European Centre for Soft Computing

Future Directions in Soft Computing

Genetic Algorithms: Basic notions and some advanced topics

Francisco Herrera

Grupo de Investigación
"Soft Computing y Sistemas de Información Inteligentes"

Dpto. Ciencias de la Computación e I.A.
Universidad de Granada
18071 – ESPAÑA
herrera@decsai.ugr.es
http://sci2s.ugr.es

DECSAI
Universidad de Granada

Genetic Algorithms:
Basic notions and some advanced topics

SESSIONS

a. Introduction to genetic algorithms

b. Advanced topics

- Multimodal problems and multiple solutions
- Multiobjective genetic algorithms
- Memetic algorithms
- Genetic Learning

Session a.
Genetic Algorithms

1. GENETIC ALGORITHMS. INTRODUCTION
2. HOW TO CONSTRUCT THEM?
3. ON THE USE OF GENETIC ALGORITHMS
4. MODELS: GENERATIONAL VERSUS STEADY STATE
5. APPLICATIONS
6. EXAMPLE: TSP
7. SOFTWARE AND IMPLEMENTATIONS
8. CONCLUDING REMARKS

1. GENETIC ALGORITHMS. INTRODUCTION

- WHAT IS A GENETIC ALGORITHM?
- THE INGREDIENTS
- THE EVOLUTION CYCLE
- GENETIC ALGORITM STRUCTURE

What is a genetic algorithm?

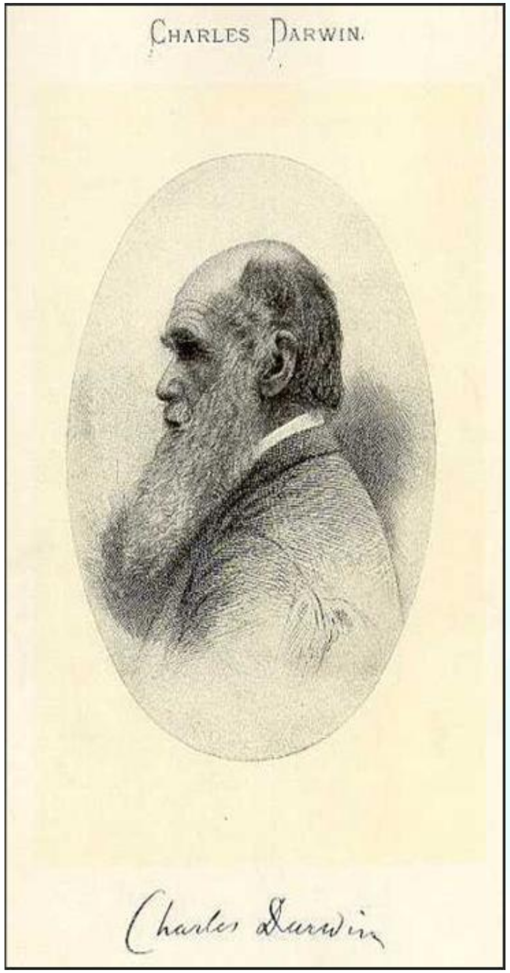
Genetic algorithms

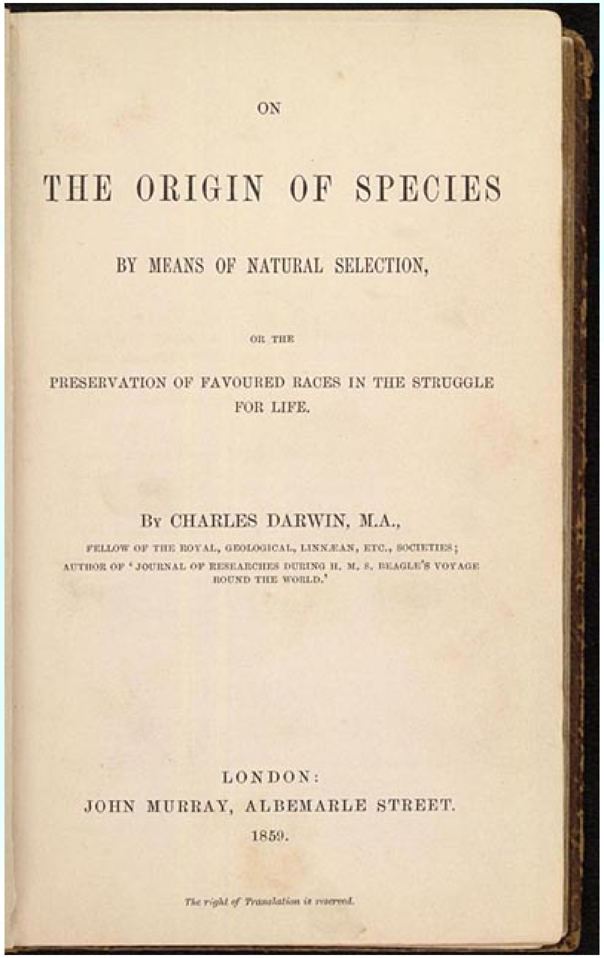
They are optimization algorithms,
search
and learning
inspired in the process of

Natural and Genetic Evolution

What is a genetic algorithm?

Natural Evolution





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, LINNÆAN, ETC., SOCIETIES;
AUTHOR OF 'JOURNAL OF RESEARCHES DURING H. M. S. BEAGLE'S VOYAGE ROUND THE WORLD.'

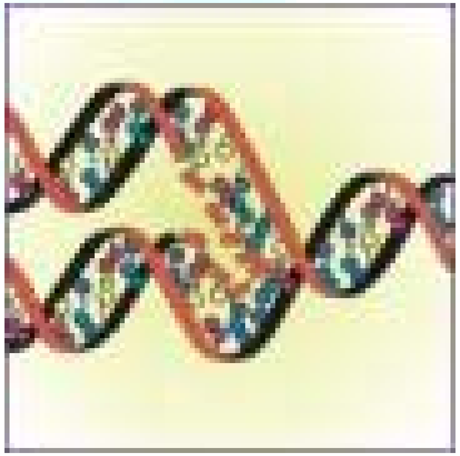
LONDON:
JOHN MURRAY, ALBEMARLE STREET.
1859.

The right of Translation is reserved.

What is a genetic algorithm?

Artificial Evolution

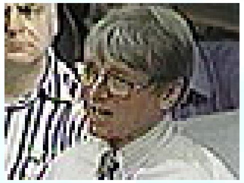
EVOLUTIONARY COMPUTATION



It is constituted by evolutionary models based on populations whose individuals represent solution to problems.

What is a genetic algorithm?
Artificial Evolution

There are 4 classic paradigms:



John Holland
Inventor of genetic algorithms
Professor of CS and Psychology at the U. of Michigan.

Genetic Algorithms. 1975, Michigan University

Evolution Strategies 1964, Technische Universität Berlin

Inventors of Evolution Strategies

Hans-Paul Schwefel
Universität Dortmund

Ing. Ingo Rechenberg
Bionics & Evolutiontechnique
Technical University Berlin
http://www.bionik.tu-berlin.de/

Evolutionary Programming. 1960-1966, Florida

Lawrence J. Fogel,
Natural Selection, Inc.
Inventor of Evolutionary Programming

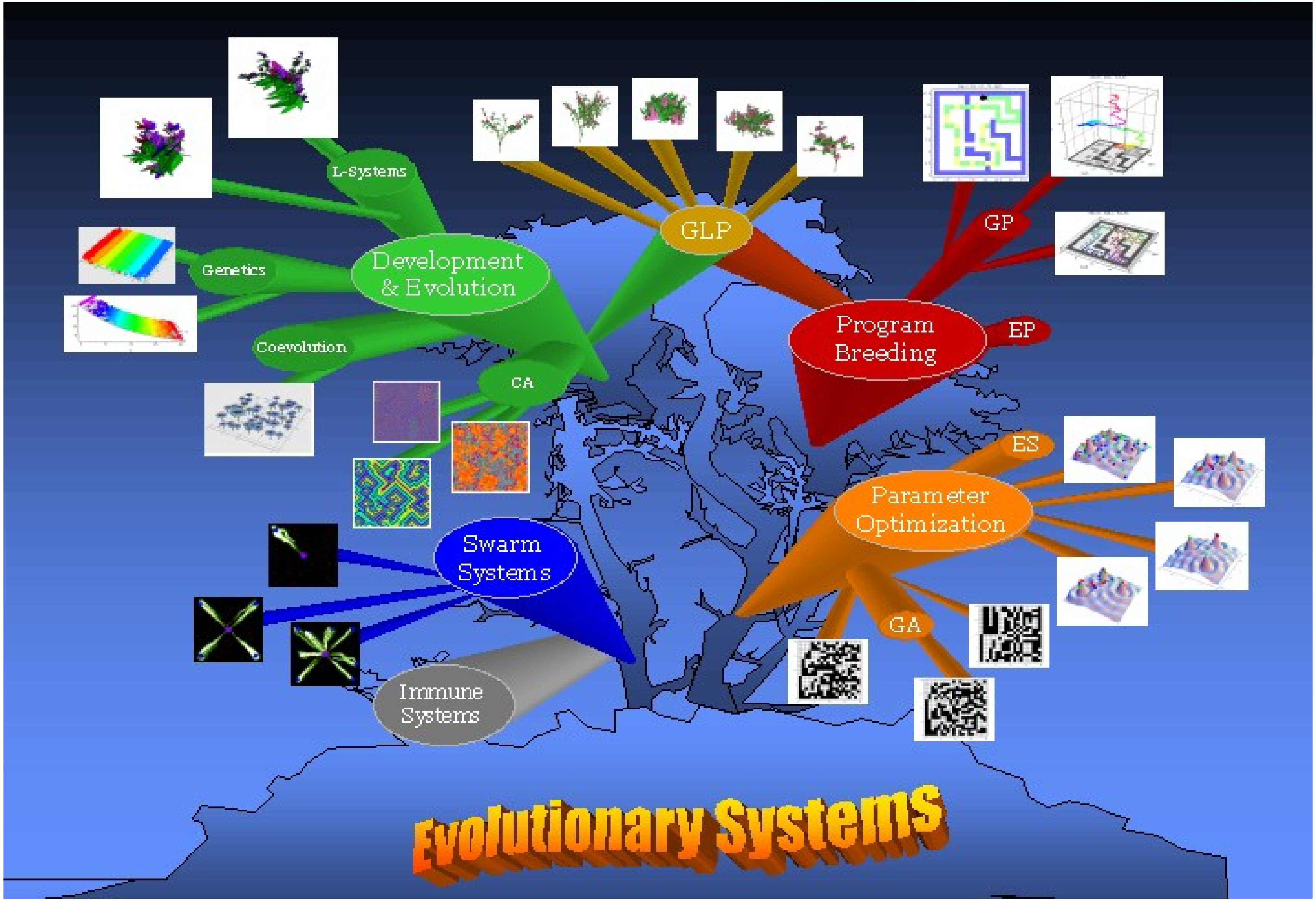
Genetic Programming. 1989, Stanford University

John Koza
Stanford University.
Inventor of Genetic Programming

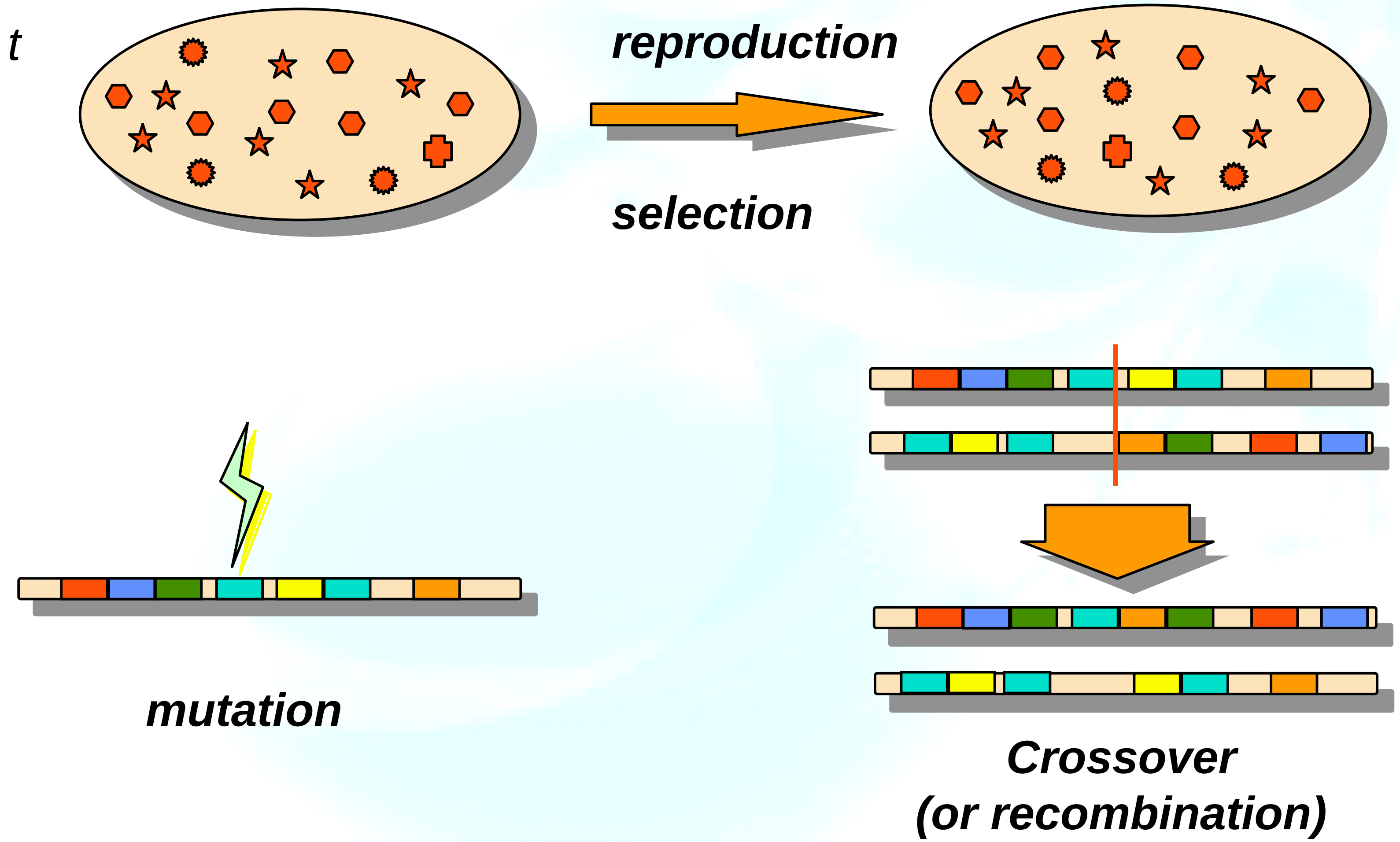
Thre exist other modelos based on population evolution

What is a genetic algorithm?

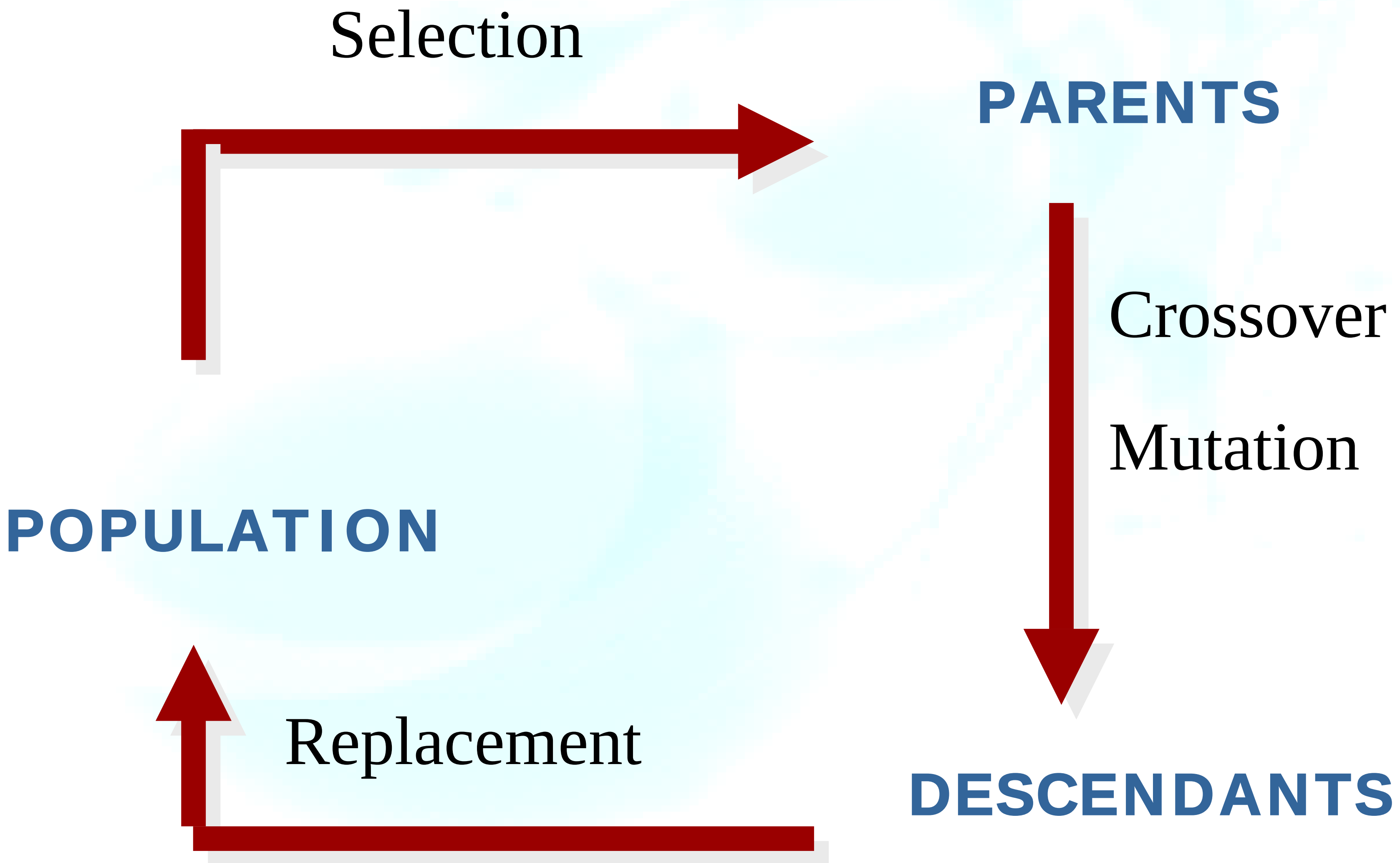
Artificial Evolution



The ingredients



The evolution cycle



Genetic Algorithm Structure

Basic Genetic Algorithms

Beginning (1)
    t = 0
    Initialization P(t)
    evalution P(t)

    While (the stop contition is not verified) do
    Beginning (2)
        t = t + 1
        selection P'(t) from P(t-1)
        P''(t) ← crossover P'(t)
        P'''(t) ← mutation P''(t)
        P(t) ← replacement (P(t-1),P'''(t))
        evaluation P(t)
    Final(2)

Final(1)

2. HOW TO CONSTRUCT A GA?

The steps for the GA construction

- Representation
- Initial population
- Fitness function (How to evaluate a GA?)
- Chromosomes selection for parents
- Design of crossover operator
- Design of mutation operator
- Chromosomes replacement
- Stop condition

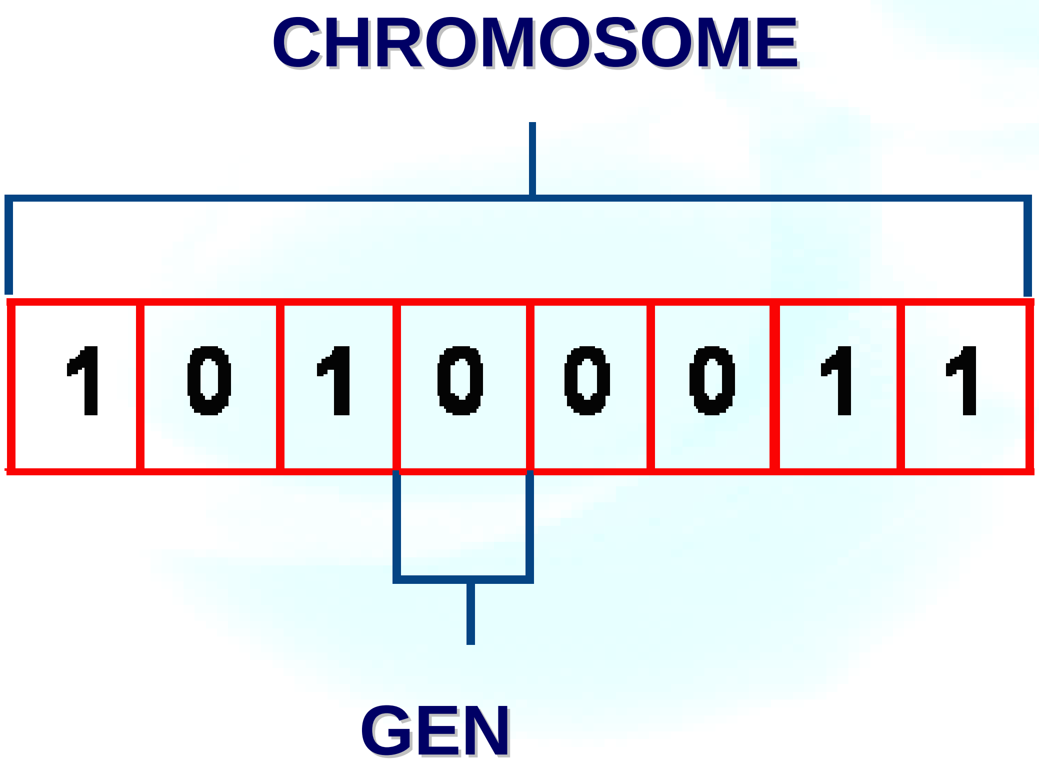
PROBLEM DEPENDENT

ALGORITHM COMPONENTS

Representación

- Genotype: Coding mechanism
- Natural representation for the problem
- Genotype representation must be decided according to the evaluation and genetic the operators.

Example: Binary representation



Example: Binary representation

8 bits genotype

1	0	1	0	0	0	1	1

Fenotype

- **integer**
- **real number**
-
- **...**
- **¿Others?**

Example: Real coding

- The chromosome can be represented by a real valued vector:

$$X = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}, x_i \in R$$

- The evaluation function associates a real value to a vector:

$$f : R^n \rightarrow R$$

Example: Order representation

- The chromosomes are presented as permutations.
- Ej. Travelling salesman problem (TSP), ...
- It needs special operators for obtaining a new permutation.

Initialization

- Uniform on the search domain ... (if possible)
  - Binary string: 0 or 1 with probability 0.5
  - Real value: uniform on the interval
- Using a heuristic for getting initial chromosomes.

Fitness function

- Step with high time cost.
- Subrutine, simulator or other external processes (ej. Robot experiment, ...)
- It is possible to use an approximation function (reducing the cost)
- Constraint problems can introduce a penalization in the fitness function.
- With multiple objectives we find a pareto (set of non-dominated solutions).

HOW TO CONSTRUCT A GA?

Selection

PARENTS

Representation

Initialization

Population

Fitness function

POPULATION

Chromosomes selection

We must guarantee that the best individuals have a major possibility for being parents.

But, worse chromosomes must have an opportunity for reproduction. They can include useful genetic information in the reproduction process.

This idea define the “selective pressure”, that determines the degree of influence of the best individuals.

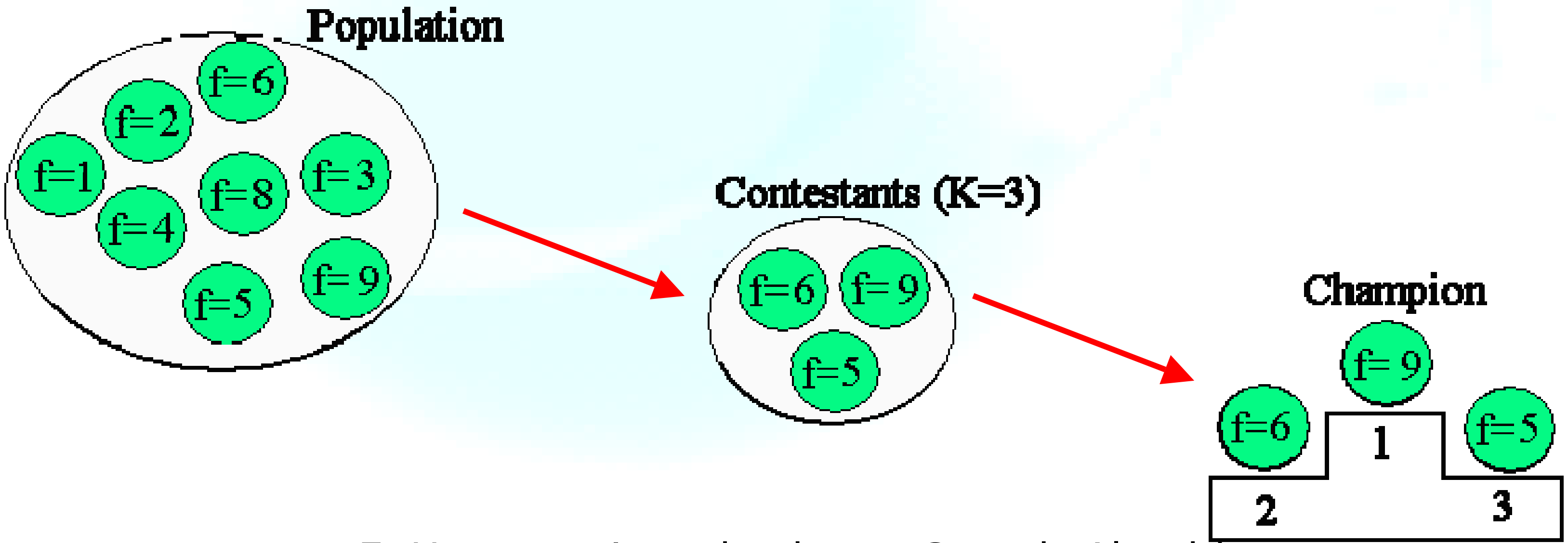
Strategy of selection

Tournament selection

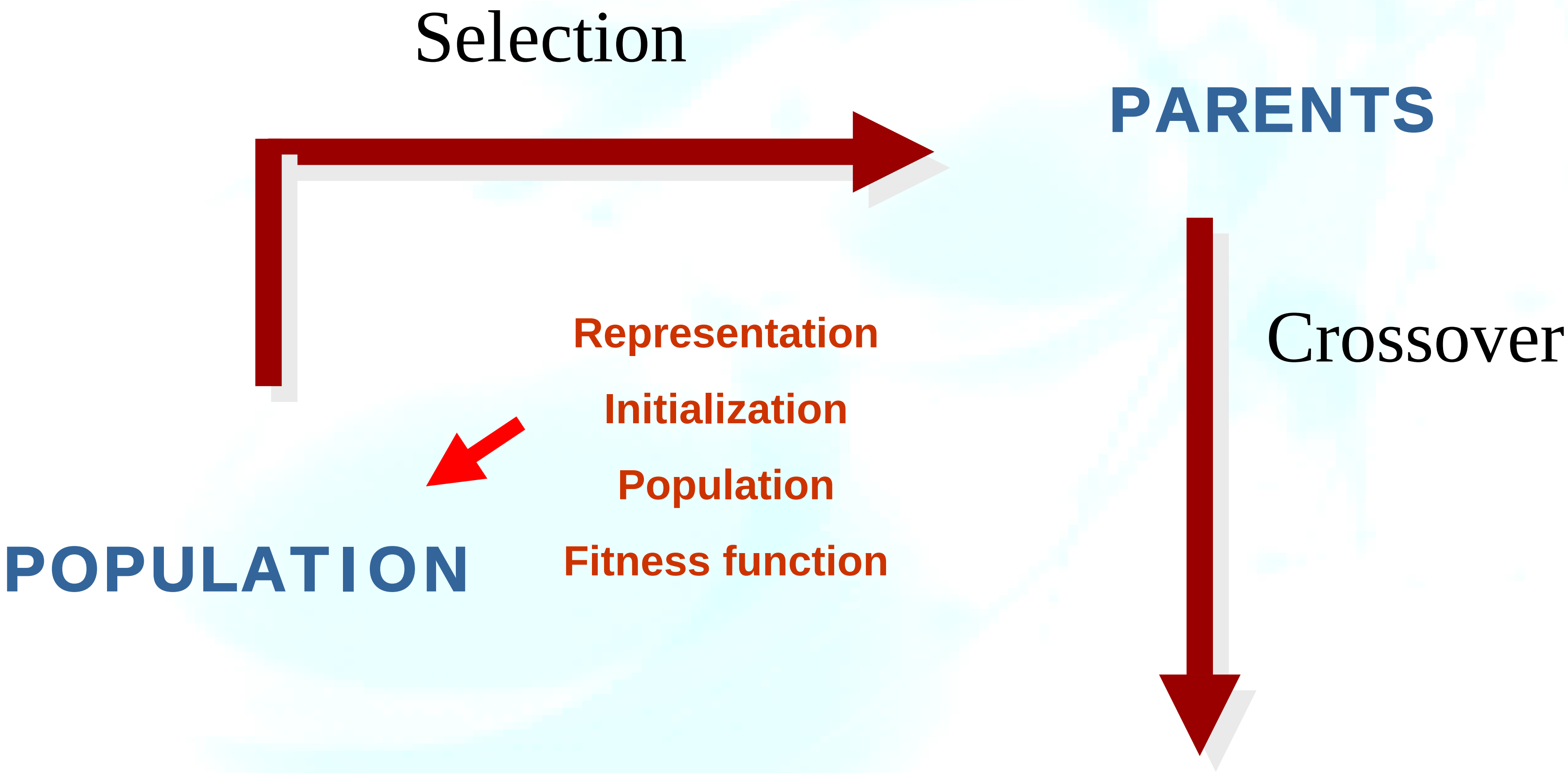
For each parent:

- Random selection of k individuals, with replacement
- Selection of the best

k is called the tournament size. A high k value, a high selective pressure and vice versa.



HOW TO CONSTRUCT A GA?



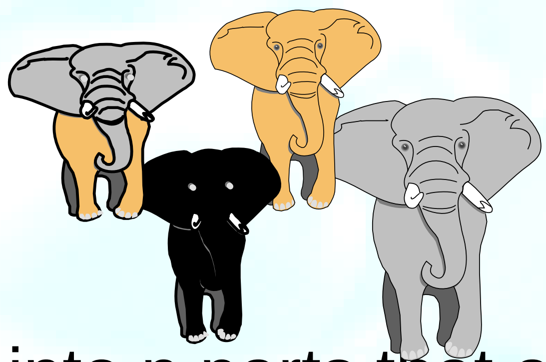
Crossover operator

Features:

- The offspring must contain a heredity from the parents, associated to the parent features. In other case it would be a mutation operator.
- It depend on the representation.
- The recombination must produce valid chromosomes.
- It uses a probability for running on the two parents (Pc between 0.6 and 0.9, usually).

Example: Simple crosover on the binary representation

Population: . . .

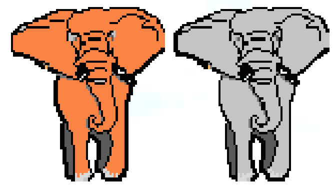


Each chromosome is divided into n parts that are recombined (example for n = 2)

cut | cut

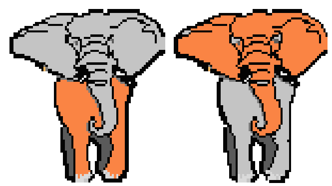
1 1 1 | 1 1 1 1 0 0 0 | 0 0 0 0

parents



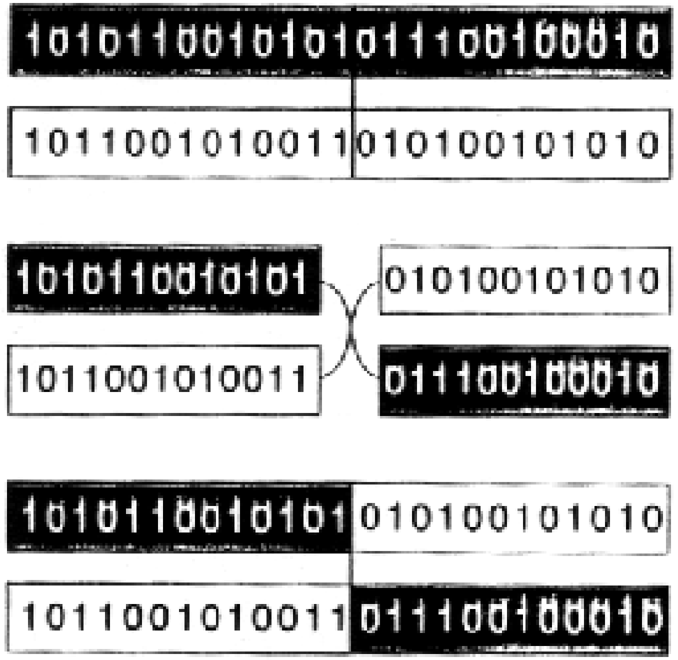
1 1 1 0 0 0 0 0 0 0 1 1 1 1

descendants



Crossover operator

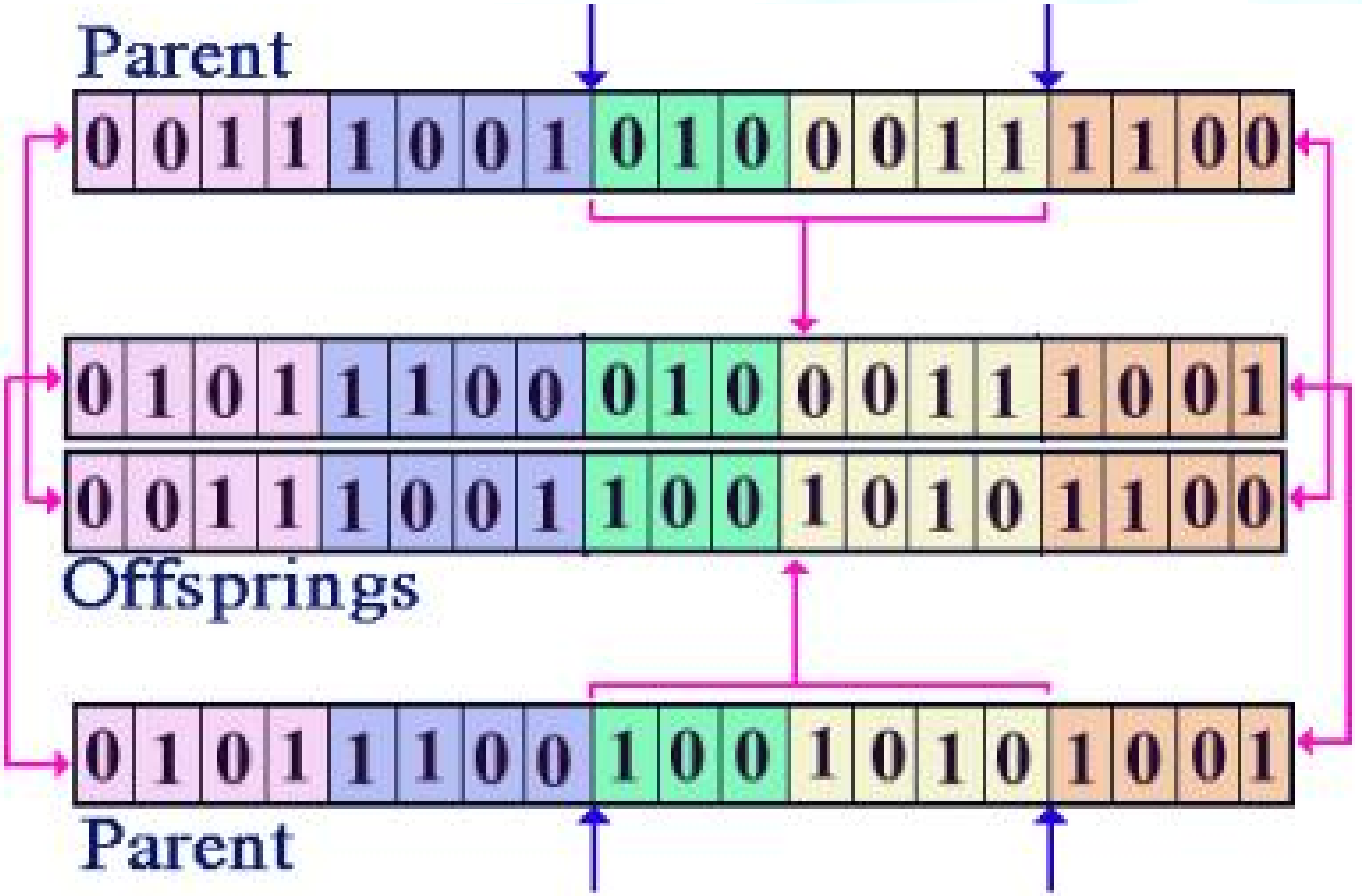
Classical image (John Holland): Biologica crosover



CROSSOVER is the fundamental mechanism of genetic rearrangement for both real organisms and genetic algorithms.

Chromosomes line up and then swap the portions of their genetic code beyond the crossover point.

Example: Two points crossover



Example: uniform crossover

a	b	c	d	e	f	g	h

A	B	C	D	E	F	G	H

→

a	b	C	d	E	f	g	H

Example: Real coding crossover operator

Arithmetic crossover:

a	b	c	d	e	f

A	B	C	D	E	F

↓

(a+A)/2	(b+B)/2	(c+C)/2	(d+D)/2	(e+E)/2	(f+F)/2

Example: real coding crossover operator **BLX-α**

- Two chromosomes

$$C_1 = (c_{11},\ldots, c_{1n}) \text{ y } C_2 = (c_{21},\ldots, c_{2n}) \; ,$$

- BLX- α generates two descendants

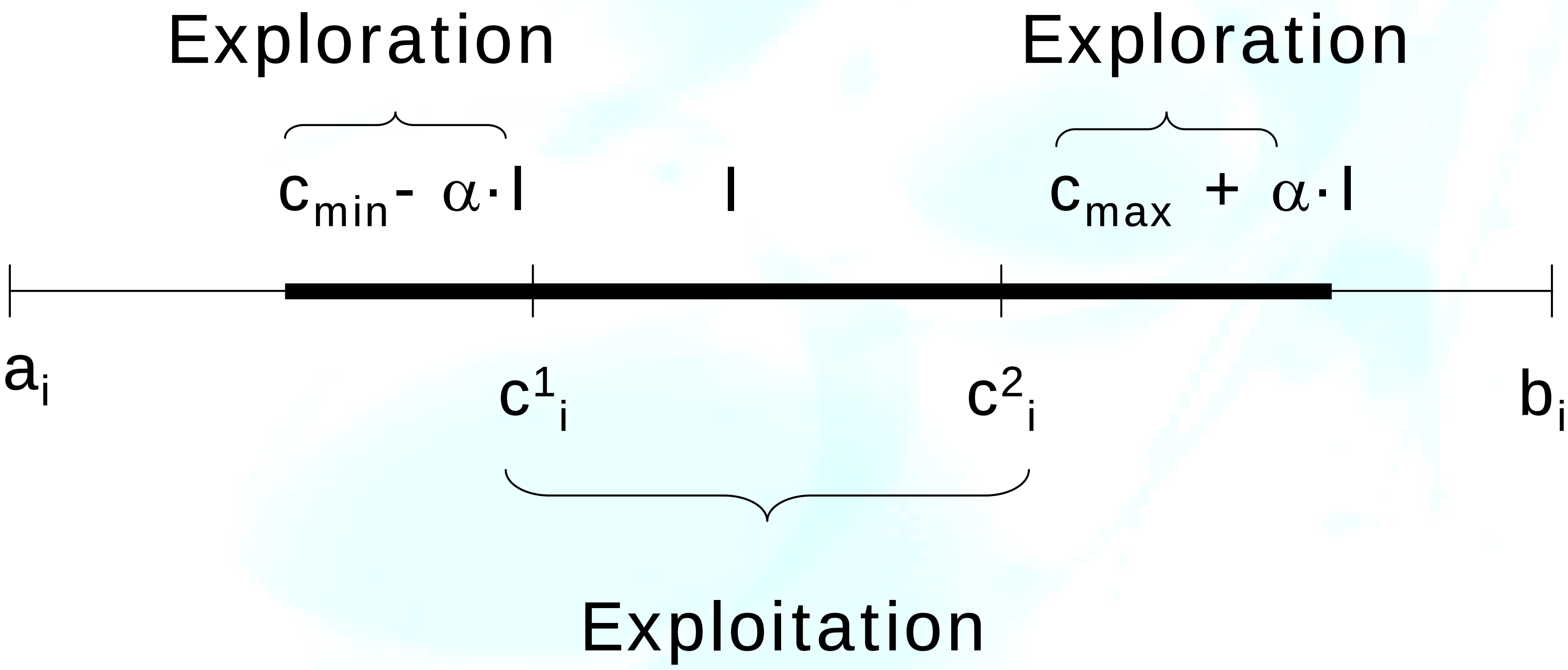
$$H_k = (h_{k1},\ldots, h_{ki},\ldots, h_{kn}) \; , \; k = 1,2$$

- where h_{ki} is a random value in the interval:

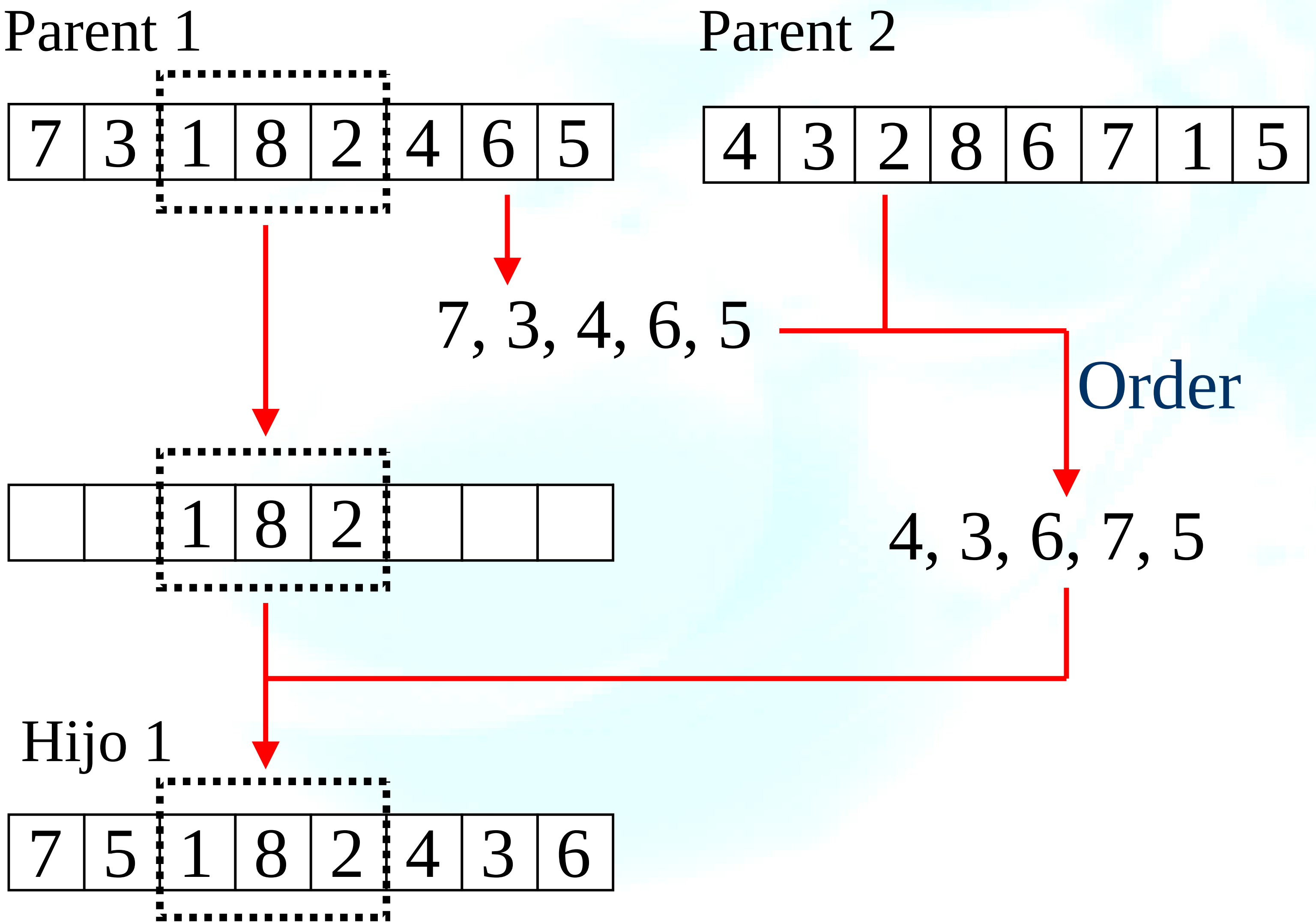
$$[C_{min} – I\cdot\alpha, \; C_{max} + I\cdot\alpha]$$

  - $C_{max} = \max \{c_{1i} \; , \; c_{2i}\}$
  - $C_{min} = \min \{c_{1i} \; , \; c_{2i}\}$
  - $I = C_{max} - C_{min} \; , \; \alpha \in [0,1]$

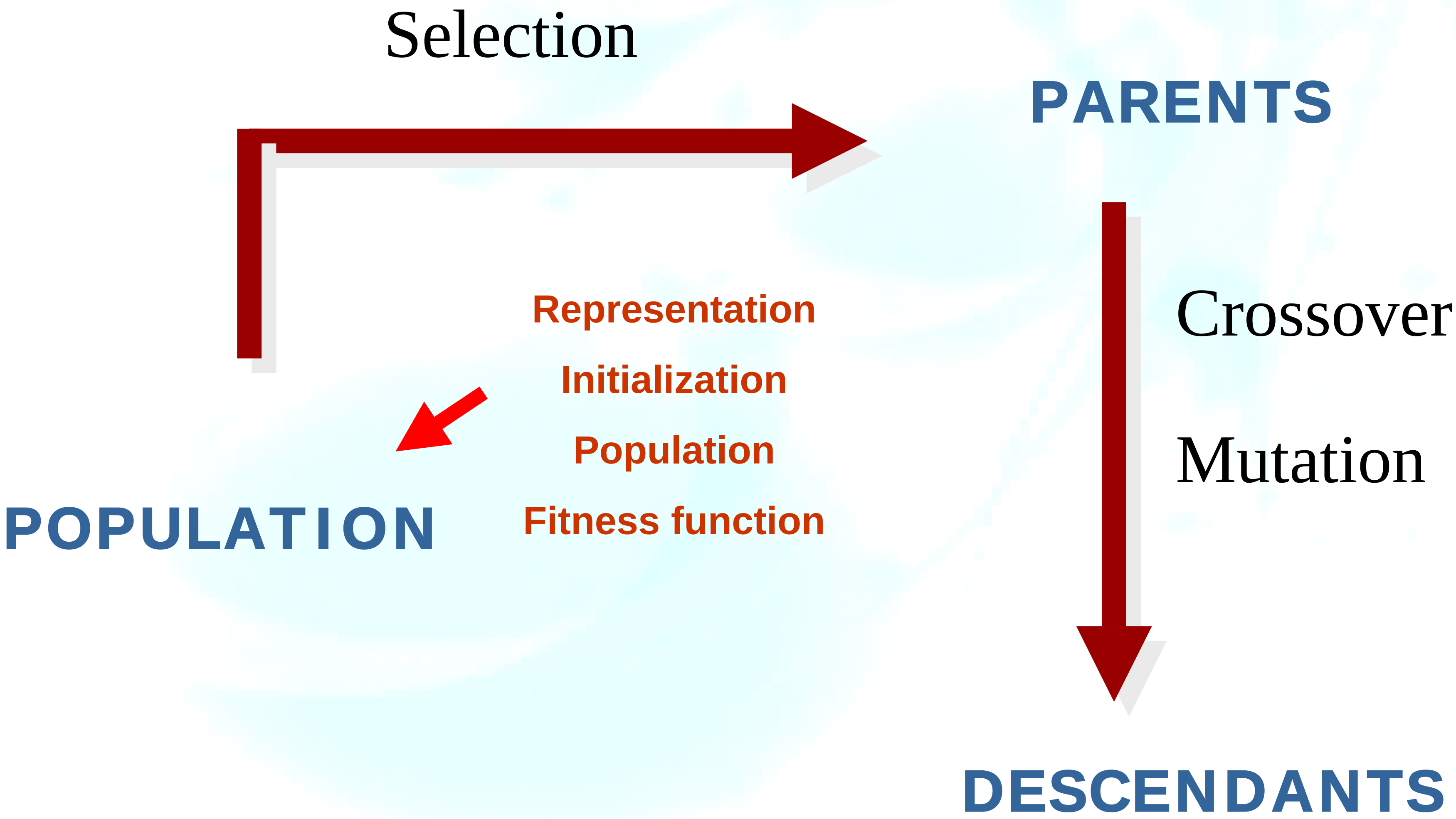
Ejemplo: Operador de cruce para representación real: **BLX-α**



Example: Crossover operator for order representation: OX



HOW TO CONSTRUCT A GA?



Mutation operator

Features:

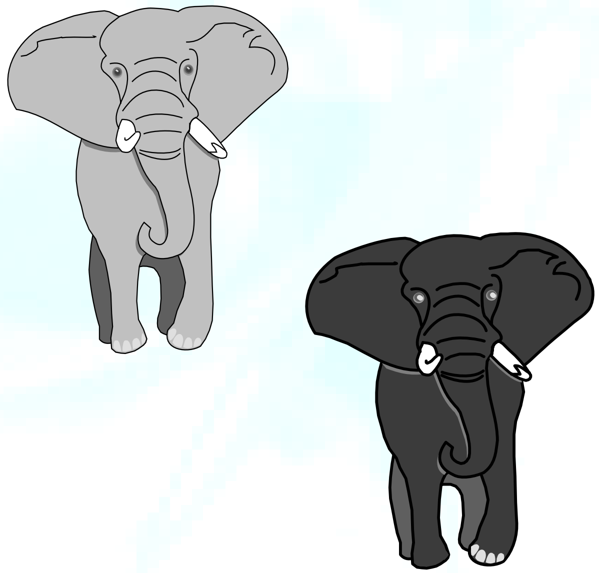
- It must allow us to reach any point through a sequence of runs.
- We must control the size.
- It must produce valid chromosomes.
- It is used with a low running probability on the descendant obtained after the application of the crossover operator.

Example: binary mutation

before 1 1 1 1 1 1 1

after 1 1 1 0 1 1 1

Mutated gen



The mutation happens with a low running probability per gen p_m

Example: real coding mutation

- Perturbation of real values via a random value.
- Using a gaussian/normal distribution $N(0,\sigma)$,
  - 0 is the mean
  - σ is the typical desviation

$$x'_i = x_i + N(0,\sigma_i)$$

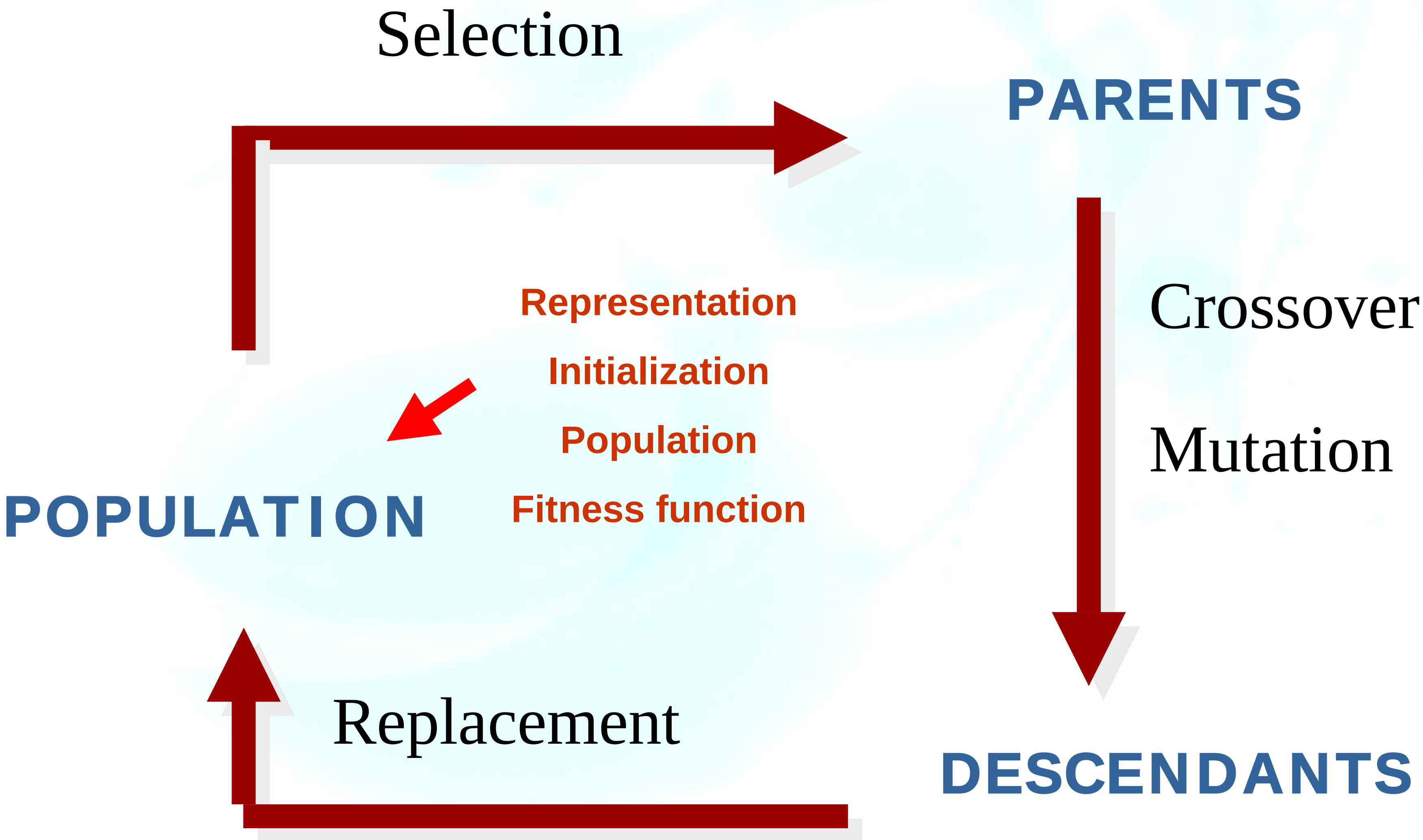
For each parameter.

Example: order representation mutation

7	3	1	8	2	4	6	5

7	3	6	8	2	4	1	5

HOW TO CONSTRUCT A GA?



Replacement strategy

Complete population

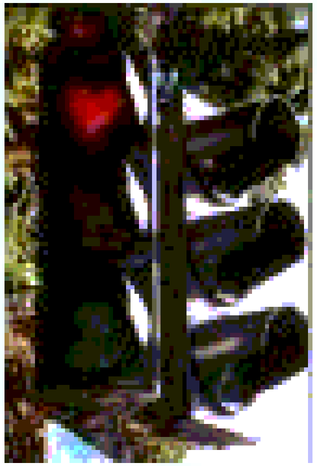
Elitism: Maintaining the best chromosome

Replacement of parents per children (via competition)

....

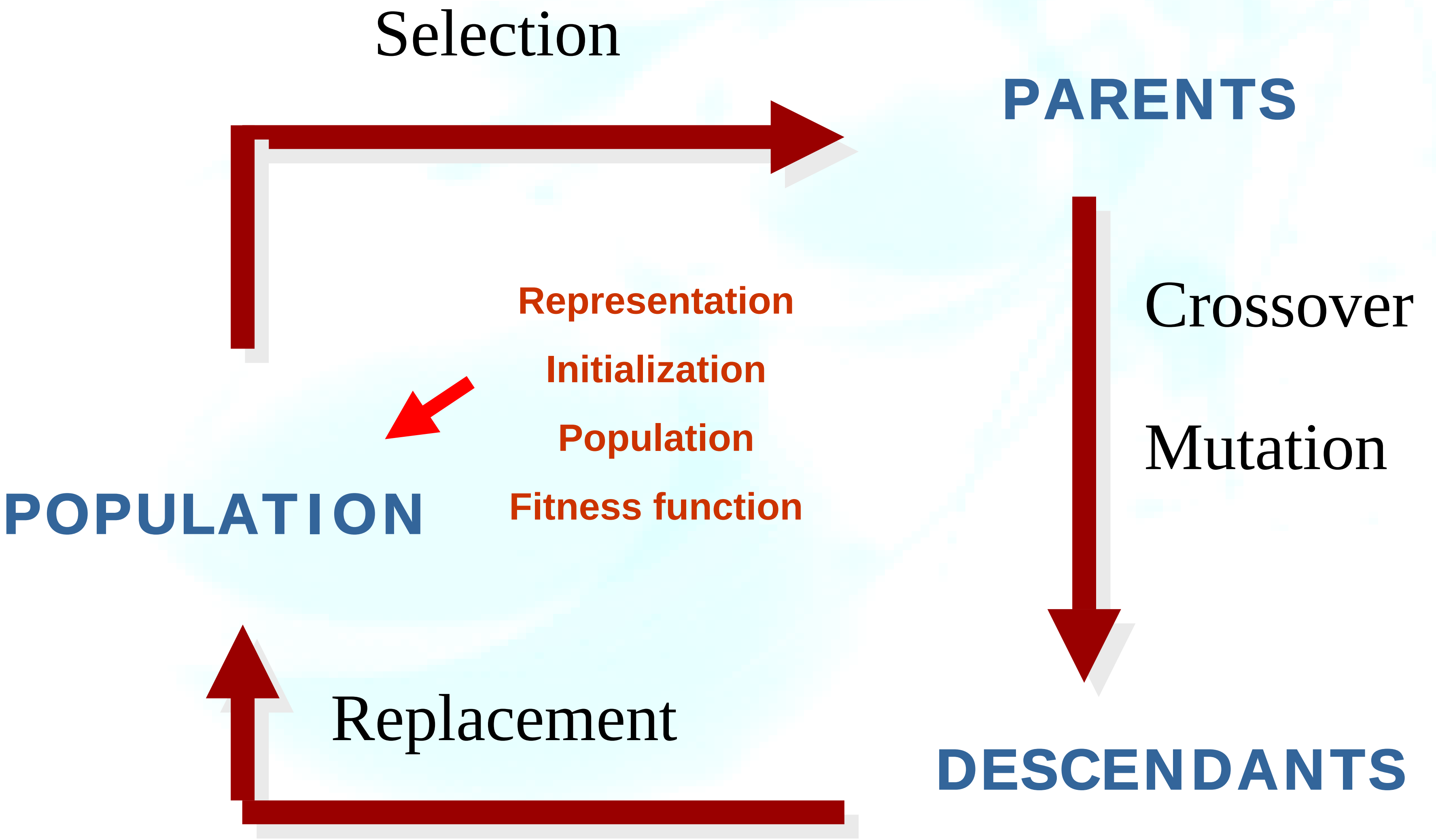
It depends on the model.

Stop condition



- ¡When we reach the optimum!
- Limited CPU:
  Maximum of evaluations
- After some iterations without any improvement.

Components


Selection
PARENTS
Representation
Initialization
Population
Fitness function
Crossover
Mutation
POPULATION
Replacement
DESCENDANTS

3. MODELS: GENERATIONAL vs STEADY STATE

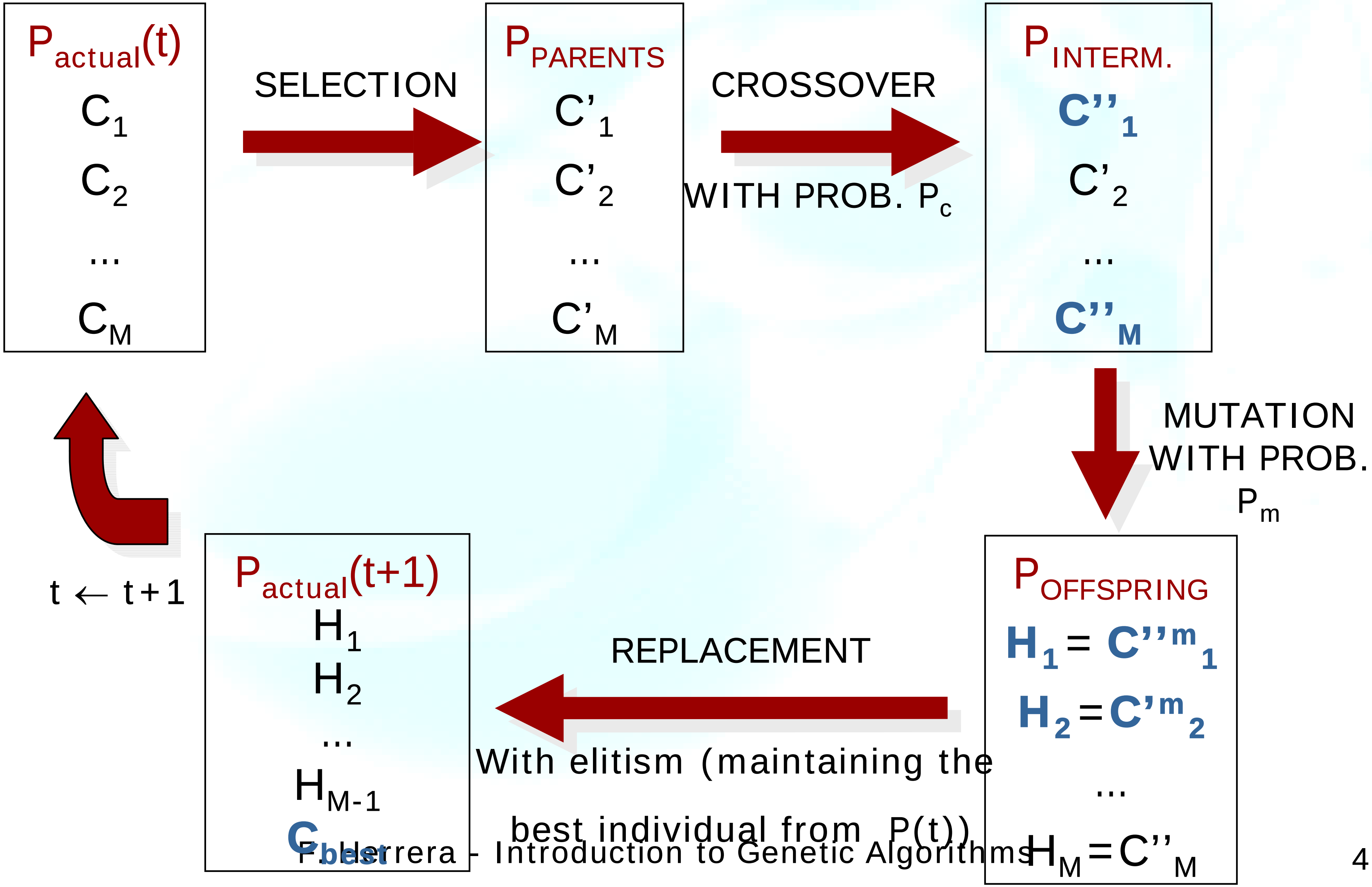
Generational model: Replacement of the complete population

Steady state model: Along each iteration two parents are used with genetic operators for getting one/two descendants.

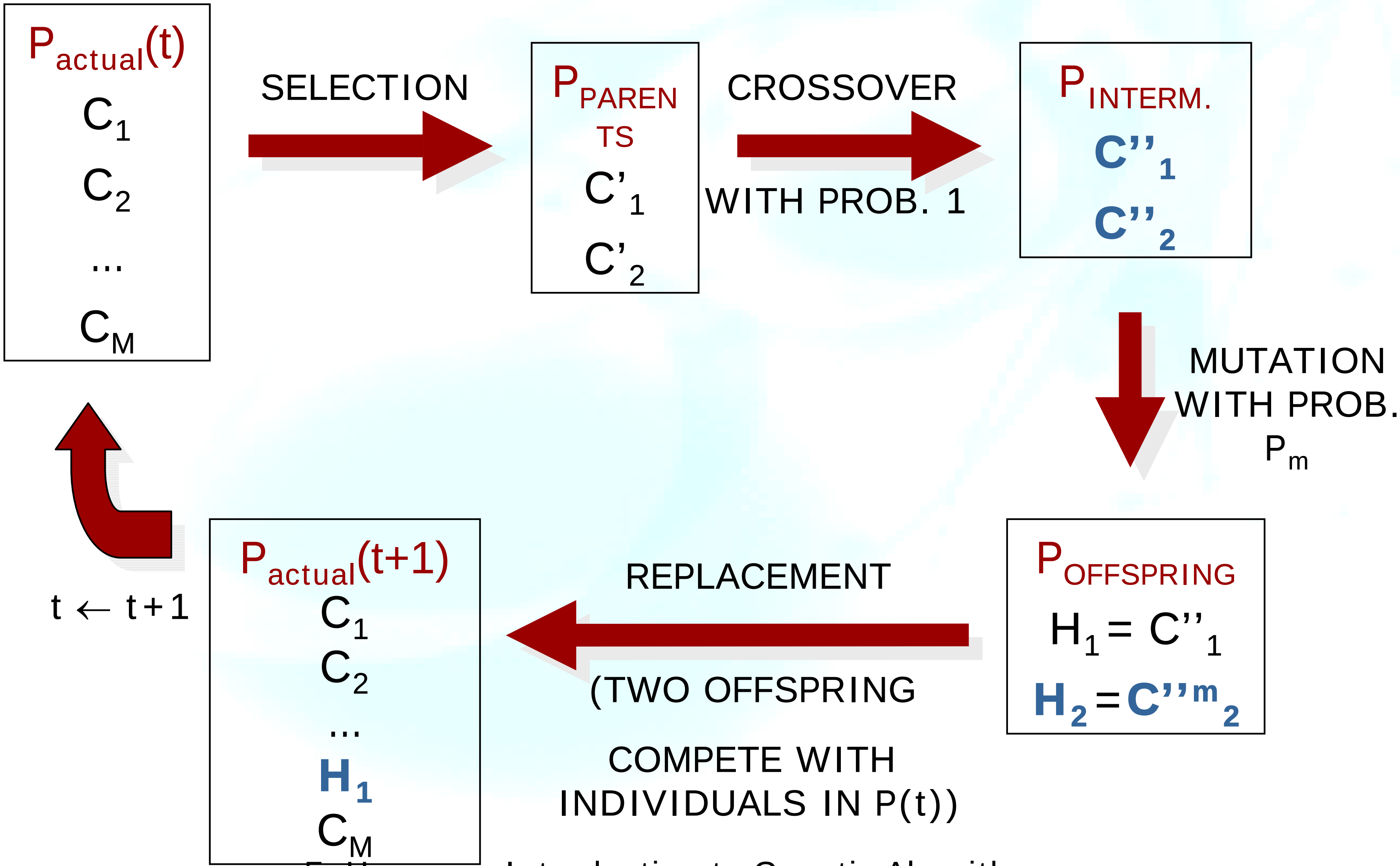
Only one/two individuals are replaced in the population.

The steady state is elitist*. *High selection pressure when we replace the worst individuals.

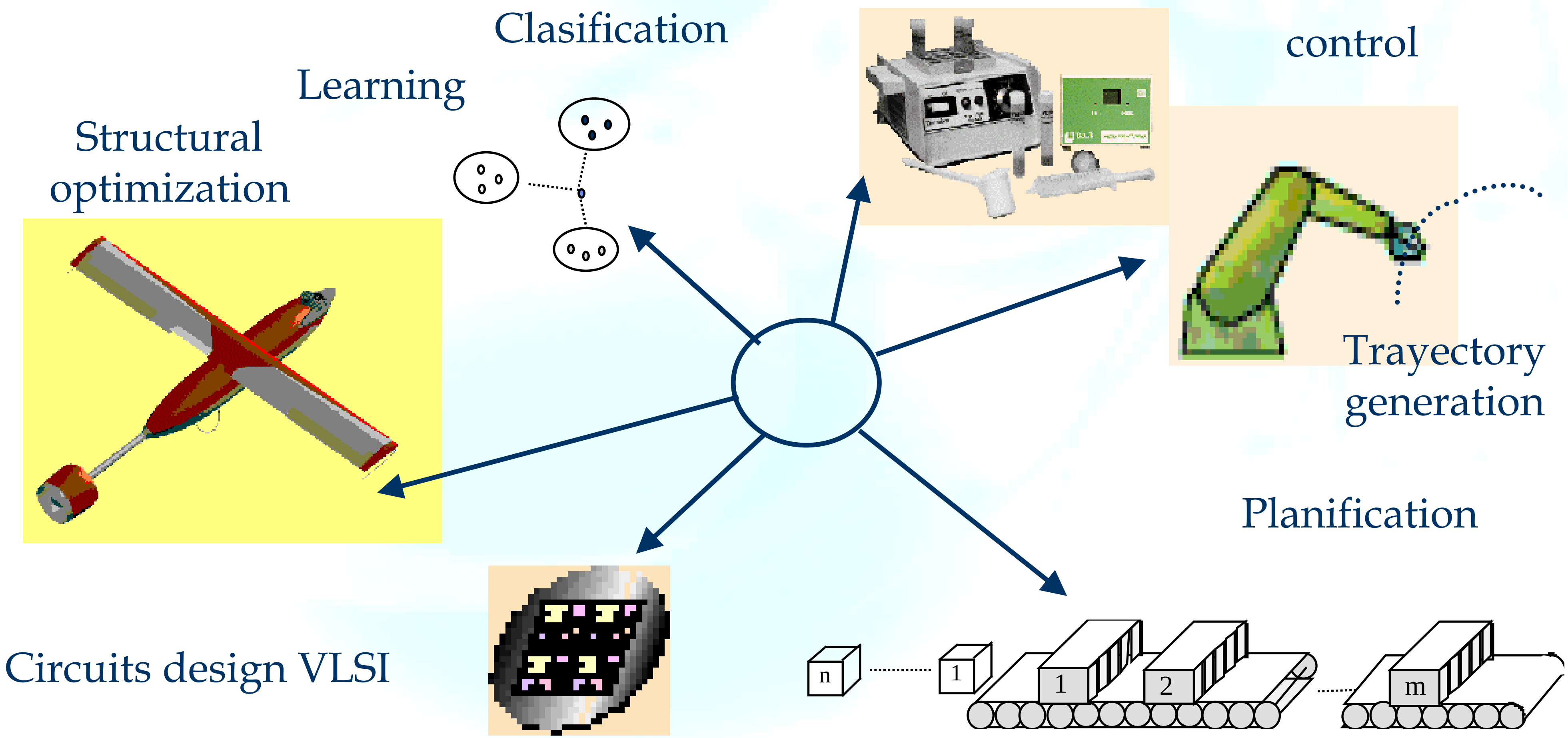
Generational model



Steady state model



4. APPLICATIONS



5. EXAMPLE: TRAVELLING SALESMAN PROBLEM

Order representation

(3 5 1 13 6 15 8 2 17 11 14 4 7 9 10 12 16)

17 cities

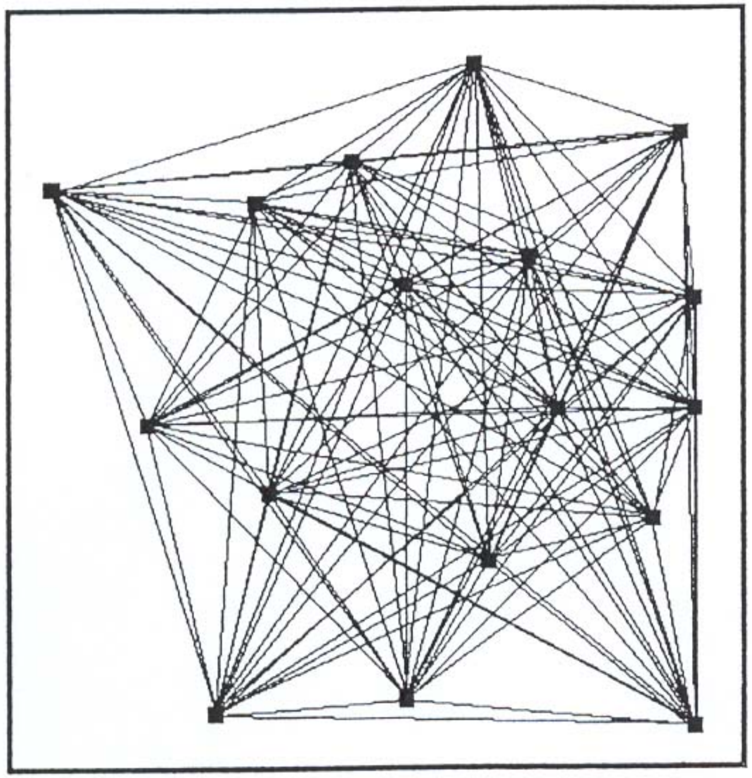
Objective: Sum of distance among cities.

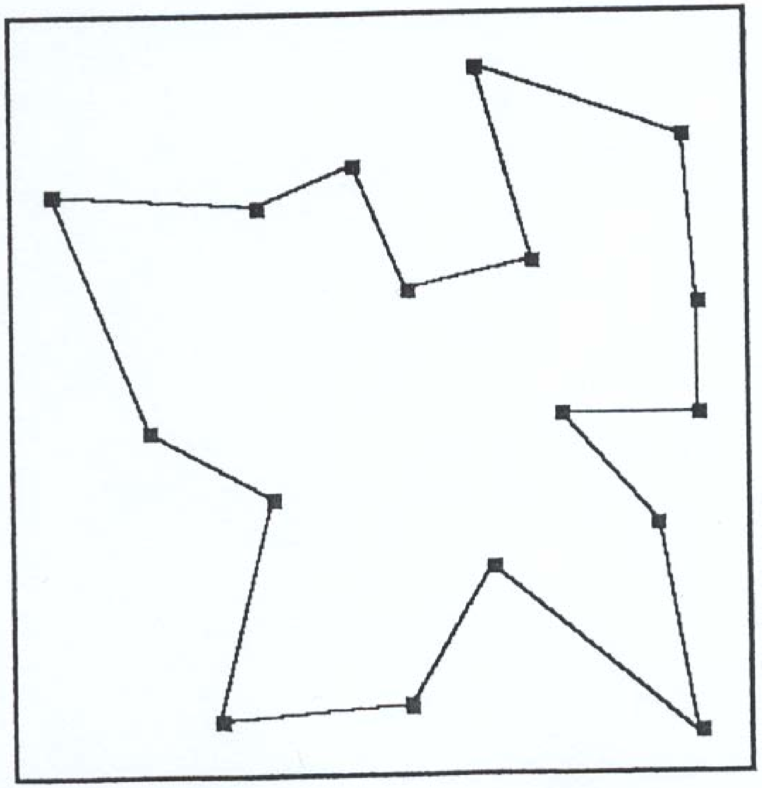
Population: 61 chromosomes - Elitism

Crossover: OX (P_c = 0,6)

Mutation: List inversion (P_m = 0,01 – chromosome)

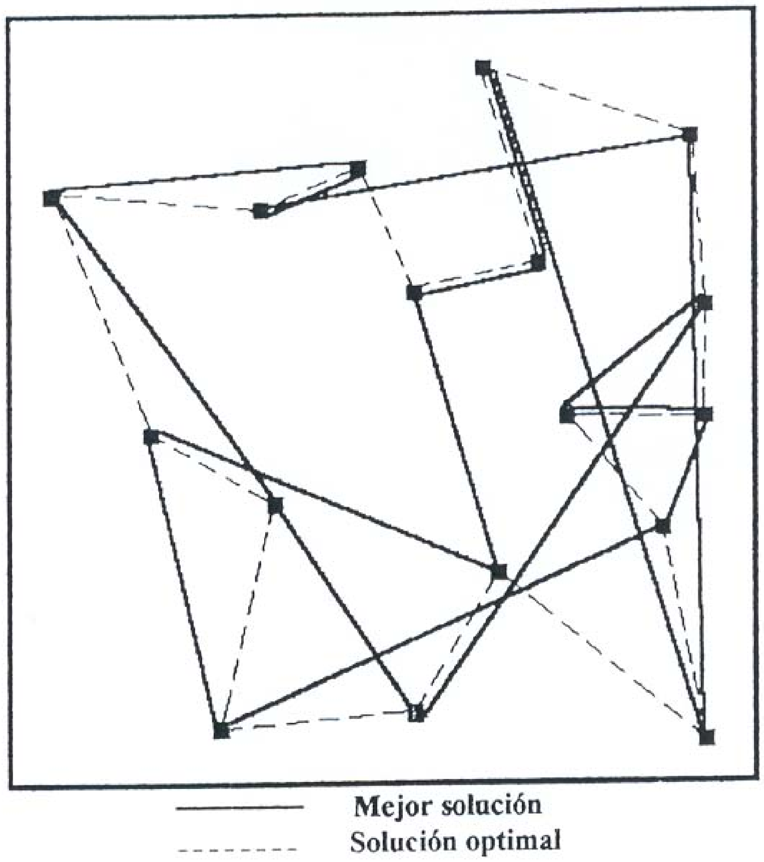
TSP



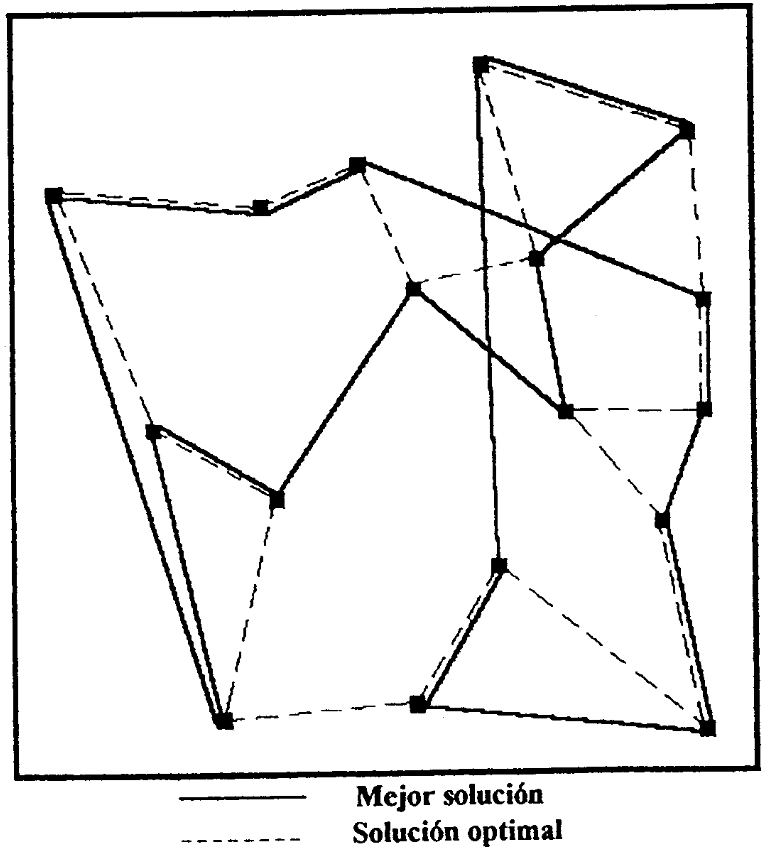


17! = 3.5568743 e14 possible solutions   Optimum solution: 226.64

TSP



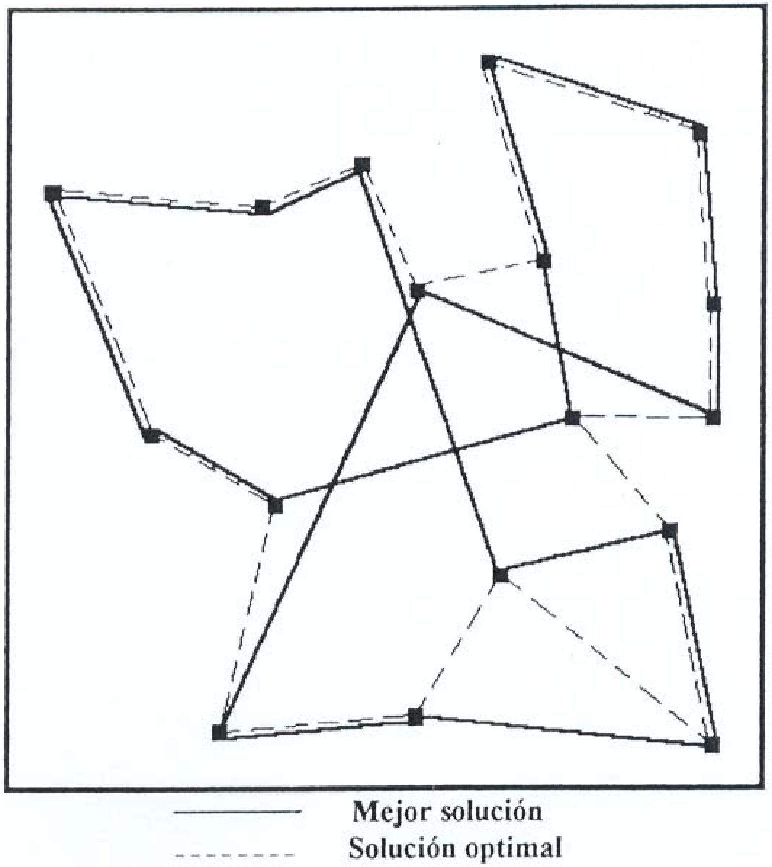
Iteration: 0 Cost: 403.7

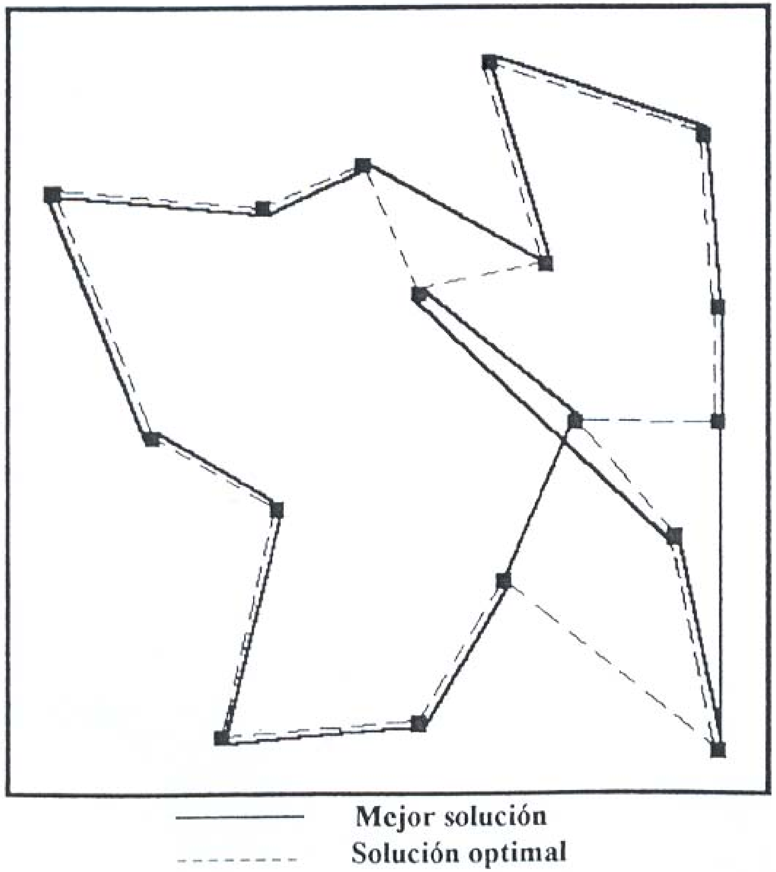


Iteration: 25 Cost: 303.86

Optimum solution: 226.64

TSP



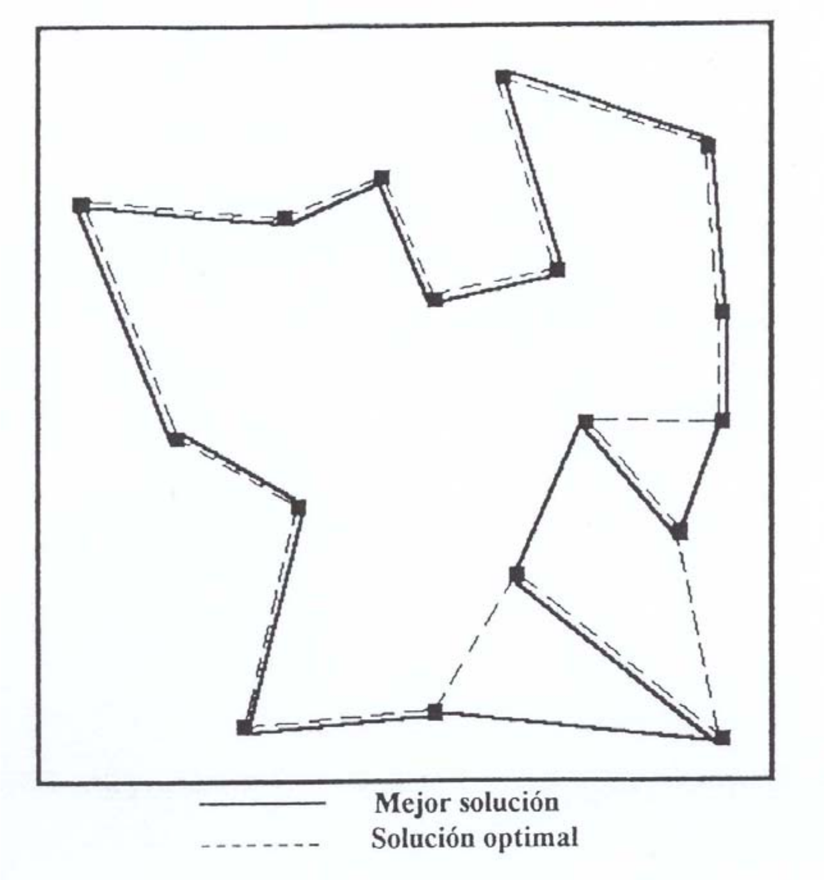


Iteration: 50 Cost: 293,6

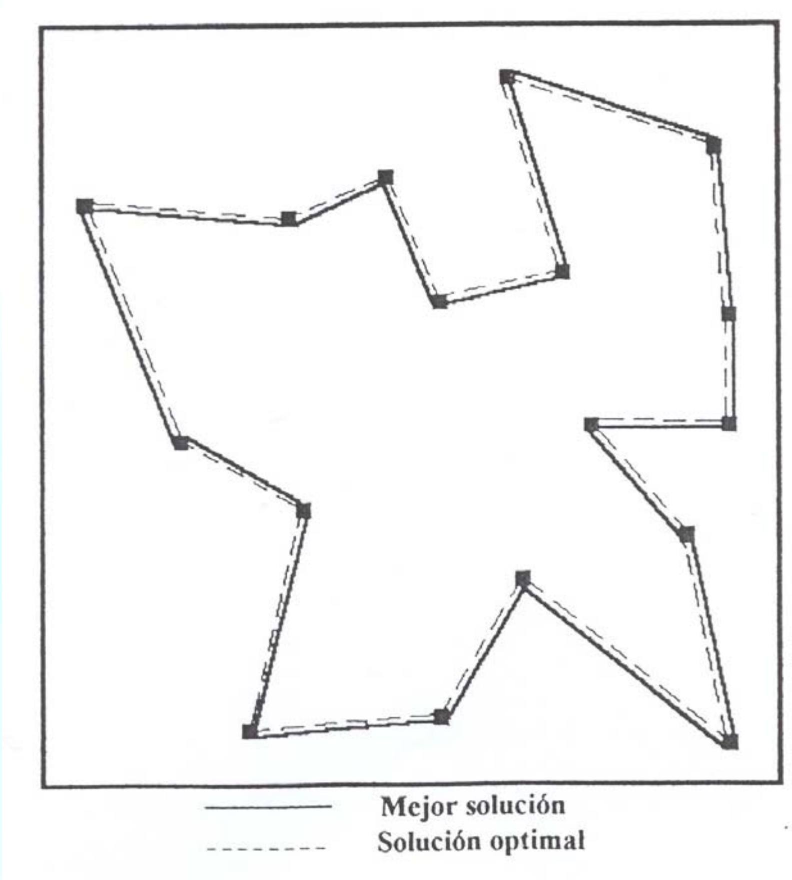
Iteration: 100 Cost: 256,55

Optimum solution: 226,64

TSP



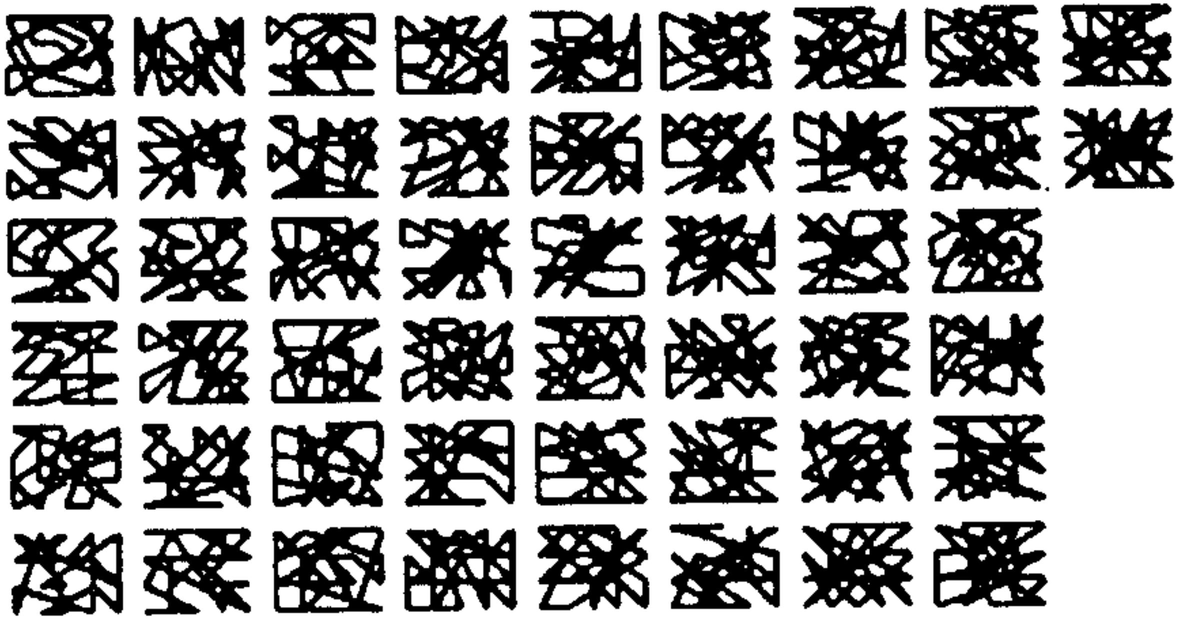
Iteration: 200 Costo: 231,4



Iteration: 250

Optimum solution: 226,64

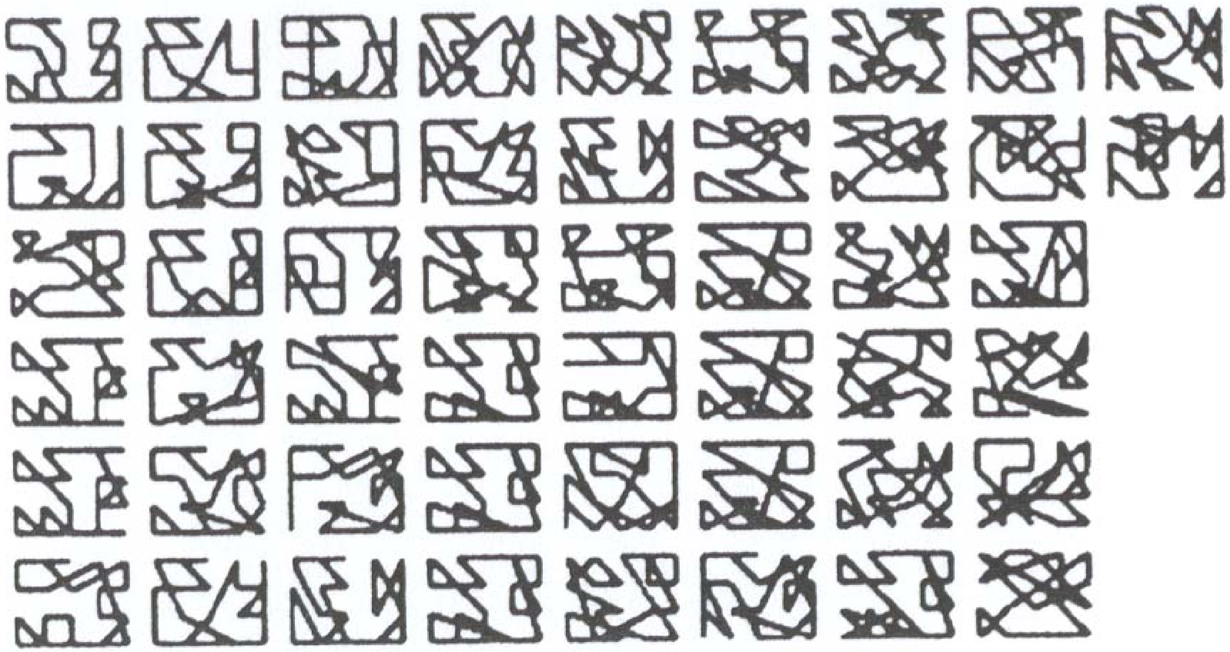
TSP



(0)

Visualization of the evolution with a population of size 50 and 70 iterations

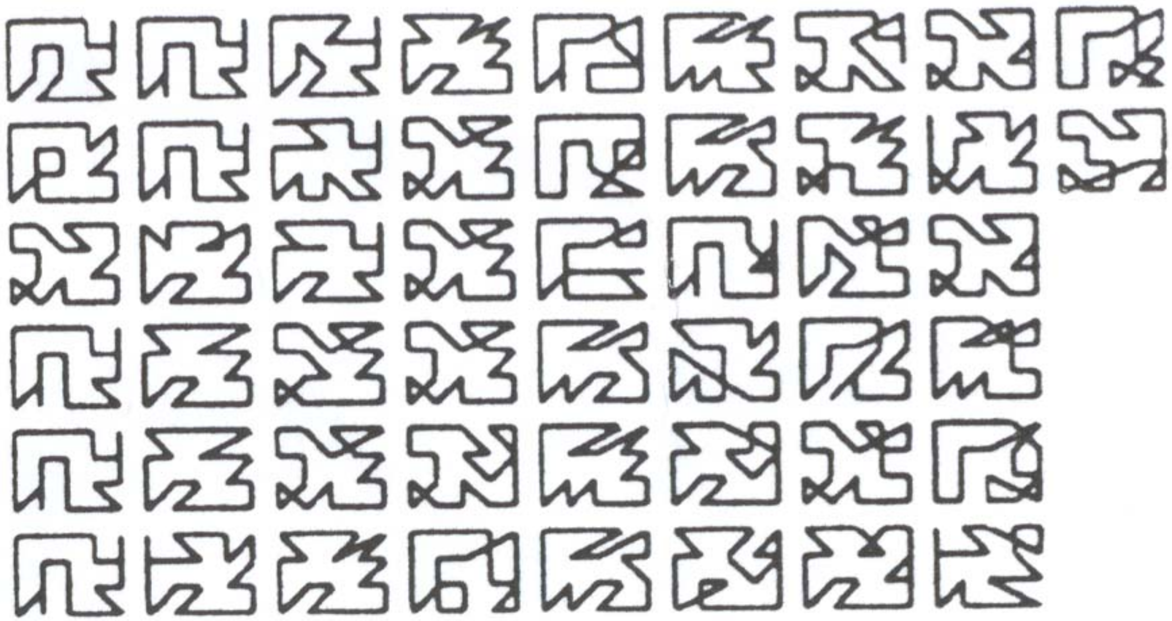
TSP



(10)

Visualization of the evolution with a population of size 50 and 70 iterations

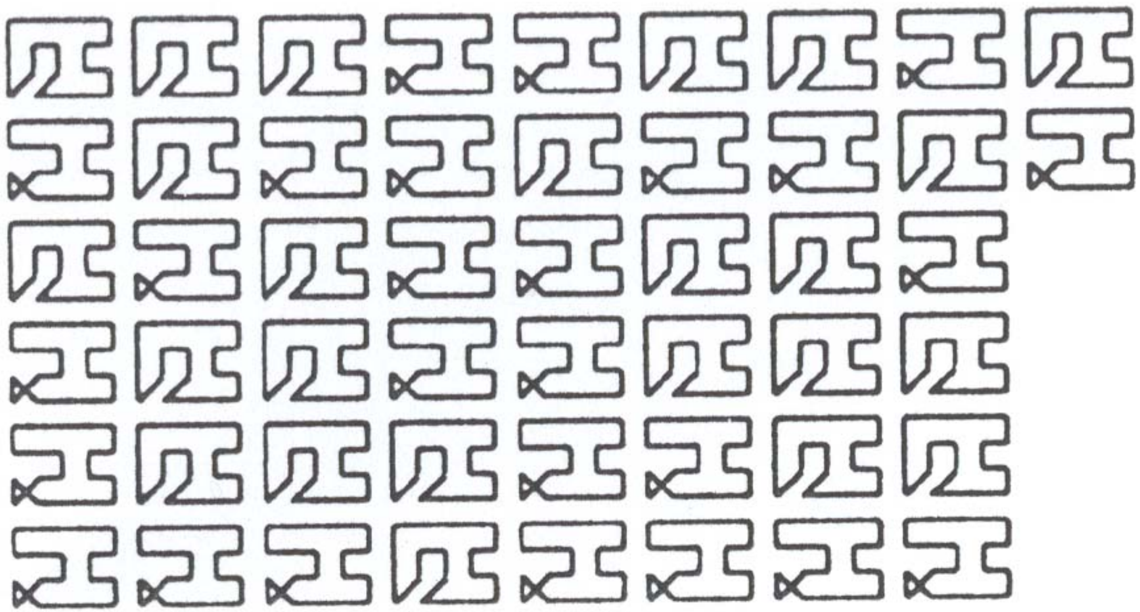
TSP



(30)

Visualization of the evolution with a population of size 50 and 70 iterations

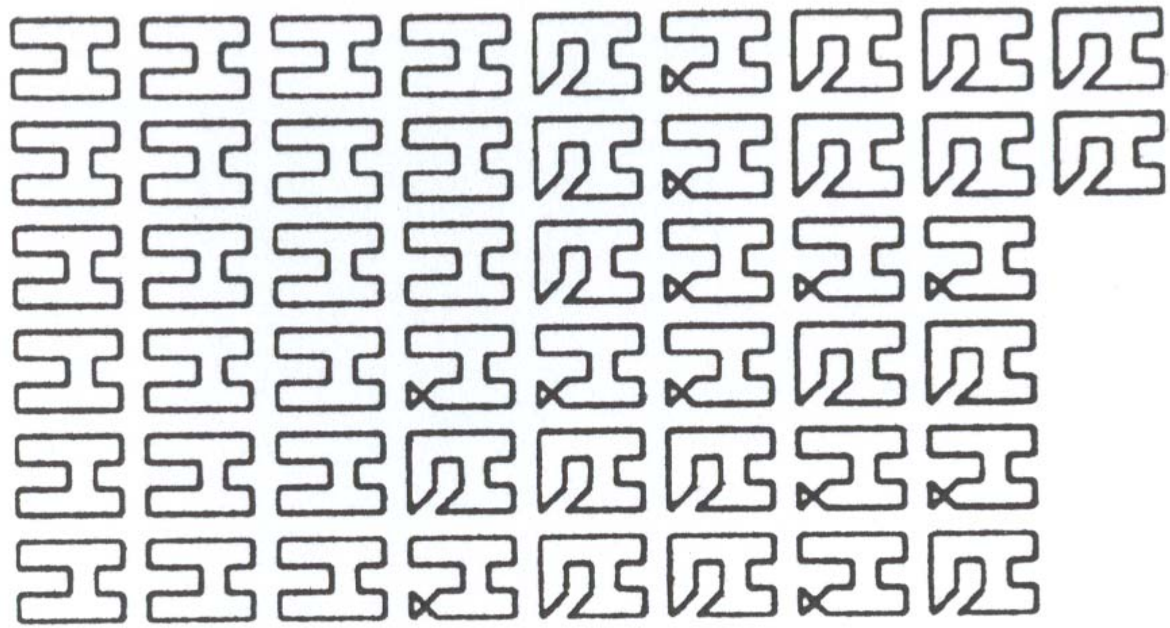
TSP



(50)

Visualization of the evolution with a population of size 50 and 70 iterations

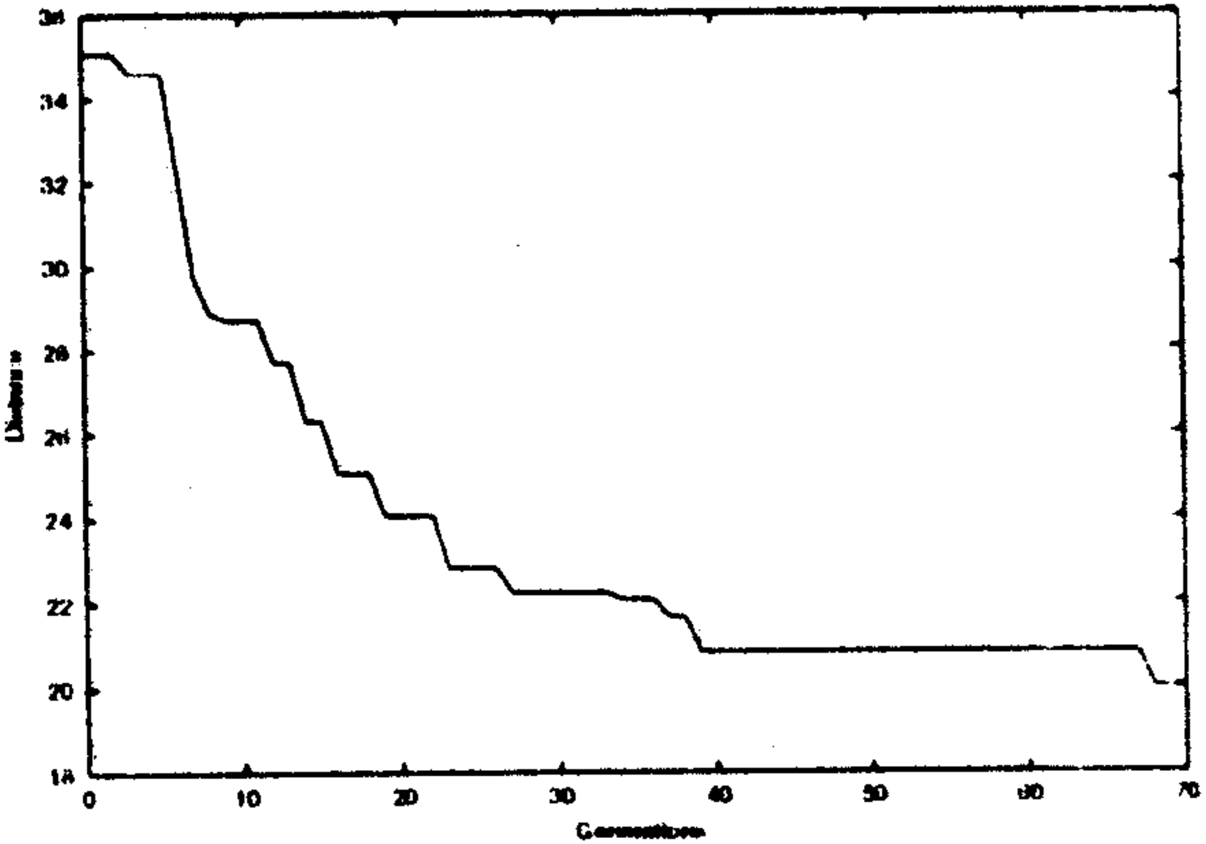
TSP



(70)

Visualization of the evolution with a population of size 50 and 70 iterations

TSP



Visualization of the evolution with a population of size 50 and 70 iterations

6. SOFTWARE AND IMPLEMENTATIONS

EO Evolutionary Computation Framework

EO is a template-based, ANSI-C++ compliant evolutionary computation library. It contains classes for almost any kind of evolutionary computation you might come up to at least for the ones we could think of. It is component-based, so that if you don't find the class you need in it, it is very easy to subclass existing abstract or concrete classes.

http://eodev.sourceforge.net/

Maintained by J.J. Merelo, Grupo Geneura, Univ. Granada
<jjmerelo@gmail.com>

6. SOFTWARE AND IMPLEMENTATIONS

JCLEC JAVA Library

JCLEC is a software system for Evolutionary Computation (EC) research, developed in the Java programming language. It provides a high-level software environment to do any kind of Evolutionary Algorithm (EA), with support for genetic algorithms (binary, integer and real encoding), genetic programming (Koza style, strongly typed, and grammar based) and evolutionary programming.

http://jclec.sourceforge.net/

Maintained: Sebastián Ventura, Universad de Córdoba (sventura@uco.es)

S. Ventura, C. Romero, A. Zafra, J.A. Delgado, C. Hervás-Martínez. JCLEC: A Java Framework for Evolutionary Computing. Soft Computing, 2007, in press.

6. SOFTWARE AND IMPLEMENTATIONS

JCLEC Features

- **Wide audience.** Software can be used by both expert people (EC researchers) and novice people (students or people from another field).
- **Several execution modes**
  - Batch mode (expert) based on a configuration file
  - Interactive mode (novice) based on a GUI with charting
- **Multiple individual encodings**
  - Linear genotype (binary, integer and real)
  - Tree genotype (expression tree and syntax tree)
  - Multiple crossover and mutation operators for each type of individual.
- **A variety of Evolutionary Algorithms**
  - Classical: SGA, Steady state and CHC
  - Multiobjective: SPEA2 and NSGA-II
  - Niching: Clearing, sequential and fitness sharing
  - Memetic: Generational and steady state

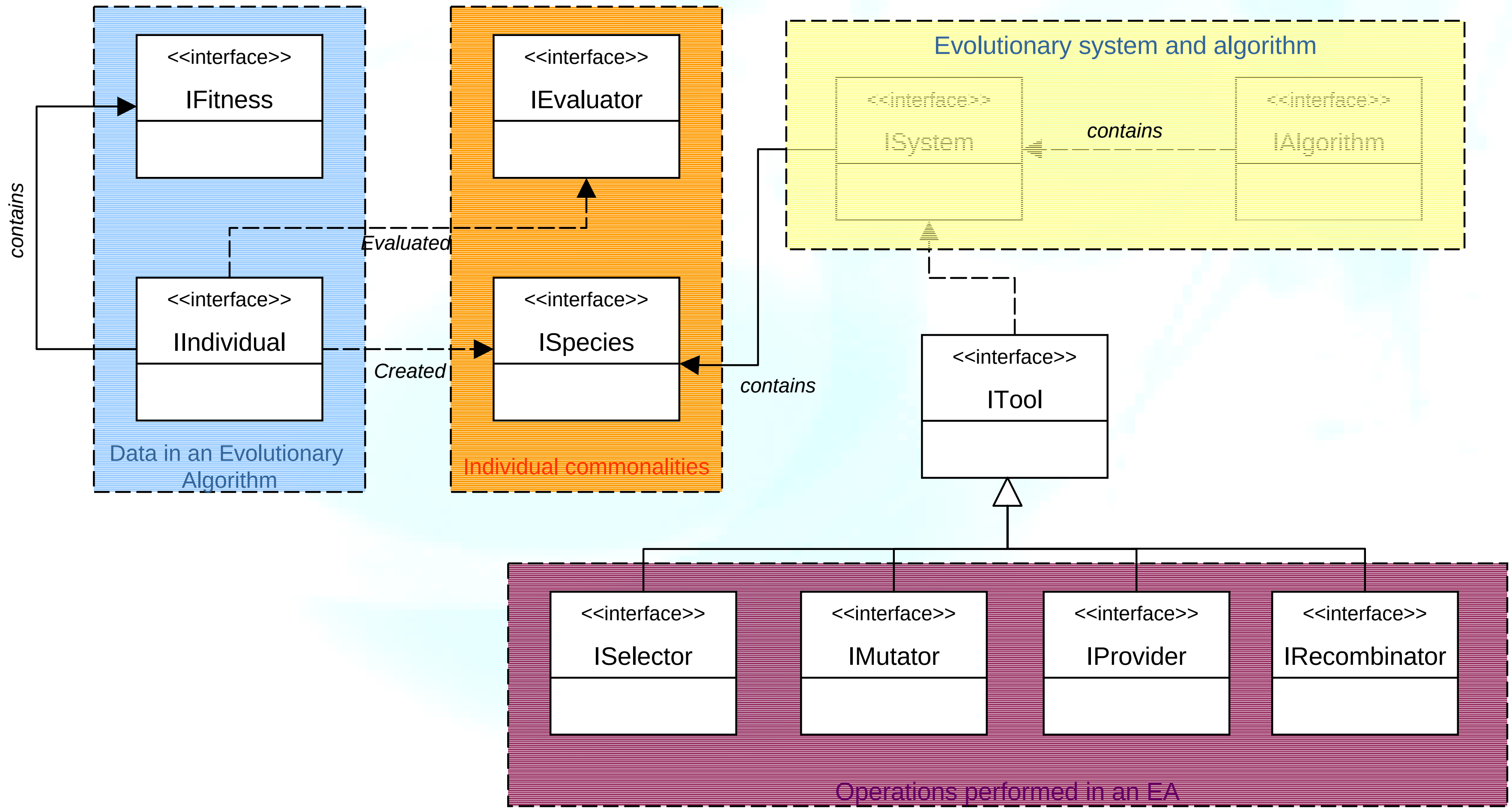
6. SOFTWARE AND IMPLEMENTATIONS

JCLEC Features (II)

- **Extensible and reusable:**
  - New problems can be easily added to the system.
  - New components (encodings, genetic operators and/or algorithms) can be easily added to the system.
- **Multithreading**
  - Speeds up evaluation in multiprocessor architectures
  - Parallel genetic algorithms implementation.
- **Future work**
  - New toolboxes planned:
    - Real optimization: ES, DE, MGG and GGG.
    - Evolutionary neural networks.
  - Native JCLEC. In complex problems, would be desirable to sacrifice the portability of the Java version to get a bigger efficiency (some applications increase their speed 10 times). This version has been developed using GNU gcj (java to native) compiler.

6. SOFTWARE AND IMPLEMENTATIONS

JCLEC Class Hierarchy



CONCLUDING REMARKS

Genetic Algorithms

- *Based in a biological metaphor: evolution*
- *high applicability*
- *very popular*
- *High performance and low cost*
- *Powerful algorithms for a lot of applications*

CONCLUDING REMARKS

EVOLUTIONARY COMPUTATION

EVOLUTIONARY CLASSIC PARADIGMS

- GENETIC ALGORITHMS
- GENETIC PROGRAMMING
- EVOLUTION STRATEGIES
- EVOLUTIONARY PROGRAMMING

OTHER EVOLUTIONARY MODELS

- ESTIMATION DISTRIBUTIION ALGORITHMS: PBIL, EDA, ...
- PARTICLE SWARM: SOCIAL ADAPTATION
- SCATTER SEARCH
- CULTURAL EVOLUTIOARY ALGORITHMS
- DIFFERENTIAL EVOLUTION
- MEMETIC ALGORITHMS

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