and the data was made publicly available since 2003 on the website <http://www.icsi.berkeley.edu/wcs>. These data concern the basic color categories of 110 languages without written forms and spoken in small-scale, non-industrialized societies. On average, 24 native speakers from each of this language were interviewed by expert field linguists. Every informant was tasked to name each of 330 color chips produced by the Munsell Color Company that represent 40 gradations of hue and maximal saturation, plus 10 neutral color chips (black-gray-white) at 10 levels of value. The chips were presented in a predefined, fixed random order, to the informant who had to name each of these colors with primarily a “basic color name” from her language (in English, “basic color names” would correspond to words like “red”, “green”, “yellow”, “blue”, etc. for more details see [7]).

The Category Game model differs from the other models defined to address similar issues [11–18] in that it accounts for the categorization of a genuinely continuous perceptual channel and it describes a categorization pattern as a continuously evolving metastable state on which the population shares a temporary consensus [1,19]. The latter characteristic is intriguing and underlies the existence of a new framework to address the puzzling problem of language change, which turns out to be at the same time propelled by the interaction among the speakers and impeded by the need of these speakers to understand each other [19]. The presence of this sort of frustration renders the dynamics of the model so slow

* Corresponding author.

E-mail address: fra.trig@yahoo.it (F. Tria).

that it has been so far impossible to investigate and quantify properly the details of the long time behavior, even for small population sizes.

Here we present a fast algorithm suitable for studying the CG dynamics over large timescales and for moderately large population sizes. The algorithm is, in spirit, similar to those suggested for accelerating Monte Carlo simulations (see [20,21] and also [22] for other examples), where the key ingredient is to avoid rejection steps (hence the “no-rejection” tag in the title). Of course, however, the dynamics we are referring to is substantially different, so new methods had to be developed in order to tackle the specific aspects of the model under consideration. In general, this area of research has gained immense popularity over the past few years and as a consequence the new field of computational science came into existence [23–25]. The rest of the paper is organized as follows. In Section 2, we outline a detailed description of the CG model. The next section presents the fast algorithm suitable for investigating the long-time CG dynamics. Section 4 compares the outcomes of the fast algorithm with the original one, showing excellent qualitative as well as quantitative agreement. In this context, a detailed investigation of a set of relevant observables is also performed, shedding new light on the “microscopic” origin of the “macroscopic” behavior of the system. In Section 5 we show the computational complexity of the proposed fast algorithm, compared with the one of the original model. We conclude in Section 6 by summarizing our contributions and pointing to possible future applications of this method.

2. The Category Game model

The Category Game model [1] is crafted to examine how a population of interacting individuals can develop through a series of language games [26] a shared form-meaning repertoire from scratch without any pre-existing categorization. We consider a population of N artificial agents each of them having, without any loss of generality, a one-dimensional continuous perceptual space spanning the $[0, 1]$ interval. A categorization can be identified as a partition of this space into discrete sub-intervals which we shall denote from now onwards as perceptual categories. Each agent has a dynamical inventory of associations linking the perceptual categories (meanings) to words (forms) that are used to name each of these categories. The perceptual categories as well as the words associated to them co-evolve over time through a series of simple communication interactions among the agents (or “games”).

In each game, two individuals are randomly selected from the population and one of them is assigned the role of a speaker while the other the role of a hearer. Both the speaker and hearer are presented with a scene of $M \geq 2^1$ stimuli (objects) where each stimulus corresponds to a real number in the $[0, 1]$ interval. By definition, no two stimuli appearing in the same scene can be at a distance closer than d_{\min} which is the only parameter of the model encoding the finite resolution power of any perception, for instance, the human Just Noticeable Difference (JND). In psychophysics, JND is defined as the minimum amount by which the stimulus intensity must be changed in order to produce a noticeable variation in sensory experience [27].

One of the objects is the *topic* of the communication. The task of the speaker is to communicate this to the hearer using the following prescription. The speaker utters a word associated with the topic while the hearer tries to guess its meaning from the word she “listened”. The speaker always checks whether the topic is the unique stimulus to lie in a specific perceptual category among all

the presented stimuli. If it is not, i.e., if the two stimuli collide on the same perceptual category, then a new boundary is created in the perceptual space at a location corresponding to the middle of the segment connecting the two stimuli. A new word is invented for each of the resultant two new categories. In addition, both of them inherit all the words corresponding to the old category. This process is termed as *discrimination*. Subsequently, the speaker utters the “most relevant” name for the category corresponding to the topic where the most relevant name is either the one used in a previous successful communication or the newly invented name in case the category has just been created due to a discrimination. For the hearer, there can be the following possibilities: (a) the hearer does not have any category containing an object and associated with the name, in which case the game is a failure, (b) there are one or more categories associated with this name and containing an object in the hearer’s inventory. In this case, the hearer randomly chooses one of them. If the category chosen corresponds to that of the topic, the game is a success, otherwise it is a failure.

Depending on the outcome of the game one or both the agents update their repertoires. In case of a failure, the hearer adds the word in her repertoire linked to the category corresponding to the topic (eventually discriminating it). In case of success, this word becomes the most relevant name for the category corresponding to the topic for both agents and they remove all other competing words from their respective repertoires linked with this category. Note that if both the speaker and the hearer already have only the successful word in the corresponding category, the inventory of both of them remains unaltered after the game. This situation, as already mentioned in the introduction, corresponds to a rejection step of the Monte Carlo algorithm. The time t of the dynamics is simply measured as the number of games played by the agents.

All the agents start without perceptual categories and without category labels. During the dynamics, discrimination creates finer and finer boundaries (“perceptual categories”) and produce more and more category labels, unsuccessful games spread such labels through the population, and successful games reduce the dictionaries associated to the categories to single winning words shared by at least two players. Quite rapidly the N agents develop a fine structure of perceptual categories represented by one or two words, shared by the population. But there is also another fundamental phenomenon which occurs unexpectedly in the dynamics: nearby perceptual categories (after a lucky sequence of games) may share the same category label. In this way, a spontaneous competition of labels arises, to *conquer* larger and larger groups of adjacent perceptual categories. These groups are what we call “linguistic categories”.

In summary, the CG dynamics results in the emergence of a hierarchical category structure comprising two distinct levels: a basic layer, responsible for the fine discrimination of the perceptual space (i.e., the perceptual categories), and a second shared linguistic layer that groups together perceptions having the same name to guarantee communicative success (linguistic categories). Note that while the number of perceptual categories is tuned by a parameter of the model and can be very large (of the order of $1/d_{\min}$), the number of linguistic categories turns out to be finite and small, as observed in natural languages (see Fig. 2). On an extremely much larger time-scale, however, tiny variations of categories and labels may occur, and eventually these linguistic categories may merge. This long time dynamics is something very interesting but extremely slow to be investigated.

3. A fast algorithm for the Category Game

The primary goal of developing a fast algorithm is to study the long time dynamics of the model. In the original algorithm

¹ Without any loss of generality in all our simulations we shall use $M=2$.

accessing such long timescales would be extremely costly because of the freezing of the dynamics into metastable states. In particular, there would be many games in which the two agents (i.e., the speaker and the hearer) would end up making no changes in the configuration of their respective inventories. The time would then increase by *one* time step. The basic idea behind the current version of the algorithm is to impose that each game produces an *outcome*, i.e., a change in one or both the inventories of the two agents that are playing. In this case, the time t has to be properly rescaled to recover the frozen dynamics. Furthermore, the correct statistical frequency of the different games (the playing order of the pairs and the probability to play in a given region) has to be reproduced in the no-rejection version of the model. In order to do so, we need to calculate both the probability that a game produces an *outcome* and the individual probabilities of each possible way in which the outcome can be obtained.

In particular, the main steps of the fast algorithm are the following (see also Algorithm 1 for the pseudocode):

Choosing the pair of players: this is the most important part of the algorithm since one has to choose a pair such that their game will produce an outcome. Let us define $p_{\text{out}}(i, j) = p_{\text{out}}(j, i)$ as the probability that a game between the two players will produce an outcome. We shall shortly describe the detailed method for computing this probability. For the time being, let us say that each of the $N(N-1)/2$ possible pairs will be extracted according to this probability².

Choosing the region for placing the topic: once the pair of players has been chosen, we impose that the game will produce an outcome. As we shall see below, an outcome can follow if the topic falls either in a mismatch region or in a soft match one (both of these terms will be defined shortly). Subsequently, we need to choose the region to place the topic proportional to the corresponding probabilities $p_{\text{out}}^{\text{MIS}}(i, j)$ (for the mismatch region) and $p_{\text{out}}^{\text{SOFT}}(i, j)$ (for the soft match region)³.

Game: the game is performed in the selected region with the same rules as in the original CG algorithm summarized in Section 2.

Rescaling time: at the end of each game, time is increased by a factor $1/p_{\text{out}}(i, j)$.

Note that, of course, each probability is also a function of time as shown in Figs. 5(a) and 7; however, we have not explicitly included t in all the variables to indicate this dependence so as to keep the notations as simple as possible. We shall maintain this implicit form from now onwards throughout the rest of the paper.

3.1. Extracting the no-rejection regions

In order to calculate the probabilities of interest, we introduce the following definitions: (i) a *match* region for the two playing

agents is a region where both the agents have the corresponding linguistic category settled (i.e., with only one label) and a unique label for it; (ii) a *mismatch* region is any interval in $[0, 1)$ that is not a match region. Note that since the match and mismatch between a pair of agents is symmetric and since all our probability calculations are based on these two values, it is obvious that $p_{\text{out}}(i, j) = p_{\text{out}}(j, i)$.

Let us now consider a game where a speaker-hearer pair and two stimuli are selected⁴. Of course, if the topic falls in a mismatch region an outcome is guaranteed. If the topic falls instead in a match region, the situation is more tricky. In this latter event, two cases are possible: either there is the necessity to discriminate (see Section 2) for one or both the agents, in which case the game produces an outcome, or the repertoire of both the speaker and the hearer remains unchanged (the outcome is null). To distinguish between these two events, let us refine the definition of a match region in the following way: we will denote a match region to be a *strict match* region if the lengths of the corresponding perceptual categories of both the speaker and the hearer are shorter than d_{min} . In this case no discrimination is possible, due to the finite resolution constraint, and the outcome of the game will be surely null. A match that is not strict shall be called a *soft match*.

3.1.1. Probability of playing in a soft match region

Since the soft match definition is based on the length of the underlying perceptual categories, it is natural to express the probability of having a game in that region as the sum of the probabilities of having a game in each of the underlying perceptual categories:

$$p_{\text{out}}^{\text{SOFT}} = \sum_a p_a^{\text{SOFT}}, \quad (1)$$

where the sum is over all the perceptual categories spanning the soft match region and we assume the dependence on the agents i, j to be implicit.

Thus, we have to calculate the probability that both the topic and the object fall in the perceptual category a which belongs to a soft perceptual match region and the game produces an outcome. Two events have to be considered simultaneously: (a) the topic falls in the match region, and (b) the object falls in the union⁵ of the two perceptual categories under consideration (i.e., of the speaker and the hearer) so as to produce a discrimination and, thereby, an outcome. As we recall from the above, the two events considered here are not independent but correlated through d_{min} . Consequently, we need to integrate all the different possibilities of placing the topic and the object maintaining this correlation. In order to write the correct expression, we define $x_{l,r}^S$ as the left and the right boundary, respectively, of the considered perceptual category of the speaker, and correspondingly for the hearer. Further, $x_{l,r}^{\text{min}} = \min(x_{l,r}^S, x_{l,r}^H)$, $x_{l,r}^{\text{max}} = \max(x_{l,r}^S, x_{l,r}^H)$, $X^{\text{max}} = \max(x_l^{\text{max}}, x_r^{\text{min}} + d_{\text{min}})$ and $X^{\text{min}} = \min(x_r^{\text{min}}, x_l^{\text{max}} - d_{\text{min}})$. An example illustrating the above terms is shown in Fig. 1. We finally obtain:

$$\begin{aligned} p_a^{\text{SOFT}} &= \int_{x_l^{\text{max}}}^{x_r^{\text{min}}} dy \int_{x_l^{\text{min}}}^{y-d_{\text{min}}} dz + \int_{x_l^{\text{max}}}^{X^{\text{min}}} dy \int_{y+d_{\text{min}}}^{x_r^{\text{max}}} dz \\ &= \frac{(x_r^{\text{min}})^2 - (X^{\text{max}})^2}{2} - (x_r^{\text{min}} - X^{\text{max}})(x_l^{\text{min}} + d_{\text{min}}) - \frac{(X^{\text{min}})^2 - (x_l^{\text{max}})^2}{2} + (X^{\text{min}} - x_l^{\text{max}})(x_r^{\text{max}} - d_{\text{min}}). \end{aligned} \quad (2)$$

² The actual probability with which each couple is extracted reads: $p_{\text{out}}(i, j) / \sum_{i' < j'} p_{\text{out}}(i', j')$.

³ Note that $p_{\text{out}}^{\text{MIS}}(i, j) + p_{\text{out}}^{\text{SOFT}}(i, j) = p_{\text{out}}(i, j)$. If we want to consider the conditional probabilities of having a game in a soft match region or in a mismatch region given that the game has an outcome, we have to divide the above defined probabilities by $p_{\text{out}}(i, j)$.

⁴ Without any loss of generality we shall consider from now onwards the first stimulus as being the topic of the game.

⁵ The union is the region in $[0, 1)$ that belongs either to the perceptual category of the speaker or of the hearer.

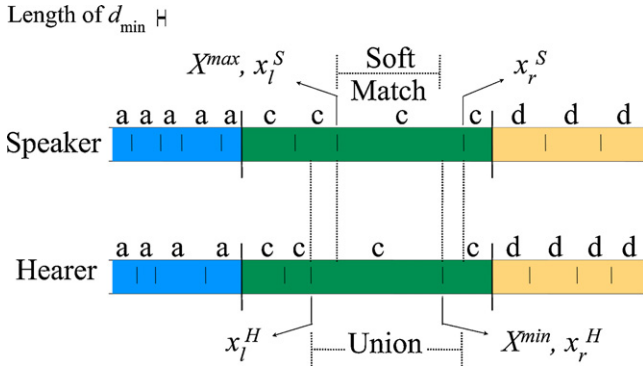


Fig. 1. An example to illustrate the different terms for computing p_a^{SOFT} . According to this figure, (a) $x_i^{\min} = \min(x_i^S, x_i^H) = x_i^H$, (b) $x_r^{\min} = \min(x_r^S, x_r^H) = x_r^H$, (c) $x_i^{\max} = \max(x_i^S, x_i^H) = x_i^S$, (d) $x_r^{\max} = \max(x_r^S, x_r^H) = x_r^S$, (e) $X^{\max} = \max(x_i^S, x_i^H + d_{\min}) = x_i^S$ (taking into account the length of d_{\min} shown in the figure), and (f) $X^{\min} = \min(x_r^S, x_r^H - d_{\min}) = x_r^H$ (taking into account the length of d_{\min} shown in the figure).

3.1.2. Probability of playing in a mismatch region

In order to obtain the probability of playing in a mismatch region, we have to consider once again the correlation due to the minimal distance d_{\min} in the extraction of the topic and the object. The probability of producing an outcome by means of a game in a mismatch region equals the probability that the topic falls in there. In order to calculate this probability, we must distinguish the case in which the first extracted object is the topic from the case it is not. In the first case, where the topic is the first extracted object, the probability that it falls in a mismatch region is simply the length of that region. In the second case, where the topic is the second extracted object, we have to consider the fact that it should be chosen at least d_{\min} far apart from the first object. This can be done in a similar way as described in the previous subsection for the calculation of the probability of playing in a soft match region and we shall call this probability. Since the first and second case occur with equal probability in the original model, we can write:

$$p_a^{\text{MIS}} = \frac{1}{2}(p_{a_{\text{first}}}^{\text{MIS}} + p_{a_{\text{second}}}^{\text{MIS}}) \quad (3)$$

$$p_{\text{out}}^{\text{MIS}} = \sum_a p_a^{\text{MIS}}, \quad (4)$$

where the sum is over all the perceptual categories spanning the mismatch region.

4. Comparison of the observables from the two algorithms

In this section, we show that this no-rejection version of the CG algorithm features the same dynamical properties of the original one. We consider all the relevant observables reported in [1] as well as new microscopic observables analyzed here for the first time.

4.1. “Macroscopic” observables

Here we look at (a) the average number of perceptual (n_{perc}) and linguistic categories (n_{ling}) per individual, (b) the success rate and (c) the perceptual and linguistic overlap across the population as functions of time for the two models (original and fast) we are comparing. We show simulations for different population sizes and a fixed $d_{\min} = 0.0143$ which is equal to the average human JND [10].

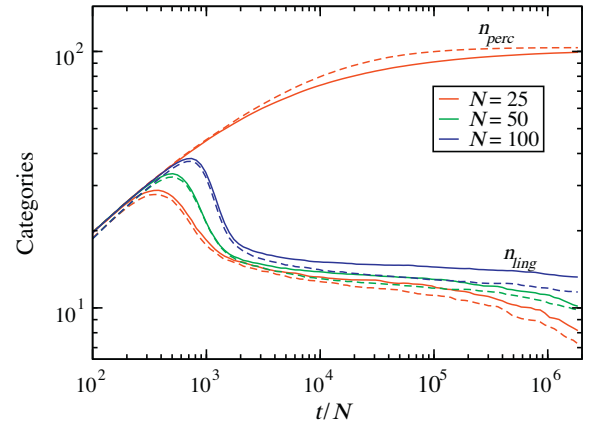


Fig. 2. Perceptual and linguistic categories obtained from the old and the new algorithm for $N=25, 50$ and 100 . Solid lines show results obtained from the old algorithm while broken lines indicate results obtained from the new algorithm. All the results are averaged over 30 samples.

Algorithm 1. A fast algorithm for the Category Game

Require: N, d_{\min}

```

1:
2:
3:
4:
5:
6:
7:
8:
9:
10:
11:
12:
13:
14:
15:
16:
17:
18:
19:
20:
21:
22:
23:
24:
25:

```

loop

extract a pair of individuals (i, j) from the population with a probability $p_{\text{out}}(i, j)$;

choose the region to place the topic proportional to the probabilities $p_{\text{out}}^{\text{MIS}}(i, j)$ (for the mismatch region) and $p_{\text{out}}^{\text{SOFT}}(i, j)$ (for the soft match region);

if the topic and the object collide on a single perceptual category **then**

discriminate by (i) adding a new boundary in the perceptual space at a location corresponding to the middle of the segment connecting the two stimuli, (ii) inventing a new word for each of the resultant two new categories and finally, (iii) adding all the words corresponding to the old category to these two new categories;

end if

the speaker transmits to the hearer the most relevant name of the category linked to the topic;

if the hearer does not have any category associated with the name **then**

the game is a failure;

end if

if there are one or more categories associated with this name in the hearer's inventory **then**

the hearer randomly chooses one of them (say c);

if c corresponds to that of the topic **then**

the game is a success;

else

the game is a failure;

end if

if the game is a success **then**

both agents delete all of the words but the transmitted one from the inventory of the category discriminating the topic;

els if the game is a failure **then**

the hearer adds the transmitted word to the category discriminating the topic;

end if

$t \leftarrow t + 1/p_{\text{out}}(i, j)$.

end loop

Fig. 2 shows the average number of perceptual⁶ and linguistic categories per individual obtained from the old and the new algorithms respectively versus the number of games per player (i.e., t/N). It is apparent from this figure that the new algorithm is not only

⁶ The average number of perceptual categories remains same across different population sizes as long as the value of d_{\min} is fixed. Therefore we only show one representative plot for the perceptual categories in Fig. 2.

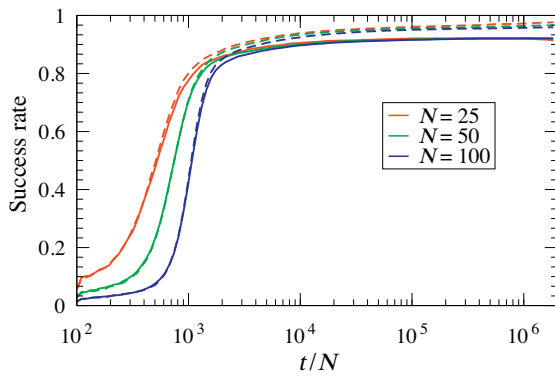


Fig. 3. Success rate obtained from the old and the new algorithm for $N=25, 50$ and 100 . Solid lines show results obtained from the old algorithm while broken lines indicate results obtained from the new algorithm. All the results are averaged over 30 samples.

able to reproduce the same phenomenology but also the outcomes are very close to what is obtained from the old algorithm.

Fig. 3 compares the success rate for the two algorithms versus t/N . The success rate is measured as the fraction of successful games over sliding time windows. The figure clearly indicates that the results from the two algorithms match (almost) accurately.

The overlap function [1] measures the degree of alignment of the category boundaries of two agents (i, j) and is defined as follows:

$$O = \frac{2}{N(N-1)} \sum_{i < j} O_{ij} \quad \text{with} \quad O_{ij} = \frac{2 \sum_{c_i} (l_{c_i})^2}{\sum_{c_i} (l_{c_i})^2 + \sum_{c_j} (l_{c_j})^2} \quad (5)$$

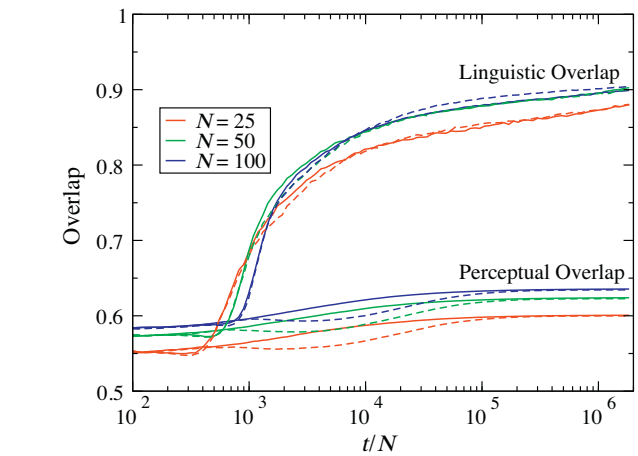


Fig. 4. Perceptual and linguistic overlap obtained from the old and the new algorithm for $N=25, 50$ and 100 . Solid lines show results obtained from the old algorithm while broken lines indicate results obtained from the new algorithm. All the results are averaged over 30 samples.

where l_c is the width of the category c , c_i is one of the categories of the i th agent and c_i^j is the generic category of the intersection set containing all of the boundaries of the agents i and j . The function O_{ij} returns a value proportional to the degree of alignment of the two category inventories reaching its maximum unitary value when they are perfectly aligned. The linguistic overlap is defined as in Eq. 5; however, only considering the boundaries between categories with different most relevant names.

Fig. 4 shows the perceptual and linguistic overlap obtained from the old and the new algorithm versus t/N . Once again there is an

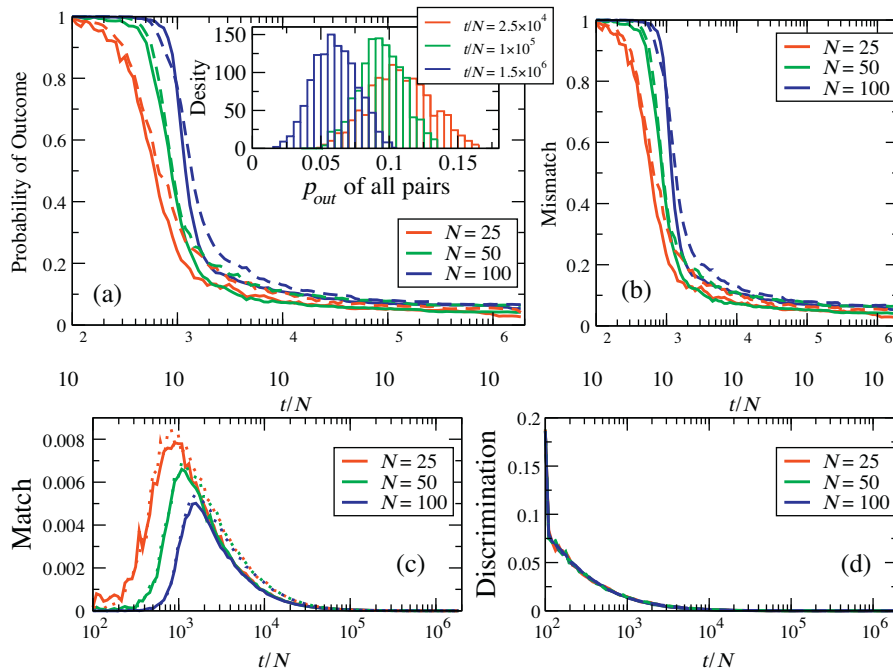


Fig. 5. Microscopic observables. (a) Probability of having an outcome. The solid lines show the average fraction of games collected in time sliding windows versus t/N for the old algorithm. The broken lines show the average values of p_{out} in the same time sliding windows versus t/N for the new algorithm. The inset shows the (representative) histogram of p_{out} for each possible pair of agents (i.e., the density of the probability values) at three different points in time for $N=50$. The fraction of games, collected in time sliding windows (b) which ended up being played in a mismatch region for the old (solid lines) and the new algorithm (broken lines), (c) which ended up being played in a match region for the old (solid lines) and the new algorithm (broken lines) and, (d) where a discrimination process occurred for the old (solid lines) and the new algorithm (broken lines). All the results are averaged over 30 samples.

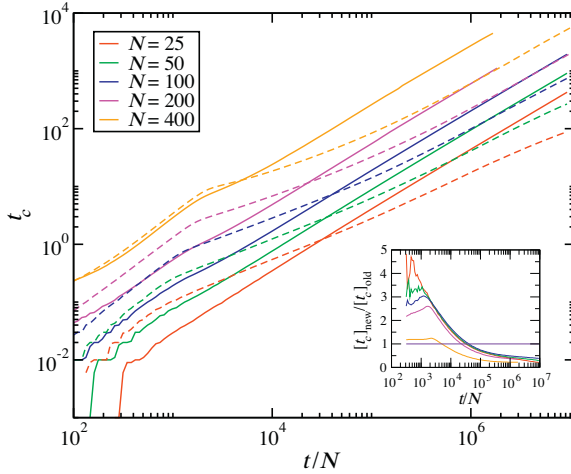


Fig. 6. Computer time (t_c) in seconds required to complete a specific number of games per player by the old and the new algorithm. Solid lines show the computer time required by the old algorithm while broken lines indicate the computer time required by the new algorithm. The inset shows the ratio of t_c for the new algorithm ($[t_c]_{\text{new}}$) to the t_c for the old algorithm ($[t_c]_{\text{old}}$) for the same population sizes as in the main figure.

excellent agreement between the results obtained from the two algorithms.

4.2. “Microscopic” observables

As pointed out in the previous sections, one of the main ingredients of the fast algorithm is the computation of the probability that at each time step a game between a randomly chosen pair of players together with a randomly selected topic in the interval $[0, 1)$ would produce a non-null outcome. Here we compare the behavior of the original and the fast algorithm with respect to this property. In particular, in Fig. 5(a) we show for the original algorithm the fraction of games, collected in time sliding windows, that produce a non-null outcome, while for the no-rejection algorithm the probability $p_{\text{out}}(i, j)$ of the selected pair (i, j) averaged over the same time windows. In the inset, we also show the (representative) histogram of p_{out} for each possible pair of agents at three different points in time for a specific population size. It is evident that the histogram is strongly peaked, which means that $p_{\text{out}}(i, j)$ is roughly similar for all pairs (i, j) thereby, allowing for an effective random choice over the pairs without altering the dynamics.

Subsequently, in Fig. 5(b)–(d) we respectively compare the two algorithms in terms of the fraction of games, collected in time sliding windows, which ended up being played in a mismatch region, or in a match region, or where a discrimination process occurred. Once again, the results exhibit a remarkable qualitative as well as quantitative agreement.

5. Comparison of the computational complexity of the two algorithms

In this section, we compare the computational complexity of the two algorithms, i.e., we compare the computer time⁷ (t_c) in seconds required to complete a specific number of games per player for the old and the new algorithms. In addition, we give more extensive results for the computational complexity of the fast algorithm. It is important to note that the primary focus of

the analysis that follows is to understand the relative advancement in the time performance of the fast algorithm rather than its absolute performance (similar in lines to [21]). Indeed, the development of this algorithm has allowed for the investigation of certain novel and interesting characteristics of the model like metastability and aging [19] which was earlier impossible even for small population sizes. All our results are obtained on the ISI cluster with the following node specification: (a) Processor—INTEL XEON E5405 2.00 GHz, (b) cache—6144 kB, (c) ISA: 64-bit and (d) RAM—8 GB.

Fig. 6 compares the computer time required to complete a specific number of games per player by the old and the new algorithm. Note that during the initial games the old algorithm takes lesser computer time than the new one. During this phase, almost all games produce an outcome and therefore the additional calculation of the probabilities required for the fast algorithm is not advantageous. However, as soon as the dynamics gets trapped in metastable states (at the onset of the plateau region in the number of linguistic categories curve in Fig. 2) the calculation of the probabilities turns out to be very advantageous and the new algorithm has a much higher velocity than the old one. Note that for larger population sizes ($N=200$ and 400) we could manage to reach only a lower value of t/N within a reasonable t_c for the old algorithm. In the inset of Fig. 6 the ratio of the two algorithms’ execution time is shown, to better appreciate the advantage of the no-rejection one.

In Fig. 7(a), we present a further analysis of the scaling of t_c with the population size for the no-rejection algorithm. In particular, we report two different quantities in this figure for $N=200$, 400 and 800 :

- (i) p_{out} versus the rescaled number of games. Note that one needs to rescale t by $N^{3/2}$ to collapse the curves. This dependence of the time of the dynamics on the population size has also been recovered in several other cases elsewhere [19,28] and usually indicates the time scaling to reach a consensus in the population. Clearly, the rate at which the values of p_{out} drop decreases with increasing t .
- (ii) the rescaled t_c versus the rescaled number of games (i.e., $t/N^{3/2}$ as in case (i)). In order to collapse these curves, especially in the “large” t regime (featuring the long-time dynamics) one has to rescale t_c by $t\sqrt{N}$. In addition the entire factor is multiplied by a large constant A ($\sim 2 \times 10^7$) in order to present a better visualization of the plots within the same figure as of p_{out} .

The most important observation is that the long-time behavior is exactly similar to that of p_{out} which indicates that the computer time required is largely determined by the probability of outcomes.

In Fig. 7(b) we show the amount of t_c required to complete $t=5 \times 10^7$, 5×10^8 steps for the old and the new algorithm for different population sizes. In all the four cases, the curves can be nicely fitted using a function of the form: $f(N) = \beta\sqrt{N}$. For the old algorithm $\beta=8.25$ and 104.92 while for the new algorithm $\beta=2.16$ and 34.66 respectively for $t=5 \times 10^7$ and $t=5 \times 10^8$. This observation once again confirms the dependence: $t_c \propto \sqrt{N}$. An important point to note is that the pre-factor β is significantly lower for the new algorithm as compared to the old one. The dependence of t_c on \sqrt{N} can be attributed to the time required by the different processes of the model (e.g., discrimination, inventory updates, etc.). A detailed analysis of this dependence is out of the scope of the current paper and shall be presented elsewhere.

⁷ We use the in-built `clock()` function of the GNU C library to estimate the value of t_c .

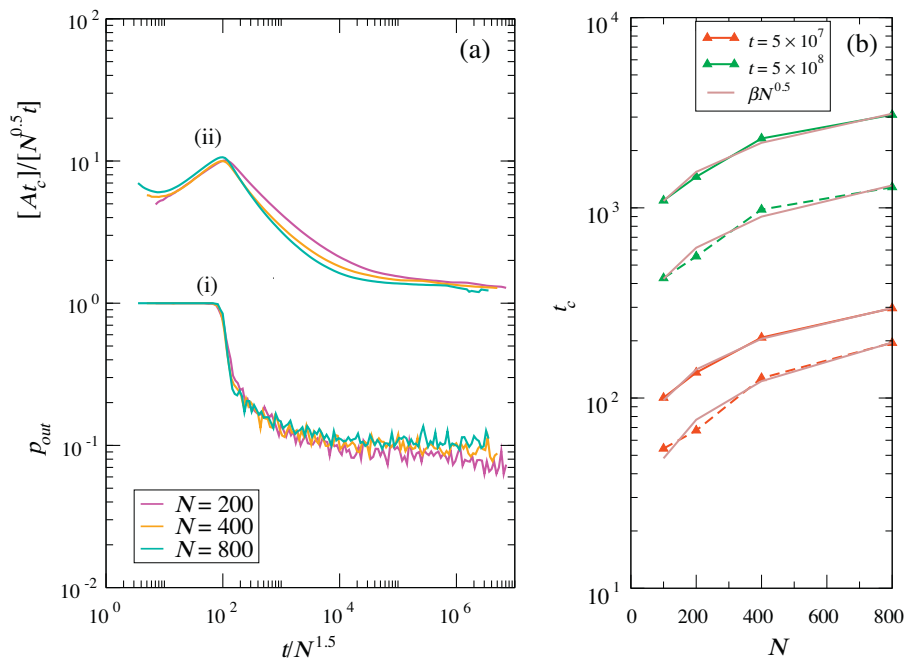


Fig. 7. (a) The scaling of t_c with the population size for the new algorithm. (i) p_{out} versus the rescaled number of games. (ii) Rescaled t_c versus the rescaled number of games. t_c is rescaled by $t\sqrt{N}$ and then the entire factor is multiplied by a large constant A ($\sim 2 \times 10^7$) in order to present a better visualization of the plots. (b) The amount of t_c required to complete $t = 5 \times 10^7$, 5×10^8 steps for the old (continuous lines) and the new (dashed lines) algorithm for different population sizes.

6. Conclusion

In this paper we have introduced a no-rejection algorithm developed to study the long time behavior of the Category Game model. The original model [1] approaches one of the most important problems in linguistics – the emergence of linguistic categories – and was shown to reproduce both qualitatively and quantitatively experimental results reported in the WCS [10]. The two main innovative aspects of the model, with respect to previously proposed ones, are (i) the dynamical emergence of a discretization from a continuous perceptual space and (ii) the representation of the present category system as a long lasting metastable state rather than an attractor of the dynamics. The last property has triggered the need for suitable methods to achieve the long time dynamics of the model. In particular, the observed dynamics was such that games which bring a modification of the state of the agents resulted progressively more rare. The analysis of the behavior of the system for suitably large time and population sizes was for that reason practically impossible. The no-rejection algorithm presented here has been crucial to access the long time dynamical properties of CG, characterized by metastability and aging [19], and thus to shed light on so far unexplored part of the model, helping to clarify the nature of the consensus states that are established during the CG dynamics, with important consequences for the understanding of such phenomena as language change and language evolution. The no-rejection model we propose, despite being *ad hoc* for the CG, presents principles and methods that can be generalized for different other models related to the evolution and emergence of language or similar semiotic phenomena all of which employ multi-agent simulation techniques. This, as a result, can trigger computationally less expensive methods suitable to investigate social phenomena.

Acknowledgements

A. Baronchelli acknowledges support from the Spanish Ministerio de Ciencia e Innovación through the Juan de la Cierva program

(European Social Fund), as well as from project FIS2010-21781-C02-01 (Fondo Europeo de Desarrollo Regional), and from the Junta de Andalucía project P09-FQM4682.

References

- [1] A. Puglisi, A. Baronchelli, V. Loreto, Cultural route to the emergence of linguistic categories, *Proc. Natl. Acad. Sci. U.S.A.* 105 (23) (2008) 7936.
- [2] J.R. Taylor, J.R. Taylor, *Linguistic Categorization*, Oxford University Press, New York, 2003.
- [3] T.W. Deacon, *The Symbolic Species: The Co-evolution of Language and the Brain*, Norton & Company, New York, USA, 1998.
- [4] H. Gardner, *The Mind's New Science: A History of the Cognitive Revolution*, Basic Books, New York, 1985.
- [5] G. Lakoff, *Women, Fire, and Dangerous Things: What Categories Reveal about the Mind*, University of Chicago Press, Chicago, 1987.
- [6] R.W. Casson, Color shift: evolution of English color terms from brightness to hue, in: C. Hardin, L. Maffi (Eds.), *Color Categories in thought and Language*, Cambridge University Press, Cambridge, 1997, pp. 224–239.
- [7] B. Berlin, P. Kay, *Basic Color Terms*, University of California Press, Berkeley, 1969.
- [8] P. Kay, T. Regier, Resolving the question of color naming universals, *Proc. Natl. Acad. Sci. U.S.A.* 100 (15) (2003) 9085–9089.
- [9] G.L. Murphy, *The Big Book of Concepts*, Bradford Book, 2004.
- [10] A. Baronchelli, T. Gong, A. Puglisi, V. Loreto, Modelling the emergence of universality in color naming patterns, *Proc. Natl. Acad. Sci. U.S.A.* 107 (2010) 2403–2407.
- [11] T. Belpaeme, J. Bleys, Explaining universal color categories through a constrained acquisition process, *Adap. Behv.* 13 (4) (2005) 293–310.
- [12] J. Bleys, M. Loetzsch, M. Spranger, L. Steels, The grounded colour naming game, in: *Proceedings Spoken Dialogue and Human-Robot Interaction Workshop at the RoMan 2009 Conference*, 2009.
- [13] M. Dowman, Explaining color term typology with an evolutionary model, *Cogn. Sci.* 31 (1) (2007) 99–132.
- [14] K.A. Jameson, N.L. Komarova, Evolutionary models of color categorization. I. Population categorization systems based on normal and dichromat observers, *J. Opt. Soc. Am. A* 26 (6) (2009) 1414–1423.
- [15] K.A. Jameson, N.L. Komarova, Evolutionary models of color categorization. II. Realistic observer models and population heterogeneity, *J. Opt. Soc. Am. A* 26 (6) (2009) 1424–1436.
- [16] N.L. Komarova, K.A. Jameson, Population heterogeneity and color stimulus heterogeneity in agent-based color categorization, *J. Theor. Biol.* 253 (4) (2008) 680–700.
- [17] N.L. Komarova, K.A. Jameson, L. Narens, Evolutionary models of color categorization based on discrimination, *J. Math. Psychol.* 51 (6) (2007) 359–382.
- [18] L. Steels, T. Belpaeme, Coordinating perceptually grounded categories through language: a case study for colour, *Behav. Brain Sci.* 28 (04) (2005) 469–489.

- [19] A. Mukherjee, F. Tria, A. Baronchelli, A. Puglisi, V. Loreto, Aging in language dynamics, *PLoS One* 6 (2) (2011) e16677.
- [20] M. Kolesik, M.A. Novotny, P.A. Rikvold, Extreme long-time dynamic Monte Carlo simulations for metastable decay in the $d=3$ using ferromagnet, *Int. J. Mod. Phys. C* 14 (1) (2003) 121–131.
- [21] M.A. Novotny, Monte Carlo algorithms with absorbing Markov chains: fast local algorithms for slow dynamics, *Phys. Rev. Lett.* 74 (1) (1995).
- [22] K. Binder, Applications of Monte Carlo methods to statistical physics, *Rep. Prog. Phys.* 60 (1997).
- [23] J. Southern, G.J. Gorman, M.D. Piggott, P.E. Farrell, M.O. Bernabeu, J. Pitt-Francis, Simulating cardiac electrophysiology using anisotropic mesh adaptivity, *J. Comput. Sci.* 1 (2) (2010) 82–88.
- [24] D. Balcan, B. Gonçalves, H. Hu, J.J. Ramasco, V. Colizza, A. Vespignani, Modeling the spatial spread of infectious diseases: the global epidemic and mobility computational model, *J. Comput. Sci.* 1 (3) (2010) 132–145.
- [25] M. Buchholz, H.-J. Bungartz, J. Vrabec, Software design for a highly parallel molecular dynamics simulation framework in chemical engineering, *J. Comput. Sci.* 2 (2) (2011) 124–129.
- [26] L. Wittgenstein, *Philosophical Investigations* (Translated by Anscombe, G.E.M.), Basil Blackwell, Oxford, UK, 1953.
- [27] D.A. Booth, R.P.J. Freeman, Discriminative feature integration by individuals, *Acta Psychol.* 84 (1) (1993) 1–16.
- [28] A. Baronchelli, M. Felici, E. Caglioti, V. Loreto, L. Steels, Sharp transition towards shared vocabularies in multi-agent systems, *J. Stat. Mech.* (2006) P06014.



Francesca Tria is a researcher at the Complex Network Lagrange Laboratory (CNLL) of the Institute for Scientific Interchange in Turin. She got her degree in physics at the Sapienza University working with Giorgio Parisi and her PhD in physics at the University of Naples Federico II working with Luca Peliti. She spent two years as a post-doc at the ICTP Institute in Trieste after which she moved to the ISI foundation in Turin where two years ago she joined the Information Dynamics group. Her background is in the physics of spin glasses and complex systems, and she is now focusing her research activity on optimization and inverse problems mainly motivated by biological and social phenomena where a statistical physics approach could play an important role.



Animesh Mukherjee, PhD (ISI Foundation, Turin) is a post doctoral researcher in the Complex Systems Lagrange Lab, ISI Foundation, Italy. He received his PhD from the Department of Computer Science and Engineering, Indian Institute of Technology, Kharagpur with a thesis on the self-organization of human speech sound inventories. His main research interests center around applying complex system approaches (mainly complex networks and agent-based simulations) to different problems in human language evolution. He also takes interest in applying statistical physics methods for natural language processing and information retrieval.



Andrea Baronchelli investigates issues of language emergence and computational cognitive science resorting to complex systems concepts and tools. Specifically, he is interested in understanding how global coordination (e.g., on a categorization system) may emerge out of local interactions. At a more fundamental level, his current research is focused on dynamical processes taking place on complex networks. He is presently a Juan de La Cierva research scientist at the Physics Department of the Polytechnic University of Catalonia (UPC) in Barcelona, Spain.



Andrea Puglisi, PhD (ISC-CNR and SMC, Rome) got his PhD at the Sapienza University of Rome in 2002 and spent two years as a Marie-Curie fellow at the University of Paris-Sud. He has devoted a large part of his research activity to non-equilibrium statistical mechanics, using granular systems as a benchmark where modern theories for fluctuations can be tested and improved: on this subject he is coordinator of the FIRB-IDEAS project “Granular-Chaos”. He has also a strong interest in information theory and statistical physics applied to computational cognitive science, where he has recently given some contribution on the problem of linguistic categorization. He has published more than 50 papers in internationally refereed journals.



Vittorio Loreto is associate professor at the Physics Dept. of Sapienza University and research scientist at the ISI Foundation in Turin where he coordinates the information dynamics group. His scientific activity is mainly focused on the statistical physics of complex systems. In the last few years he has been active in the fields of granular media, complexity and information theory, complex networks theory, communication and language evolution. He has coordinated the European project TAGora (<http://www.tagora-project.eu>), focused to the study of online social communities as well as several Italian national projects and the Rome team of the IST ECAgents project (<http://www.ecagents.org>). He's presently coordinator of the European project EveryAware, focused on the study of the opinion dynamics through Information and Communication Technologies. He published over 100 papers in internationally refereed journals and chaired several workshops and conferences. He was the vicechairman of STATPHYS23, the 23rd International Conference on Statistical Physics.