

Modeling language evolution

October 16, 2002

Linguists' view on language & evolution

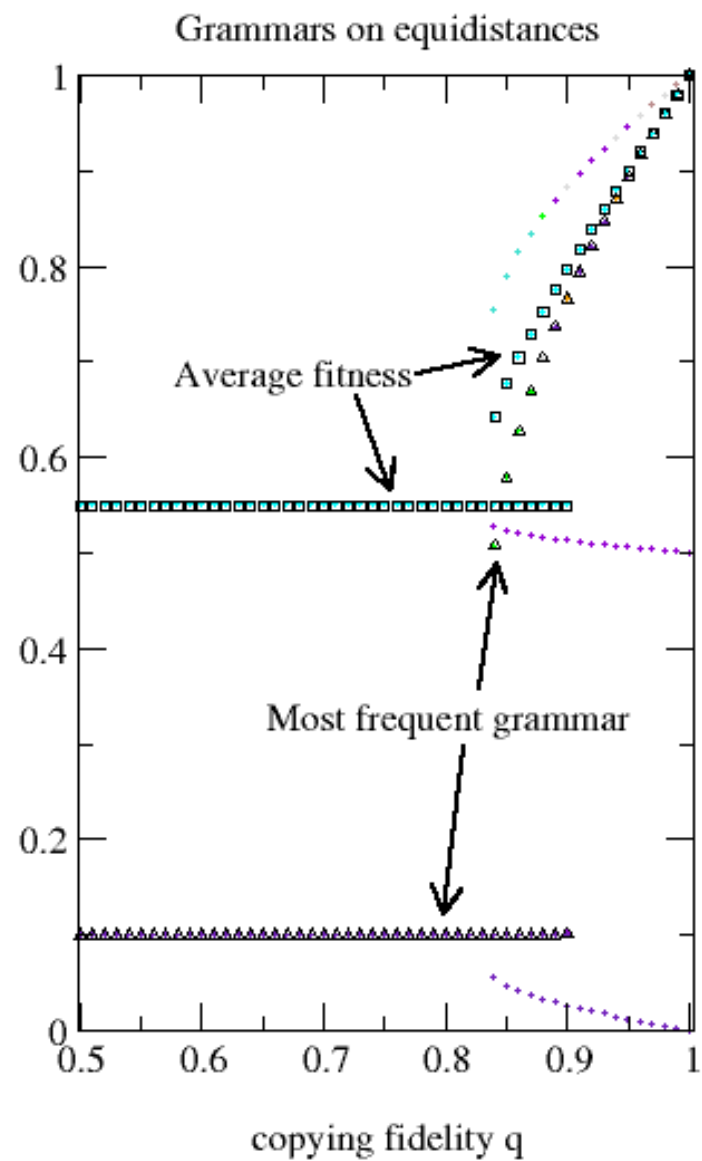
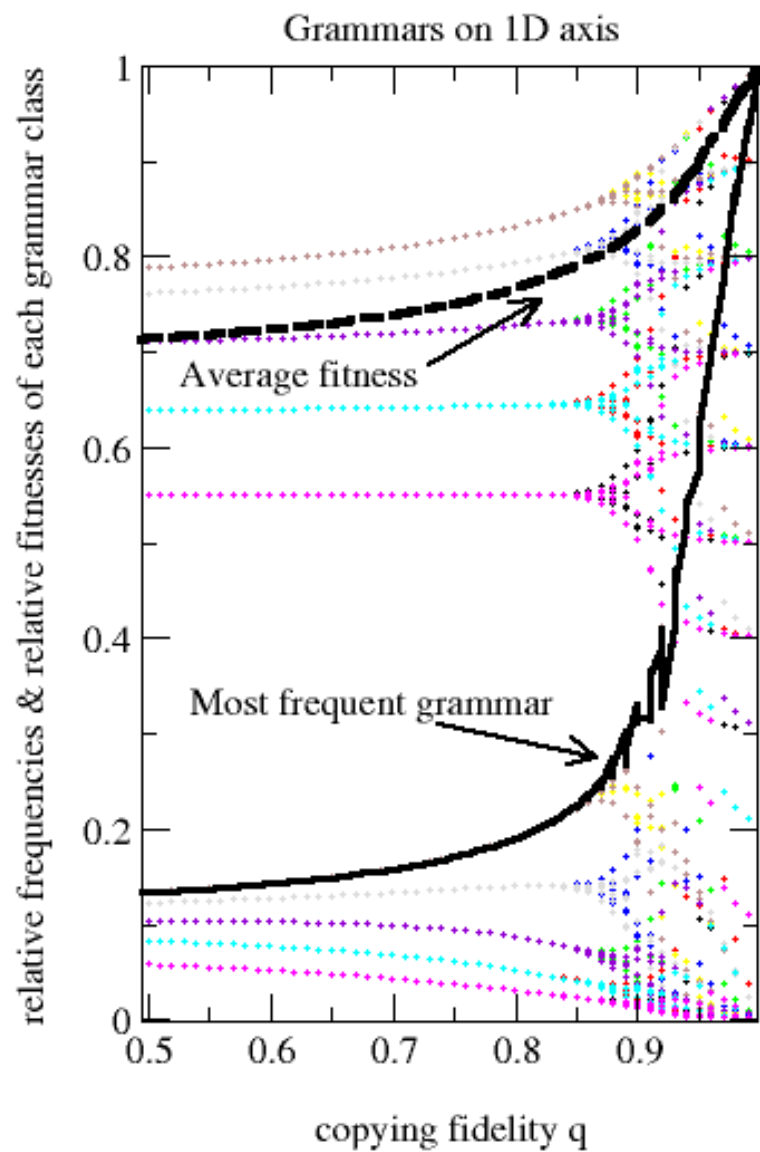
1. Human language is productive and infinite
2. It is so by virtue of compositionality and recursion
3. Therefore, it must consist of symbols and rules (i.e. rewriting grammars)
4. Non-trivial classes of rewriting grammars are not learnable from positive data alone
5. Therefore, crucial aspects of human language must be innate (Universal Grammar)
6. Human language is extremely useful
7. Evolution leads to useful things
8. Universal Grammar has evolved by Natural Selection

Formal models of language evolution (Nowak et al, 2001)

- assume there are N different possible grammars
- x_i is the relative abundance of grammar i
- f_i is the fitness of an individual using grammar i
- Q_{ji} is the probability that a parent j gets offspring i
- ϕ is the average fitness

$$\dot{x}_i = \sum_{j=0}^N (x_j f_j Q_{ji}) - \phi x_i \quad (1)$$

- Successful grammars are more likely to be transmitted (fitness, role model) $(f_i = \sum_j(x_j F_{ij}))$
- Every grammar is equally likely, is equally expressive and is equally similar to every other grammar $Q_{ii} = q$



Evolution Universal Grammar

- There is a minimum learning accuracy q_0 necessary to maintain grammatical coherence in the population. Because the best possible learner (the “batch learner”) needs a minimum amount b_c of sample sentences to reach q_0 , and b_c is proportional to the number of possible grammars n , the Universal Grammar can only be of small size (Nowak et al, 2001).
- A Universal Grammar that leads to more efficient communication will be selected for

The role of natural selection in language evolution

- If language is for transmitting information, there is no apparent advantage for the speaker to share this information
- If there is an advantage for the speaker of successful communication, there is a disadvantage of introducing innovations that are not understood.

The role of cultural evolution in language evolution

- Language are transmitted culturally from generation to generation
- Mistakes are made in learning
- Aspects of languages that make them better learnable, are more likely to be retained
- Over time, languages will be better learnable than one would expect from a random sample

Representation: context-free grammars

$S \mapsto NP VP$	(1)	$Art \mapsto the$		a	(6ab)
$NP \mapsto Art N$	(2)	$N \mapsto cat$		dog	(7ab)
$N \mapsto N SP$	(3)	$V \mapsto chases$		$admires$	(8ab)
$VP \mapsto V NP$	(4)	$S \mapsto the\ cat\ fears\ the\ dog$			(9)
$SP \mapsto that\ VP$	(5)	$S \mapsto the\ dog\ fears\ the\ cat$			(10)

- terminal alphabet: $\{a, b, c, d\}$
- nonterminal alphabet: $\{S, T, U, V, W\}$

Mutations / Learning

1. Random replacement/addition of symbols, deletion/duplication of rules
2. Learning algorithm

Incorporation: extend the language, such that it includes the encountered string

Compression: substitute frequent and long substrings with a nonterminal, such that the grammar becomes smaller and the language remains unchanged

Generalization: equate two nonterminals, such that the grammars becomes smaller and the language larger

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teach(i, j)
  repeat T times
    teacher i generates random string s from  $L_i$ 
    student j calls incorporate(s)
  repeat until  $G_j$  doesnot change anymore
    student j calls compress()
  repeat until  $G_j$  doesnot change anymore
    student j calls generalize()
    repeat N times, or until generalization is rejected
      student j generates random string  $s'$  from  $L_j$ 
      if ( $s' \notin L_i$ ) reject generalization
  if ( $size(L) < M$ )
    repeat  $M - size(L)$  times
      generate random string s of maximum size  $l_0$ 
      student i calls incorporate(s)

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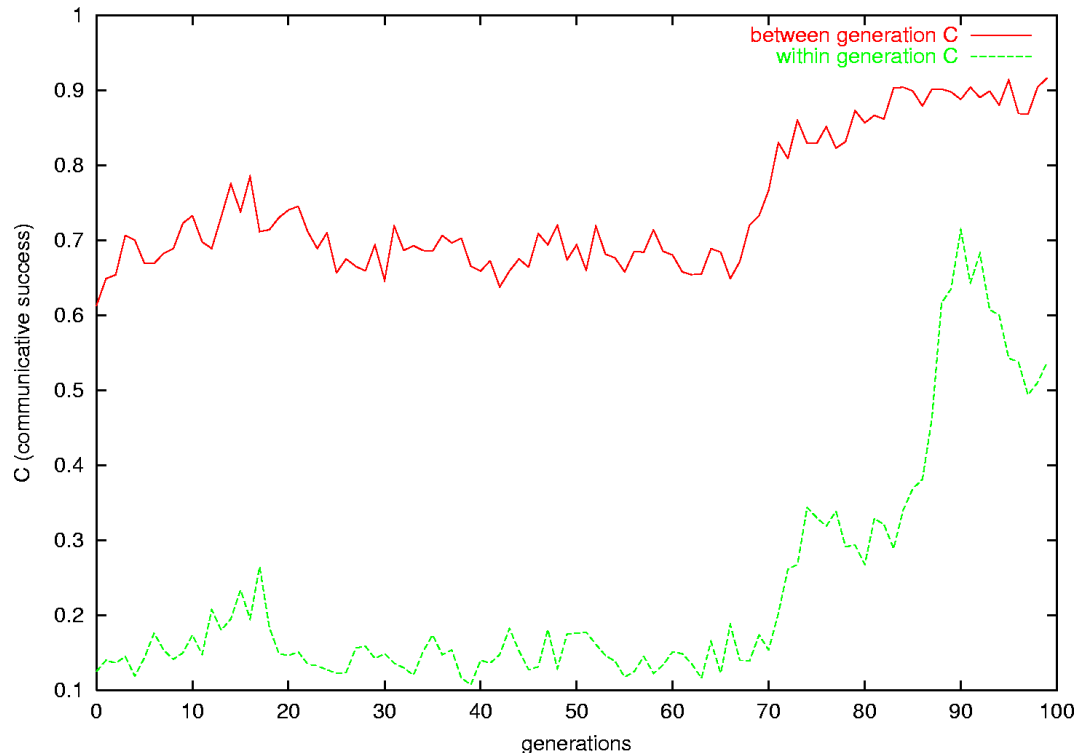
Transmission

Iterated learning : agents in a *chain* learn from the previous agent and teach to the next;

Fitness proportional selection : the fitness of an agent is determined by its success in communicating with the agents of its own generation. The expected number of offspring is proportional to this fitness.

- *Mutual benefit*: the fitness is calculated by counting the number of times an agent is successful as a hearer and as a speaker
- *Hearer benefit*: the fitness is calculated by counting the number of times an agent is successful only as a hearer.

Results



Parameters are: symbiotic condition, $V_t = \{0, 1, 2, 3\}$,
 $V_{nt} = \{S, a, b, c, d, e, f\}$, $P=20$, $T=100$, $M=100$, $l_0=12$

There are regions of grammar space where the dynamics are apparently under the “coherence threshold”, while there are other regions where the dynamics are above this threshold. The parameters, including the number of sample sentences T , are still the same, but the language has adapted itself to the **bias** of the learning algorithm.

Conclusions

- In this model, language adapts to the bias of the learning algorithm. The algorithm therefore needs less training samples than Nowak et al. predict as a lower bound.
- Results that “prove” the need for Universal Grammar (i.e. restrictions of the search space / representation bias) are based on the assumption that any target grammar from that space is equally likely. Here we show that in iterated learning that assumption is not reasonable.
- Limitations of the learning procedure make the learning in future generations easier. The collective dynamics give “emergent” restrictions; the “logical problem of language acquisition” can be solved without binary and a priori restrictions of the search space.