Self-emergence of Lexicon Consensus in a Population of Autonomous Agents by means of Binary-strings Evolution Strategies

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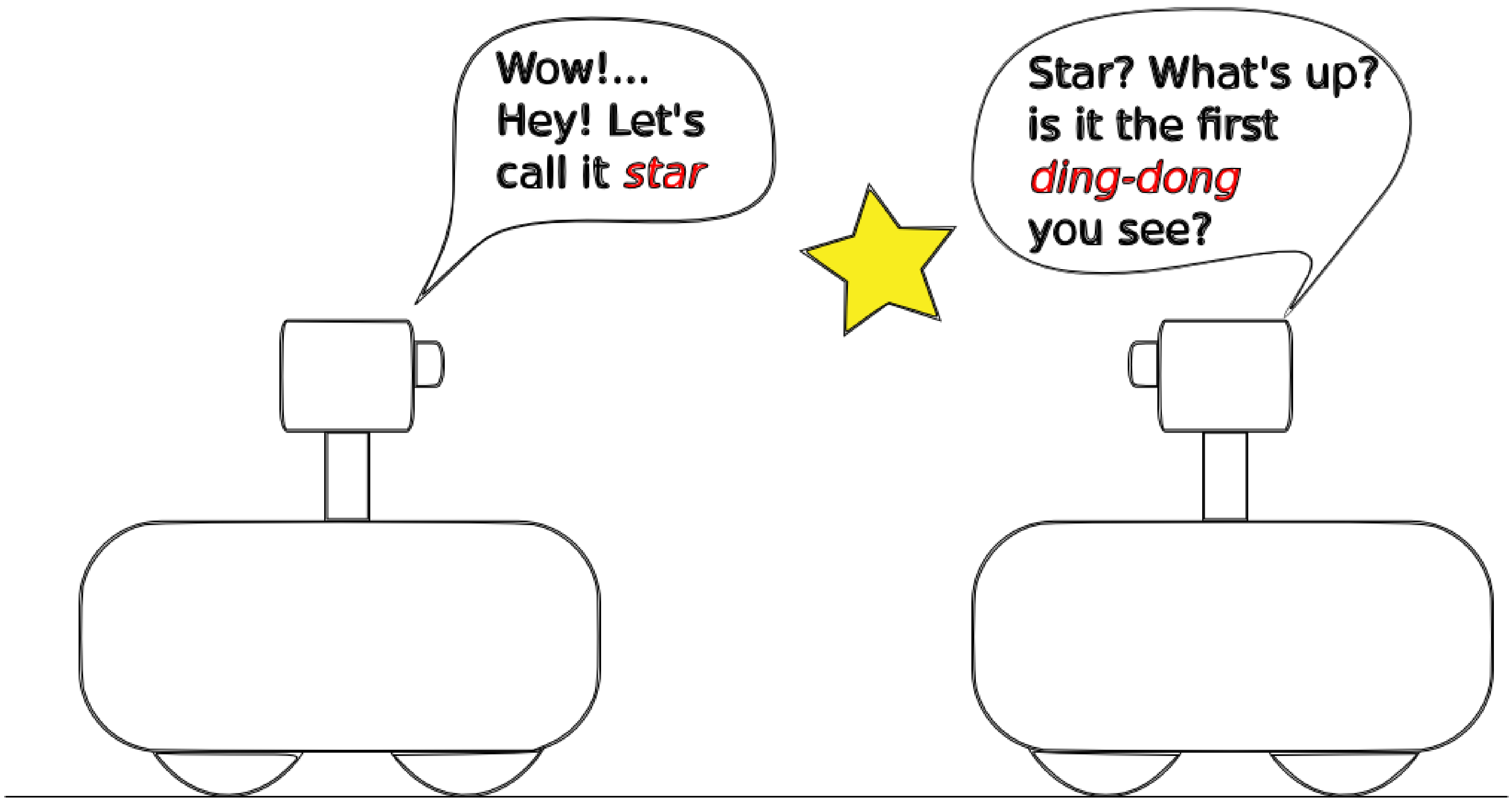

Wow!...
Hey! Let's
call it *star*
Star? What's up?
is it the first
ding-dong
you see?

Preliminary Comments - I

- Communication and language in multi-agent systems. **Grounded symbolic** communication (by grounded symbols we understand that the meanings of symbols are acquired through sensory channels).
- In this paper Language is interpreted as a vocabulary or lexicon.
- Lexicon: the- association between meanings (i.e. objects and situations) and symbols and signals. The concept of Lexicon is also known as Ontology in Multi-agent Systems.
- In human languages, these associations, according to the Semiotic tradition, are **arbitrary** and **conventional .**
- **The symbolic language communication in Multi-agent Systems has two separated but related spheres: (1) The cognitive sphere concerning the way by which each individual agent processes the sensory information coming from the external world in order to categorize and to build concepts and (2) the symbolic sphere concerning the way the collective of agents communicate among them via a symbolic language. In this paper we focus our interest on the second sphere, as we depart from already acquired meanings or concepts and we study mechanisms for obtaining an efficient language for the population of agents.**

Preliminary Comments - II

- Our aim is to investigate how a population of agents can build, in an autonomous and decentralized way, a common lexicon or ontology in order to attain an optimal communication: **language as a social and collective coordination process.**
- On-line learning approach and evolutionary approach to language coordination. Cultural transmission of language versus evolutive language inheritance.
- We have focused our experiments on the evolutionary emergence of language.
- We have applied binary-strings evolution strategies to solve this multi-agent coordination problem.
- Similar and previous work: The Talking Heads Project of Luc Steels at Sony Laboratories using Aibo as an experimental platform. Also, the numerous research works on language acquisition and language evolution, particularly, in those cases in which language is reduced to a vocabulary or lexicon, without considering grammatical and syntactic structures.

Formal Definitions

1.- Multi-agent Communication System:

We define a Communication System, CS, in a population of agents as the triple:

$$\mathbf{CS=<M, \sum , A_i>}$$

Where $\mathbf{M = \{m_1, . . . ,m_n \}}$ is the set of meanings (i.e. the object or states of the environment that can be of relevance for communication for the population of agents.

$\mathbf{\sum= \{s_1, . . . , s_p\}}$ is the set of symbols or signals used by the agents in their communication acts and which represent the actual meanings.

$\mathbf{A_i}$ is the association matrix or lexicon of Agent-i / i=1,2…………………… N agents

Lexicon

- The vocabulary or lexicon of each agent is defined by an association matrix Ai that gives the numerical strength of the associations between the posible meanings (objects and situations) and the symbols and signals:

$M \backslash \Sigma$	s_1	s_2	…	s_p
m_1	a_{11}	a_{12}	…	a_{1p}
m_2	a_{21}	a_{22}	…	a_{2p}
…	…	…	…	…
m_n	a_{n1}	a_{n2}	…	a_{np}

$$A_i = (a_{rj})_i \;;\; i = 1, \dots, N \text{ agents}$$

- The entries a_{rj} of the matrix A are nonnegative real numbers such that :

$$0 \leq a_{rj} \leq 1, (r = 1, \dots, n; j = 1, \dots, p) ;$$

$$a_{rj} = 0 \dashrightarrow \text{No association}$$

$$a_{rj} = 1 \dashrightarrow \text{Total association}$$

Optimal Association Matrix

- Optimal association matrix: pure binary matrix with a single “1” in each row(no synonyms) and a single ”1” in each column (no homonyms and no polysemia).
- Optimal 2x2 Association Matrices:

$$M_1^2 = \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix} \qquad M_2^2 = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$$

- Optimal 3x3 Association Matrices:

$$M_1^3 = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \qquad M_2^3 = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 1 & 0 \end{pmatrix} \qquad M_3^3 = \begin{pmatrix} 0 & 1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

$$M_4^3 = \begin{pmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 1 & 0 & 0 \end{pmatrix} \qquad M_5^3 = \begin{pmatrix} 0 & 0 & 1 \\ 0 & 1 & 0 \\ 1 & 0 & 0 \end{pmatrix} \qquad M_6^3 = \begin{pmatrix} 0 & 0 & 1 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \end{pmatrix}$$

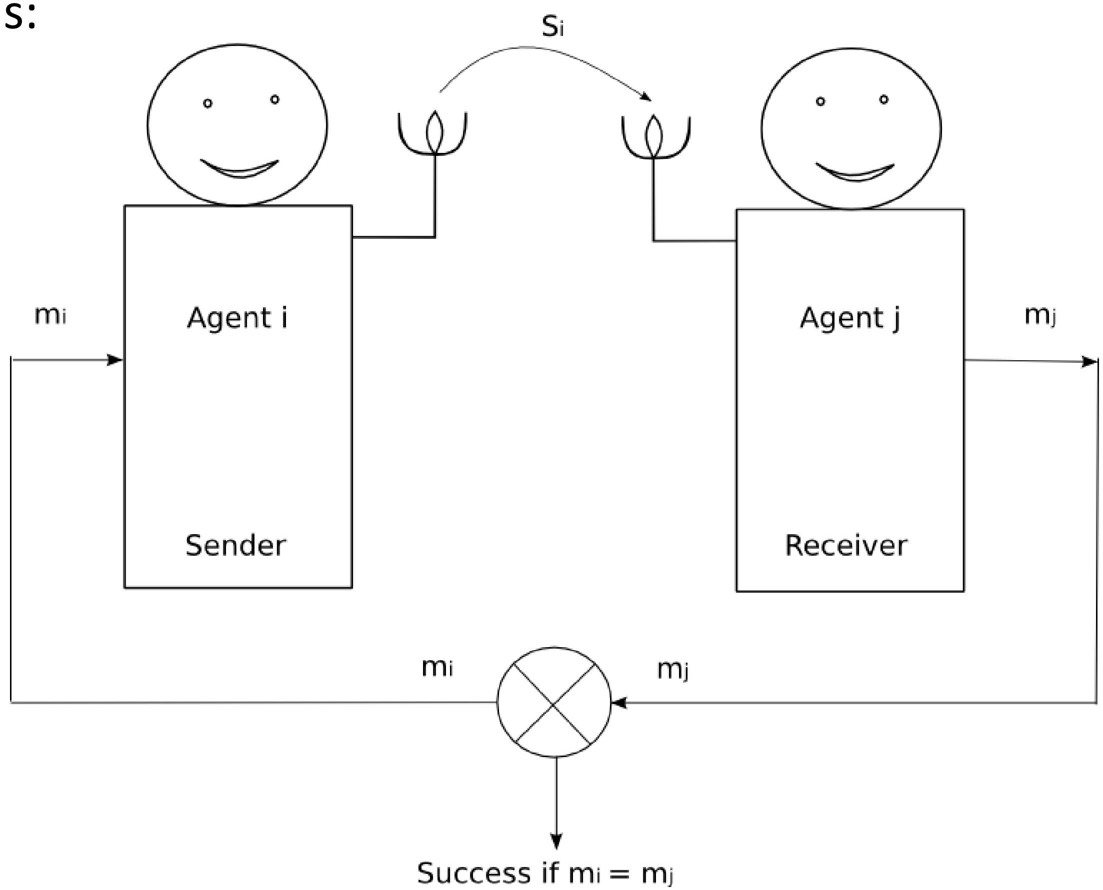
Language games

Wittgenstein´s theory of meaning as use.

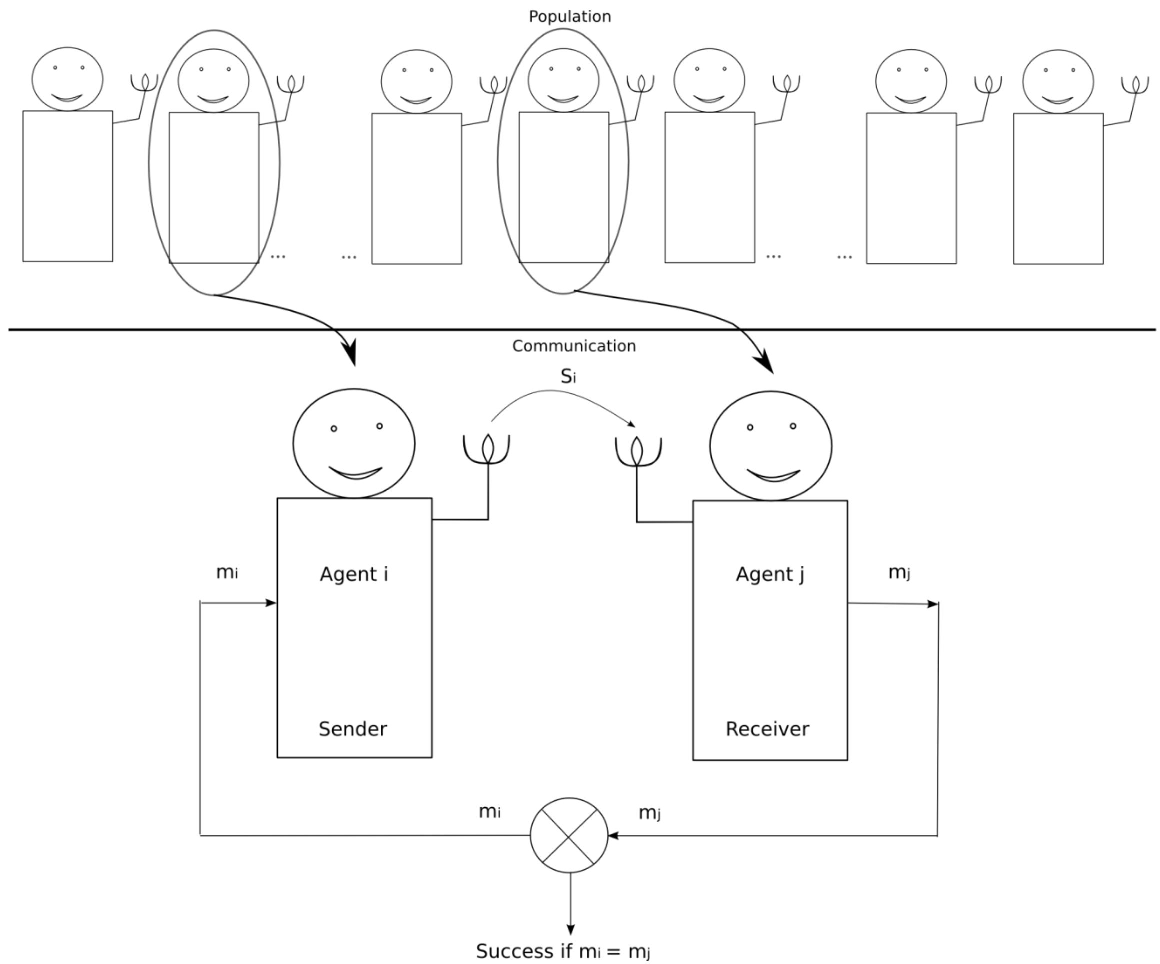
- John Searle´s speech acts , Habermas´ Theory of communicative action and Lewis´signaling games
- The main idea is to implement communicative interactions of the agents to check whether they are able to converge to a global consensus on the lexicon use.
- Coordination games: iterated, repeated games and evolutionary games.

Communicative Interactions

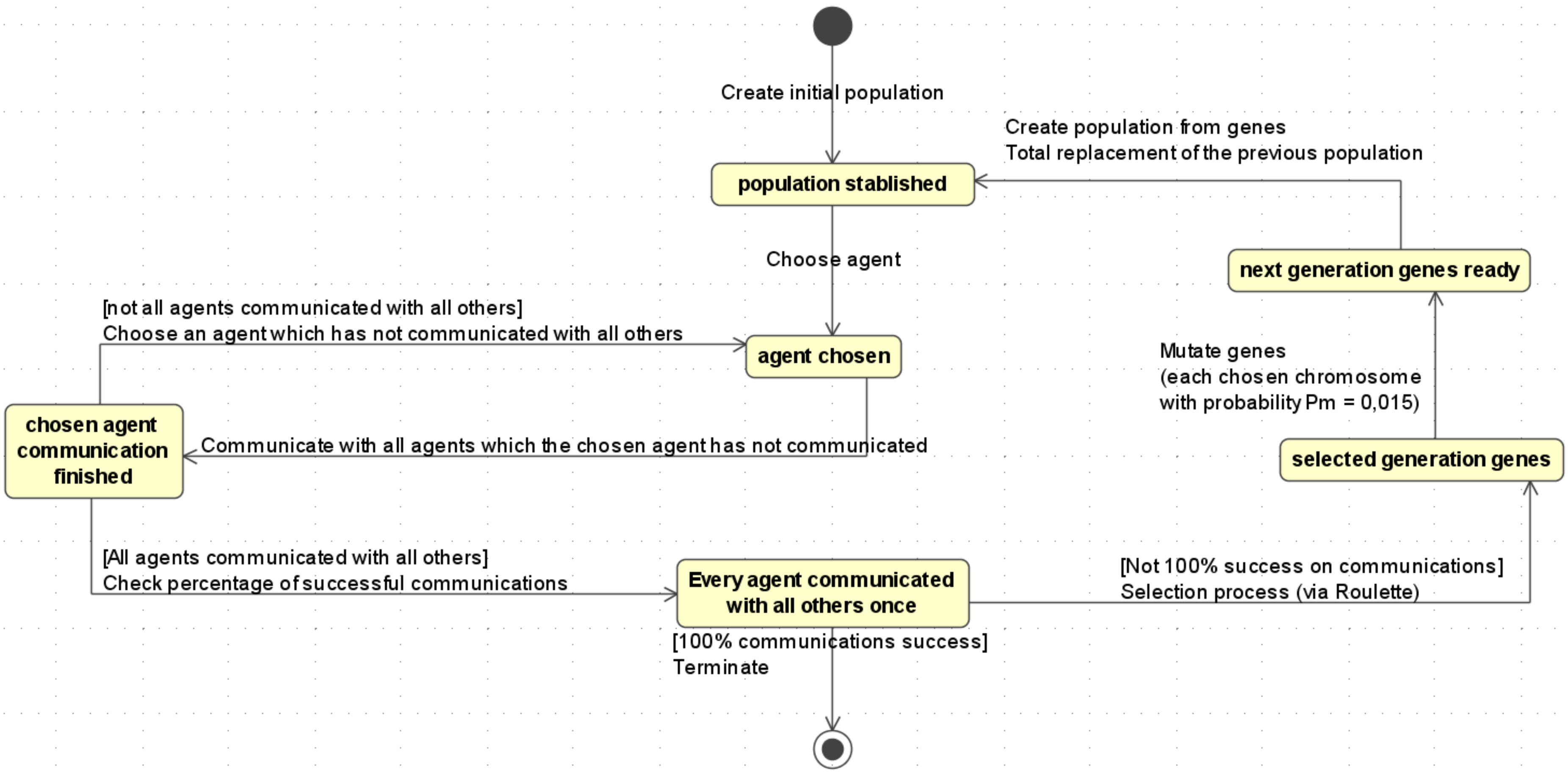
- Each individual agent communicates with all the remaining agents through what we call **communicative acts** or **signaling games** played by a pair of individuals:



Population- based Communicative Interactions



Flow-Chart of Evolutive Language Consensus Process



Binary-strings Evolution Strategies

- Agent’s chromosome encoding:

- Each element of the association matrix is directly mapped into the agent’s chromosome as a gene.

$$\begin{pmatrix} 0 & 0 & 1 \\ 0 & 1 & 0 \\ 1 & 0 & 0 \end{pmatrix} \longrightarrow [0, 0, 1, 0, 1, 0, 1, 0, 0]$$

Binary-strings Evolution Strategies - II

- Mutation Operator

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For each selected chromosome:
   If random < pre-established mutation probability
   - P_m=0,015 -
      Then: one single of its genes is chosen
            randomly and its value is changed.

      Else: chromosome is not mutated
```

- E.g:

[0, 0, 1, 0, 1, 0, 1, 0, 0]

[0, 0, 1, 0, 1, 1, 1, 0, 0]

Experimental Results-I

The aim is to check if , by applying binary-strings evolution strategies , it is possible that a population of N agents converges to the optimum Saussurean communication system in which all the agents share the same optimal matrix.

$$M_1^2 = \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix} \qquad M_2^2 = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$$

2x2 Optimal matrices

$$M_1^3 = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \qquad M_2^3 = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 1 & 0 \end{pmatrix} \qquad M_3^3 = \begin{pmatrix} 0 & 1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

$$M_4^3 = \begin{pmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 1 & 0 & 0 \end{pmatrix} \qquad M_5^3 = \begin{pmatrix} 0 & 0 & 1 \\ 0 & 1 & 0 \\ 1 & 0 & 0 \end{pmatrix} \qquad M_6^3 = \begin{pmatrix} 0 & 0 & 1 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \end{pmatrix}$$

3x3 Optimal matrices

For every experiment the maximum possible fitness is given by the formula:

*Maximum fitness = (Population Size - 1) * Number Objects*

Experimental Results - II

- First case 2x2 Matrices

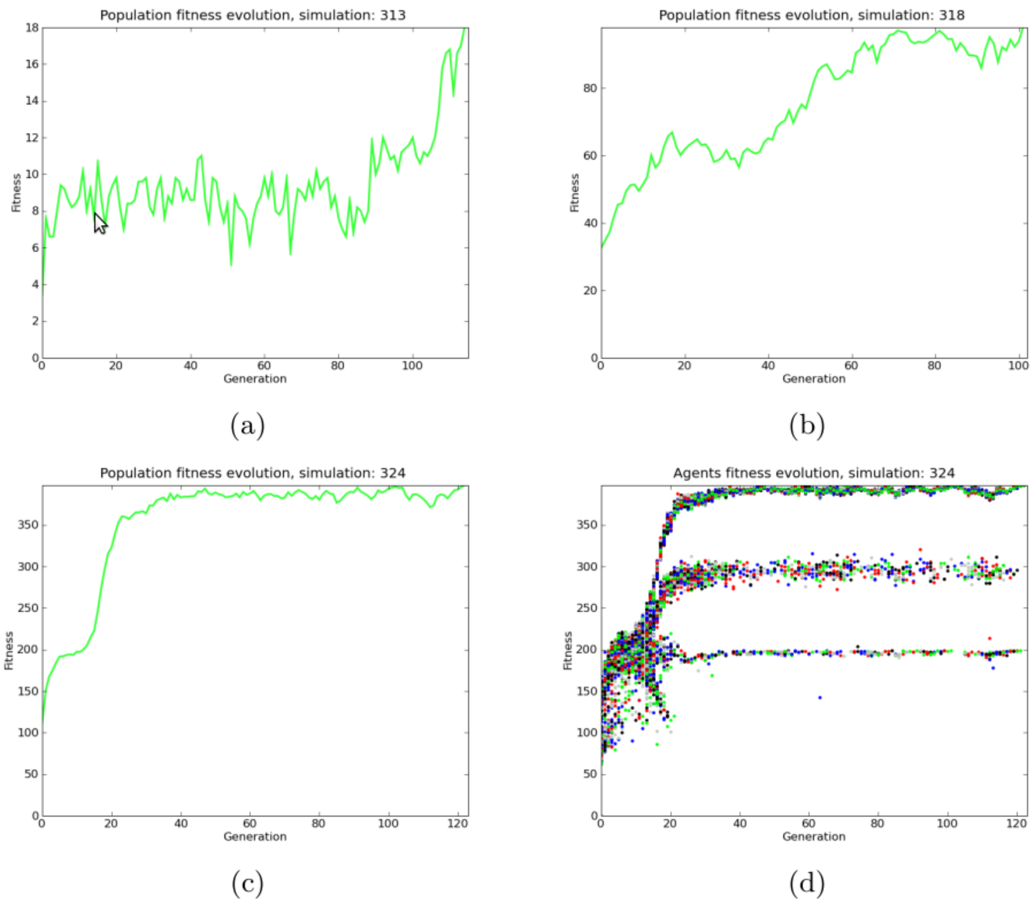

Fig. 2. Population average fitness for (a) $N = 10$, (b) $N = 50$, and (c) $N = 200$. (d) Agents fitness evolution for $N = 200$.

-Notice the counter-intuitive phenomenon that increasing the number of agents speeds-up the consensus convergence.
-(b):
*Max_fitness=(N-1)*n= 98*
-(c),(d): Max_fitness=398

Experimental Results - III

- Second case 3x3 matrices

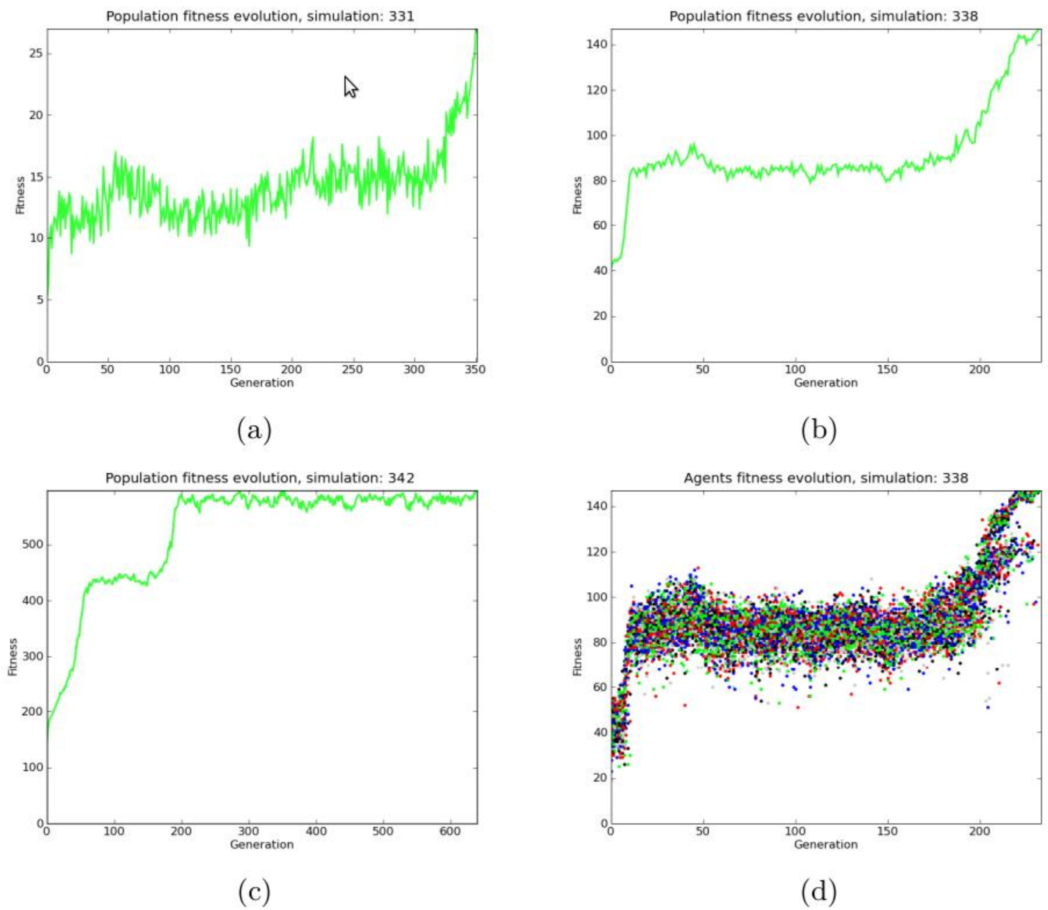

Fig. 3. Population average fitness for (a) $N = 10$, (b) $N = 50$, and (c) $N = 200$. (d) Agents fitness evolution for $N = 50$.

-Again, notice the counter-intuitive phenomenon that increasing the number of agents speeds-up the consensus convergence.
*-(a) : Max_fitness=(N-1)*n=27*
-(b),(d): Max_fitness=147
-(c): Max_finess=597

Concluding Remarks and Future Work

- Binary-strings Evolution Strategies allow the self-emergence of lexicon consensus in a population of autonomous agents.
- Application of the PBIL algorithm to high dimensional association matrices, and application of Genetic Programing to more complex linguistic communication like grammars and syntax.
- On-line learning methods: heuristic reinforcement schemes , stochastic learning automata, and associative neural networks. Comparison with evolutionary methods.
- Implementation on physical robots using machine vision and sound synthesizers.