Evolutionary Computation

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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

Characteristics

- Robustness
- Adaptivity
- *Subsymbolic* models
  (no explicit symbolic computation)

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!

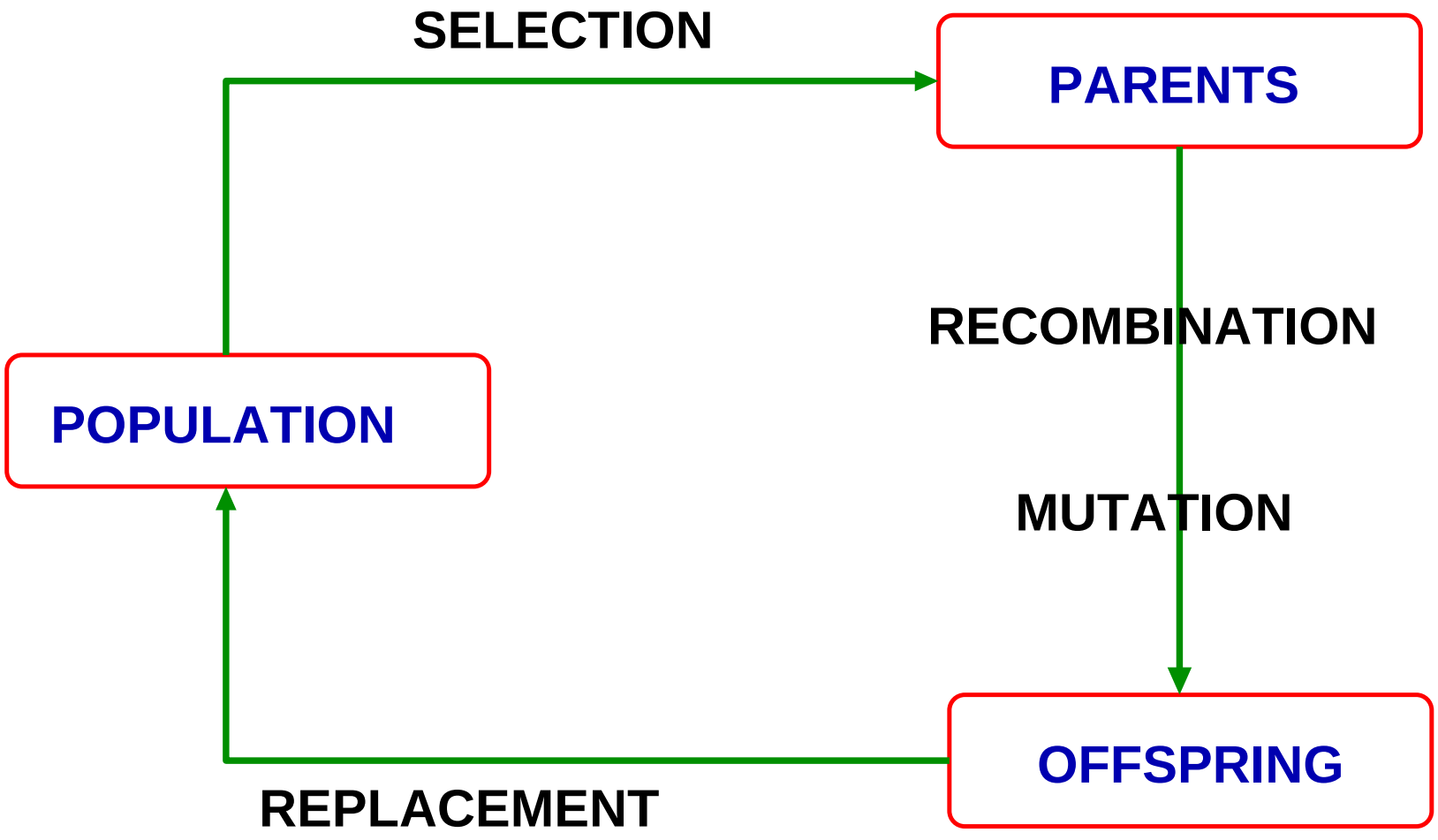
The Metaphor

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

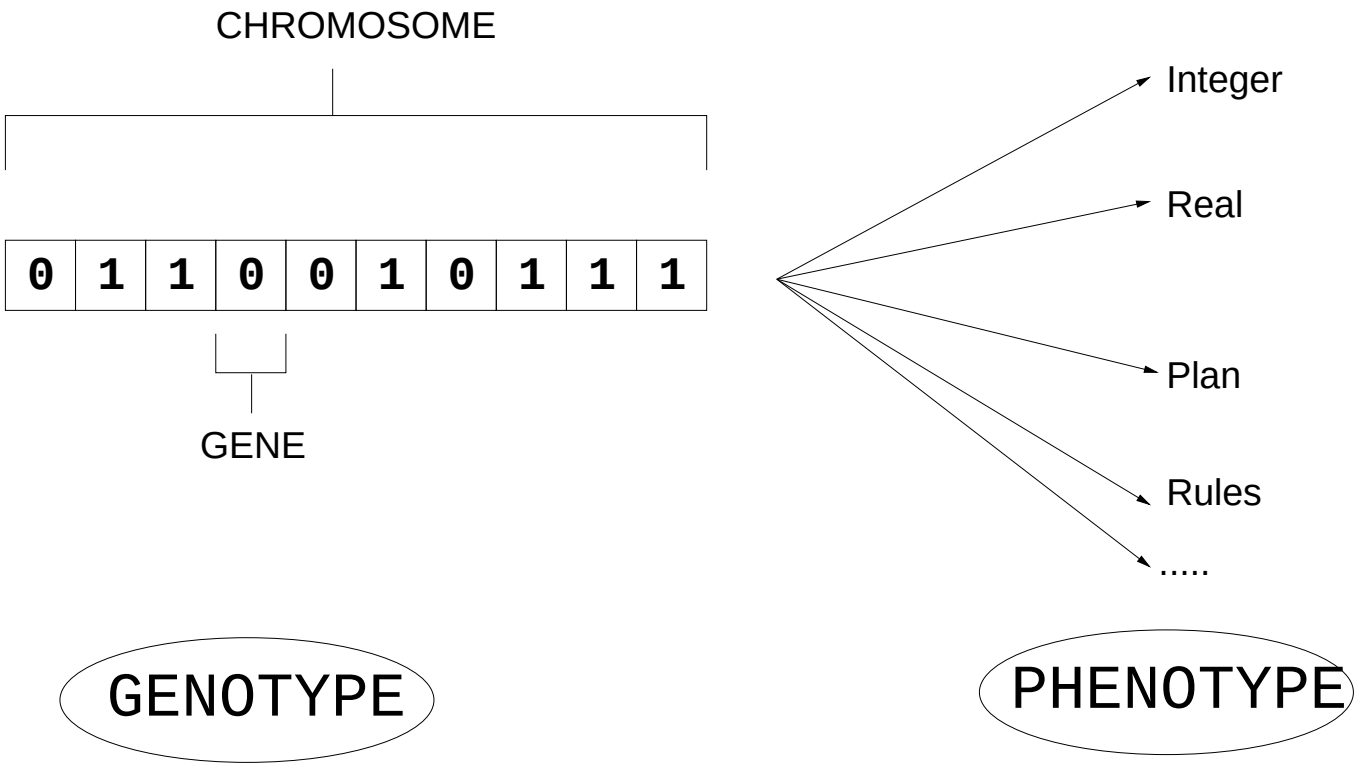
Simple Genetic Algorithm

- 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**



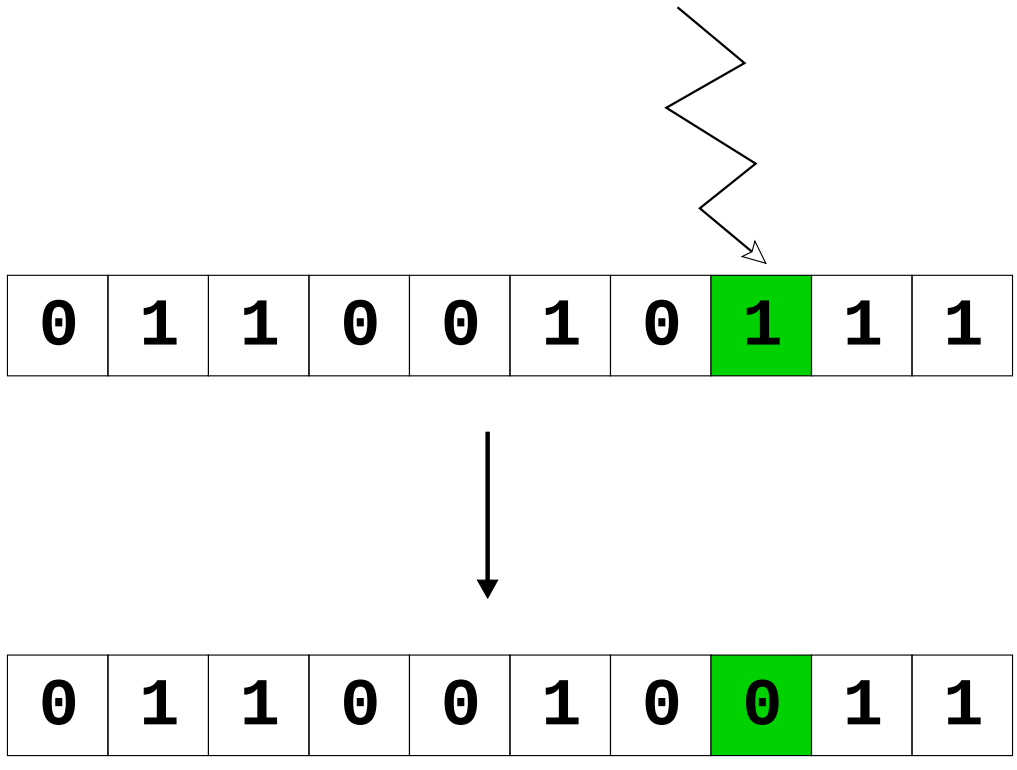
Example

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

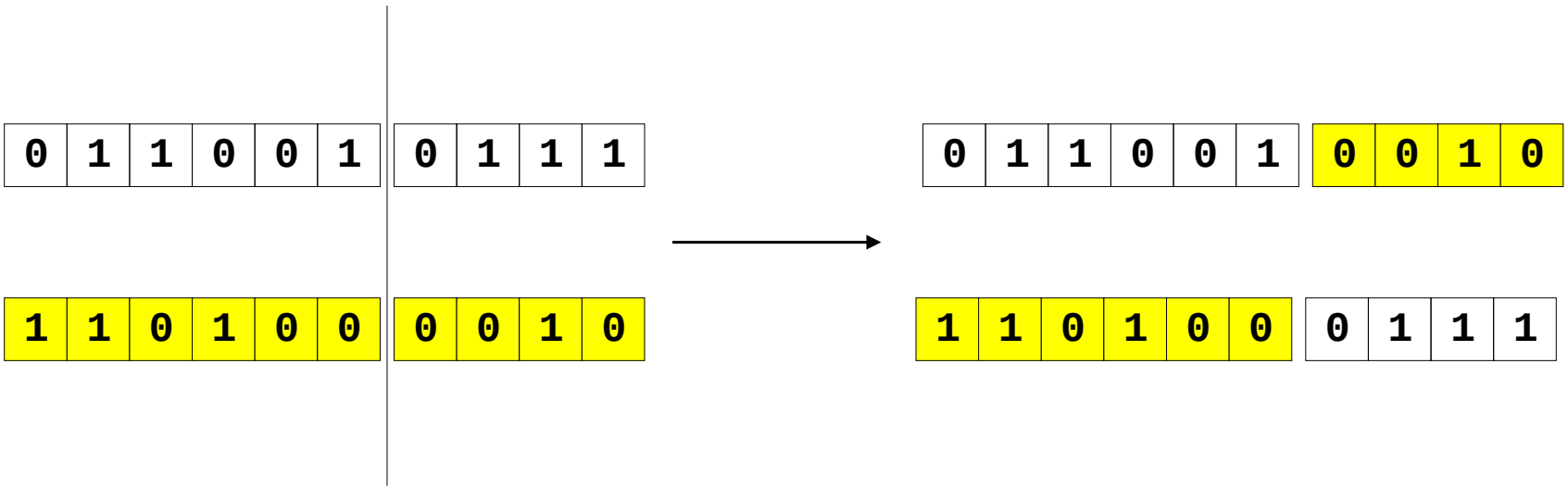
Genetic operators (1)

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



Genetic operators (2)

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



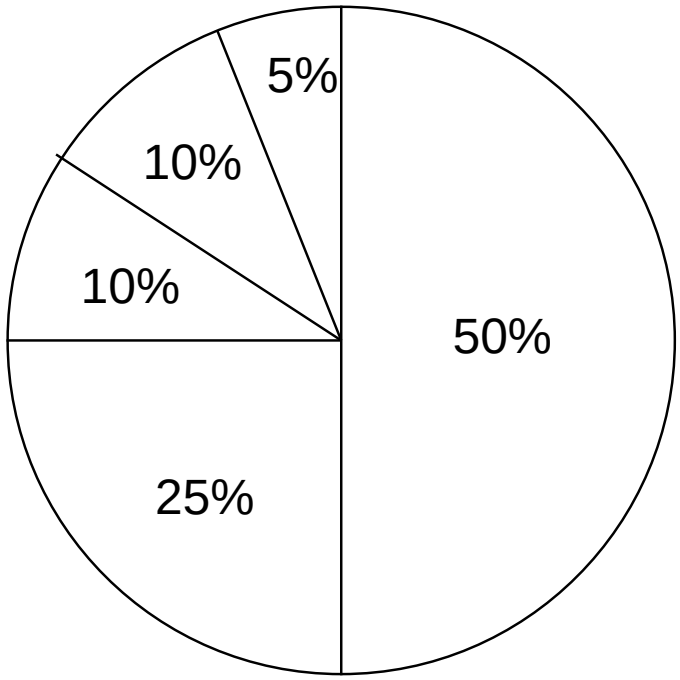
Genetic operators (3)

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

$\rightarrow$ **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 $\leftarrow$ 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

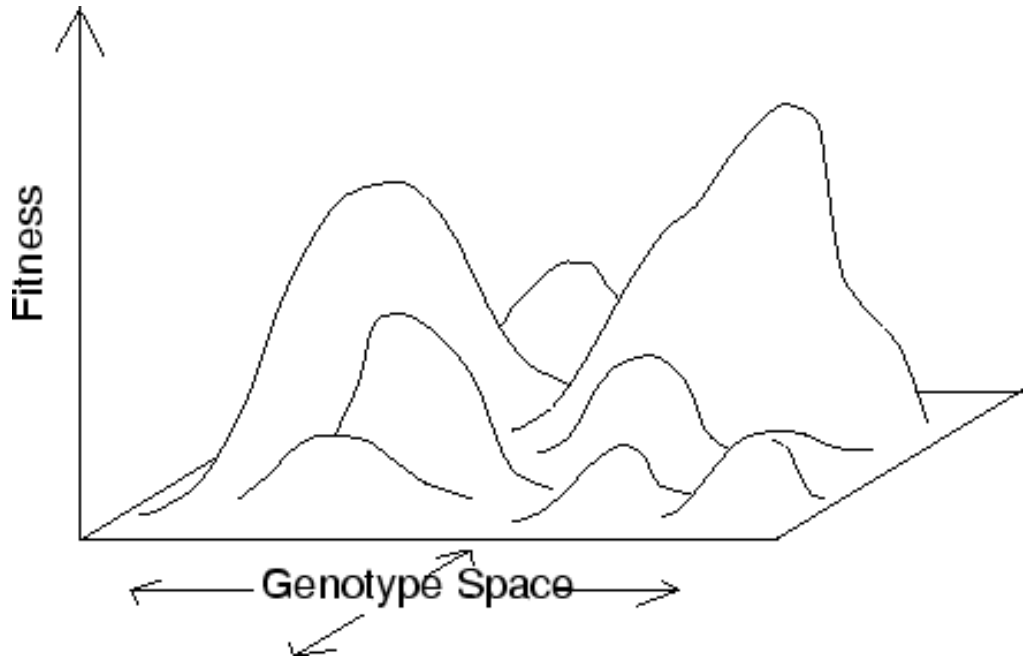
Apply crossover: from G_1, G_2 we get G'_1, G'_2
$r \leftarrow$ Random(1,$l_{chromosome}$)$\{$crossover point$\}$
for $i = 1$ to $r - 1$ **do**
  $G'_1[i] \leftarrow G_1[i]$
  $G'_2[i] \leftarrow G_2[i]$
end for
for $i = r$ to $l_{chromosome}$ **do**
  $G'_1[i] \leftarrow G_2[i]$
  $G'_2[i] \leftarrow G_1[i]$
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

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

Why does it work?

Holland explains (also theoretically, but with strong hypotheses) why the SGA 'works'

Two basic elements:

- **Schemata**
- **Building blocks**

Schemata

- A *schema* is a kind of mask: $001*1**0$
- The symbol $*$ represents a wildcard: both 0 and 1 fit
- E.g., $1*0$ represents 100 and 110

Building blocks

- A *building block* is a pattern of contiguous bits
- HP: good solutions are composed of good building blocks
- The crossover puts together short building blocks and destroys large ones

Implicit parallelism

- Every individual corresponds to a set of schemata
- The number of the best schemata increases exponentially
- The solution space is searched through schemata (hence implicit parallelism)

When does it work well?

A SGA works well if:

1. Short good building blocks (correlate genes are adjacent)
2. Loose interaction among genes (low *epistasis*)

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:

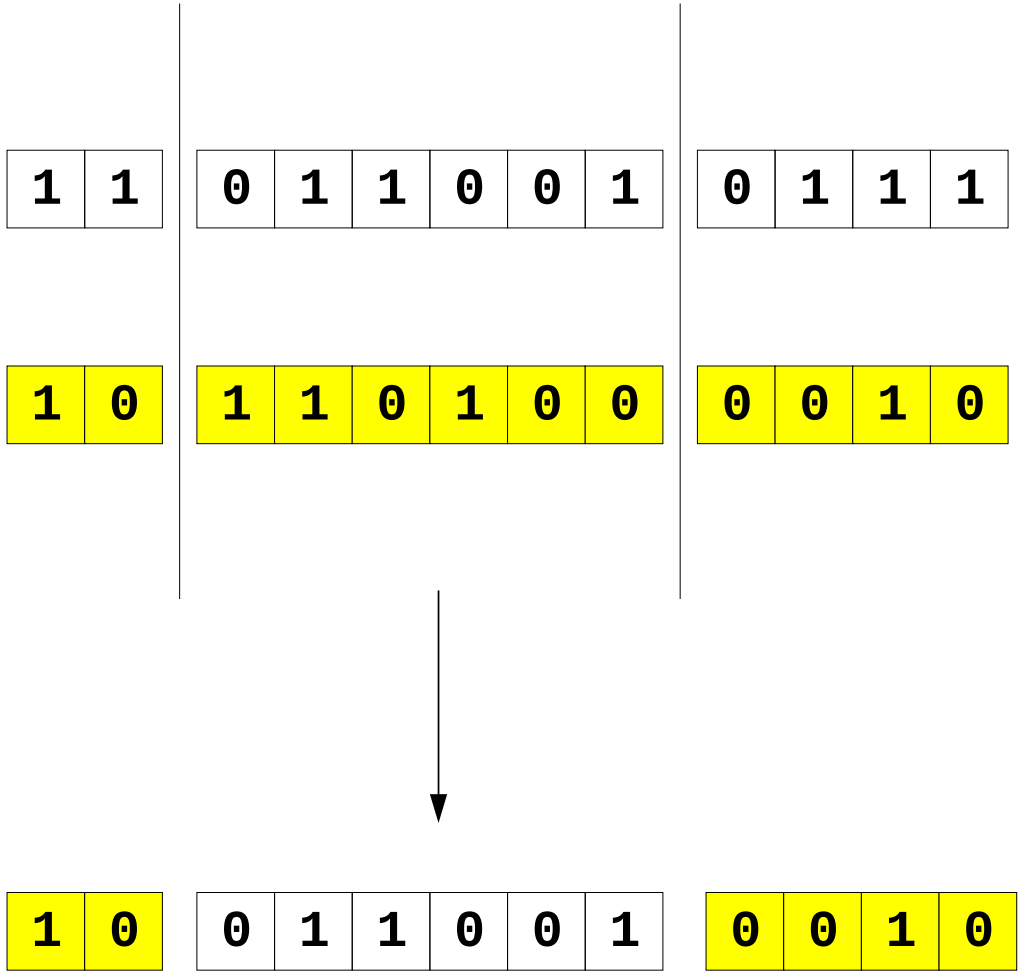
- Solution coding (e.g., bit strings, programs, arrays of real variables, etc.)
- Define a way of evaluating solutions (e.g., objective function value, result of a program, behavior of a system, etc.)
- Define recombination operators (*crossover*, *mutation*)
- Define the selection and replacement/insertion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

Toward *less simple* GA

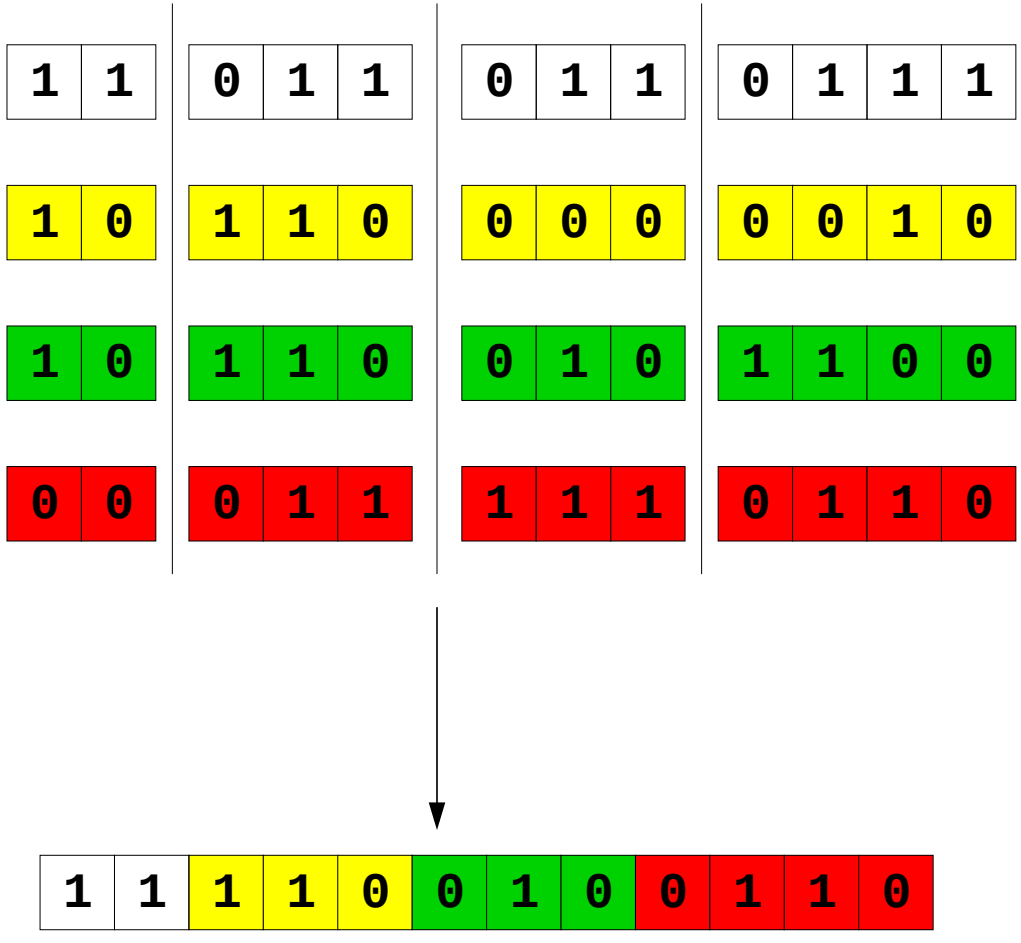
Recombination:

- *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)

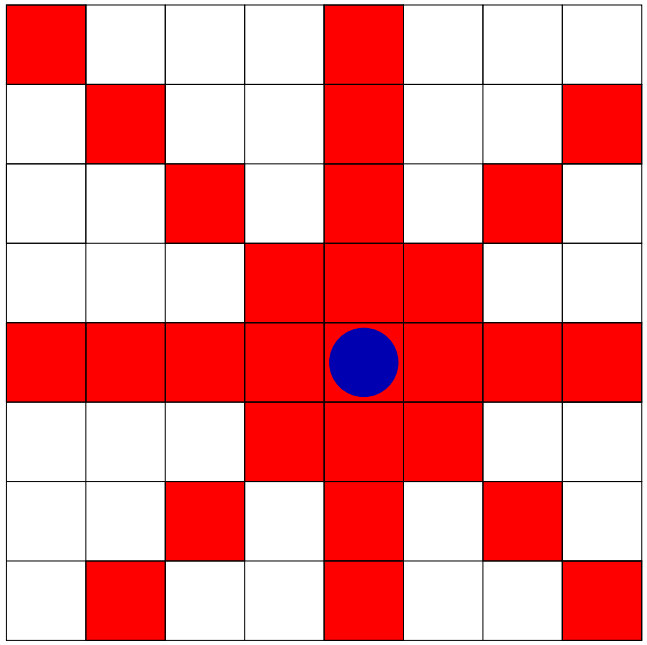
Ex: real valued variables

- Solution: $x \in [a, b],\ a, b \in \mathbb{R}$
- Mutation: random perturbation $x \rightarrow x \pm \delta$, 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

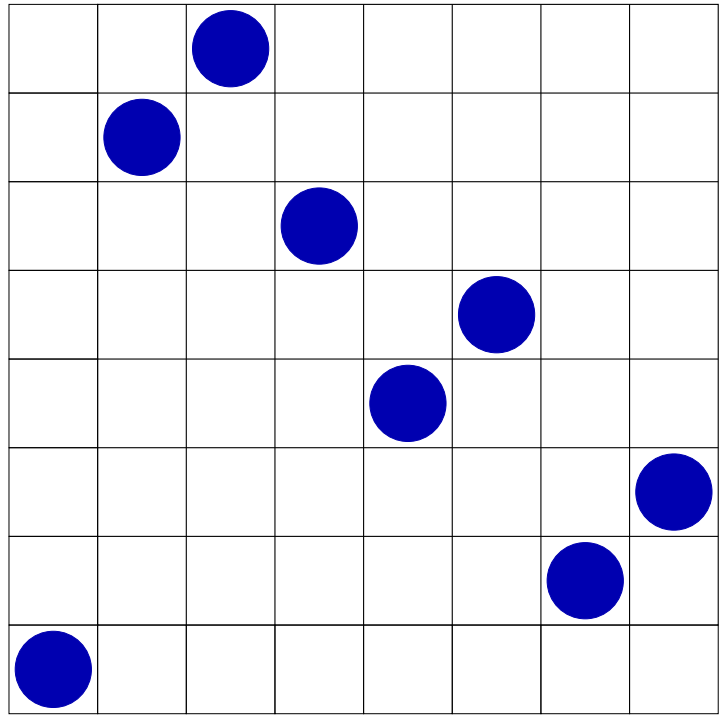


Place 8 queens on a 8×8 chessboard in such a way that the queens cannot attack each other.

Eight Queens

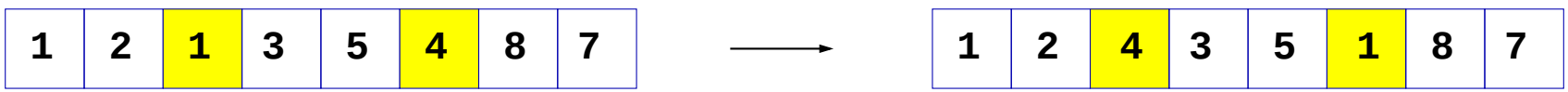
Genotype: a permutation of the numbers 1 through 8

3	2	4	6	5	8	7	1



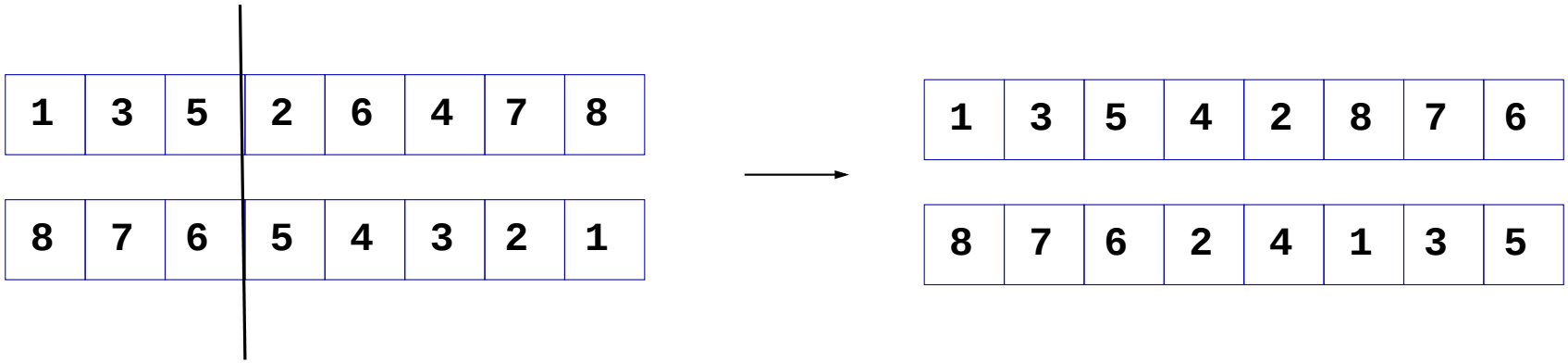
Eight Queens

Mutation: exchanging two numbers



Eight Queens

Crossover: combining two parents



Eight Queens

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

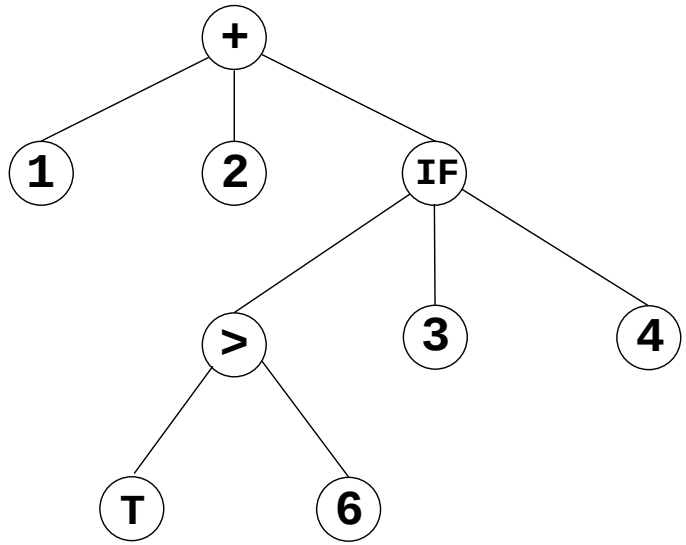
The fitness of the configuration is the sum of the single penalties.

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

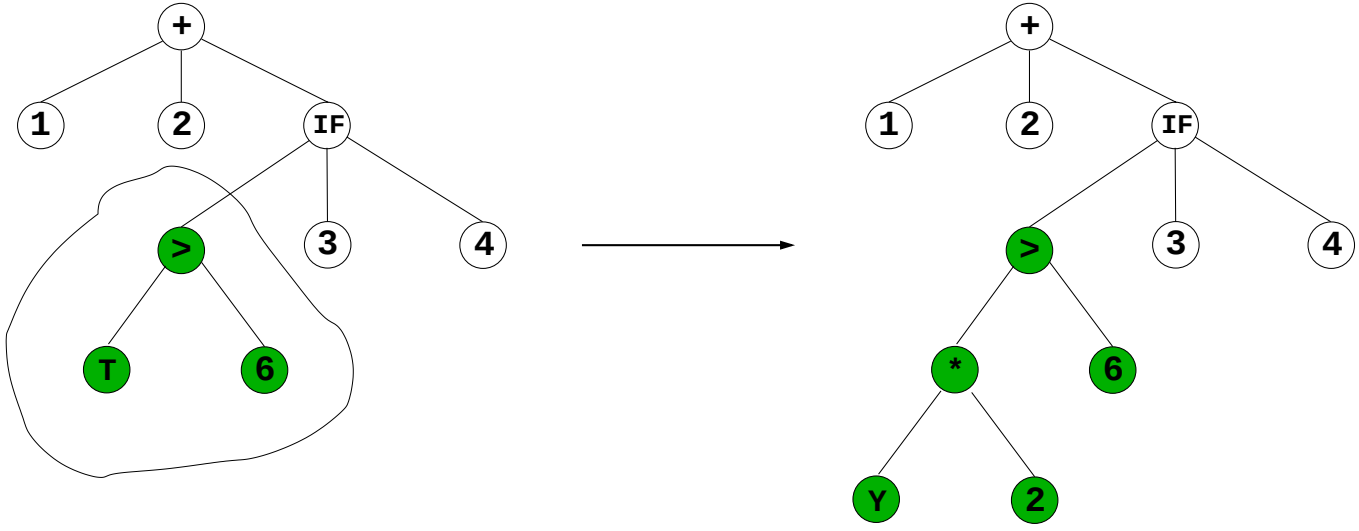
Individuals are *trees* which encode programs.



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

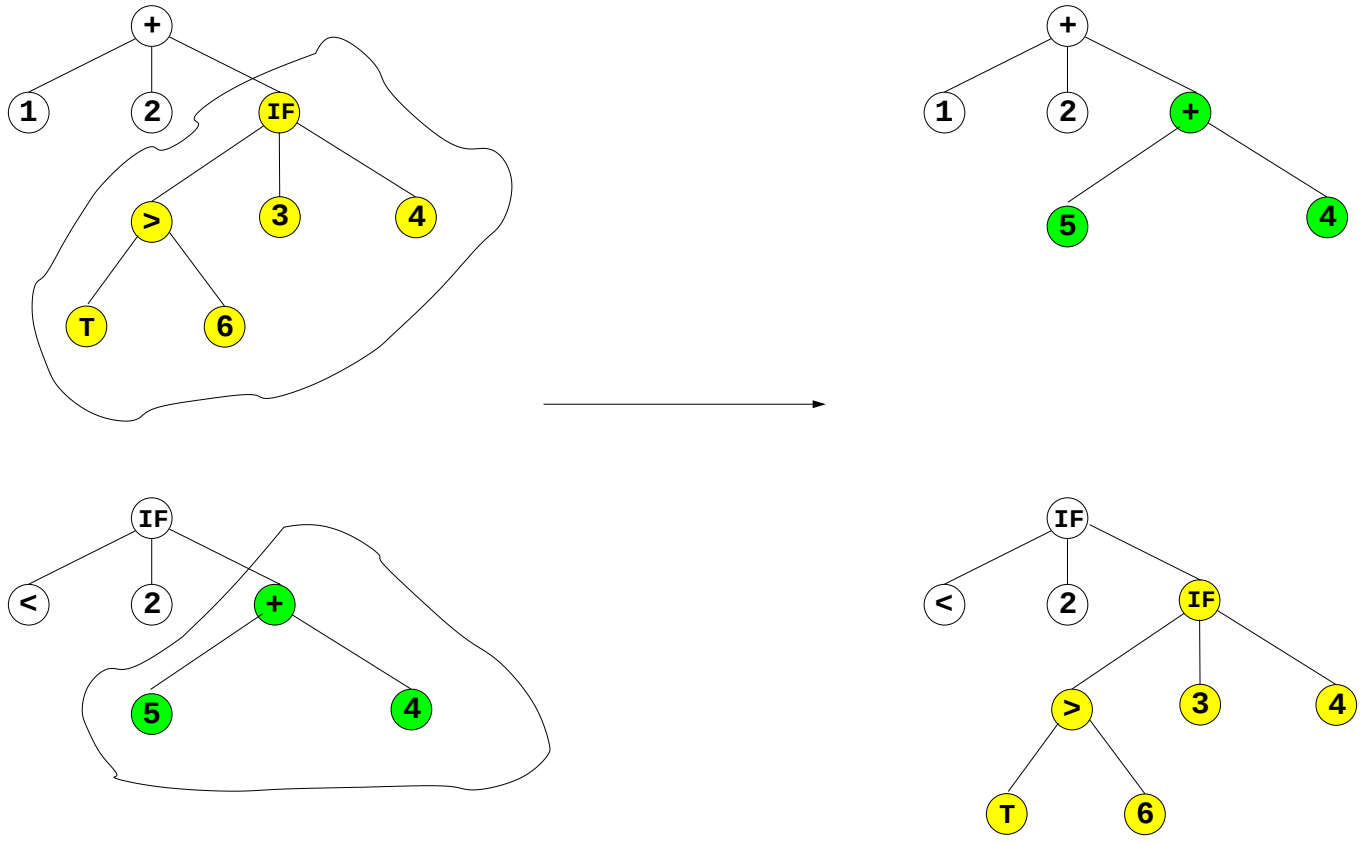
Operators

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

$\longrightarrow$ ***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.

EC and Artificial Life

Tierra

- Artificial evolution of computer programs (T. Ray, early ’90s)
- Environment: virtual computer
- Individuals: self-replicating assembler programs
- Resources: CPU time and memory

Tierra

Results of evolution: several kinds of nontrivial behaviors and dynamics

- parasites
- immunity to parasites
- circumvention of immunity to parasites
- social individuals
- . . . and others

EC and Games

Axelrod and The Prisoner's Dilemma

- Game strategies evolved through genetic algorithms
- Dynamic environment (a player plays against other different players)
- Best strategy evolved by GA is the best human strategy
- Analysis of the arising of cooperation

The Prisoner's Dilemma

- The two players in the game can choose between two moves, either *cooperate* or *defect*.
- Each player gains when both cooperate, but if only one of them cooperates, the other one, who defects, will gain more.
- If both defect, both lose (or gain very little) but not as much as the ”cheated” cooperator whose cooperation is not returned.

The payoff matrix

Action of A \ Action of B	**Cooperate**	**Defect**
Cooperate	$+5$	-10
Defect	$+10$	0

Problem encoding

Suppose that the memory of each player is one previous move. E.g., player A cooperated and player B defected becomes: `CD`.

The strategy is defined with a move for each possible past move. E.g.:

```
If CC then C
If CD then D
If DC then C
If DD then D
```

$\rightarrow$ the string is `CDCD`

Classifier Systems

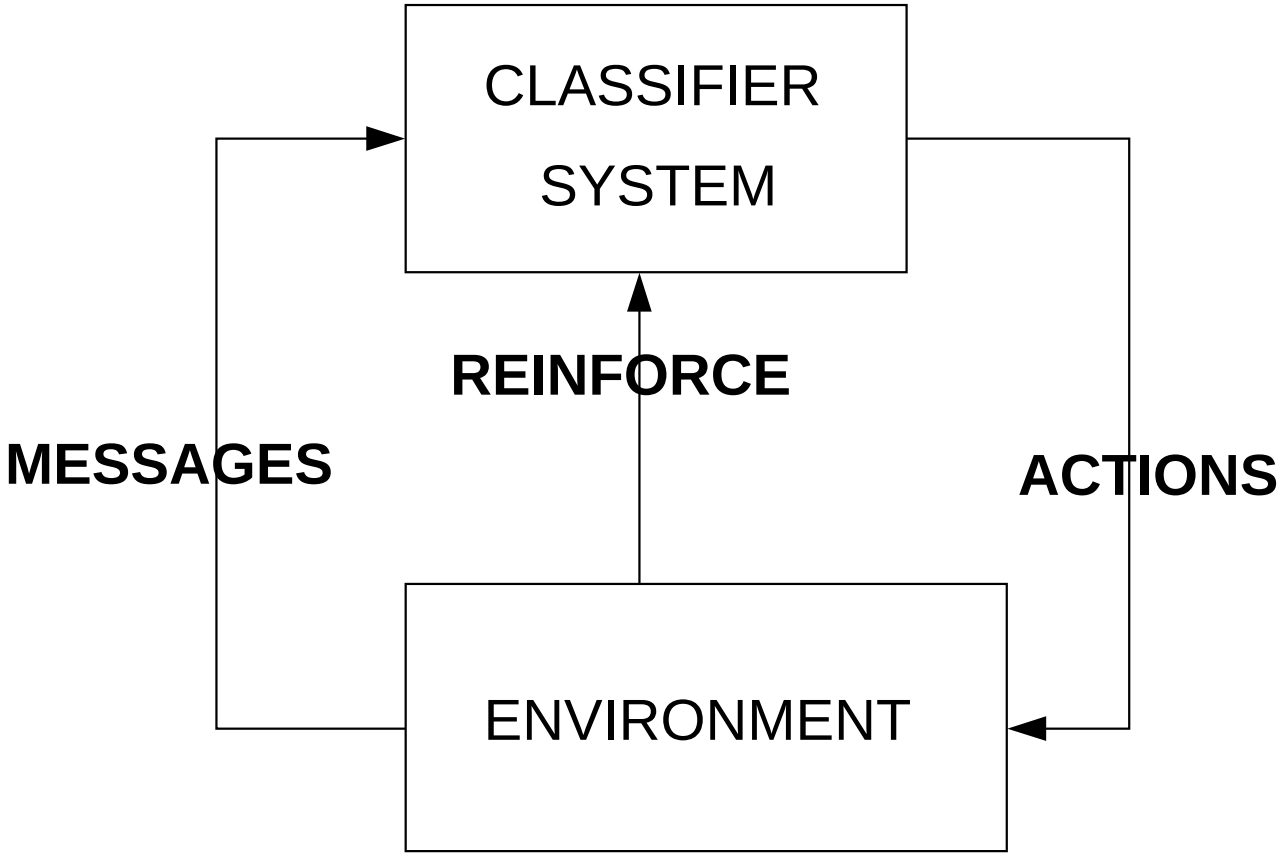
Systems composed of **rules** like

```
IF [conditions] THEN [actions]
```

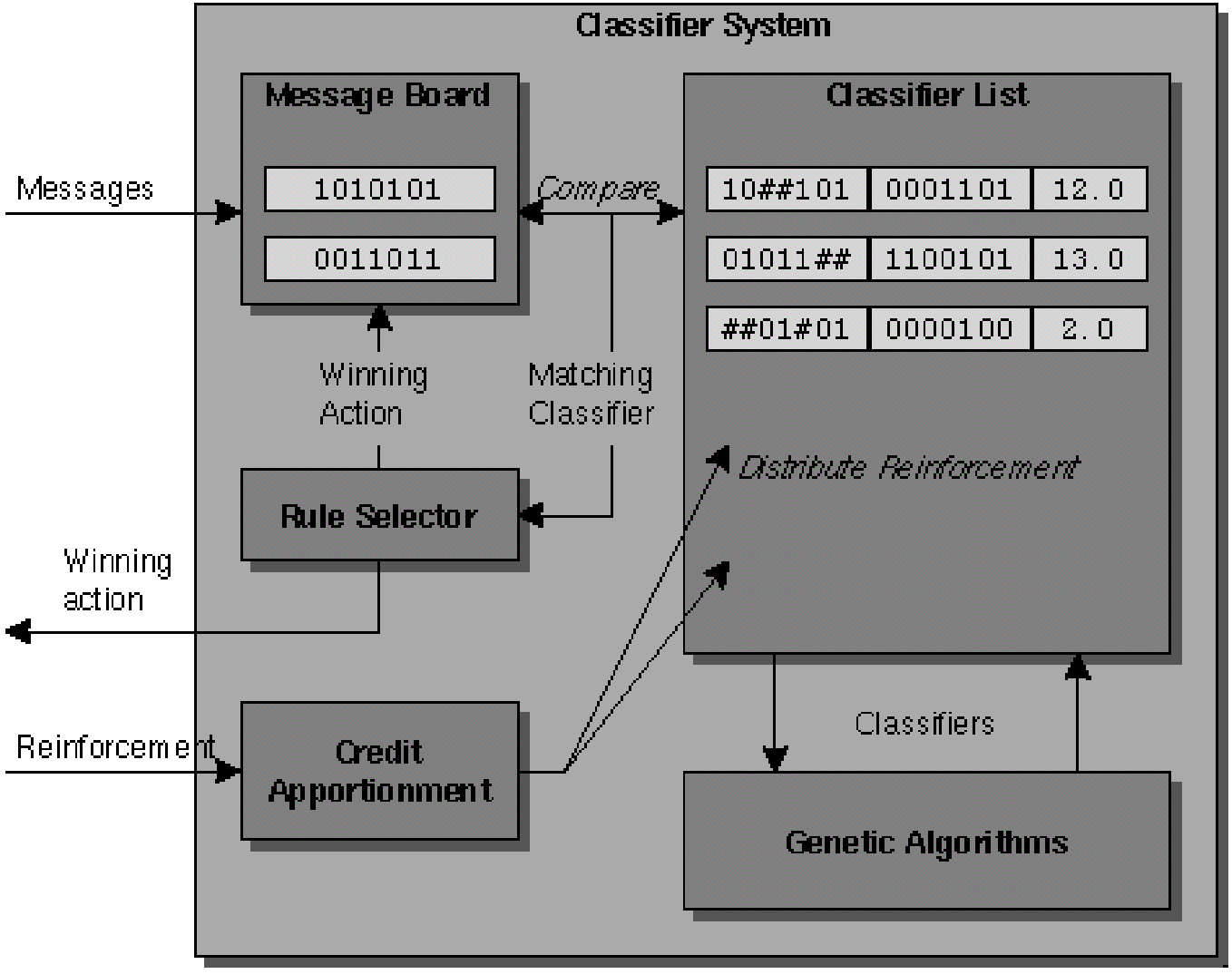
```
IF (sensor1 is active) THEN (move)
IF (sensor3 is inactive and sensor4 is active) THEN (stop)
IF (sensor4 is inactive) THEN (turn right)
```

Rules are usually coded as bitstrings and evolved by means of usual application of EC operators.

Classifier Systems



Classifier Systems



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