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Bit-strings and other modifications of Viviane model for language competition

P.M.C. de Oliveira[a,b,*], D. Stauffer[a,c], F.W.S. Lima[d], A.O. Sousa[a,e], C. Schulze[c], S. Moss de Oliveira[a,b]

[a]Laboratoire PMMH, École Supérieure de Physique et de Chimie Industrielles, 10 rue Vauquelin, F-75231 Paris, France
[b]Instituto de Física, Universidade Federal Fluminense, Av. Litorânea s/n, Boa Viagem, Niterói 24210-340, RJ, Brazil
[c]Institute for Theoretical Physics, Cologne University, D-50923 Köln, Germany, Euroland
[d]Departamento de Física, Universidade Federal do Piauí, 57072-970 Teresina - PI, Brazil
[e]SUPRATECS, University of Liège, B5, Sart Tilman, B-4000 Liège, Belgium, Euroland

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Abstract

The language competition model of Viviane de Oliveira et al. is modified by associating with each language a string of 32 bits. Whenever a language changes in this Viviane model, also one randomly selected bit is flipped. If then only languages with different bit-strings are counted as different, the resulting size distribution of languages agrees with the empirically observed slightly asymmetric log-normal distribution. Several other modifications were also tried but either had more free parameters or agreed less well with reality.

Keywords: Linguistics; Monte Carlo simulation; Language size distribution

1. Introduction

The competition between languages of adult humans, leading to the extinction of some, the emergence of new and the modification of existing languages, has been simulated recently by many physicists [1–11] and others [12–14], see also Ref. [15] for the learning of languages by children. The web site http://www.isrl.uiuc.edu/amag/langev/ lists 10^3 linguistic computer simulations, and recent reviews of language competition simulations were given in Refs. [16–18]. Perhaps the empirically best-known aspect of language competition is the present distribution n_s of language sizes s, where the size s of the language is defined as the number of people speaking mainly this language, and n_s is the number of different languages spoken by s people. We leave it to linguists and politicians to distinguish languages from dialects and rely on the widely used "Ethnologue" statistics [19–22] repeated in Fig. 1. This log–log plot shows a slightly asymmetric

*Corresponding author. Instituto de Física, Universidade Federal Fluminense, Av. Litorânea s/n, Boa Viagem, Niterói 24210-340, RJ, Brazil.
E-mail address: pmco@if.uff.br (P.M.C. de Oliveira).

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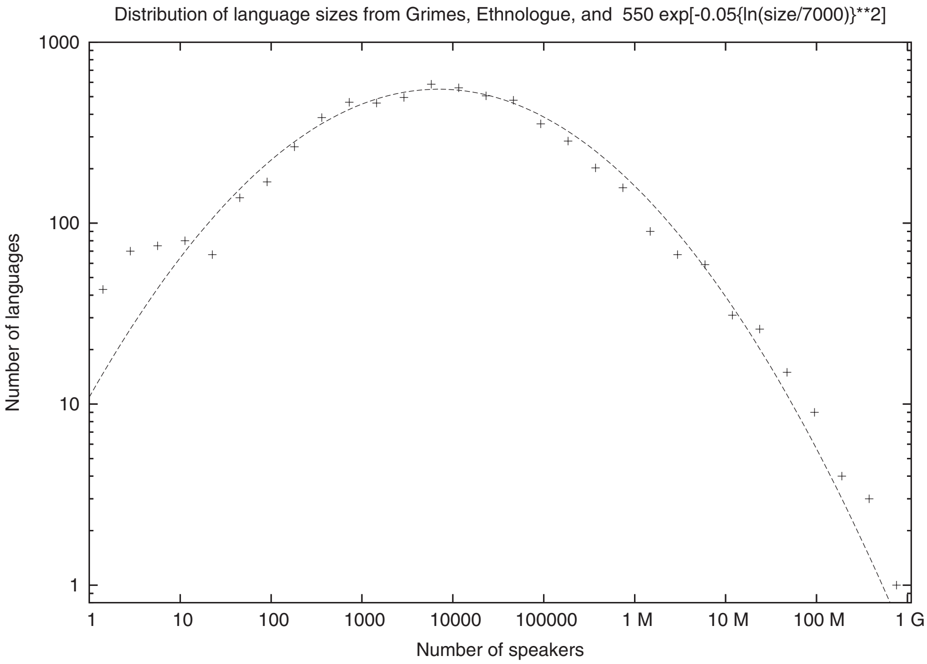


Fig. 1. Empirical size distribution of the $\sim 10^4$ present human languages, binned in powers of two. The curve shows a fitted parabola, corresponding to a log-normal distribution. Real numbers of languages are for small languages higher than this parabolic fit. From Ref. [23].

parabola, corresponding to a log-normal distribution with enhancement for small sizes $s \sim 10$. Our aim is to reproduce this empirically observed distribution in an equilibrium simulation; previously it was achieved only for non-equilibrium [23].

Of the many models cited above only the "Schulze" model [4] and the "Viviane" model [8] gave thousands of languages as in reality. The Schulze model gave a reasonable n_s distribution in non-equilibrium [23], when observed during its phase transition between the dominance of one language spoken by most people and the fragmentation into numerous small languages. The Viviane model does not have such a phase transition [17], and we now attempt to get from it a realistic n_s in equilibrium.

The next section defines the standard Viviane model [8] for the reader's convenience. Section 3 gives our bit-string modification and the improved resulting n_s, while Section 4 lists other attempts to get a good size distribution. The concluding Section 5 compares our various attempts.

2. Viviane model

The original Viviane model [8] simulates the spread of humans over a previously uninhabited continent. Each site j of an $L \times L$ square lattice can later be populated by c_j people, where c_j is initially fixed randomly between 1 and $m \sim 10^2$. On a populated site only one language is spoken. Initially only one single site i is occupied by c_i people. "Neighbours" on our lattice are the four nearest-neighbour sites.

Then as in Eden cluster growth or Leath percolation algorithm, at each time step one surface site (= empty neighbour j of the set of all occupied sites) is selected randomly, and then occupied with probability c_j/m by c_j people. Which of the previously occupied neighbours of this surface site occupies that surface site is determined randomly, with a probability proportional to the fitness of the language of the previously occupied sites. This fitness F_k is the total number of people speaking the language k of that site, summed over all lattice sites occupied at that time. (In Ref. [9], this fitness was bounded from above by a maximum M_k selected randomly between 1 and $M_{\max} \sim 20\,m$.) After we selected which previously occupied sites invades the surface

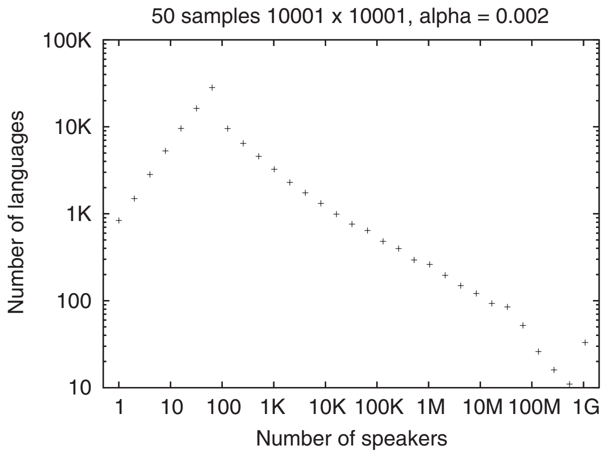


Fig. 2. Language size distribution n_s for the standard Viviane model, with s varying from 1 to 10^9. The absolute value of the slope to the right is smaller than one on the left, in contrast to reality, Fig. 1. $m = 127$, $M_{\max} = 16m$, also in Figs. 3,5,6,8.

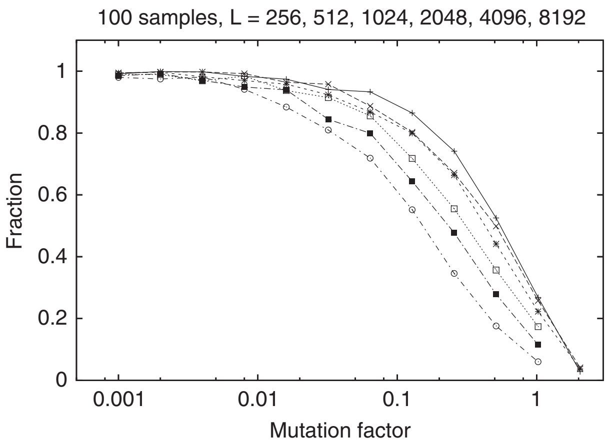


Fig. 3. Variation of the fraction of people speaking the largest language. The linear lattice size L increases from right to left. For mutation factor $\alpha = 0$ by definition everybody speaks the language of the initially occupied site.

site, the language of this previously occupied site is accepted by the new site but mutated into another language with probability α/F_k with a mutation factor α typically between 10^{-3} and 1. The mutation flips one randomly selected bit. This mutation factor is a fixed input parameter. From then on the population and language of the just occupied lattice site remain constant. Equilibrium is reached when all lattice sites have become occupied and the simulation stops. As a result of this algorithm, the various languages are numbered $1, 2, 3, \ldots$ without any internal structure of the languages.

The resulting language size distribution n_s in Fig. 2 has a sharp maximum near $s \sim m$, and follows one power law (exponent 1) to the left of the maximum and another power law to its right. As in reality it extends from $s = 1$ to 10^9 for the number s of people speaking one language. But the sharp maximum is not seen in reality, Fig. 1, and the simulated slope on the right of the maximum is weaker than the one at its left, while reality shows the opposite asymmetry: less slope on the left than on the right.

With increasing mutation factor α, the fraction of people speaking the largest language decreases smoothly, Fig. 3, without showing a sharp phase transition (in contrast to the Schulze model). For increasing lattice size L the curves shift slightly (logarithmically ?) to smaller α values, that means: to get for larger lattices about the same results as for smaller lattices, we have to decrease the input parameter α when increasing the lattice size L.

(The program listed in Ref. [17] gave a limiting fitness M_j to each site j, instead of an M_k to each language. Thus before the mutations are simulated we need there the line `f(lang(j)) = min(limit(lang(j)), f(lang(j)) + c(j)*fac)`. This mistake barely affects the n_s, Fig. 2, but after correction the resulting size effect in our Fig. 3 is weaker than in Fig. 3 of Ref. [17].)

The next sections try to get good agreement with reality, Fig. 1. Once we have a model agreeing with reality, we can apply this model to other linguistic questions (requiring an identification of space and time scales), or search for alternative models also giving good agreement with Fig. 1.

3. Bit-string modification

We now improve the Viviane model in two ways:

(i) We give the Viviane languages an internal structure by associating with each language a string of, say, $\ell = 16$ bits, initially all set to zero. At each mutation of the language at the newly occupied site, one randomly selected bit is flipped, from 0 to 1 or from 1 to 0. We count languages as different only if they have different bit-strings. Otherwise the standard algorithm is unchanged. Thus our new bit-strings do not influence the dynamics of the population spread, only the counting of languages.

(ii) Thus far the populations c_j per site j were homogeneously distributed between 1 and m. In reality, there are more bad than good sites for human settlement. We approximate this effect by assuming that the values of c, to be scattered between 1 and m, no longer are distributed with a constant probability but with a probability proportional to $1/c$. Mathematically, the probability distribution function $P(c)$ for the carrying capacities c before was $P(c) = \text{const}$ for $1 \leqslant c \leqslant m$ and $P(c) = 0$ elsewhere; now it is $P(c) \propto 1/c$ for $1 \leqslant c \leqslant m$ and $P(c) = 0$ elsewhere.

(As a minor improvement we may count a neighbour language only once if two or more neighbours of the just occupied site speak that language. Also, instead of occupying one randomly selected surface site i with probability proportional to c_i, we saved lots of computer time by randomly selecting two such surface sites and occupying the one with the bigger c.)

Fig. 4 shows that these modifications are good enough to result in reasonable agreement with reality, Fig. 1. The shape of the curve is robust against a wide variation of the parameters. We do not show plots for different m since $1 \leqslant F_j \leqslant m$ and for fixed $m/M_{\max}$ the simulations depend only on the ratio α/F_j. The total number of languages is only 5×10^3, less then the real [19] value 7×10^3 for which we would need bigger lattices than our computer memory can store.

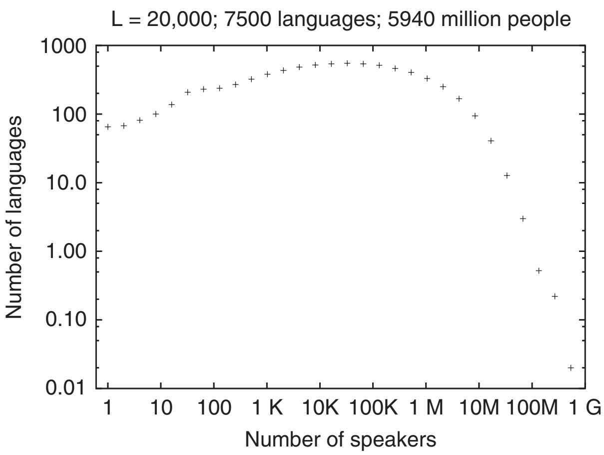
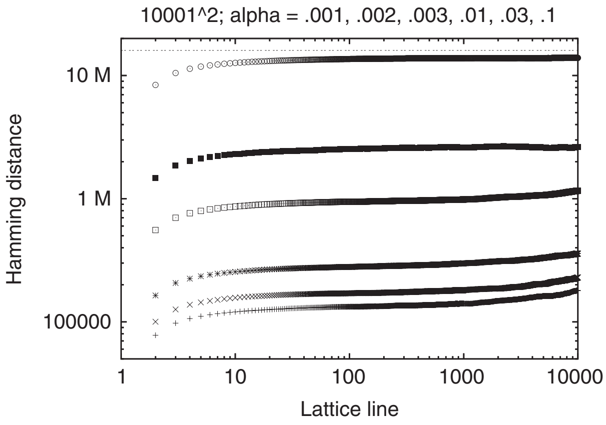


Fig. 4. Language size distribution for bit-string version, $L = 20\,000$, $m = 64$, $M_{\max} = 256$, $\alpha = 0.1$, $\ell = 13$ bits, averaged over 100 samples.



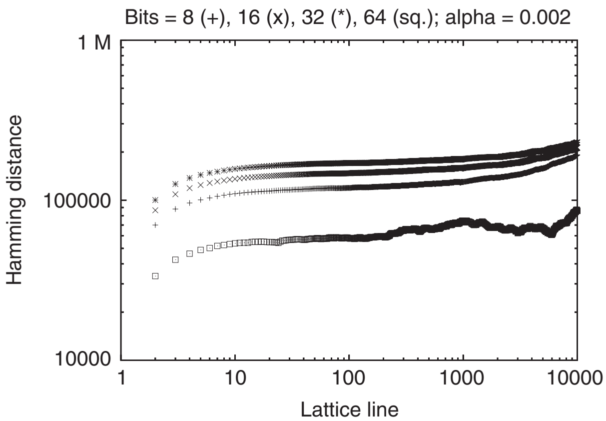


Fig. 5. Summed Hamming distance versus geometric distance. Upper part: increase with increasing mutation factor, with the straight line on top giving the limit of uncorrelated bit-string. Lower part: variation with the length ℓ of our bit-string, taken as $\ell = 32$ in the upper part.

As in Ref. [24] for the Schulze model, the bit-strings allow a study of spatial correlations: What is the Hamming distance for languages separated by a distance r? The Hamming distance for two bit-strings, used already in Refs. [25,24] for the Schulze model, is the number of bits which differ from each other in a position-by-position comparison of the two bit-strings. Thus initially we occupy the top line of the $L \times L$ lattice with L different languages, all having bit-string zero, then start the standard Viviane dynamics, and at the end we sum over all Hamming distances of all sites on lattice line r, compared with the corresponding sites on the first lattice line. (By definition, this Hamming distance is zero for $r = 1$.) Fig. 5 shows our correlation functions, similar to reality [24,26]; the higher the mutation factor α, the higher the Hamming distance. This simulation for Fig. 5 used only modification (i) and involved no counting of languages.

4. Other modifications

4.1. Noise

Ref. [23] improved the language size distribution of the Schulze model by applying random multiplicative noise, that means by multiplying at the end of one simulation each n_s repeatedly by a random number taken between 0.9 and 1.1. This modification approximates external influences from outside the basic model. Such noise is applied in Fig. 6 to the standard Viviane model with the additional modification of correlations: each random number is used twice, one after the other. Here we multiplied each n_s thousand times by a factor $(0.9 + 0.2z)^2$ at each iteration, and we summed over thousand samples. (Here z is a random number

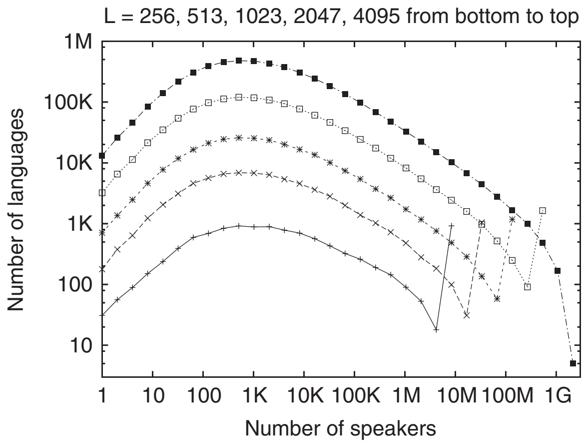


Fig. 6. Language size distribution from multiplicative noise and varying mutation factor (Viviane model without bit-strings).

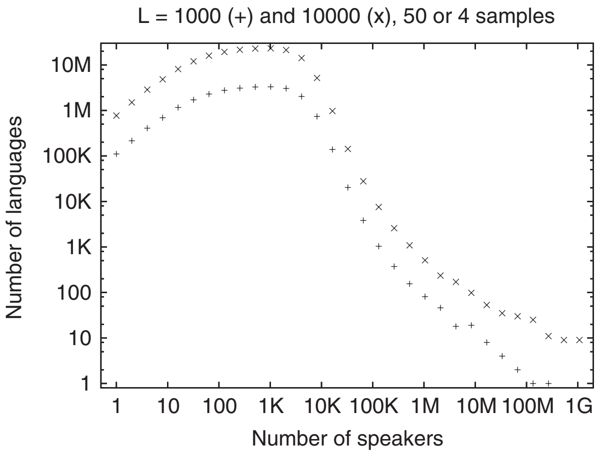


Fig. 7. Language size distribution with power law distribution for the c_j and random multiplicative noise; $m = 8192$, $M_{\max} = 16m$ (Viviane model without bit-strings).

homogeneously distributed between 0 and 1.) We start the simulations with a small mutation factor $\alpha = 0.001$ and for each iteration this grows linearly until it reaches a values of $\alpha = 0.916$, for all lattices sizes used here: $L = 257, 513, 1023, 2047$ and 4095. Fig. 6 shows a slightly asymmetric parabola, but as in Fig. 2 with the wrong asymmetry: too slow decay on the right.

4.2. *Power law for populations per site*

Using only modification (ii) of Section 3, and adding random multiplicative noise (100 multiplications with $0.9 + 0.2z$, without correlations), Fig. 7 now shows reasonable asymmetric parabolas for equilibrium, similar to Ref. [23] for the non-equilibrium Schulze model.

4.3. *Indigenous population*

We modified the standard Viviane model by assuming that initially the lattice is not empty but is occupied by a native population which in our simulation is then overrun by some foreign invaders. Thus initially each

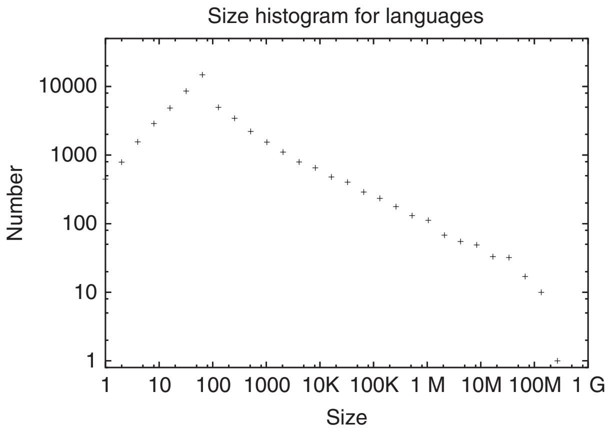


Fig. 8. Results similar to Fig. 2 but with a native population at the beginning of the conquest.

lattice site gets a native fitness $1/z$ where z is a random number homogeneously distributed between zero and one. In the later conquest by the foreign invaders, this site is conquered only if the fitness of the invader is larger than the native fitness (minus 10). It is possible that a few sites cannot be conquered, since they are defended by Asterix, Obelix or other powerful natives.

We found that this modification barely changes the final distribution of language sizes. For various mutation factors α, Fig. 8 shows that again we have two power laws (straight lines in this log–log plot) for small and for large language sizes. The time after which the "conquistadores" finish their conquest varies very little from sample to sample (not shown). Adding as before random multiplicative noise by 100 multiplications by $0.9 + 0.2z$ makes the maximum more smooth (not shown), but still with the wrong asymmetry.

5. Conclusion

While we have offered various modifications in order to improve the results from the standard Viviane model, we think the one of Section 3 is the best since it is simple and introduced no new free parameters except ℓ. We have seen a reasonable agreement with the slightly asymmetric log-normal distribution of language sizes. Future work could replace the bits by integer variables between 1 and Q as in some Schulze models [17], or look at language families [27].

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