Evolutionary computation

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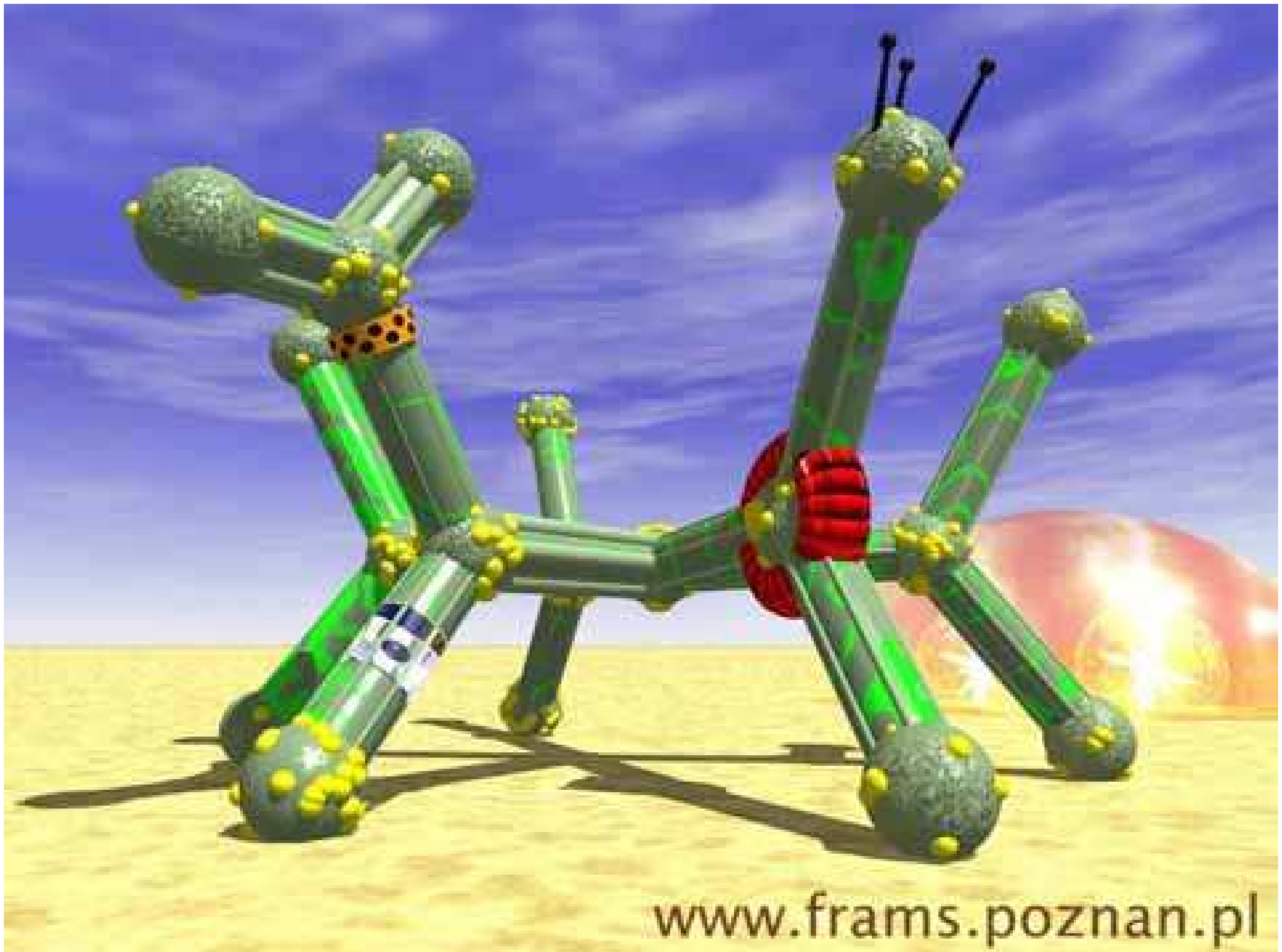
Evolutionary Computation



Evolutionary Computation

Inspiring principle: theory of **natural selection**

"Species face the problem of searching for beneficial adaptations to the environment. The *knowledge* that each species has gained is embodied in the makeup of the chromosomes of its members." (Davis, *Genetic Algorithms and Simulated Annealing*, 1987)

Example: rabbits. . .

Evolutionary Computation

Evolutionary Computation (EC) encompasses:

- Genetic Algorithms
- Genetic Programming
- Evolution Strategies
- Estimation of Distribution Algorithms

Objectives

- Problem solving
- Optimization
- Adaptive systems design
- Simulation

Some applications

- System design (e.g., airplanes, electronic circuits, mechanical elements)
- Neural network training (e.g., robotics)
- Signal processing (e.g., artificial vision)
- Optimization (discrete and continuous)

More applications

- ▷ Time series analysis and forecasting (e.g., financial forecasting)
- ▷ Artificial Life (e.g., cellular automata, analysis of complex adaptive systems)
- ▷ Games (e.g., Prisoner's Dilemma)

Challenge: find a problem where EC has NOT been applied!

Genetic Algorithms

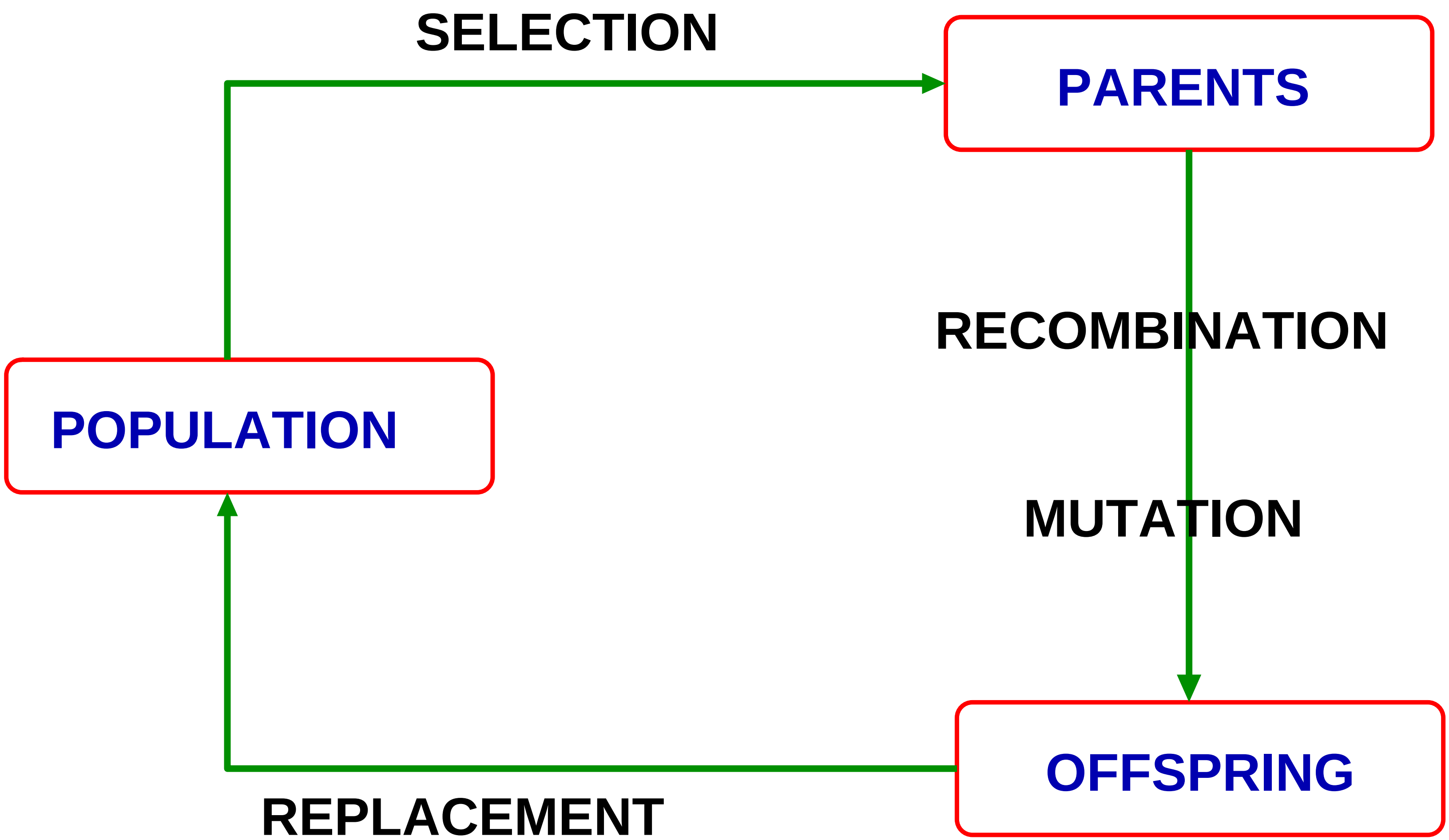
The Metaphor

NATURAL EVOLUTION		ARTIFICIAL SYSTEMS
Individual	$\leftrightarrow$	A possible solution
Fitness	$\leftrightarrow$	Quality
Environment	$\leftrightarrow$	Problem

A bit of terminology

- A **population** is the set of individuals (solutions)
- Individuals are also called **genotypes** or **chromosomes** (if one solution $\leftrightarrow$ one chromosome)
- Chromosomes are made of units called **genes**
- The domain of values of a gene is composed of **alleles** (e.g., a binary variable/gene has two alleles)

The Evolutionary Cycle



Genetic operators

- Mutation
- Recombination
- Selection
- Replacement/insertion

Genetic operators

- ▷ EC algorithms define a basic computational procedure which uses the genetic operators.

- ▷ The definition of the genetic operators specifies the actual algorithm.

- ▷ The definition of the genetic operators depends upon the problem at hand.

Genetic Algorithms

Developed by John Holland (early ’70) with the aim of:

- Understand adaptive processes of natural systems
- Design robust (software) artificial systems

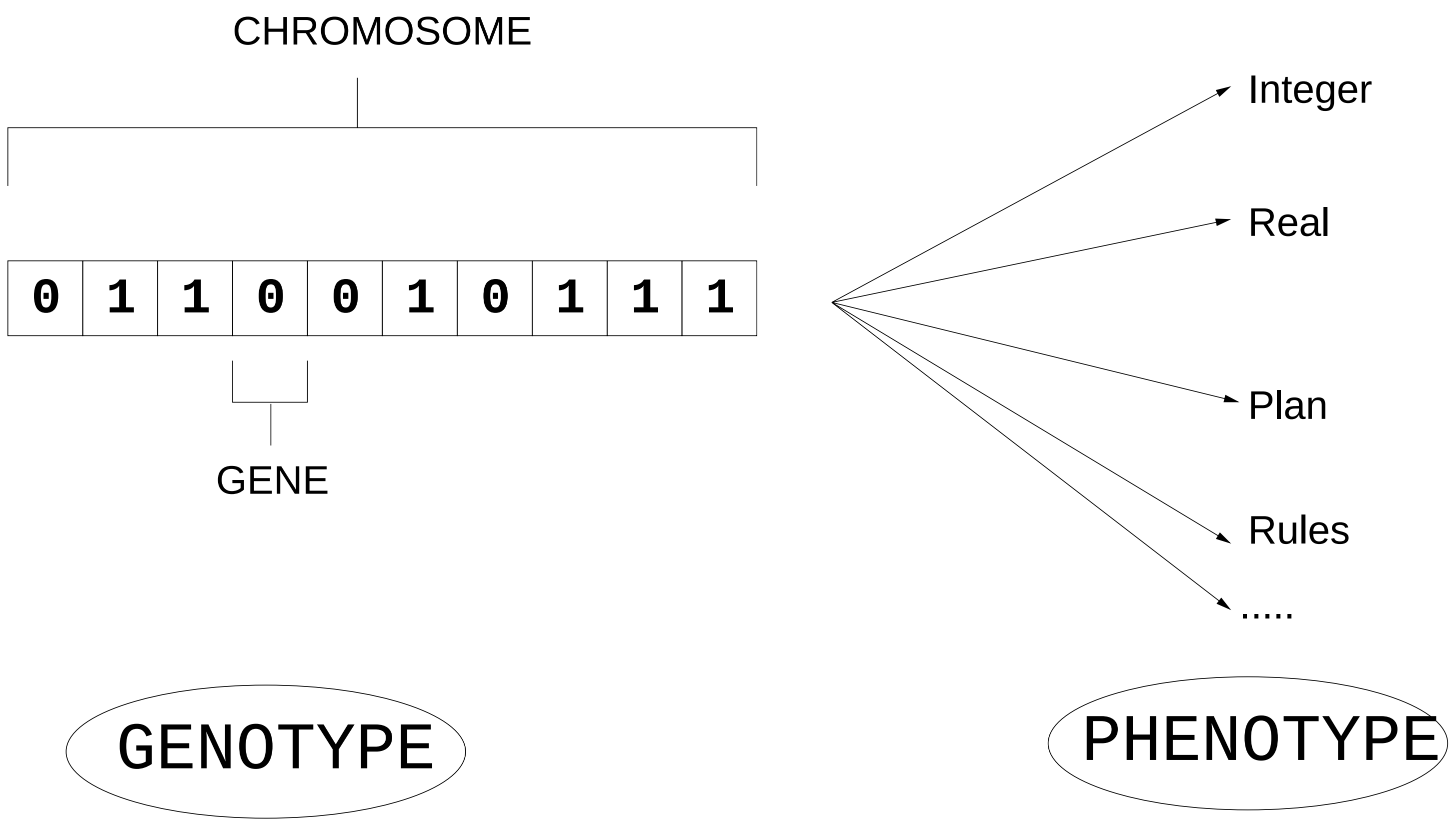
Simple Genetic Algorithm

- Derived from the natural metaphor
- Very simple model
- ‘Programming oriented’

You can take it as a first step toward evolutionary algorithms in general

Simple Genetic Algorithm

Solutions are coded as **bit strings**



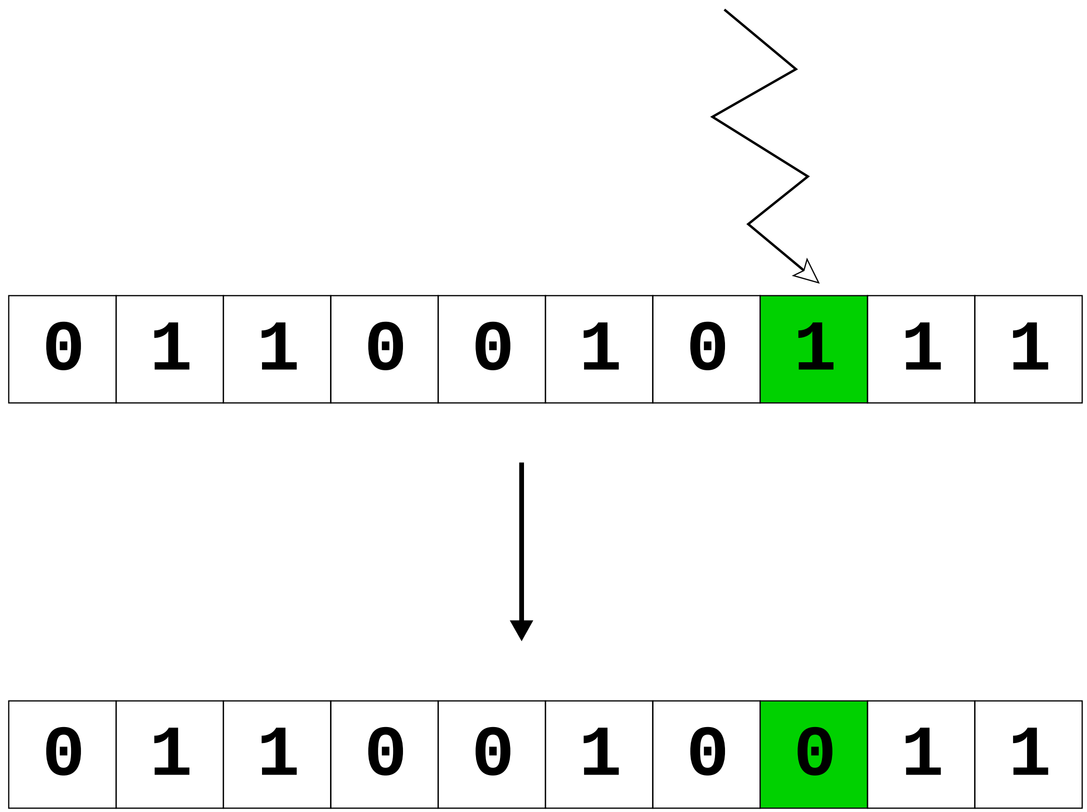
Example

Optimization of a function of integer variable $x \in [0, 100]$:

- binary coding $\longrightarrow$ string of 7 bit
- 4 bits per digit $\longrightarrow$ string of 12 bit

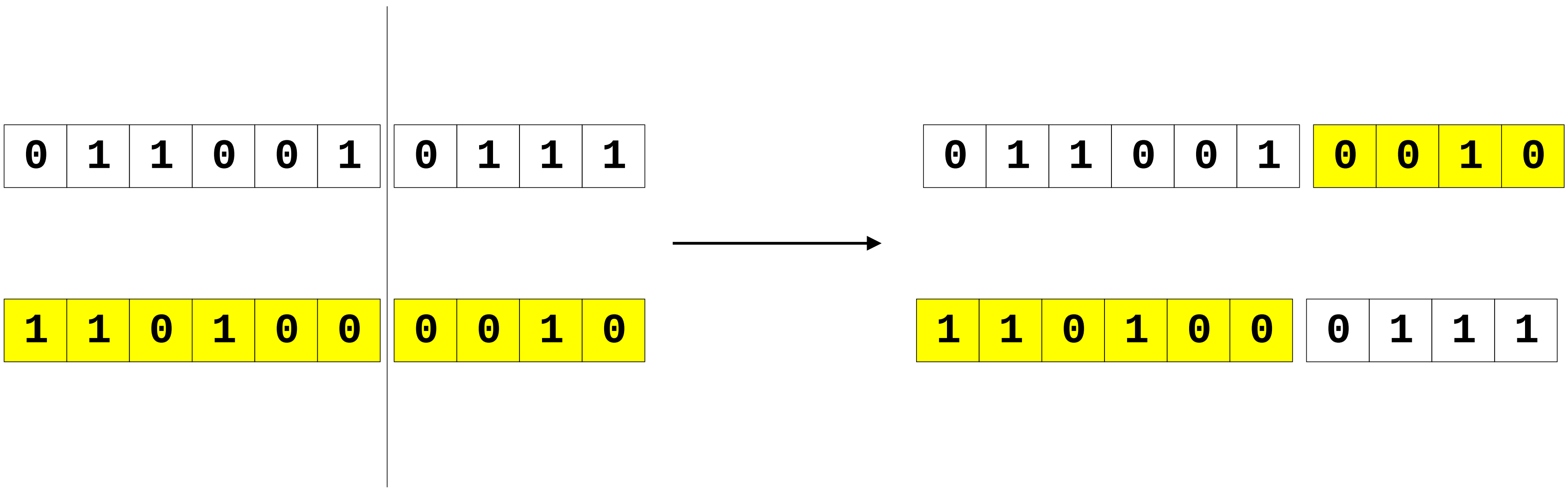
Genetic operators (1)

Mutation: each gene has probability p_M of being modified ('flipped')



Genetic operators (2)

Crossover: cross-combination of two chromosomes (loosely resembling human crossover)



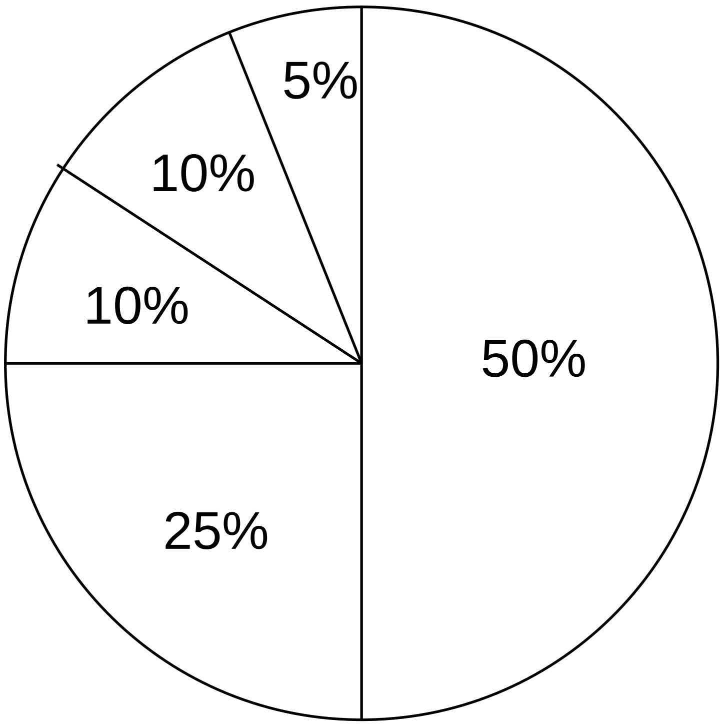
Genetic operators (3)

Selection acts in the choice of parents and produces the *mating pool*.

$\longrightarrow$ **Proportional selection**: the probability for an individual to be chosen is proportional to its fitness.

Genetic operators (3)

Roulette wheel



I_1	50
I_2	25
I_3	10
I_4	10
I_5	5

Genetic operators (4)

Generational replacement: The new generation replaces entirely the old one.

- Advantage: very simple, computationally not (extremely) expensive, easier theoretical analysis.
- Disadvantage: we could loose good solutions

High-level algorithm

```
Initialize Population
Evaluate Population
while Termination conditions not met do
   while New population not completed do
      Select two parents for mating
      Apply crossover
      Apply mutation to each new individual
   end while
   Population ← New population
   Evaluate Population
end while
```

Termination conditions

The basic question is: **when to stop?**

- Execution time limit reached
- We are satisfied with the solution(s) obtained
- Stagnation (limit: the population converged to the same individual)

Simple Genetic Algorithm

Initialize Population{N_{pop} individuals $X_1, \ldots, X_{N_{pop}}$}

for $i = 1$ to N_{pop} **do**

  $X_i \leftarrow$ InitialSolution() {e.g., random}

end for

Evaluate Population{Individual X_i has fitness F_i}

for $i = 1$ to N_{pop} **do**

  $F_i \leftarrow$ Eval(X_i)

end for

Simple Genetic Algorithm

Select parents: G_1, G_2 {Roulette wheel selection}

$lung \leftarrow 0$

for $i = 1$ to N_{pop} **do** {all fitness values are summed up}

  $lung \leftarrow lung + F_i$

end for

for $m = 1$ to 2 **do**

  $r \leftarrow$ Random(0,$lung$); $sum \leftarrow 0$; $i \leftarrow 1$

  while $i < N_{pop}$ AND $sum < r$ **do**

    $sum \leftarrow sum + F_i$; $i \leftarrow i + 1$

  end while

  $G_m \leftarrow X_i$

end for

Simple Genetic Algorithm

Apply crossover: from G_1, G_2 we get G'_1, G'_2

$r \leftarrow$ Random(1,$l_{chromosome}$){crossover point}

for $i = 1$ to $r - 1$ **do**

$G'_1[i] \leftarrow G_1[i]$

$G'_2[i] \leftarrow G_2[i]$

end for

for $i = r$ to $l_{chromosome}$ **do**

$G'_1[i] \leftarrow G_2[i]$

$G'_2[i] \leftarrow G_1[i]$

end for

Simple Genetic Algorithm

Apply mutation to individual X

for $i = 1$ to $l_{chromosome}$ **do**

  $r \leftarrow$ Random(0,1)

  if $r \leq p_M$ **then**

    Complement $X[i]$

  end if

end for

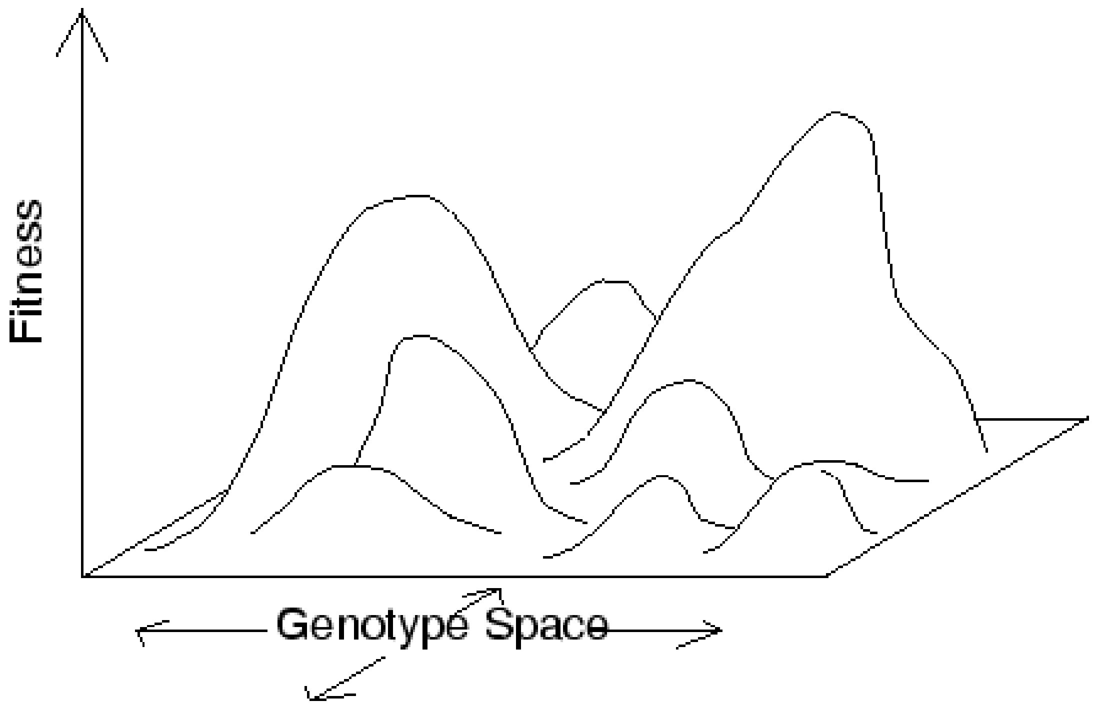
SGA: Example

Maximization of a real function

Taken from: `http://www.evonet.polytechnique.fr/CIRCUS2/`

Fitness Landscape

Representation of the space of all possible genotypes, along with their fitness.



Fitness Landscape

Caution!

- Different landscapes for different operators
- In many cases fitness landscapes are *dynamic*
- Landscape ‘intuition’ might be misleading
- Use of term *local optimum* used and abused everywhere

Why does it work?

Intuition:

- Crossover combines good parts from good solutions (but it might also destroy. . . sometimes)
- Mutation introduces diversity
- Selection drives the population toward high fitness

SGA: pros and cons

Pros:

- Extremely simple
- General purpose
- Theoretical models

Cons:

- Coding
- Too simple genetic operators

A recipe

The ingredients to prepare a GA:

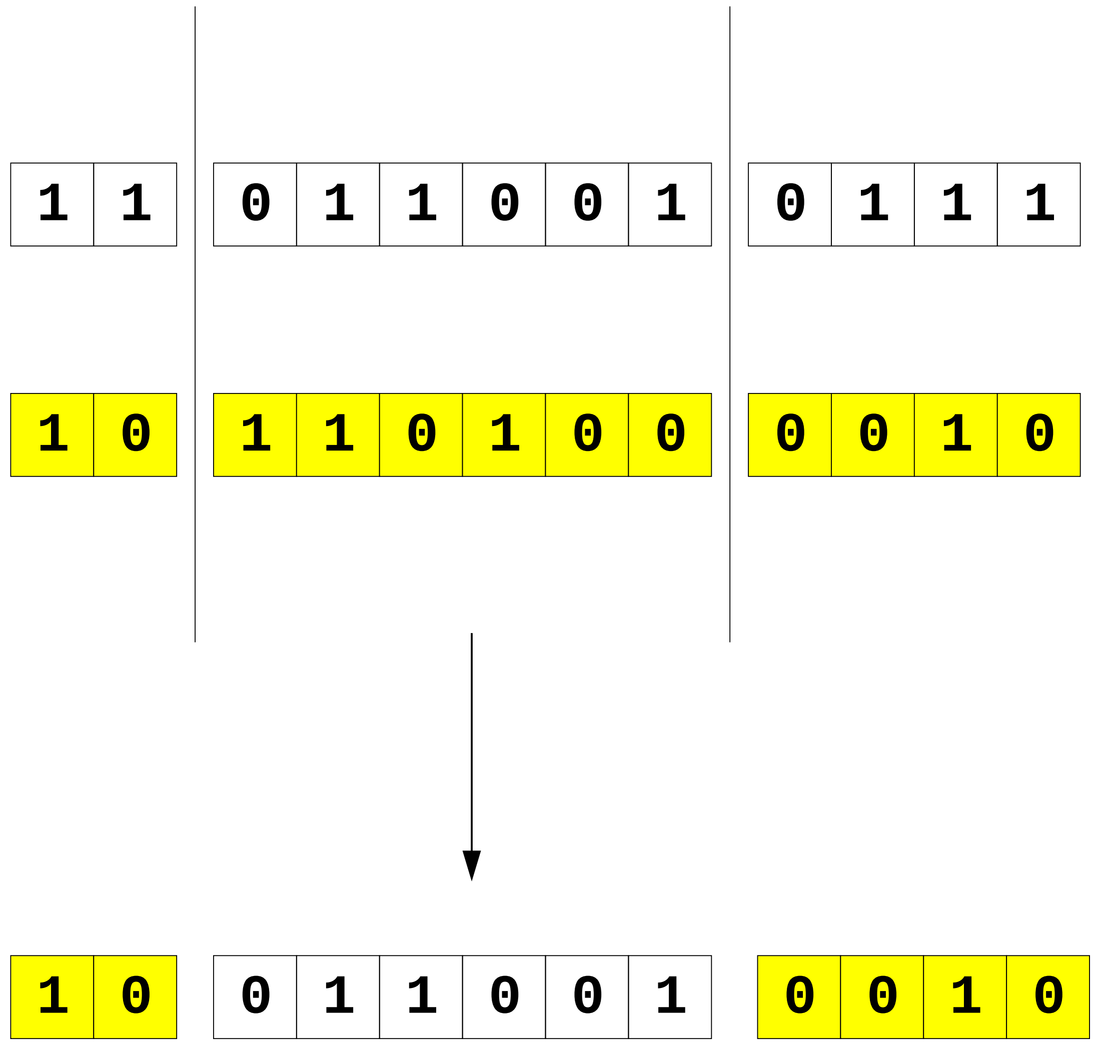
- Solution coding (e.g., bit strings, programs, arrays of real variables, etc.)
- Define a way of evaluating solutions (e.g., objective function value, result of a program, behavior of a system, etc.)
- Define recombination operators (*crossover* , *mutation*)
- Define the selection and replacement/insertion mechanisms

Toward *less simple* GA

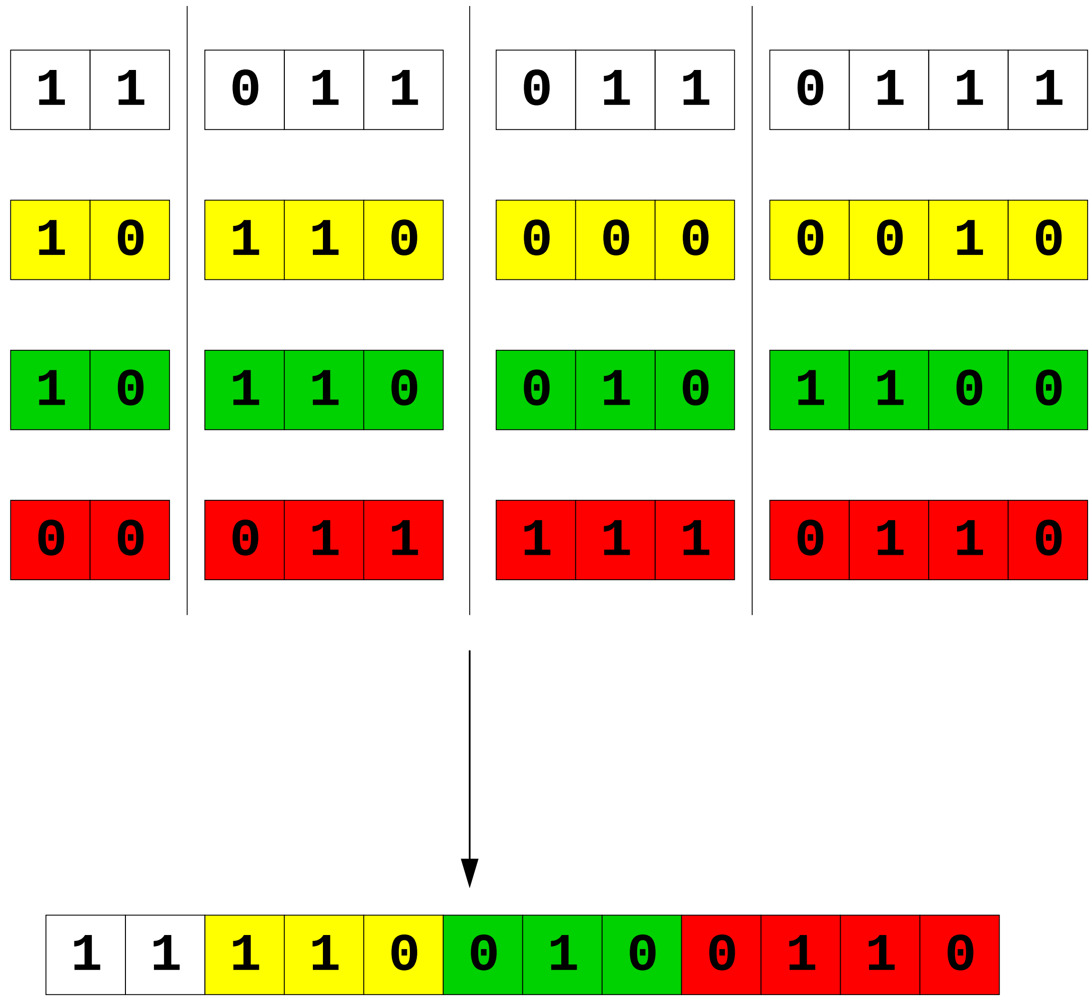
Recombination:

- *Multi-point crossover* (recombination of more than 2 “pieces” of chromosomes)
- *Multi-parent crossover* (an individual is generated by more than 2 parents)
- *Uniform crossover* (children created by randomly shuffling the parent variables at each site)

Multi-point crossover



Multi-parent crossover



Toward *less simple* GA

Mutation:

- Learning applied to modify the chromosome
- In optimization, hill-climbing or more complex local search algorithms can be applied

Interesting topic: Evolution & Learning,

`www.cogs.susx.ac.uk/users/ezequiel/alife-page/evolearn.html`

Toward *less simple* GA

Selection:

- Different probability distribution (e.g., probability distribution based on the *ranking* of individuals)
- *Tournament Selection* (iteratively pick two or more individuals and put in the *mating pool* the fittest)

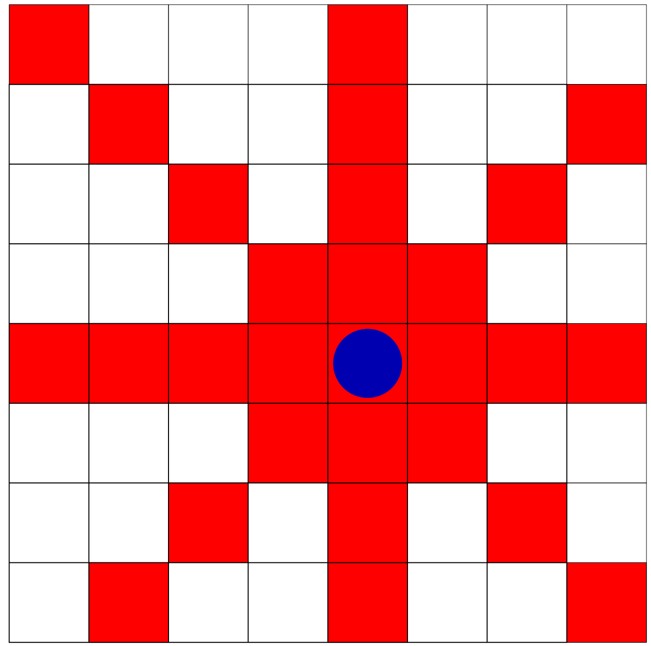
Ex: real valued variables

- Solution: $x \in [a, b],\ a, b \in \mathbb{R}$
- Mutation: random perturbation $x \to x \pm \delta$, accepted if $x \pm \delta \in [a, b]$
- Crossover: linear combination $z = \lambda_1 x + \lambda_2 y$, with λ_1, λ_2 such that $a \leq z \leq b$.

Example: permutations

- Solution: $x = (x_1, x_2, \ldots, x_n)$ is a permutation of $(1, 2, \ldots, n)$
- Mutation: random exchange of two elements in the n-ple
- Crossover: like 2-point crossover, but avoiding value repetition (see next example).

Eight Queens

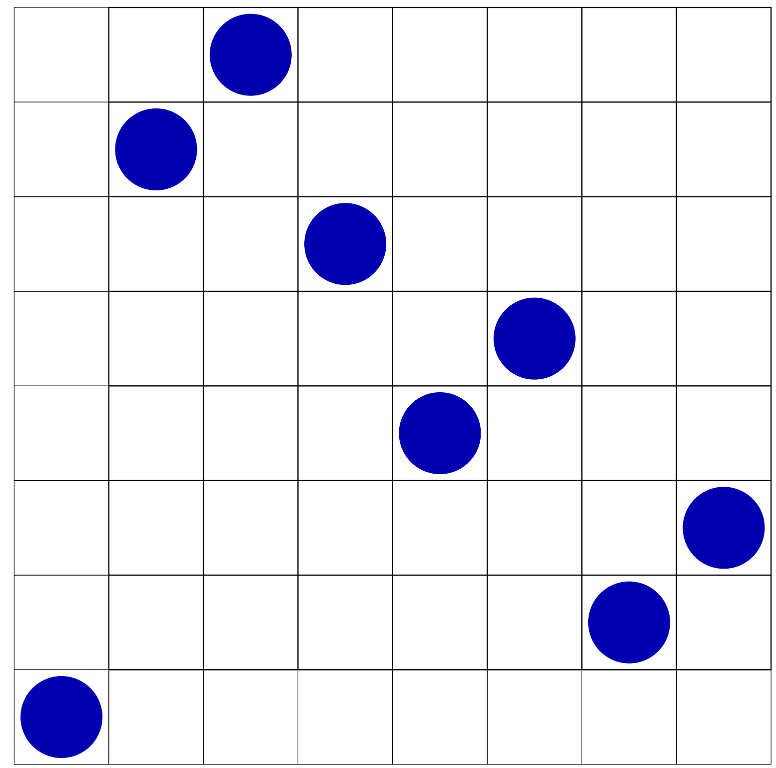


Place 8 queens on a 8×8 chessboard in such a way that the queens cannot attack each other.

Eight Queens

Genotype: a permutation of the numbers 1 through 8

3	2	4	6	5	8	7	1



Eight Queens

Mutation: exchanging two numbers

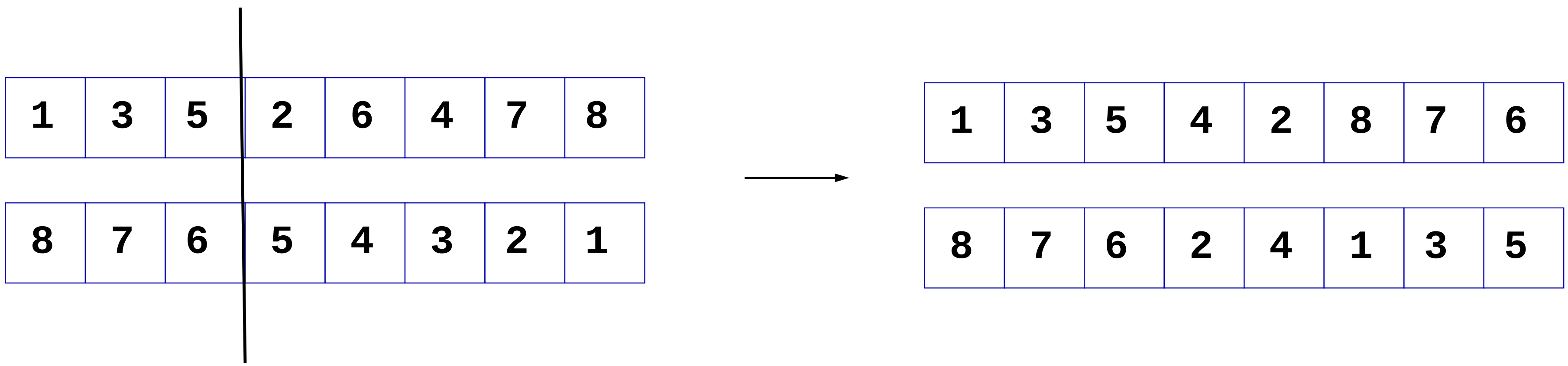
1	2	1	3	5	4	8	7

$\longrightarrow$

1	2	4	3	5	1	8	7

Eight Queens

Crossover: combining two parents



Eight Queens

Fitness: penalty of a queen is the number of queens it can check.

The fitness of the configuration is the sum of the single penalties.

Example

Traveling Salesman Problem

Taken from:

`http://ouray.cudenver.edu/~da0todd/neural/third_homework/dave/test/TSP_Genetic_Algorithm.htm`

Mondriaan Art

Mondriaan Art

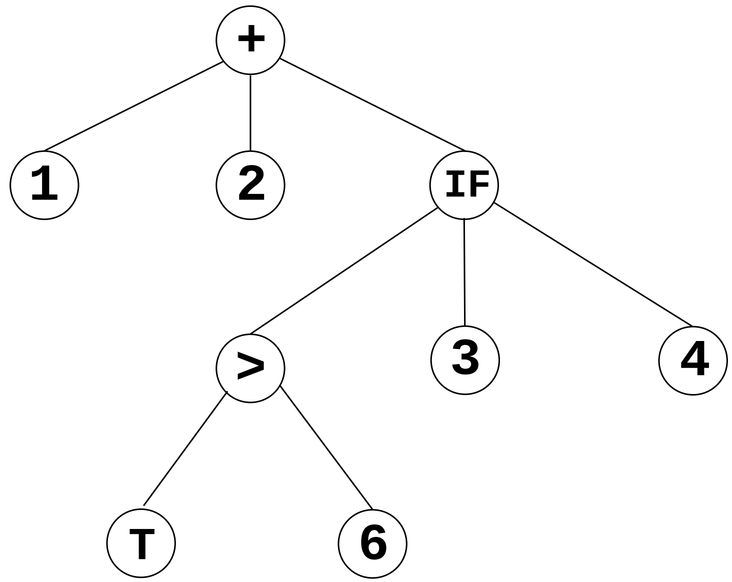
Taken from: `http://www.evonet.polytechnique.fr/CIRCUS2/`

Genetic Programming

- Can be seen as a ‘variant’ of GA: individuals are **programs**
- Used to build programs that solve the problem at hand ($\Rightarrow$ specialized programs)
- Extended to *automatic design* in general (e.g., controllers and electronic circuits)

Genetic Programming

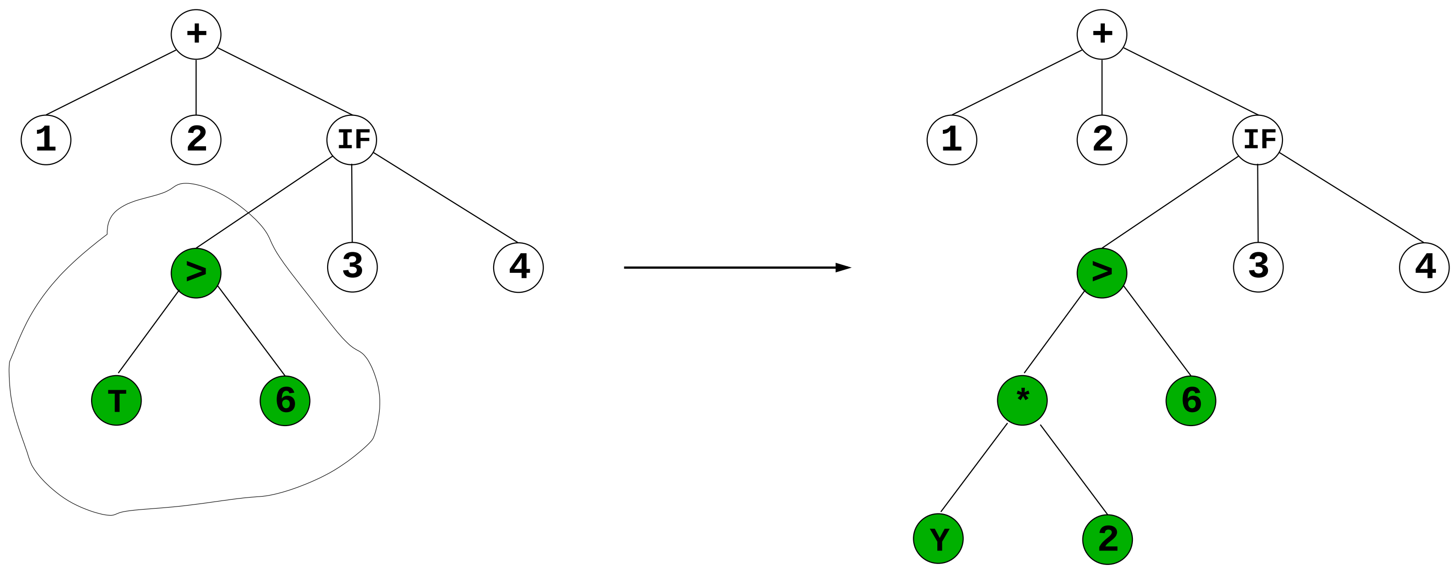
Individuals are *trees* which encode programs.



Fitness given by the evaluation of the program “behavior” (based upon some defined criteria)

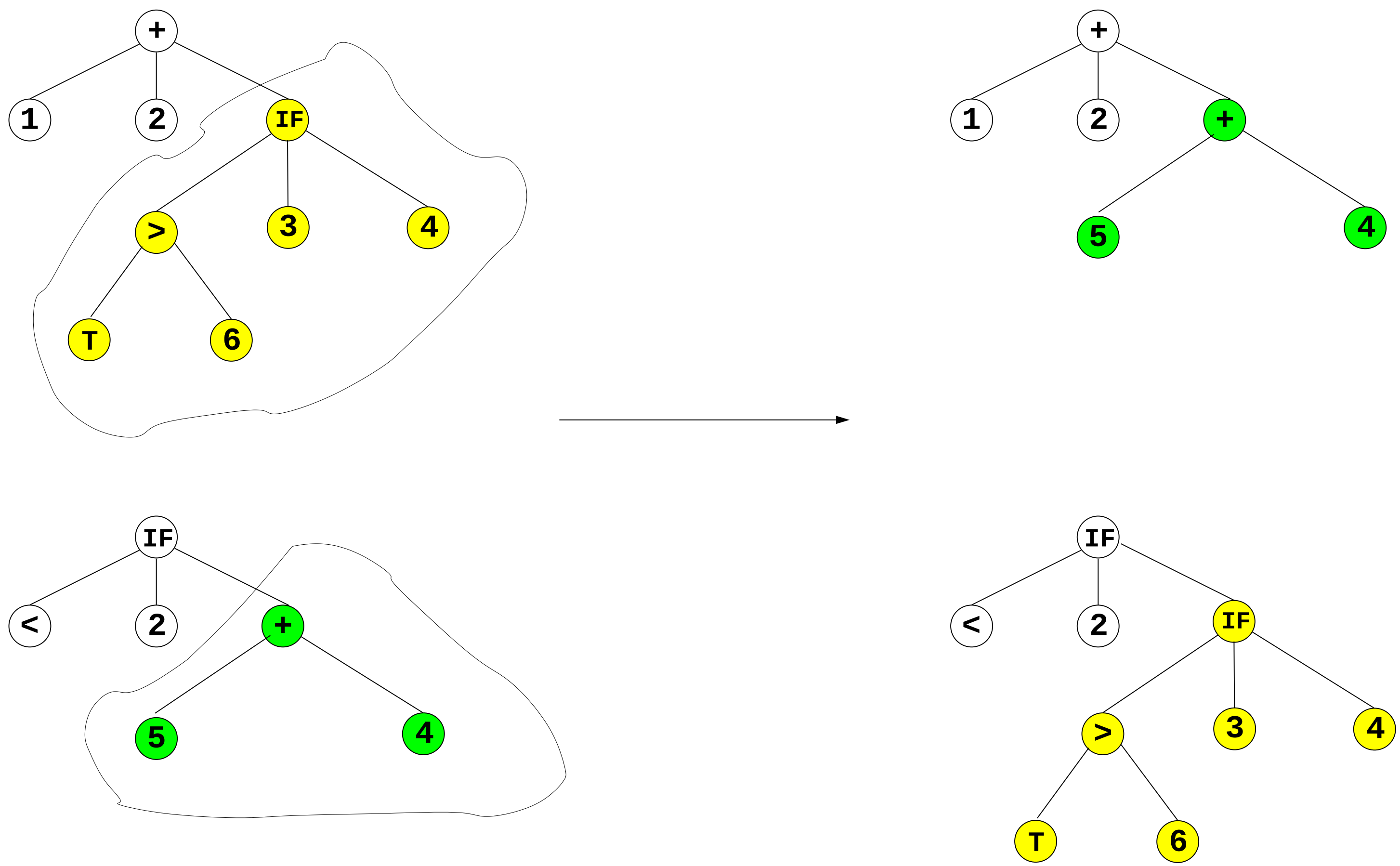
Operators

Mutation: Random selection of a subtree which is substituted by a *well formed* random generated subtree



Operators

Crossover: Exchange two randomly picked subtrees.



Operators

Selection and replacement

Fitness is evaluated depending on the application.

- For *assembler worms* the fitness can be the memory they occupied.
- For controllers, the fitness can be the percentage of correct actions

The realm of GP

- *Black art* problems. E.g.,automated synthesis of analog electrical circuits, controllers, antennas, and other areas of design
- *Programming the unprogrammable*, involving the automatic creation of computer programs for unconventional computing devices. E.g.,cellular automata, parallel systems, multi-agent systems, etc.

Coevolution

Species evolve in the same environment

$\rightarrow$ ***dynamic* environment**

Two kinds:

- Competitive
- Cooperative

Competitive Coevolution

▷ Species evolve trying to face each other

- E.g., prey/predator, herbivore/plants.

Applications: ALU design for Cray computer, (pseudo-)random number generator.

Cooperative Coevolution

▷ Species evolve complementary capabilities to survive in their environment

- E.g., host/parasite.

Applications: ‘niche’ genetic algorithms for *multi-criteria* optimization.

Some references

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- W.B.Langdon, R.Poli. *Foundations of Genetic Programming*. Springer, 2001.

On the Internet

- EvoNet: http://www.evonet.polytechnique.fr/
- www.genetic-programming.com
- GALib http://lancet.mit.edu/ga/
- http://www.aic.nrl.navy.mil/galist/
- www.isgec.org