Evolutionary Algorithms

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Talk outline

• Evolution

• Evolutionary algorithms

• History

• Genetic algorithms

• Examples

• Genetic algorithms: Mechanisms

• Extensions and variations

• Final example

Evolutionary Algorithms
Moshe Sipper, LSL, EPFL
ON

THE ORIGIN OF SPECIES

BY MEANS OF NATURAL SELECTION,

OR THE

PRESERVATION OF FAVOURED RACES IN THE STRUGGLE
FOR LIFE.

BY CHARLES DARWIN, M.A.,
FELLOW OF THE ROYAL, GEOLOGICAL, LINNEAN, ETC., SOCIETIES;
AUTHOR OF 'JOURNAL OF RESEARCHES DURING H. M. S. BEAGLE'S VOYAGE
ROUND THE WORLD.'

LONDON:
JOHN MURRAY, ALBEMARLE STREET.
1859.

The right of Translation is reserved.
in any great degree my theory; but none of the cases of difficulty, to the best of my judgment, annihilate it. On the other hand, the fact that instincts are not always absolutely perfect and are liable to mistakes; — that no instinct has been produced for the exclusive good of other animals, but that each animal takes advantage of the instincts of others; — that the canon in natural history, of 'natura non facit saltum' is applicable to instincts as well as to corporeal structure, and is plainly explicable on the foregoing views, but is otherwise inexplicable, — all tend to corroborate the theory of natural selection.

This theory is, also, strengthened by some few other facts in regard to instincts; as by that common case of closely allied, but certainly distinct, species, when inhabiting distant parts of the world and living under considerably different conditions of life, yet often retaining nearly the same instincts. For instance, we can understand on the principle of inheritance, how it is that the thrush of South America lines its nest with mud, in the same peculiar manner as does our British thrush: how it is that the male wrens (Troglodytes) of North America, build 'cock-nests,' to roost in, like the males of our distinct Kitty-wrens, — a habit wholly unlike that of any other known bird. Finally, it may not be a logical deduction, but to my imagination it is far more satisfactory to look at such instincts as the young cuckoo ejecting its foster-brothers, — ants making slaves, — the larvae of ichneumonidae feeding within the live bodies of caterpillars, — not as specially endowed or created instincts, but as small consequences of one general law, leading to the advancement of all organic beings, namely, multiply, vary, let the strongest live and the weakest die.

**The Origin of Species**

Charles Darwin, 1859.
Evolution

In nature, the evolutionary process occurs when the following four conditions are satisfied:

- An entity has the ability to reproduce itself.

- There is a population of such self-reproducing entities.

- There is some variety among the self-reproducing entities.

- Some difference in ability to survive in the environment is associated with the variety.
4. Natural Selection as an Algorithmic Process

What limit can be put to this power, acting during long ages and rigidly scrutinising the whole constitution, structure, and habits of each creature,—favouring the good and rejecting the bad? I can see no limit to this power, in slowly and beautifully adapting each form to the most complex relations of life.

—Charles Darwin, Origin, p. 469

The second point to notice in Darwin’s summary is that he presents his principle as deducible by a formal argument—if the conditions are met, a certain outcome is assured. Here is the summary again, with some key terms in boldface.

If, during the long course of ages and under varying conditions of life, organic beings vary at all in the several parts of their organization, and I think this cannot be disputed; if there be, owing to the high geometric powers of increase of each species, at some age, season, or year, a severe struggle for life, and this certainly cannot be disputed; then, considering the infinite complexity of the relations of all organic beings to each other and to their conditions of existence, causing an infinite diversity in structure, constitution, and habits, to be advantageous to them, I think it would be a most extraordinary fact if no variation ever had occurred useful to each being’s own welfare, in the same way as so many variations have occurred useful to man. But if variations useful to any organic being do occur, assuredly individuals thus characterized will have the best chance of being preserved in the struggle for life; and from the strong principle of inheritance they will tend to produce offspring similarly characterized. This principle of preservation, I have called, for the sake of brevity, Natural Selection. [Origin, p. 127 (facs. ed. of 1st ed.).]

The basic deductive argument is short and sweet, but Darwin himself described Origin of Species as “one long argument.” That is because it

6. The ideal of a deductive (or “nomologico-deductive”) science, modeled on Newtonian or Galilean physics, was quite standard until fairly recently in the philosophy of science, so it is not surprising that much effort has been devoted to devising and criticizing various axiomatizations of Darwin’s theory—since it was presumed that in such a formalization lay scientific vindication. The idea, introduced in this section, that Darwin should be seen, rather, as postulating that evolution is an algorithmic process, permits us to do justice to the undeniable a priori flavor of Darwin’s thinking without forcing it into the Procrustean (and obsolete) bed of the nomologico-deductive model. See Sober 1984a and Kitcher 1985a.
A pessimistic estimate of the time required for an eye to evolve

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SUMMARY

Theoretical considerations of eye design allow us to find routes along which the optical structures of eyes may have evolved. If selection constantly favours an increase in the amount of detectable spatial information, a light-sensitive patch will gradually turn into a focused lens eye through continuous small improvements of design. An upper limit for the number of generations required for the complete transformation can be calculated with a minimum of assumptions. Even with a consistently pessimistic approach the time required becomes amazingly short: only a few hundred thousand years.

I. INTRODUCTION

When Charles Darwin (1859) presented his theory of evolution he anticipated that the eye would be a favourite target for criticism. He openly admitted that it was 'by far the most serious difficulty' and he wrote: 'that the eye...could have been formed by natural selection seems, I freely confess, the highest possible degree'. Although the principle of evolution is still valid, it gradually lost its potency, and has now almost become a curiosity. But eye evolution continues to evolve, although the question is now one of process rather than one of principle.

Estimates of the number of generations needed to achieve a certain change to a simple character are easily made if the phenotypic selection intensity and heritability of the character are known (Falconer 1989). The evolution of an eye, however, involves a modification of a large number of separate quantitative characters, and there may be discrete innovations. The unknown number of hidden but necessary changes makes it difficult to prevent evolution rate estimates for other complex structures. An eye is a complex structure because the structures necessary for vision, treated as local modifications of pre-existing structures, require a patch of pigmented light-sensitive cells as a starting point, we avoid the monstrous problem of photoreceptor cell evolution (1999; Land & Fernald 1992). Thus, if the number of generations needed to achieve a certain change is limited to finding the number of generations required for the evolution of an eye's optical system becomes solvable.

We have made such calculations by leading from a light-sensitive patch of cells into a focused lens eye. Every part of the eye, and every part of the entire eye is the most serious difficulty'. Although the principle is still valid, it gradually lost its potency, and has now almost become a curiosity. But eye evolution continues to evolve, although the question is now one of process rather than one of principle.

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Evolutionary algorithms

• Adaptive search techniques based on an analogy with mechanisms of natural evolution.

• Key ideas:
  – Population of individuals (solutions).
  – Survival of the fittest.
  – “Genetic” operators:
    crossover (recombination), mutation.
History

• Pioneering work: 1950s and 1960s.
  L. J. Fogel, A. J. Owens, M. J. Walsh, J. Holland (USA).
  I. Rechenberg, H. -P. Schwefel (Germany).

• 1985:
  – First International Conference on Genetic Algorithms (ICGA).
  – Less than 10 groups worldwide.

• Today:
  – Hundreds of groups.
  – Several conferences and journals.
  – Industrial applications.
Application areas

- Optimization
- Automatic programming
- Machine learning
- Economics
- Operations research
- Immune systems
- Ecology
- Population genetics
- Studies of evolution and learning
- Social systems
Genetic algorithms

- *Population* of individuals.

- Each individual is represented by a finite string of symbols, known as the *genome*.

- A genome *encodes* a possible solution in a given *problem space*. Known also as the *search space*: all possible solutions to the problem at hand.

- *Genotype*: the genetic composition of an individual, i.e., the information contained in the genome.  
*Phenotype*: the expressed traits of an individual, i.e., its physical and mental characteristics.

- The genotype gives rise to the phenotype. Fitness is due to the phenotype.
Standard genetic algorithm

• Generate initial population at random.

• Every evolutionary step, known as a generation, the individuals in the current population are decoded and evaluated according to some predefined quality criterion, referred to as the fitness, or fitness function.

• To form a new population (the next generation):
  - Selection (reproduction): Individuals are selected in accordance with their fitness values.
  - Crossover: Individuals are recombined.
  - Mutation: Small changes are randomly applied to individuals.

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begin GA
  g:=0 \{ generation counter \}
  Initialize population $P(g)$
  Evaluate population $P(g)$
  while not done do
    g:=g+1
    Select $P(g)$ from $P(g - 1)$
    Crossover $P(g)$
    Mutate $P(g)$
    Evaluate $P(g)$ \{ i.e., compute fitness values \}
  end while
end GA
Figure 2. The GA cycle.
Genetic operators

- **Fitness-proportionate selection.**
  "Roulette-wheel sampling": give each individual a slice of a roulette wheel equal in area to the individual’s fitness.
  
  \[ f_1 = 0.5 \]
  
  \[ f_2 = 0.5 \]
  
  \[ f_3 = 0.8 \]
  
  \[ f_4 = 0.2 \]

- **One-point crossover.**

  \[
  \begin{array}{c}
  0101001 | 10101 \\
  1111111 | 00000 \\
  \downarrow \\
  0101001 | 00000 \\
  1111111 | 10101
  \end{array}
  \]

- **Mutation.**

  \[
  \begin{array}{c}
  111111110101 \\
  \downarrow \\
  111111011010
  \end{array}
  \]
with all hermaphrodites two individuals, either occasionally or
habitually, concur for the reproduction of their kind. This view,
I may add, was first suggested by Andrew Knight. We shall
presently see its importance; but I must here treat the subject
with extreme brevity, though I have the materials prepared for
an ample discussion. All vertebrate animals, all insects, and some
other large groups of animals, pair for each birth. Modern re-
search has much diminished the number of supposed herma-
phrodites, and of real hermaphrodites a large number pair; that
is, two individuals regularly unite for reproduction, which is all
that concerns us. But still there are many hermaphrodite ani-
imals which certainly do not habitually pair, and a vast majority
of plants are hermaphrodites. What reason, it may be asked, is
there for supposing in these cases that two individuals ever con-
cur in reproduction? As it is impossible here to enter on details,
I must trust to some general considerations alone.

In the first place, I have collected so large a body of facts,
showing, in accordance with the almost universal belief of
breeders, that with animals and plants a cross between different
varieties, or between individuals of the same variety but of an-
other strain, gives vigour and fertility to the offspring; and on
the other hand, that close interbreeding diminishes vigour and
fertility; that these facts alone incline me to believe that it is a
general law of nature (utterly ignorant though we be of the
meaning of the law) that no organic being self-fertilises itself
for an eternity of generations; but that a cross with another
individual is occasionally — perhaps at very long intervals —
indispensable.

On the belief that this is a law of nature, we can, I think,
understand several large classes of facts, such as the following,
which on any other view are inexplicable. Every hybridizer
knows how unfavourable exposure to wet is to the fertilisation
of a flower, yet what a multitude of flowers have their anthers
and stigmas fully exposed to the weather! but if an occasional
cross be indispensable, the fullest freedom for the entrance of
pollen from another individual will explain this state of ex-
posure, more especially as the plant’s own anthers and pistil
generally stand so close together that self-fertilisation seems

The Origin of Species,
Charles Darwin, 1859.
Figure 2. A generational cycle of the Simple Genetic Algorithm.
Example

Function optimization.

\[ f(x) = -|x \sin(\sqrt{|x|})| + C \]

Find \( x^* \), \( x^* \in [-512, 512] \), such that \( f(x^*) \) is minimal.
Example (cont’d)

• Individual = binary string, representing a value in the range $[0, 512]$ (note- $f(x)$ is symmetric about 0).

• Length of string determines precision.
  10 bits = 1024 distinct values (= size of search space).
  $[0, 512] \leftrightarrow [0000000000, 1111111111]$. Example: $x = 0000000011 = 1.5$.

• Fitness of individual = $f(x)$.
  Lower = better.
  Choose constant $C$ such that $f(x) \geq 0$ since probabilities are involved.

• Apply genetic algorithm: fitness-proportionate selection, one-point crossover, mutation.
Example (cont’d)

<table>
<thead>
<tr>
<th>Generation</th>
<th>Best</th>
<th>Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1.0430</td>
<td>268.70</td>
</tr>
<tr>
<td>3</td>
<td>1.0430</td>
<td>78.61</td>
</tr>
<tr>
<td>9</td>
<td>0.00179</td>
<td>32.71</td>
</tr>
<tr>
<td>18</td>
<td>0.00179</td>
<td>14.32</td>
</tr>
<tr>
<td>26</td>
<td>0.00179</td>
<td>5.83</td>
</tr>
<tr>
<td>36</td>
<td>0.00179</td>
<td>2.72</td>
</tr>
<tr>
<td>50</td>
<td>0.00179</td>
<td>1.77</td>
</tr>
<tr>
<td>69</td>
<td>0.00179</td>
<td>0.15</td>
</tr>
</tbody>
</table>

- Minimum found at generation 9. Average continues to improve.
**TEST FUNCTIONS**

The following functions have been used to test the Parallel Genetic Cellular Automata:

- **De Jong Functions**

- **"Hard" Functions**

\[ P_6(x) = \sum_{i=1}^{6} [x_i^2 - \cos(A \cdot x_i)] \]

\[ x_i \in [-5.12, 5.12] \]

\[ P_7(x) = \sum_{i=1}^{10} -x_i \cdot \sin(\sqrt{|x_i|}) \]

\[ x_i \in [-500.0, 500.0] \]

\[ P_8(x) = \sum_{i=1}^{10} \frac{x_i^2}{4000} - \prod \cos\left(\frac{x_i}{\sqrt{i}}\right) + 1 \]

\[ x_i \in [-600.0, 600.0] \]
Genetic algorithms: Mechanisms

- Genetic algorithms work by discovering, emphasizing, and recombining good building blocks of solutions in a highly parallel fashion.

- Good solutions tend to be made up of good building blocks: combinations of bit values that confer higher fitness.

- Example: fitness = number of 1s.
  
  111 * * * * * * *

  is a "good" building block = better-than-average substring.

  ("*" = don't care = 0 or 1).

- *Exploitation* versus *exploration* issue.
  Exploit "good" regions of search space while at the same time explore new ones. Depends on the algorithm and its parameters.

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*Moshe Sipper, LSL, EPFL*
Figure 1: Operation of a generic hill climbing method (allegory). From a randomly chosen starting point (panel [A]), the direction of maximum slope is followed (panel [C]) until one reaches a point where all surrounding directions are downhill (panel [D]). Landing (panel [B]) is not problematic from the computational point of view.
Rule of Global Optimization, also known as

THE DIRTY HARRY RULE:

"You should never feel lucky"

Faced with the landscape of Figure 2 the most straightforward solution lies with a technique called iterated hill climbing. This is a fancy name for something very simple, as illustrated on Figure 3. You just run your favorite local hill climbing method repeatedly, each time from a different randomly chosen starting point. While doing so you keep track of the various maxima so located, and once you are satisfied that all maxima have been found you pick the tallest one and you are done with your global optimization problem. As you might imagine, deciding when to stop is the crux of this otherwise straightforward procedure.
Figure 3: An iterated hill-climbing scheme. After landing, each trial proceeds as on Fig. 1.
Extensions and variations

- Genome encoding. Use alphabets other than binary: character-based encodings, real-valued encodings, tree representations.

- Tree encoding schemes.
  
  Example: Genetic Programming.

![Tree Diagrams]

\[(A \times B) + (C / 0)\]

Fig. 3. Above: parent individuals. Below: offspring. Crossover points are marked by a cross in the parents.

- Selection: rank selection, tournament selection.

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after 20 runs. After increasing the population size to 8,000, a solution was not found until the eighth run, suggesting that the even-5-parity function is a very difficult function to learn. The solution appeared on generation 27 of run 8 and contained 347 points as shown below:

\[
\begin{align*}
&\text{NAND (NAND (OR (AND (AND (OR D2 D3) (OR D4 D2)) (AND (OR D4 D0) (AND D1 D1))))) (NOR (NOR D1 D4) (OR (NOR D3 D4) (NOR D0 D2)))) (NOR (NOR (NAND (AND (OR D1 D0) (OR D3 D2)) (OR D1 D3))) (NOR D1 D2)) (NOR (AND (NAND D4 D3) (NAND D0 D2)) (NAND (NAND D4 D0)) (NAND (AND D0 D4) (NAND (NOR D1 D4) (OR D1 D0)))) (NAND (AND D4 D1) (OR D2 D0)))) (AND (AND (NAND D4 D3) (OR D3 D0)) (OR D2 D1))) (NOR (NOR (AND (AND D1 D1) (NOR (NAND (NAND D4 D2) (NAND D4 D0))) (OR D2 D0) (AND D4 D1))) (NAND (OR (AND (OR (AND D3 D0)) OR D4 (NAND (OR (NOR D1 D2) D3) D4))) (NAND (NAND D0 D1) (NAND D2 D2))) (NAND (AND (NOR D0 D1) (OR D3 D4)) (OR (NAND D3 D4) (AND D3 D1))) (NAND (NAND D4 (AND (D1 D0) (OR D3 D2))))) (NAND (OR (NAND D1 D0) (NOR D2 D0) (NAND D3 D2))) (NAND (AND (NAND (NAND D3 D4) (AND D0 D4)) (OR (AND D1 D4) (NOR D2 D2))) (AND (OR (NOR D1 D3) (NOR (AND D2 D2) (NOR D2 D1)) (AND (NAND D4 D0) (NAND (NAND D4 D4) (NOR D0 D4))) (NOR D0 D4) (NOR D3 D3) (AND D4 D1))) (AND (OR (NOR D3 D4) D1) (AND (OR D1 D0) (OR D3 D2)))) (NAND (AND (AND D1 D4) (NAND D1 D3) (OR D3 D1))) (OR (OR D2 D3) (NAND D0 D0)) (AND D4 D1)) (AND (OR D1 D4) (NAND D1 D3) (OR D3 D1)))) (AND (OR D2 D3) (NAND D3 D0)) (AND (OR (NOR D3 D4) D3) (AND (OR D1 D0) (OR D3 D2)))).
\end{align*}
\]

Our usual computation for the number of individuals that must be processed to solve a problem with 99% probability requires making enough runs that successfully solve the problem to produce a reasonable estimate for the values of probability \(P(M, i)\) between generations 0 and 50. The fact that only one solution of the even-5-parity problem appeared after eight runs suggests that a large number of lengthy runs would be required to accumulate the necessary data to permit construction of our usual performance curves. If we ignored the relatively simple nature of these eight runs, our usual calculation...
Extensions and variations (cont’d)

Genetic operators.

• Crossover:

  – Two-point:
    0 1 0 1 1 | 1 1 1 | 0 1 0 1 0
    1 0 1 1 1 | 0 0 1 | 1 1 0 1 1
    ↓
    0 1 0 1 1 | 0 0 1 | 0 1 0 1 0
    1 0 1 1 1 | 1 1 1 | 1 1 0 1 1

  – Uniform: select each bit from one or the other parent at random.
    0 1 0 1 1 0 1
    1 1 1 0 0 1 0
    random bit choices: 1 2 2 1 2 1 2
    ↓
    0 1 1 1 0 0 0
    1 1 0 0 1 1 1

• Mutation: adaptive mutation.
Extensions and variations (cont’d)

• Steady-state genetic algorithm.
  – *Generational*: entire population changes each generation.
    Drawbacks: good individuals may not get a chance to reproduce, or may proliferate too quickly.
  – *Steady-state*: replace only a few individuals each generation (usually least-fit).

• Coevolution. Two interacting populations, one of potential solutions, the other of test cases, where not only do the solutions evolve (as in the standard genetic algorithm) but so, concomitantly, do the test cases.
Extensions and variations (cont’d)

- Parallel evolutionary algorithms: speed-up computation, closer to nature.

- Two major types:
  - coarse-grained (island)
  - fine-grained (grid)
Fig. 4. Illustration of the Island model of semi-isolated populations

Fig. 5. A 2-D spatially extended population of individuals. A possible neighborhood of an individual (black) is marked in gray.

semi-isolated niches of genetically homogeneous individuals emerge across the grid as a result of slow individual diffusion. This phenomenon is called isolation.
Further material

- **WWW:**
  http://lslwww.epfl.ch/~moshes/caslinks.html

- **Journals:**
  Major journals:
  
  - Evolutionary Computation
  - IEEE Transactions On Evolutionary Computation
  - BioSystems

  Related journals:
  
  - Adaptive Behavior
  - Artificial Life
  - Complexity
  - Complex Systems
  - International Journal of Modern Physics C
  - Physica D
• Conferences:
  - IEEE International Conference on Evolutionary Computation (ICEC)
  - Parallel Problem Solving from Nature (PPSN)
  - International Conference on Genetic Algorithms (ICGA)
  - Genetic Programming (GP)
  - International Conference on Evolvable Systems: from Biology to Hardware (ICES)
  - International Conference on Artificial Neural Networks and Genetic Algorithms (ICANNGA)
  - Genetic ALgorithms in Engineering Systems: Innovations and Applications (GALESIA)
  - Evolution Artificielle
There is grandeur in this view of life, with its several powers, having been originally breathed into a few forms or into one; and that, whilst this planet has gone cycling on according to the fixed law of gravity, from so simple a beginning endless forms most beautiful and most wonderful have been, and are being, evolved.

Charles Darwin, The Origin of Species, 1859
Algorithme Parallèle

Implantation sur Connection Machine:

\text{géométrie virtuelle de la CM} = \text{géométrie de l'automate}

\text{for each cell } i \text{ do in parallel }

\text{générer } X_i \text{ D aleatoirement}

\text{end parallel do}

\text{while not done do}

\text{for each cell } i \text{ do in parallel }

\text{évaluer } f(X_i)

\text{Cire } p^N, p^S, p^E, p^W

\text{Cire } x^N, x^S, x^E, x^W

f_i \leftarrow \text{opt } \{ p^N, p^S, p^E, p^W \}

(X_i', X_i'') \leftarrow X_i \otimes X_i^0

\text{évaluer } f(X_i') \text{ et } f(X_i'')

f_i^0 \leftarrow \text{opt } \{ f(X_i), f(X_i'), f(X_i'') \}

X_i^0 \leftarrow X_i

\text{mutation de } X_i \text{ avec probabilité } p_m

\text{end parallel do}

\text{end while}
AVEC "Migration" arbitraire: PGCA2

while not done do
  for each cell i do in parallel
    { sélection et croisement comme pour PGCA0 }
    { phase de migration }
    if génération mod fréquence = 0 then
      choisir le site j au hasard et "cire" l'individu j { j → i }
      \( f_i^0 \leftarrow \text{opt}\{ f_i, f_j \} \)
      \( X_i \leftarrow X_i^0 \)
    end if
  end parallel do
end while
while not done do
    for each cell $i$ do in parallel
        
        \{ selection et crossover comme PGCA $\Phi$ \}
        
        \{ phase de migration \}
        
        choisir une direction au hasard
        entre N, S, E, W;
        
        Sauter de $m$ pas dans cette direct.
        
        $f^0_i < \text{opt}\{f_i^0, f_j\}$ \{ $i \rightarrow i$ \}
        
        \ $X_i \leftarrow X_i^0$
        
        end parallel do
    end while
individu = automate = solution potentielle d'un Pdonna
le nombre d'états d'un tel automate peut être très
grand, mais il demeure fini.

Règle de transition (arbitraire):
1 - chaque automate évalue son état
2 - chaque automate regarde les valeurs de
ses proches voisins
3 - chaque automate fait une "hybridation"
(crossover) avec le "meilleur" de ses
voisins
4 - le "meilleur" entre l'individu et les deux
"fils" est retenu à la place de l'individu
original
AUTRES SIGNE DE MATURITÉ :

• LA TECHNIQUE COMMENCE À PARTIR DANS L'INDUSTRIE
  (SIE MENS, PHILIPS, KLM, DAIMLER-BENZ,
  DASSAULT, HEWLETT PACKARD, ...)

• CRÉATION DE RÉSEAUX D'INFORMATION ET DE COOPÉRATION :
  EN EUROPE : ECO NET
  (NETWORK OF EXCELLENCE ON EVOLUTIONARY COMPUTATION)

• DIFFICILE DE RECENCER LES TÈS
  NOMBREUX GROUPES TRAVAILLANT DANS LE
  DOMAINE DANS LE MONDE

• INFRASTRUCTURE WEB Très développée

PAR EX. VOIR :

http://eslwww.epfl.ch/staff/MS/MS.html

+ Complex adaptée système linéaire
Aujourd'hui

4 conférences majeures

- ICGA
- PPSN
- ICEC (IEEE)
- GP

(Très proches)

- ARTIFICIAL LIFE
  - ECAL
  - SAB

Beaucoup de conférences spécialisées et sessions EC dans ces conférences AI et ANN

Journaux spécialisés

(MIT Press, IEEE Transactions... )
Evolutionary Engineering

with forthcoming atomic scale (nano) technologies:
- Enormous number of components ($\sim 10^{23}$)
- Analysis nearly impossible

⇒ systems will probably be "evolved" instead of being built following a blueprint

Project: Automatic evolution and synthesis of logic circuits
(ex: big Artificial Neural Networks)
CONCLUSIONS

- Genetic Algorithms are especially suitable for:
  - exploring enormous search spaces.
  - optimizing hard, discontinuous, nondifferentiable, noisy functions.
- Genetic Algorithms naturally lend themselves to parallel implementations.
- Genetic Algorithms can be conveniently used together with problem-specific heuristics.
- Genetic Algorithms have been applied successfully to a wide range of problems.