Bio-Inspired Algorithms for Intelligent Systems

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Optimization problems

- In engineering, there are problems that a computer cannot solve in a feasible time as the problems increase.
- This types of problems are called NP-complete. As the problems growth, the computer will need more time to find the optimal solution. And this solution is unknown.
- How much time do you think a simple problem can take?

Example Problem

- A shipping company wants to send a truck with items that clients bought.
- Each item i has a weight $w_i$and a priority value p_i. The truck has a maximum weight of W. The company want to send a truck which maximizes the summation of all the priorities.
- How much time do you think that a computer needs in order to find the best solution?

Relation between the size of the problem and time used by the computer

Number of Items	Number of Combinations	Time expend by the computer
10	1,024	0.001 second
20	1,048,576	0.03 seconds
30	1,073,741,824	18 minutes
40	1,099,511,627,776	13 hours
50	1,125,899,906,842,624	36 years

Assuming that a computer can calculate 1,000,000 of different combinations in a second.

Bio-inspired Optimization algorithms

- Ant Colony Optimization
- Artificial bee colony algorithm
- Bat Algorithm
- Differential Evolution
- Firefly Algorithm
- Genetic Algorithm
- Particle Swarm Optimization
- …

EVOLUTIONARY COMPUTATION (EC)

- EC: simulate natural selection in a computer program to improve system performance automatically

- Like natural selection, EC aims to facilitate stochastic search in problem space

- EC conducts randomized, parallel beam search. It becomes more popular with advancement of computer hardware.

Family of Evolutionary Computation

- **Genetic algorithms**
- **Genetic programming**
- **Differential Evolution**
- Memetic algorithm

AGENDA

- Genetic algorithm
  - What is it?
  - Types
  - Important parts

- Differential Evolution
- Genetic Programing
- Ant Colony Optimization
- Particle Swarm Optimization

Genetic Algorithms

What is a Genetic Algorithm (GA)?

The genetic algorithms

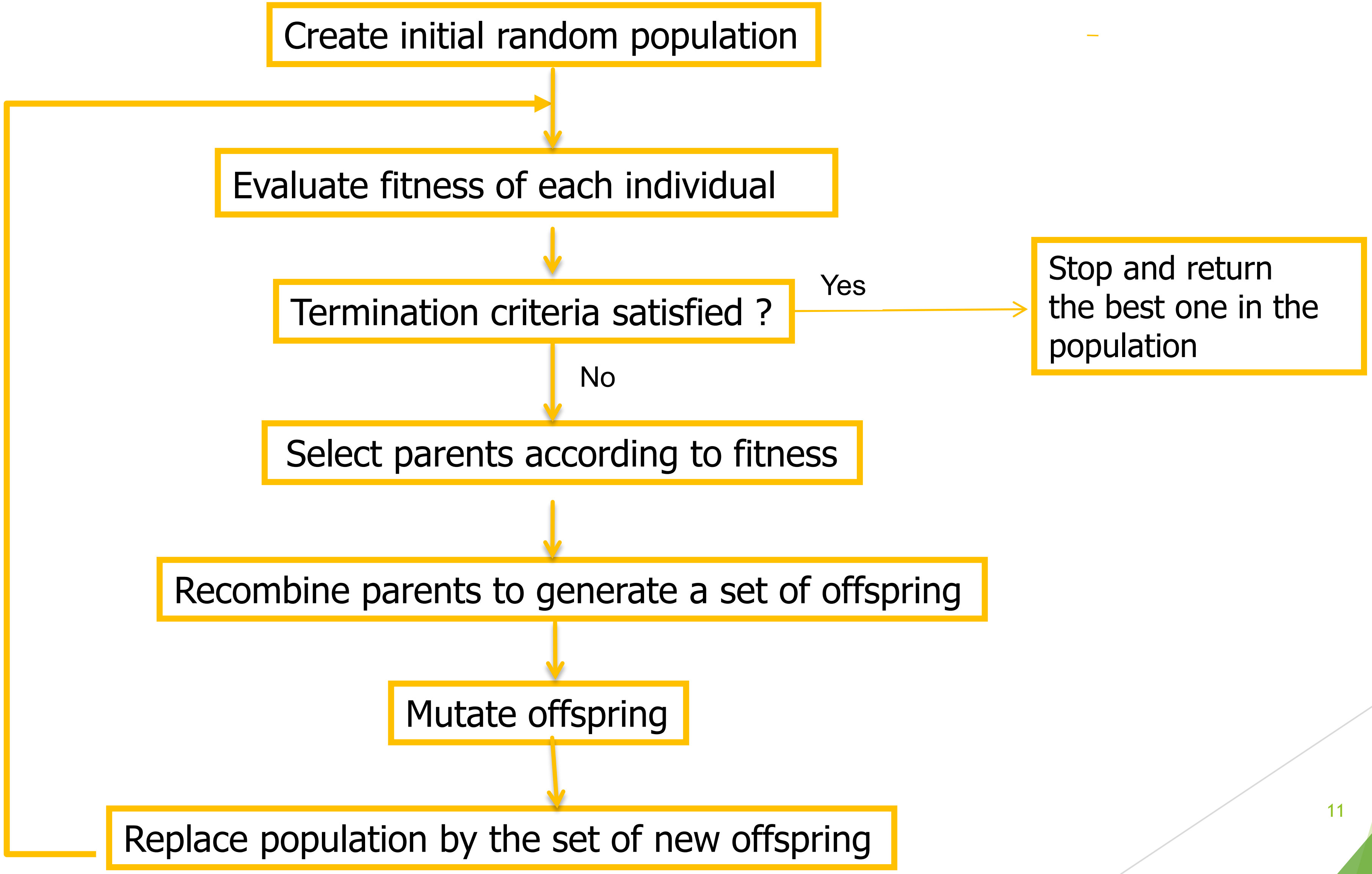
are a class of algorithms for optimization, search and learning, which are inspired by

Natural Evolution

and

Genetic Evolution

Flow Chart of Traditional Genetic Algorithm



Two models: Gerenational and stationary

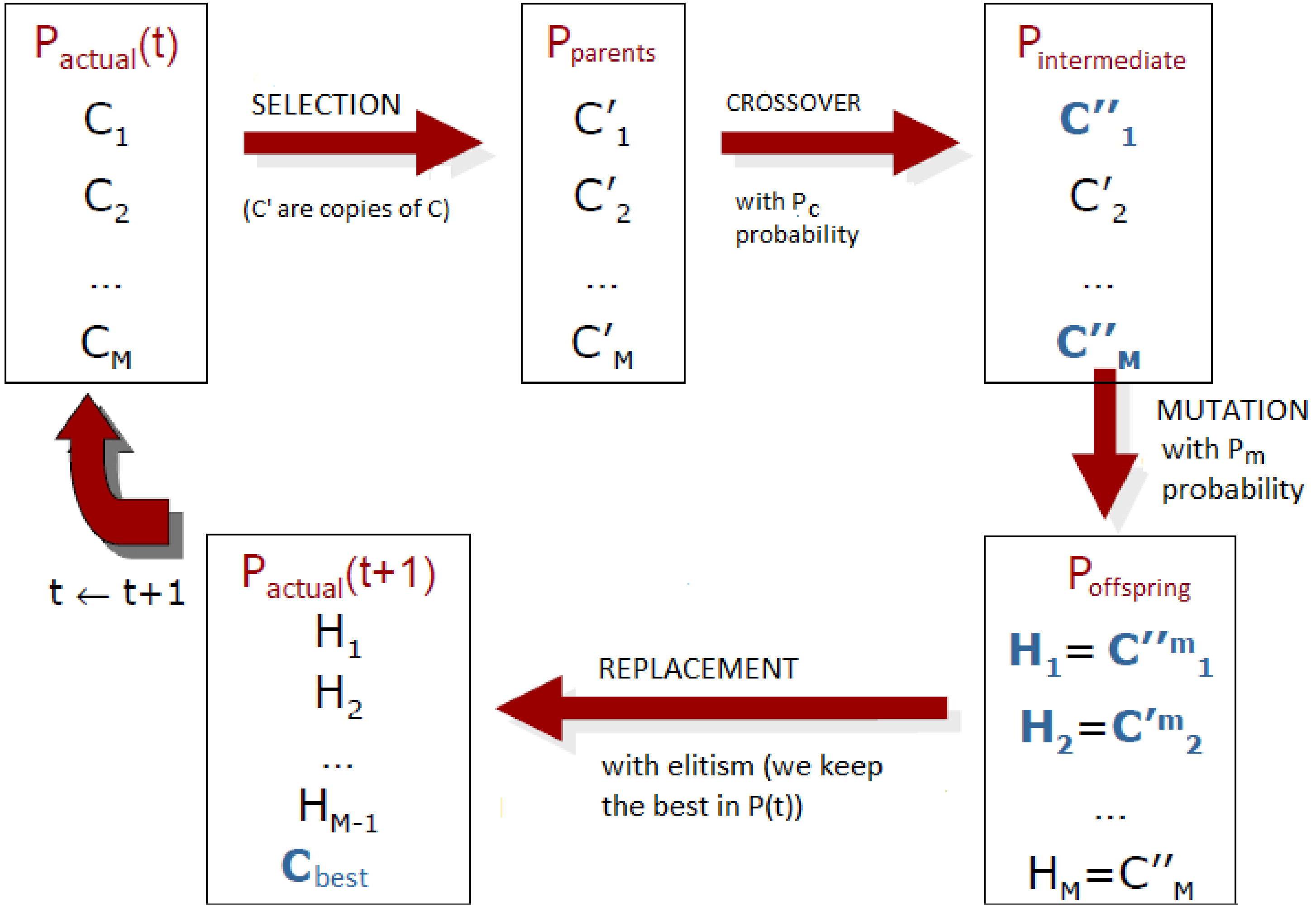
- **<u>Generational model:</u>** A completely new population of new individuals is created in every iteration.

  The new population replace the old one.

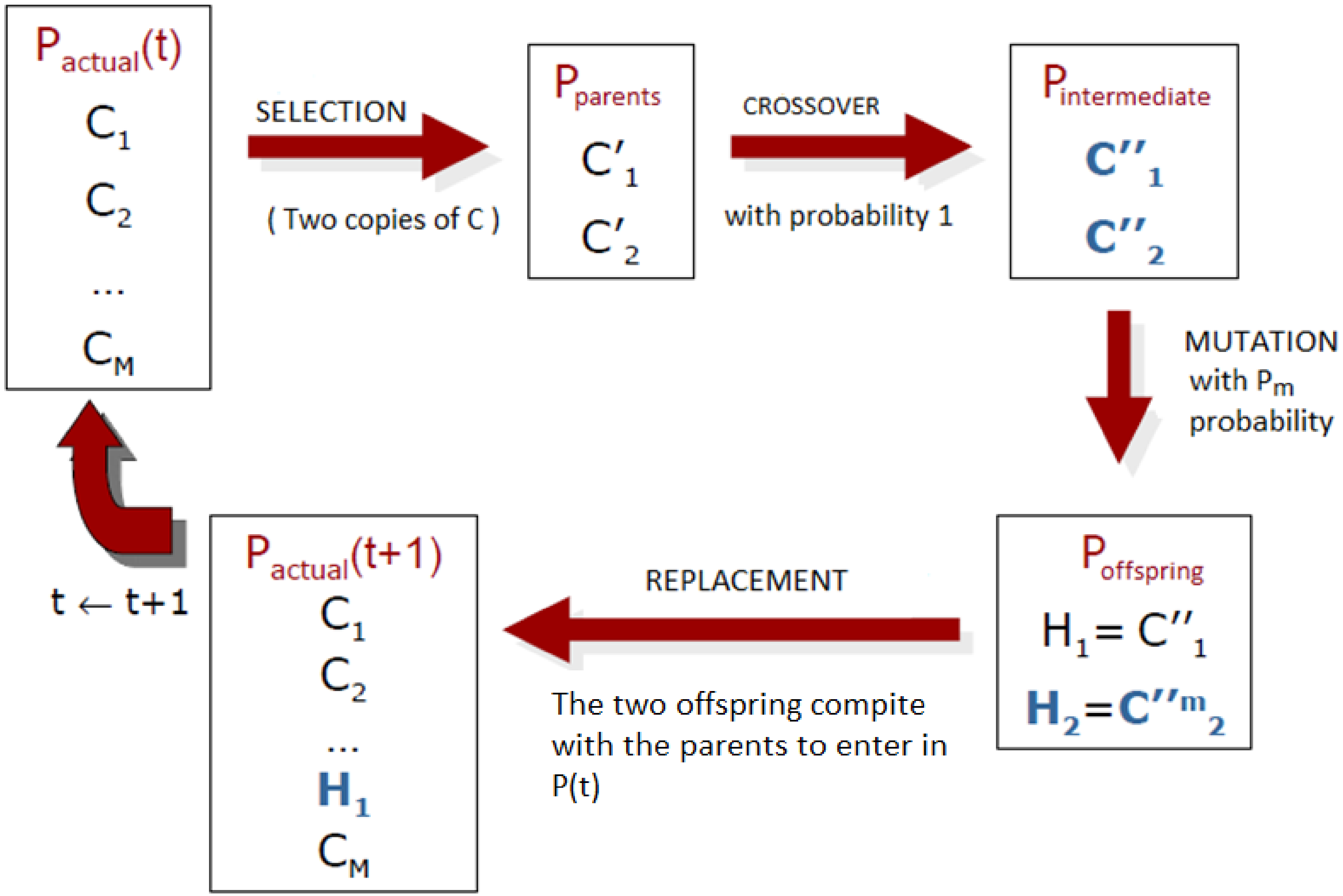
- **<u>Stationary model:</u>** Two parents are chosen and the genetic operators (crossover and mutation) are applied to produce offspring. **Only the best individuals from the parents and offspring survive in the next generation.**

1 0 1 1 1 1 0

Generational model



Stationary model



How to build a genetic algorithm?

$x = \{x_0, x_1, \ldots, x_i, \ldots, x_n\}$

$x_i \in \{0, 1\}$

- Design a representation $x = \boxed{1\,|\,1\,|\,1\,|\,1\,|\,1}$
- Decide how to initialize a population
- Design a way to evaluate an individual (fitness function)
- Decide how to select the parents
- Design a crossover operator
- Design a mutation operator
- Decide how to replace the individuals
- Decide when to stop

Representation

There is several kinds of representation. The two more common are:

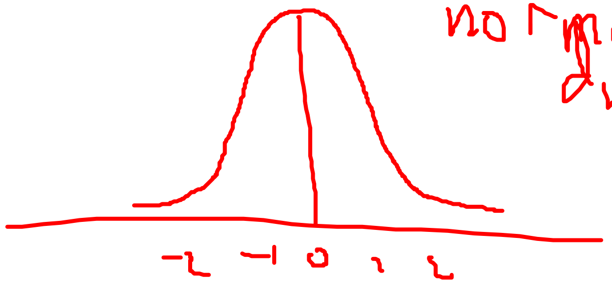
- Binary representation:

1	0	1	1	1	0	1	0

- Real representation:

7	3	6	8	2	4	1	5

Intizialize



normal dist.

Two ways:

(0, 10)

- Randomly created in the search space:
  - Binary representation: 0 or 1 with probability 0.5
  - Real representation: Uniform inside the range.

5.6 3 4.75

- Choose the initial population to contain solution(s) from a previous search.

item 1 $\{W=10,\ p=3$

item2 $= \{W=7,\ p=5$

item3 $\{W=5,\ p=2$

Selection strategy

$X_1 = \boxed{1|0|1}$

$X_2 = \boxed{0|1|1}$

X_1	$=5$	5%
x_2	7	70%
x_3	6	10%
x_4	10	50%

- **Tournament Selection (TS):** Choose the best from the k randomly selected individuals from the population. K is the size of the tournament.
- **Linear Order(LS):** The population is ordered according the fitness value and then a probability is given according to the order.
- **(NAM):** The first parent is chosen randomly. The other is chosen according to the distance with the first one. So the most different individual will be chosen.
- **Roulette Selection:** A probability is assigned to an individual, proportional to the fitness of this individual.

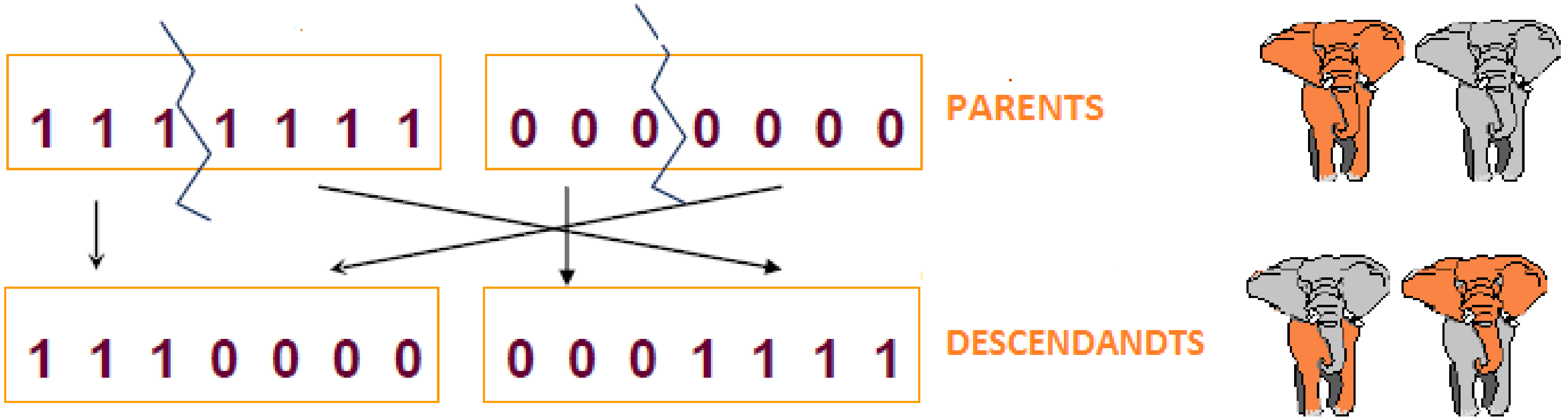
$$P(S_i) = \frac{Fit(S_i)}{\sum_j Fit(S_j)}$$

$P(x_1) = \frac{5}{28}$

$P(x_2) = \frac{7}{28}$

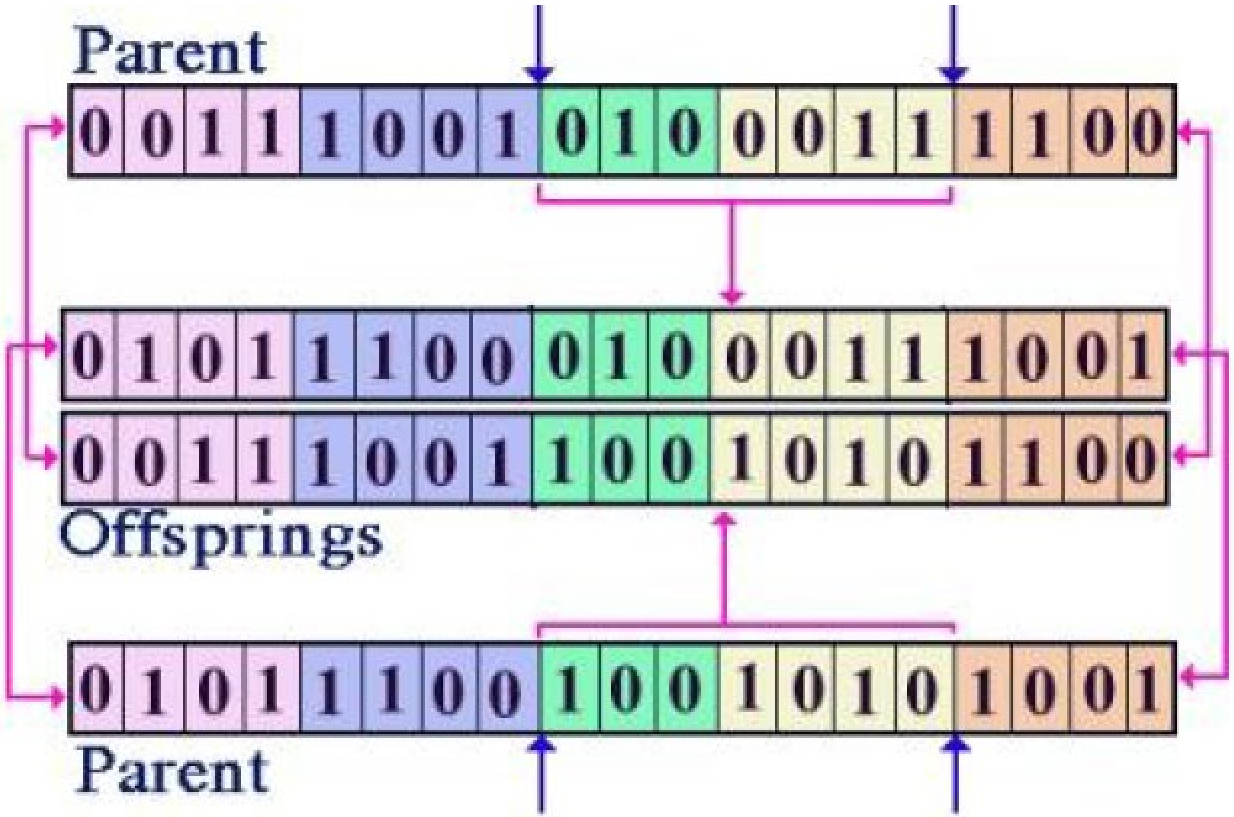
Crossover (1)

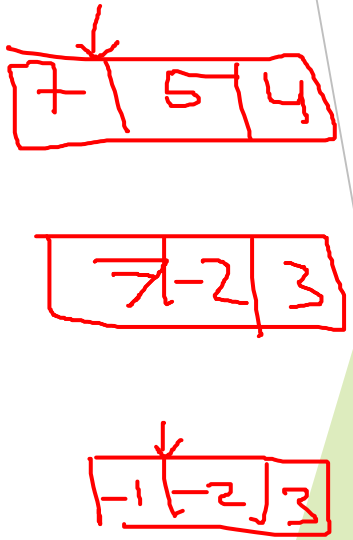
Crossover operator with binary representation (example 1):



Crossover (2)

Crossover operator with binary representation (example 2):





Crossover (3)

Crossover operator with a real representation (Example 1).

Arithmetic Recombination.

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

Crossover (4)

Crossover operator with a real representation (Example 2).

BLX-α.

- Given 2 individuals

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

C_1 = {3, 2}, C_2 = {-2, 3}

H_1 = {2, 2.3}
H_2 = {-1.05, 3.1}

- BLX- α creates two descendants

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

- where h_{ki} is created randomly in the interval:

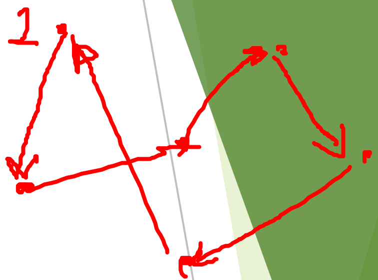
$$[C_{min} - I\cdot\alpha,\ C_{max} + I\cdot\alpha]$$

[-2.5, 3.5]
[1.4, 3.1]

  - $C_{max} = \max\{c_{1i}, c_{2i}\}$ = {3, 3}
  - $C_{min} = \min\{c_{1i}, c_{2i}\}$ = {-2, 2}
  - $I = C_{max} - C_{min}$, $\alpha \in [0,1]$ = 0.1

I = {5, 1}

Crossover (5)



- Crossover operator with a order representation (Example 1).

Parent 1

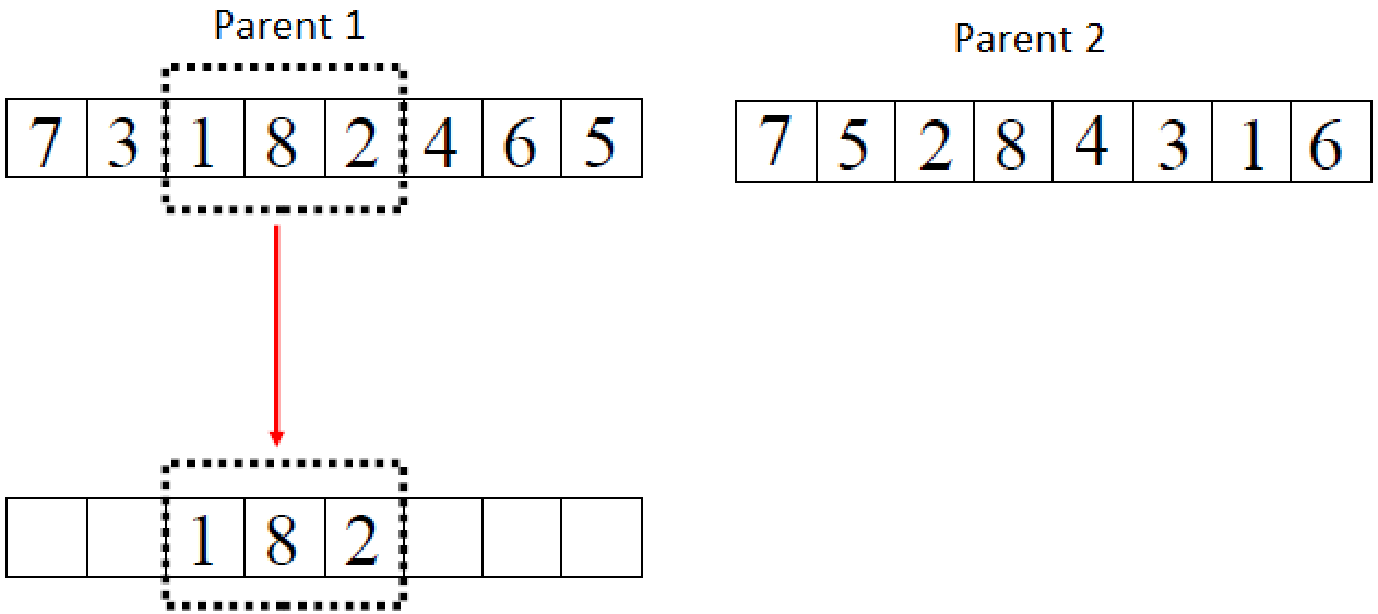
7	3	1	8	2	4	6	5

Parent 2

7	5	2	8	4	3	1	6

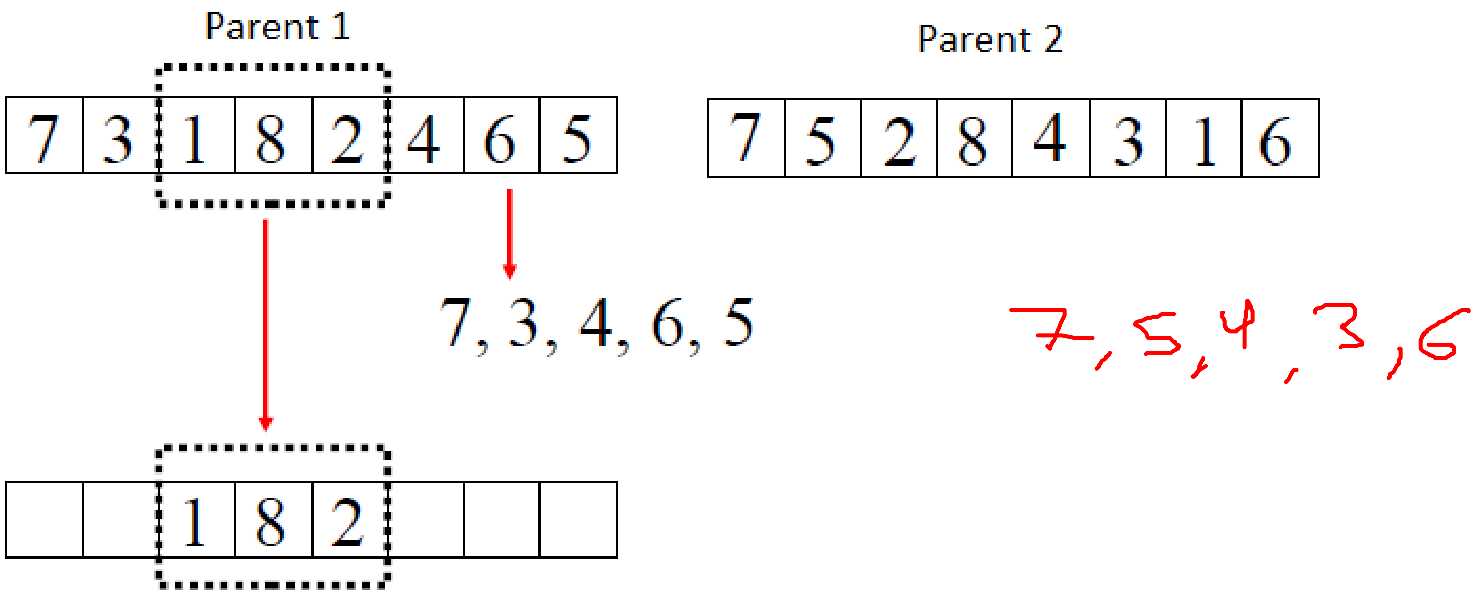
Crossover (5)

- Crossover operator with a order representation (Example 1).



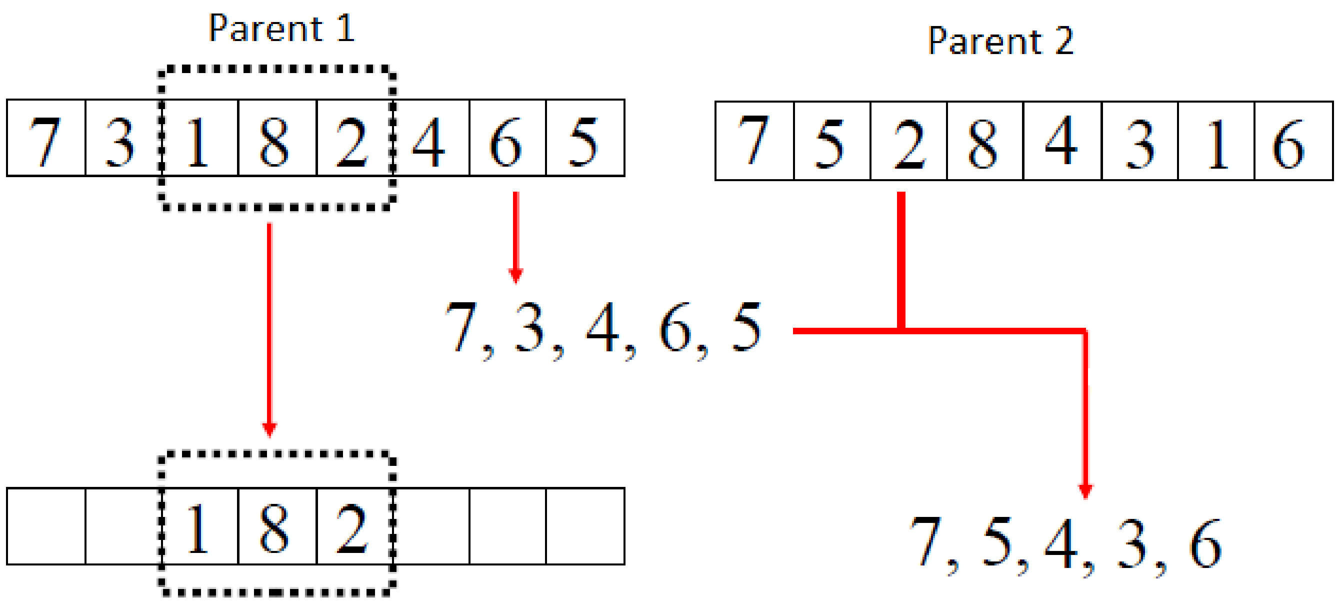
Crossover (5)

- Crossover operator with a order representation (Example 1).



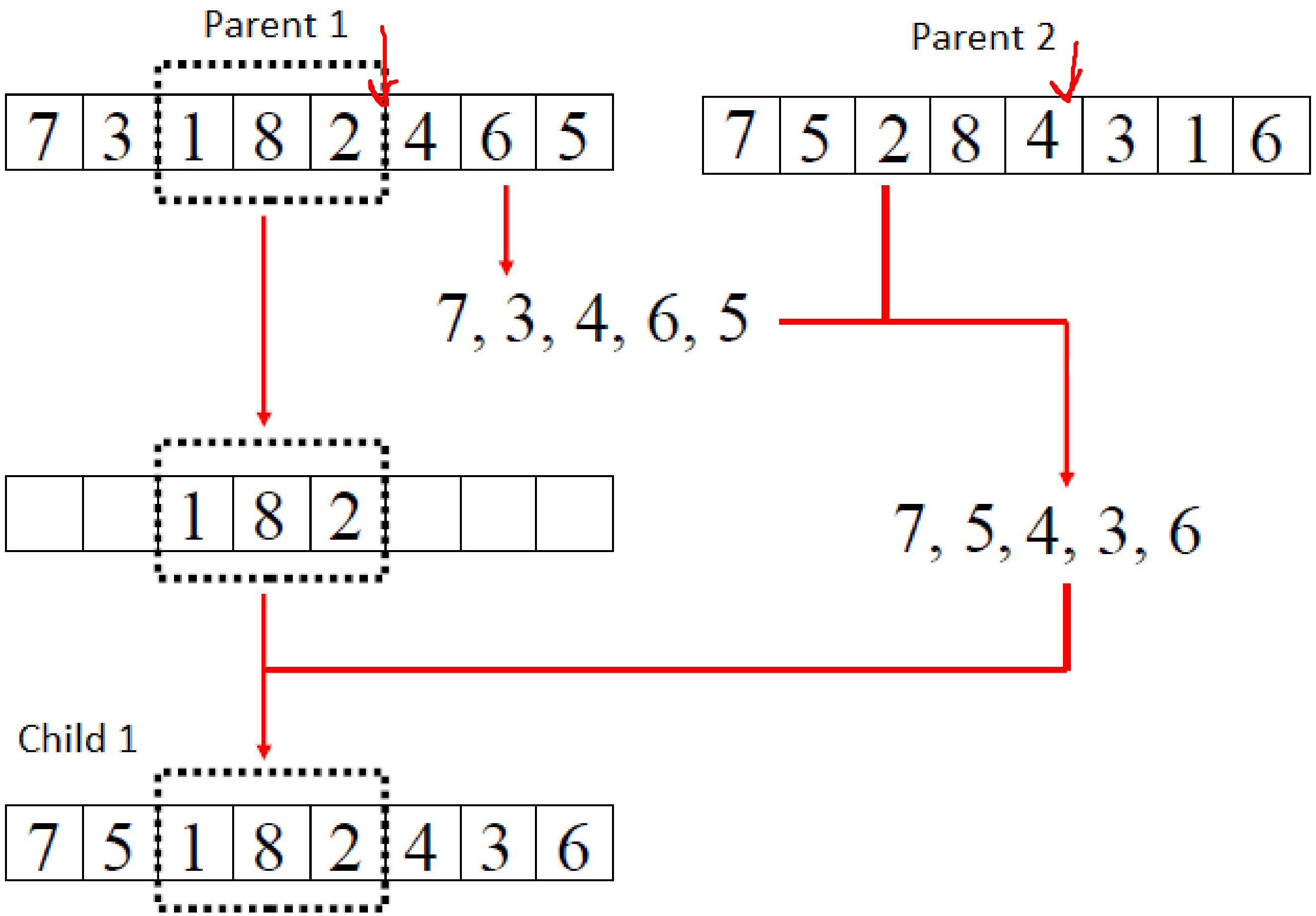
Crossover (5)

- Crossover operator with a order representation (Example 1).



Crossover (5)

- Crossover operator with a order representation (Example 1).



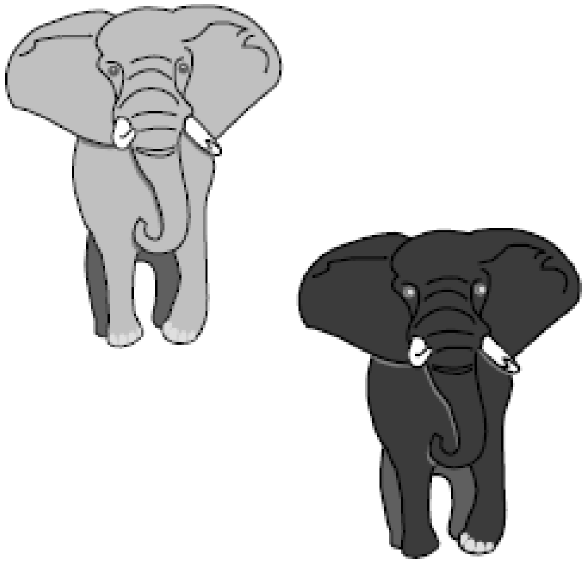
Mutation (binary representation)

Mutation operator with binary representation:

before 1 1 1 1 1 1 1

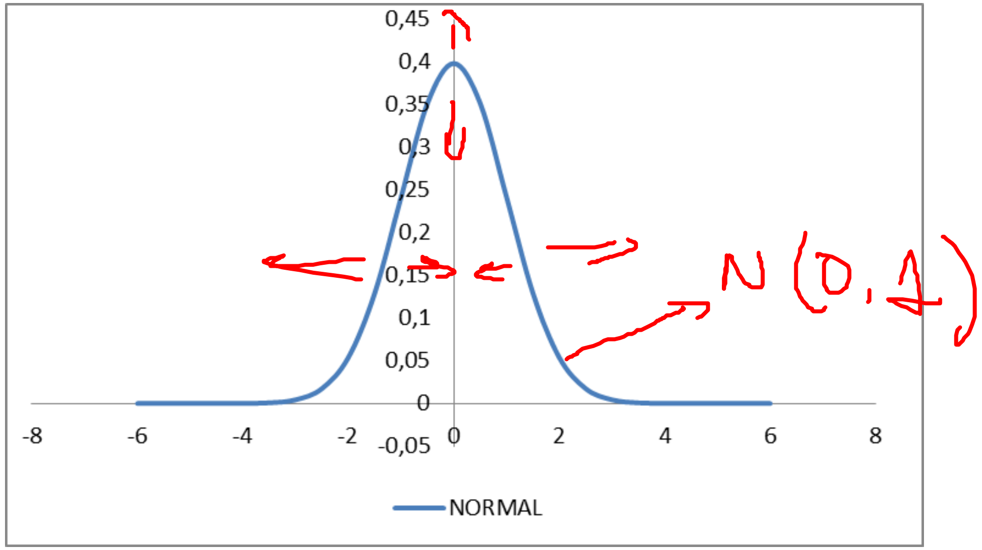
after 1 1 1 0 1 1 1

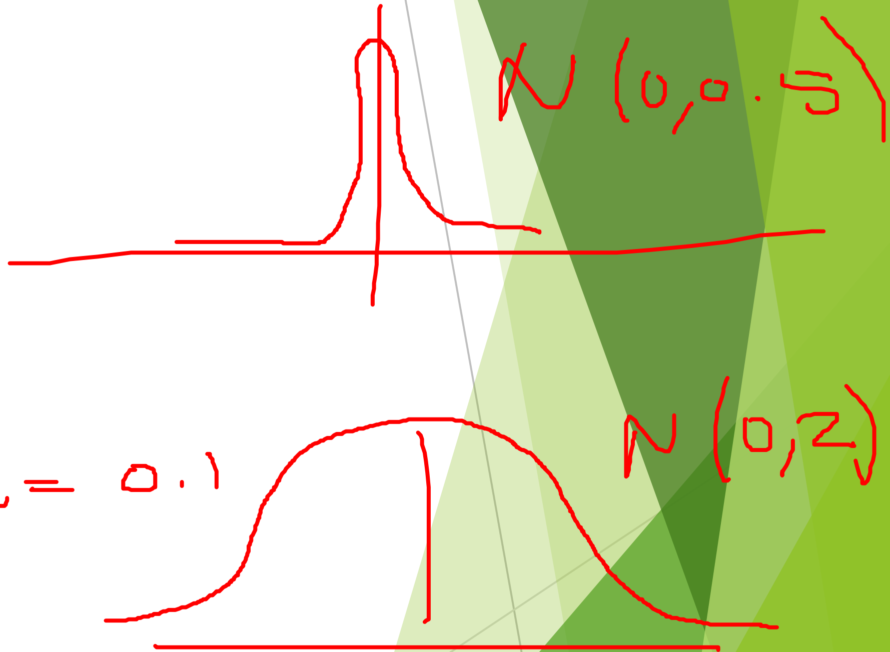
mutated



Mutation (real representation)

- Given an offspring string $X=[x_1, x_2, \ldots, x_n]$, mutation can be done by adding to each number in the string a random disturbance $\boldsymbol{u_i}$, which is subject to a normal density function N(0, δ).





u = 0.1

- Consequently, we will have mutated offspring as: 10%

$$X'=[x'_1, x'_2, \ldots, x'_n]$$ n = 100

with $x'_i=x_i+u_i$ = 3.1

- For example, in matlab we have the function sqrt(δ) * randn(1).

Mutation (order representation)

- Select two random positions and change the elements.

7	3	1	8	2	4	6	5

↓

7	3	6	8	2	4	1	5

7 3 6 4 2 8 1 5

Replacement (generational model)

- The offspring replace the entire population.
- We can decide to keep the best individual: **ELITISM**

  (It is recommended to use elitism)
- It is possible to have high grade of elitism, keeping N best individuals in the population.

Replacement (stationary model)

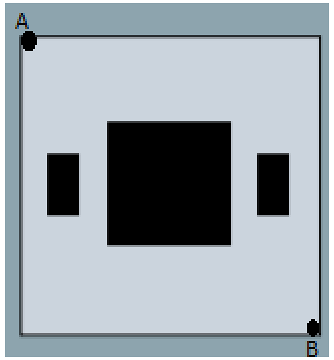
- **Replace the worst in the population (RW).**
- **Restricted tournament (RTS):** The offspring replaces the most similar individual among w (w=3,4,…) individuals previously selected.
- **Worst between similar (WAMS):** We select a group of individuals most similar to the offspring individual. The offspring replaces the worst individual in the group.

Stop criterion

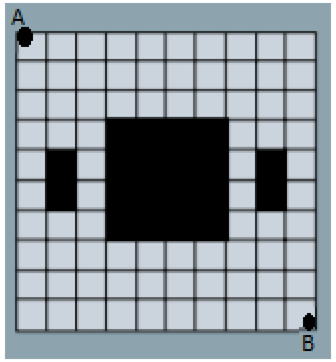
- If we find the optimum!!
- Maximum number of evaluations.
- Maximum number of iterations (generations)
- Limit of the user:
  - Time
  - After some iterations without improvement

Navigation problem

- We have the following map:



- How can we go from A to B using GA?
  - First we have to divide the map in squares (this is only a possible option):

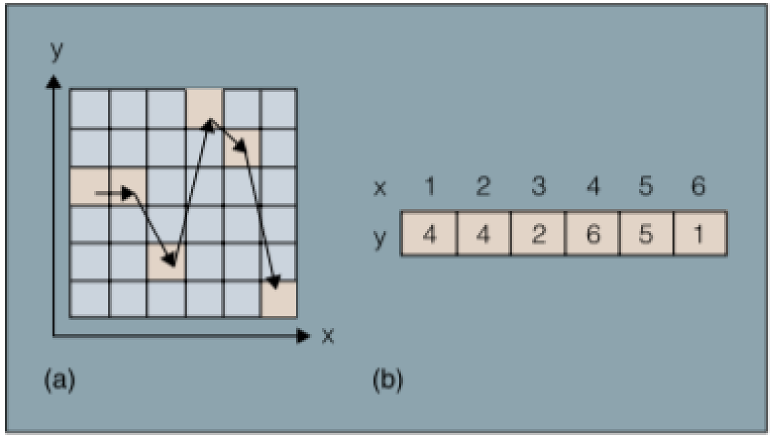


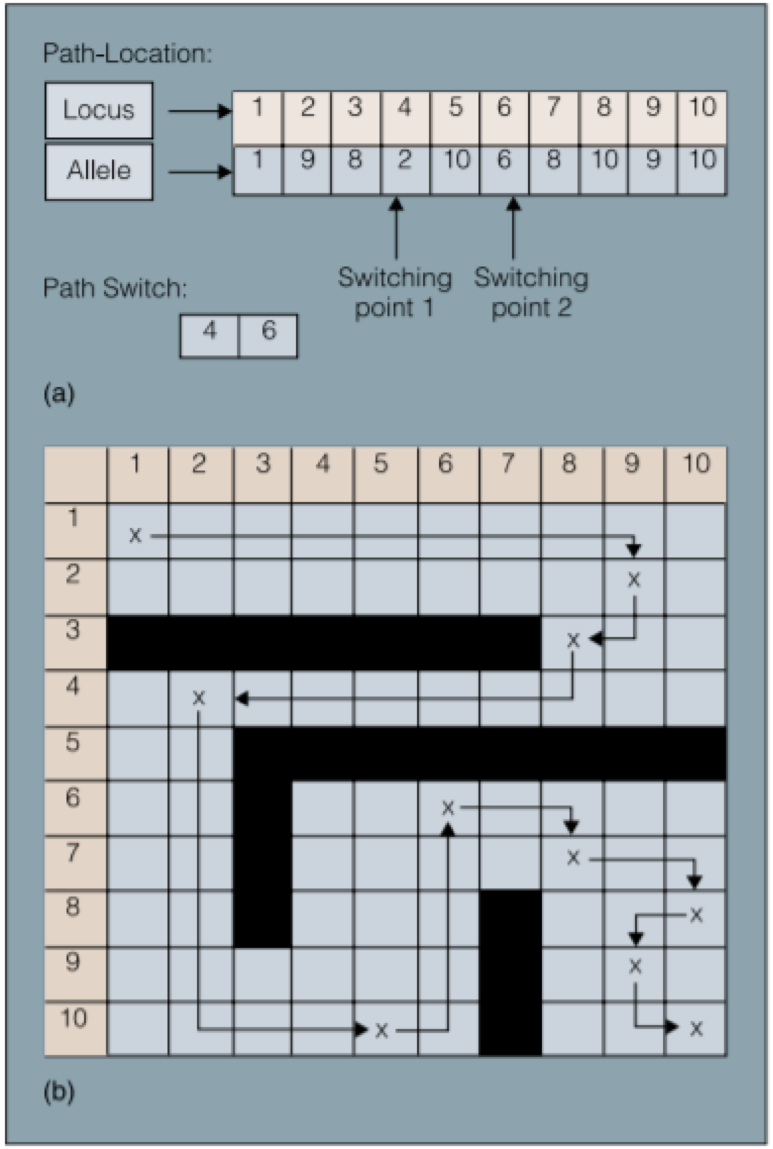
- Source: T. Manikas, K. Ashenayi, R. Wainwright. Genetic Algorithms for autonomous robot navigation. IEEE instrumentation and measurements, 10, 6.

Navigation problem (2)

- When using GA what are the questions you have to answer?
  - How do you represent a possible solution to the problem?
  - What are the restrictions to the problem?
  - How do we evaluate the performance of a solution?
  - How do you perform selection, crossover ....?
  - When to stop the search?

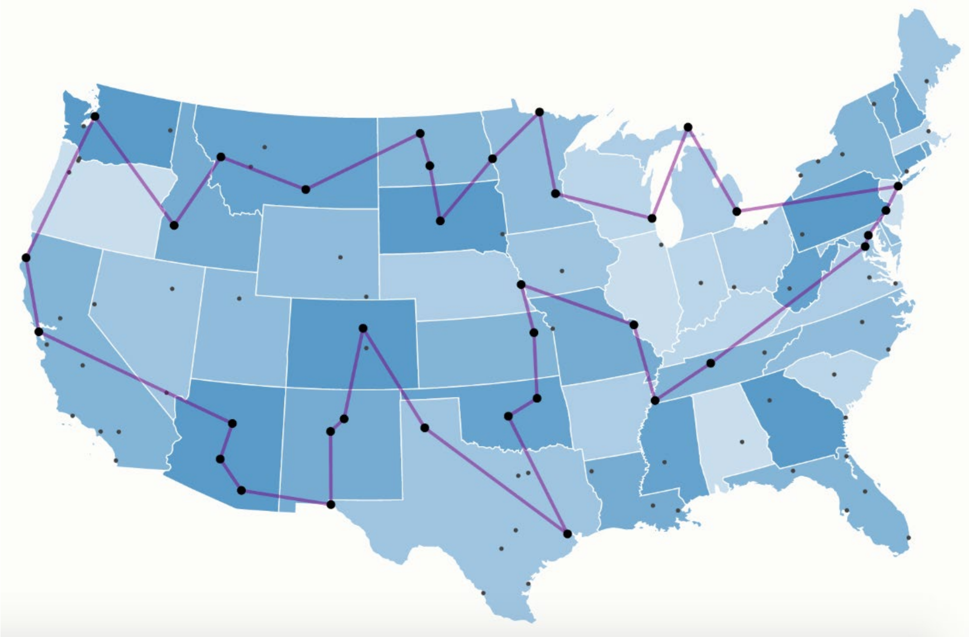
Navigation problem (3)





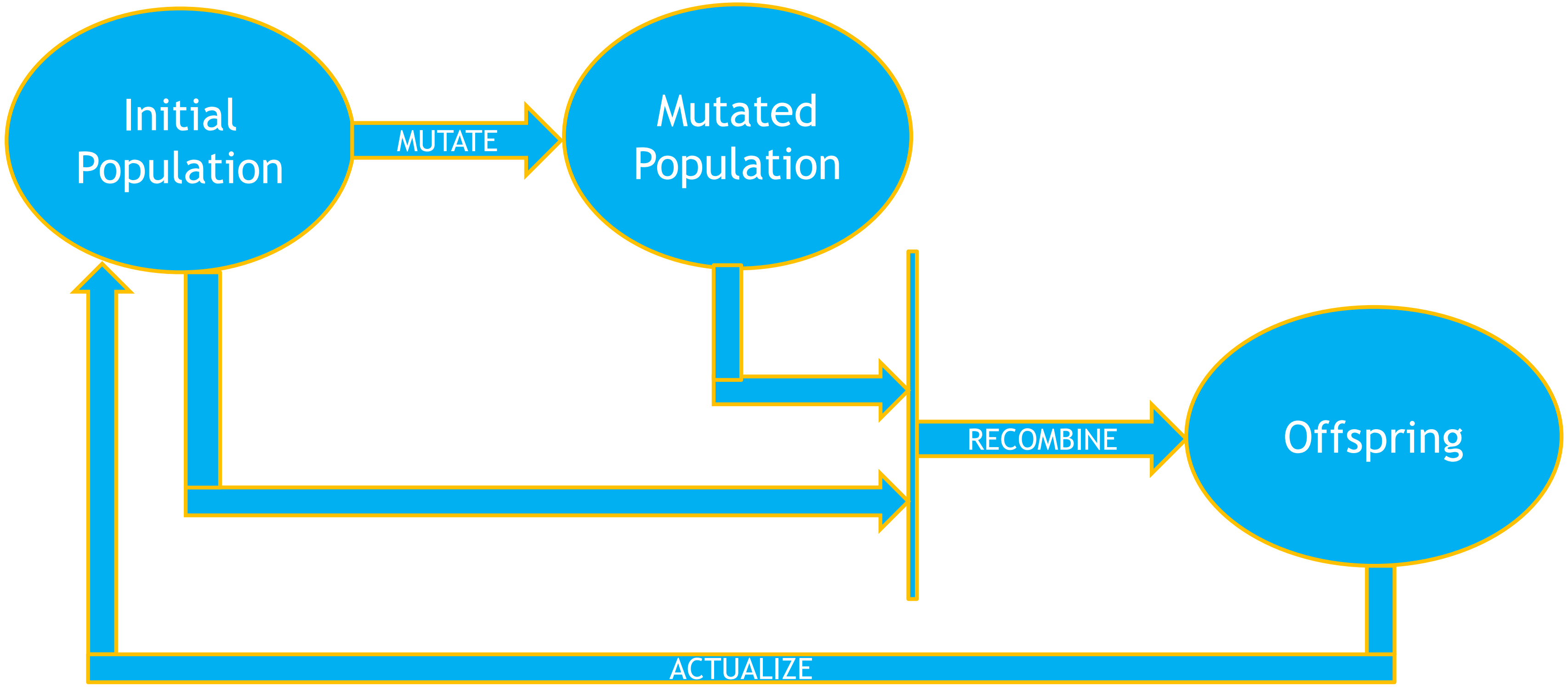
Travelling Salesman Problem

- We have a number of cities in a map. We have to visit all of them onlly once. Which is the path with the minimum distance?

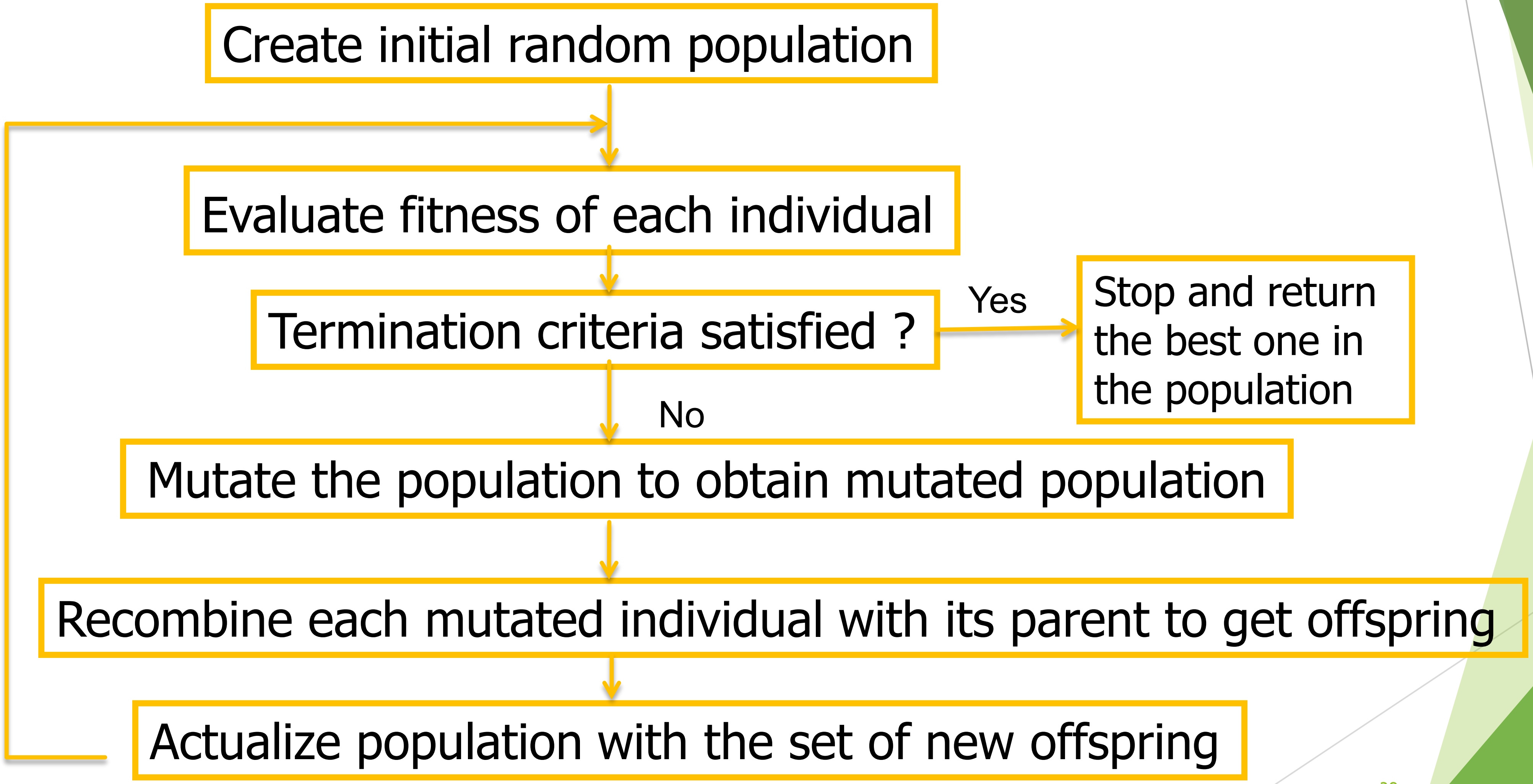


- Now, Imaging that those cities are objects in a room and your vehicle has to find the order in which each objects is picked. How could you apply GA?

Differential Evolution (DE)

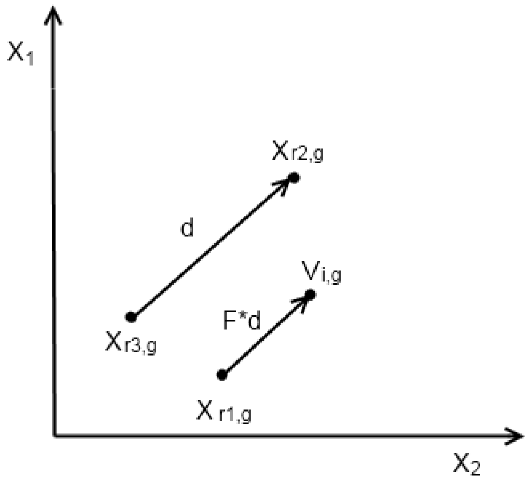


Flow chart of Differential Evolution



DE - Mutation

- The most common mutation strategy is Random Mutation Strategy, it is represented by DE/rand/1
- Equation: $V_{i,g} = X_{r1} + F * (X_{r2} - X_{r3})$



Vi,g: mutated individual
Xr1,g , Xr2,g and Xr3,g: individual from the population randomly chosen
F: Scaling factor, $F \in [0,2]$

DE - Recombination

- The most common recombination strategy is binomial, it is represented by bin.
- Equation:

$$Ti,g[\mathrm{j}] = \begin{cases} Vi,g[j] \; if \; randValue < \Pr or \; j = jrand \\ Xi,g[j] \qquad\qquad otherwise \end{cases}$$

Ti,g: Trial vector (one offspring)
Vi,g: mutated individual
Xi,g: individual i from the population
Pr: Recombination Probability, Pr ∈ [0,1]
randValue: Random Value between 0 and 1

DE - Selection

- The last step is to actualize the population to the generation g + 1.
- Equation (searching minimum):

$$Xi,g+1 = \begin{cases} Ti,g \ \ if \ \ f(Ti,g) \leq f(Xi,g) \\ Xi,g \qquad\qquad\qquad\qquad otherwise \end{cases}$$

Ti,g: Trial vector (one offspring)
Xi,g: Individual i from the population
Xi,g+1: Individual i in the population for the next generation
f(vector): fitness of the vector

Popul.

$r_2 \to X_1 = \boxed{3.5 \mid 3 \mid -1}$

$X_2 = \boxed{-2 \mid -3 \mid 2}$

$r_1 \to X_3 = \boxed{1 \mid 2 \mid 3}$

$r_3 \to X_4 = \boxed{0 \mid 1 \mid -2}$

Mutated Pop

$V_1 = \boxed{2.75 \mid 3 \mid 3.5}$

$V_2 = \boxed{\mid 3 \mid 2}$

$V_3 =$

$V_4 =$

Offspring

$T_1 = \boxed{2.75 \mid 3 \mid -1}$

$T_2 = \boxed{-2 \mid 3 \mid 2}$

T_3

T_4

$V_1 = X_{r1} + F \cdot (X_{r2} - X_{r3})$

$F = 0.5$

$X_{r2} = \boxed{3.5 \mid 3 \mid -1}$

$- X_{r3} = \boxed{0 \mid 1 \mid -2}$

$F \cdot \boxed{3.5 \mid 2 \mid 1} + \boxed{1 \mid 2 \mid 3}$

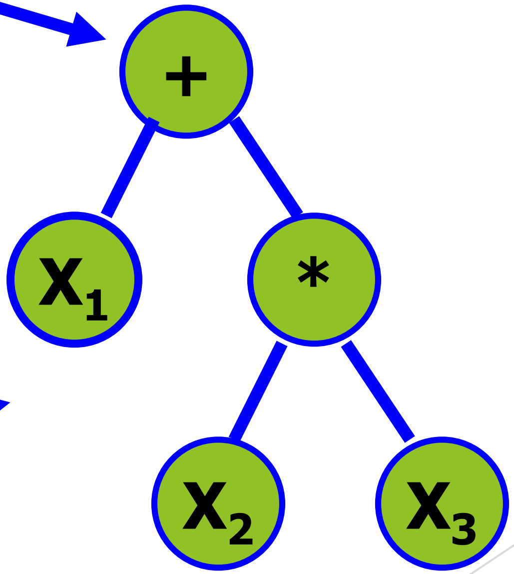
$P_r = 0.5$

$T_i[j] = \begin{cases} V_i[j], & r < P_r \\ X_i[j] & \text{otherwise} \end{cases}$

Genetic Programming

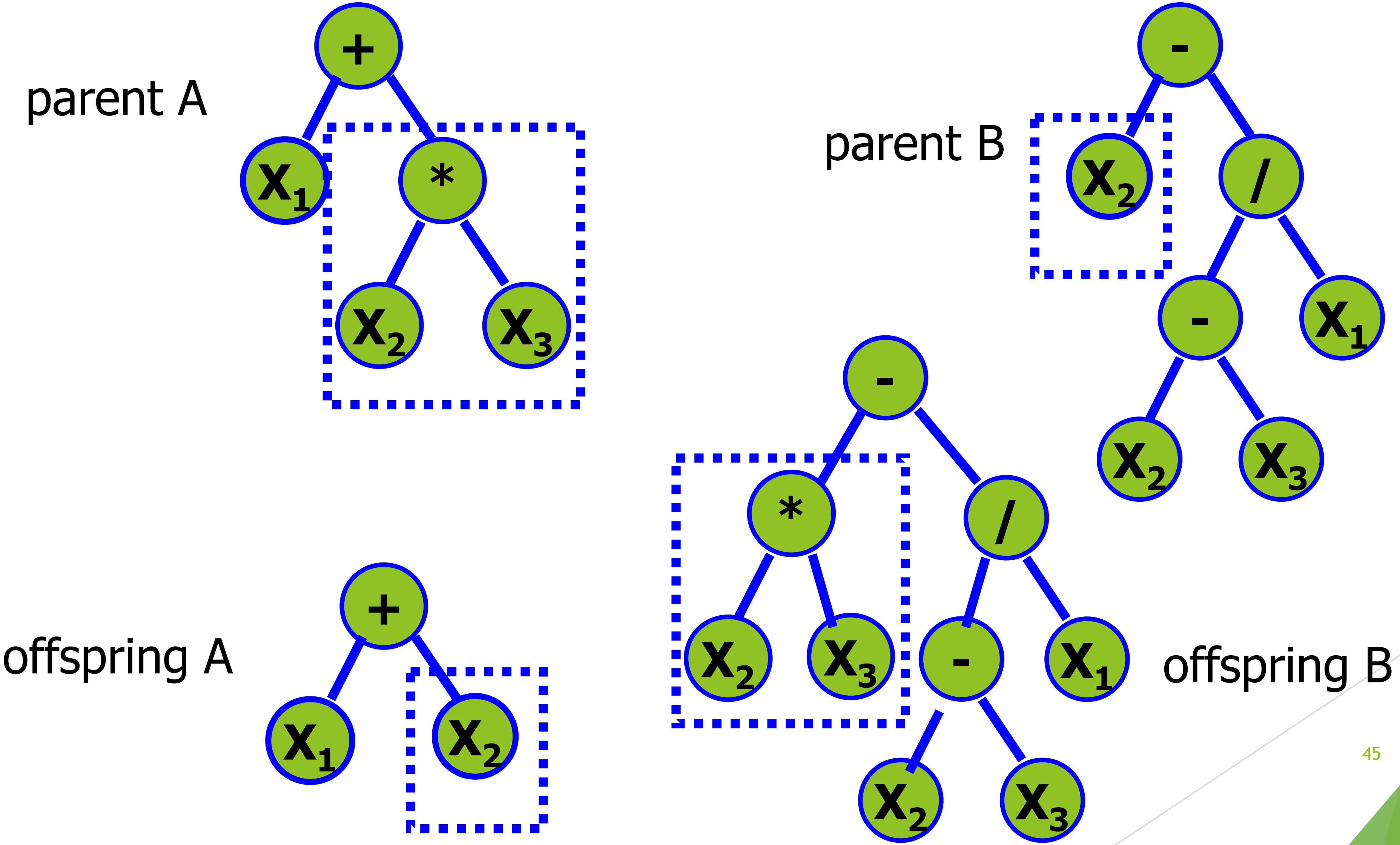
- Automatic generation of computer programs by means of natural evolution
- Individuals in population are programs represented as trees
- Tree nodes correspond to functions :
  - arithmetic functions {+,-,*,/}
  - logarithmic functions {sin,exp}
- Leaf nodes correspond to terminals :
  - input variables $\{X_1, X_2, X_3\}$
  - constants {0.1, 0.2, 0.5 }

$X_1+(X_2*X_3)$



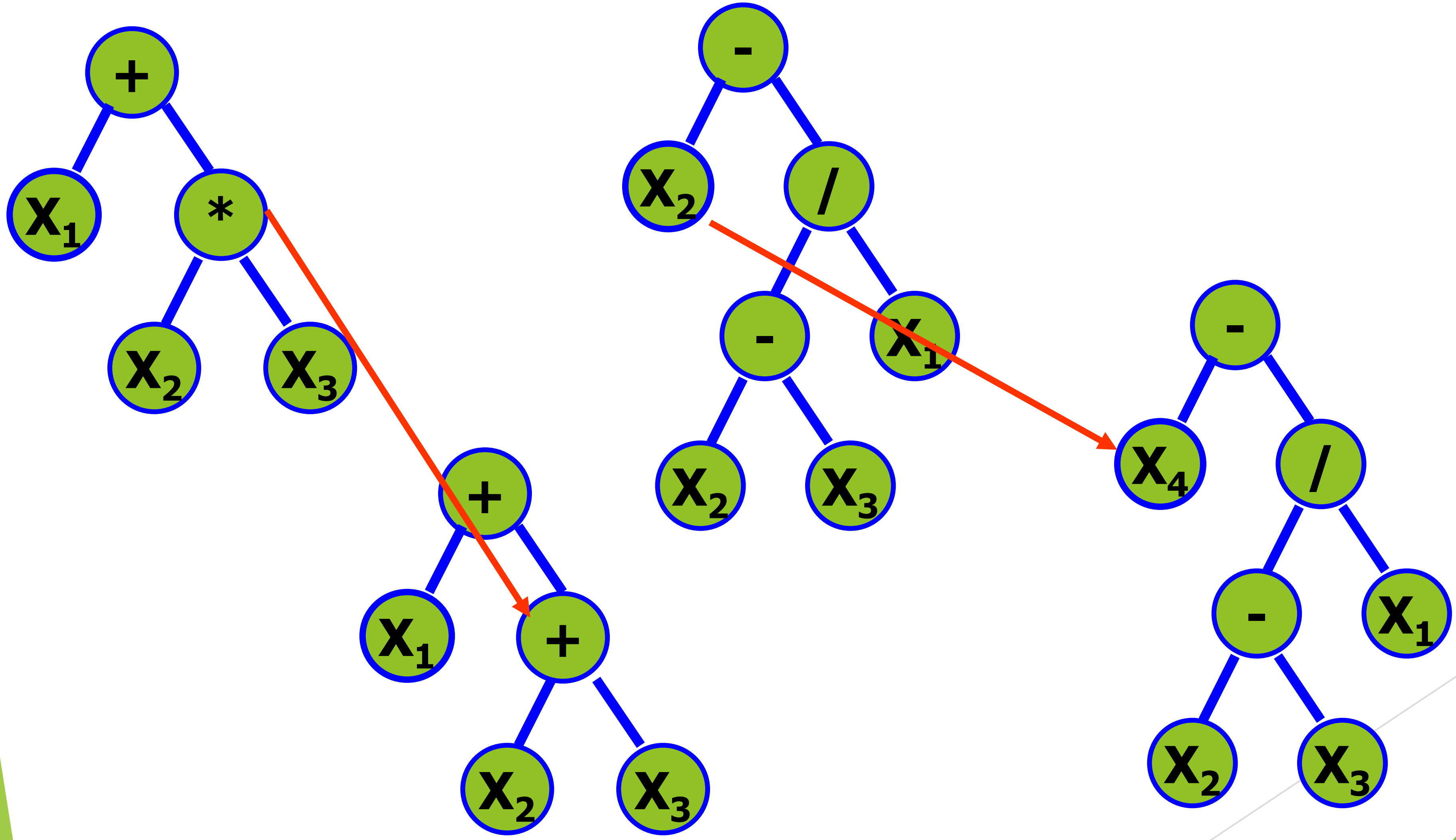
Genetic Programming : Crossover

Crossover is performed by exchanging randomly chosen parts between parents



Genetic Programming: Mutation

- A mutation operator can randomly change any function or any terminal in the tree.



Particle Swarm Optimization

Particle Swarm Optimization (PSO)

- Particle Swarm Optimization is a population based algorithm inspired by the social flight of the birds and the movement of the fishes.
- PSO was created in 1995 by Russ C. Eberhart and James Kennedy.
- PSO is used in continuous optimization.

Basics

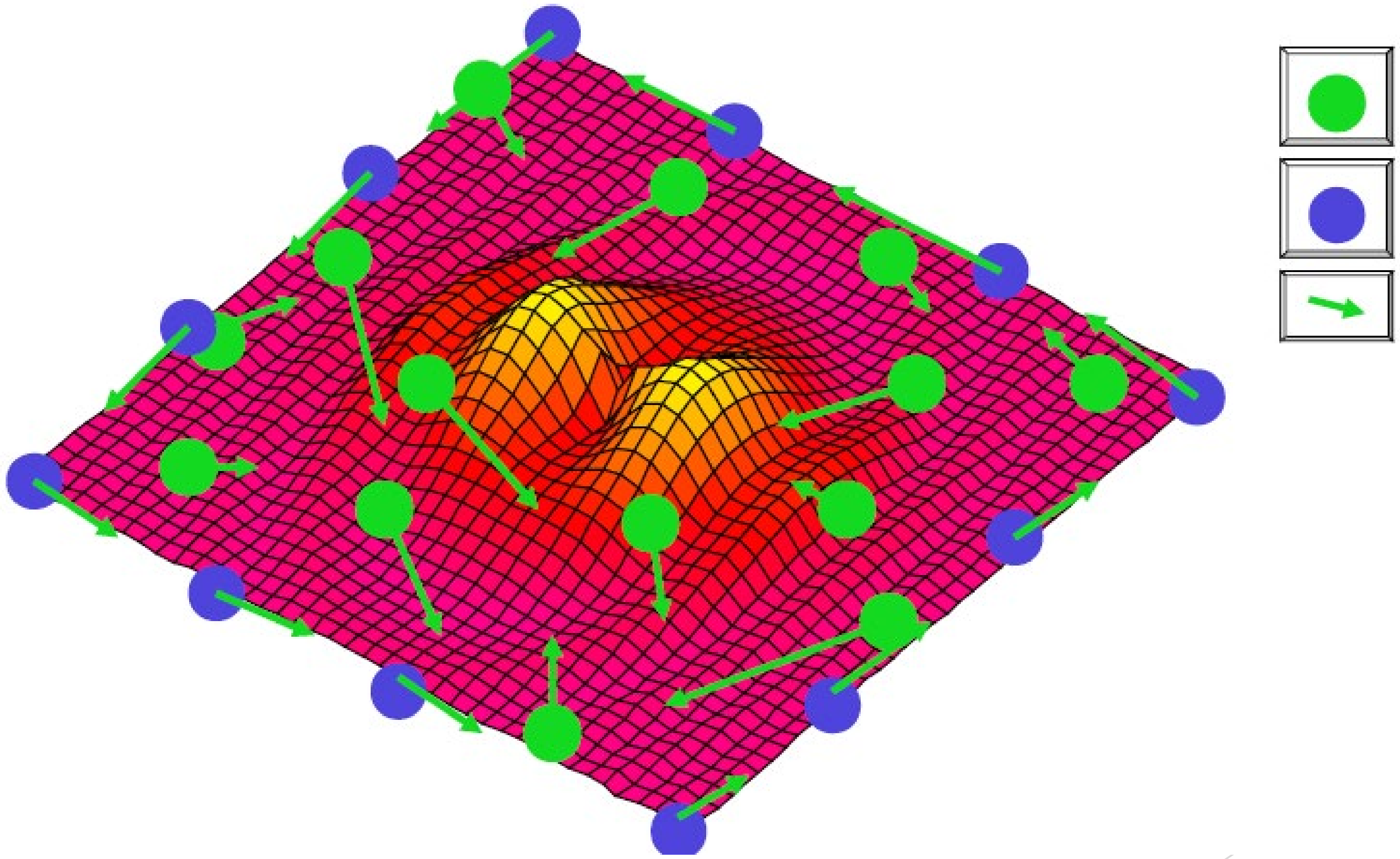
- PSO simulate the behavior of the flock of birds.
- Imagine that one of this flock is searching food in an area and there is only one piece of food in that area.
- The birds do not know were the food is but they know the distance to it.
- The most efficient strategy will be to follow the bird that is closer to the food.

Basics (2)

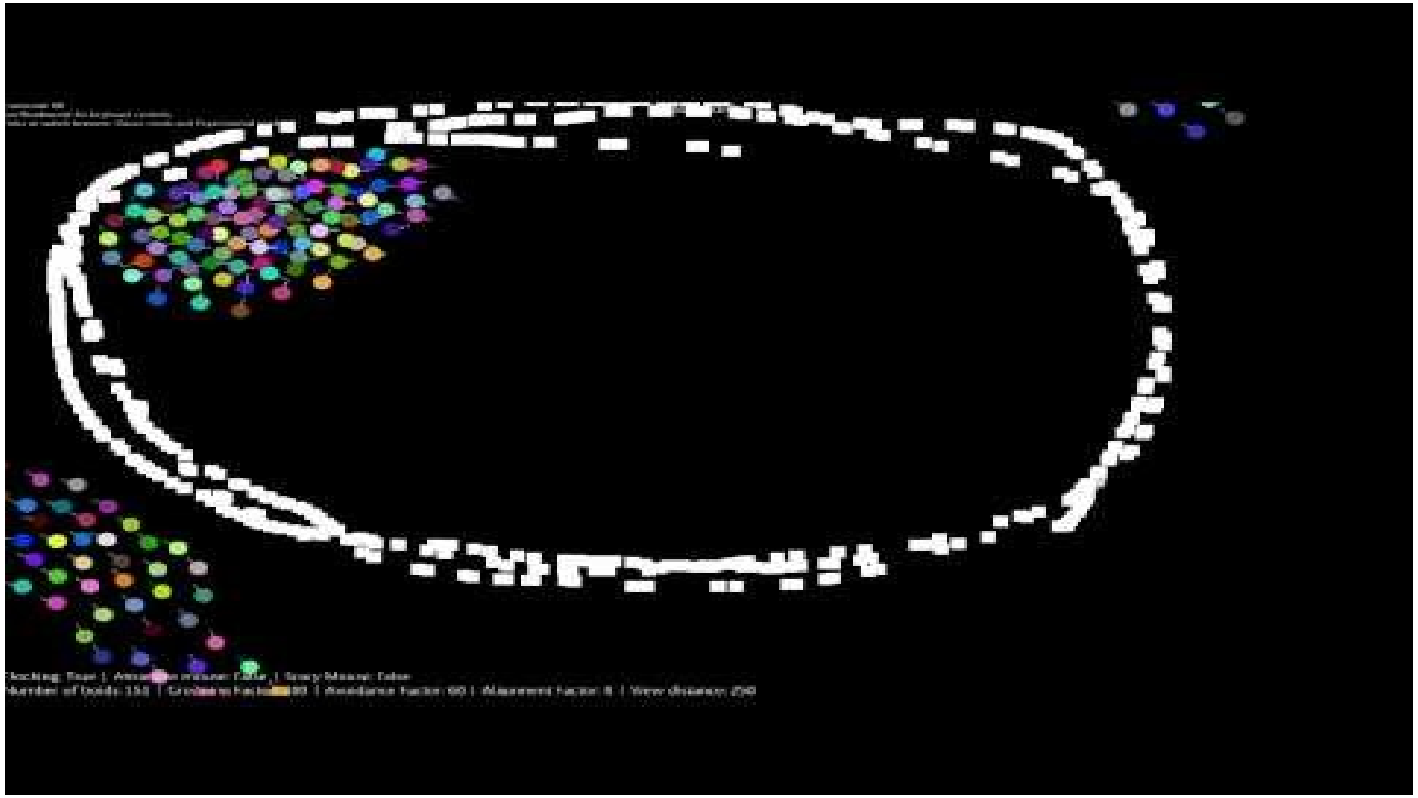
- The population will be a multi-agent system where every bird or particle will be an agent.

- Every particle will have a fitness (in this case distance to the food), a position in the space and a velocity vector (the direction that the particle is tacking)

Initialization of the particles



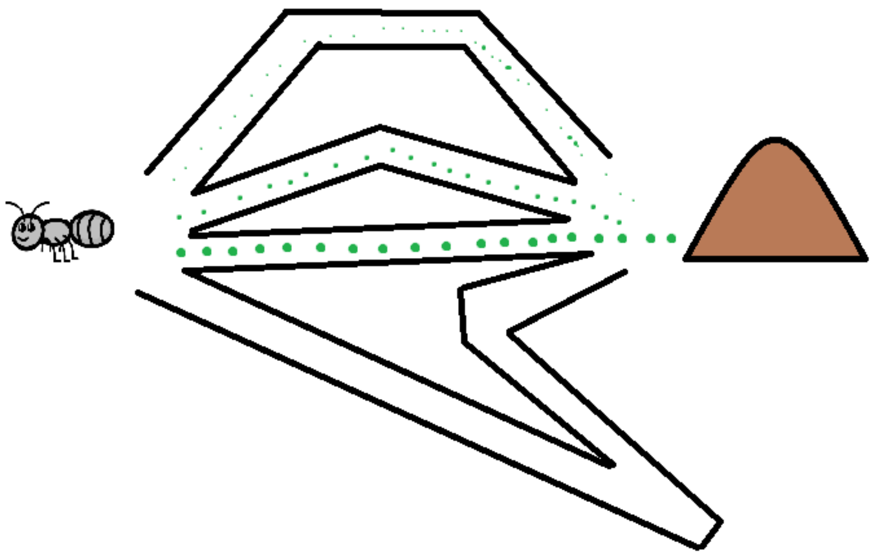
Multiple robot searching



Ant colony optimization

Ant Colony Optimization (ACO)

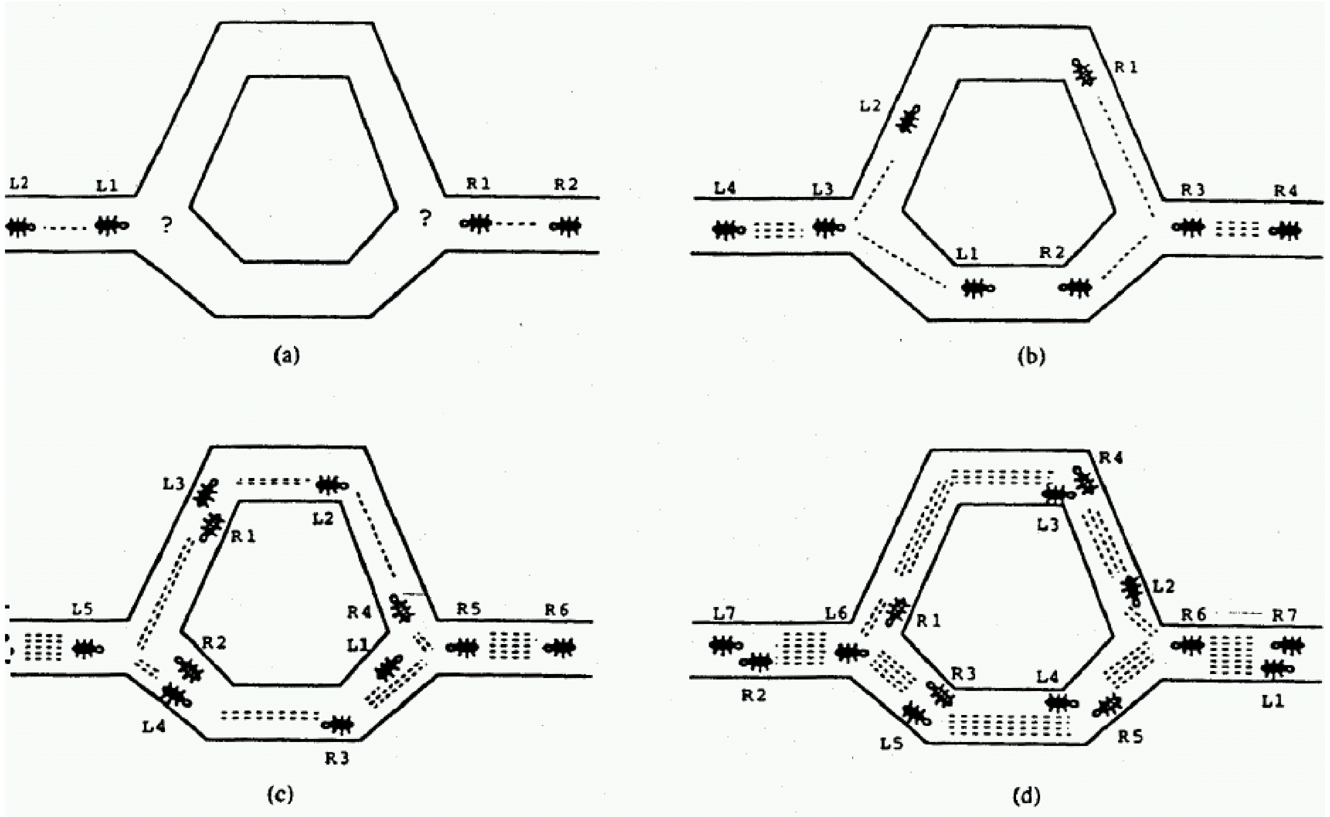
- Ant Colony System was invented by Marco Dorigo in 1992
- This algorithm is based on the behavior of real ants
- It is used to find the shortest path in a graph



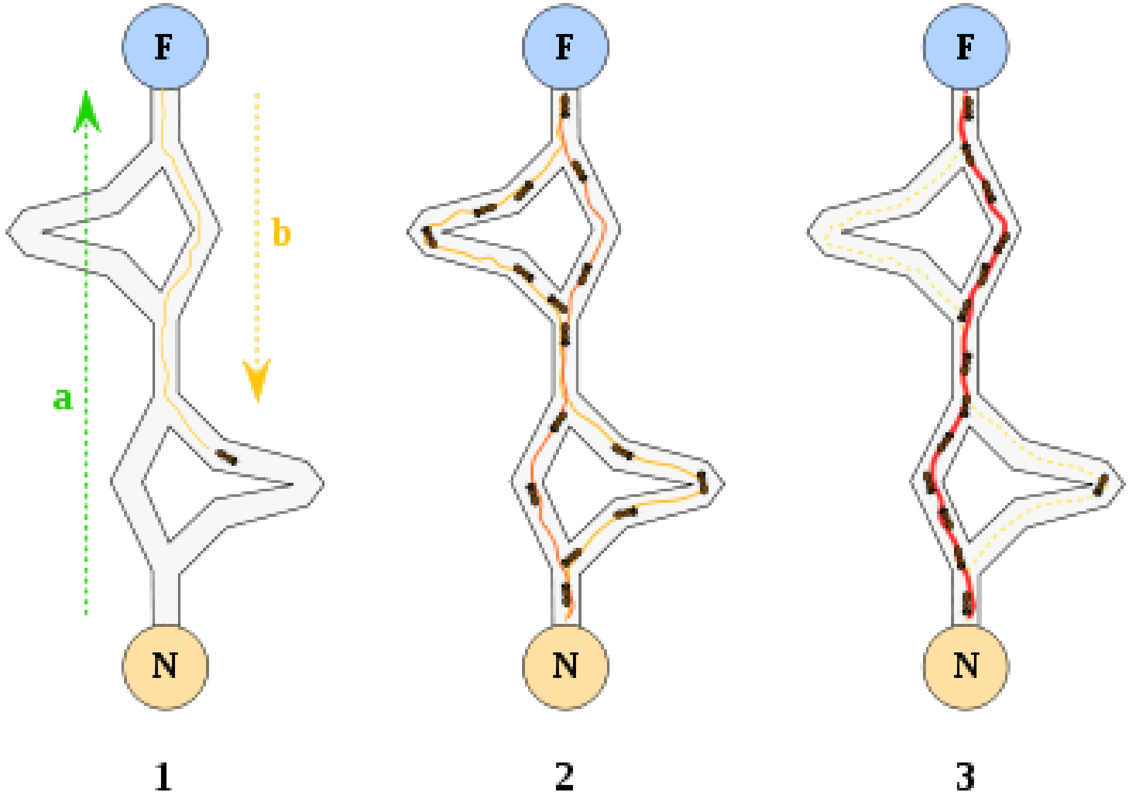
Ant Colony Optimization (ACO): Basics

- The ants are BLIND (not all of them).
- The ants are attracted by pheromones in neighbor nodes.
- Once an ant leave the nest start leaving pheromone on the way it walked.
- When they find the food, they come back, placing pheromone again.
- The next time they leave the nest they will take the path with more pheromone.

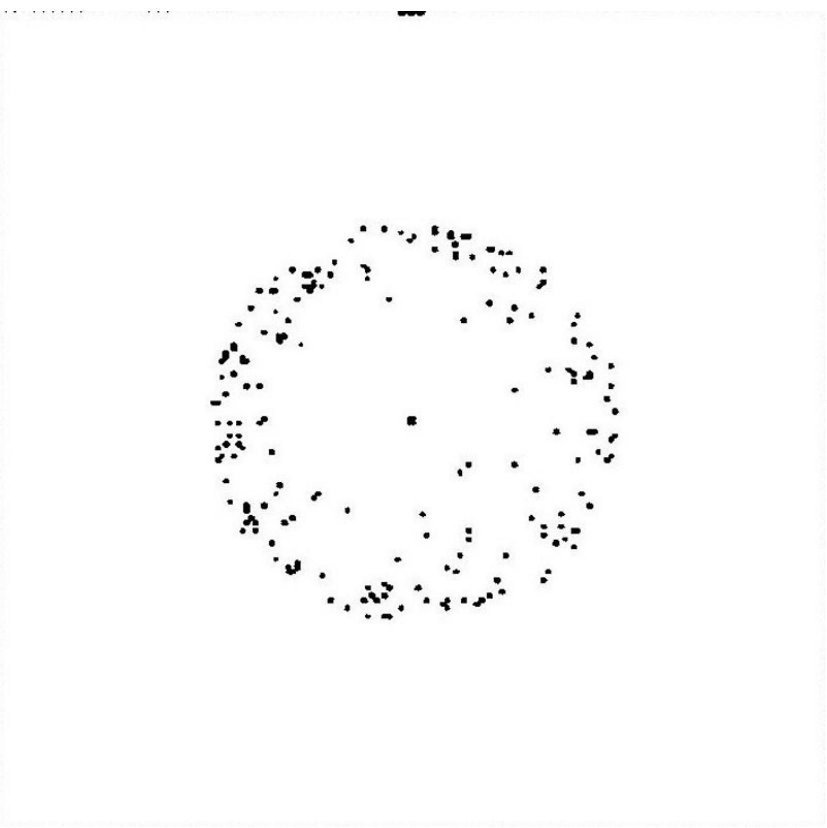
Ant Colony Optimization (ACO): example



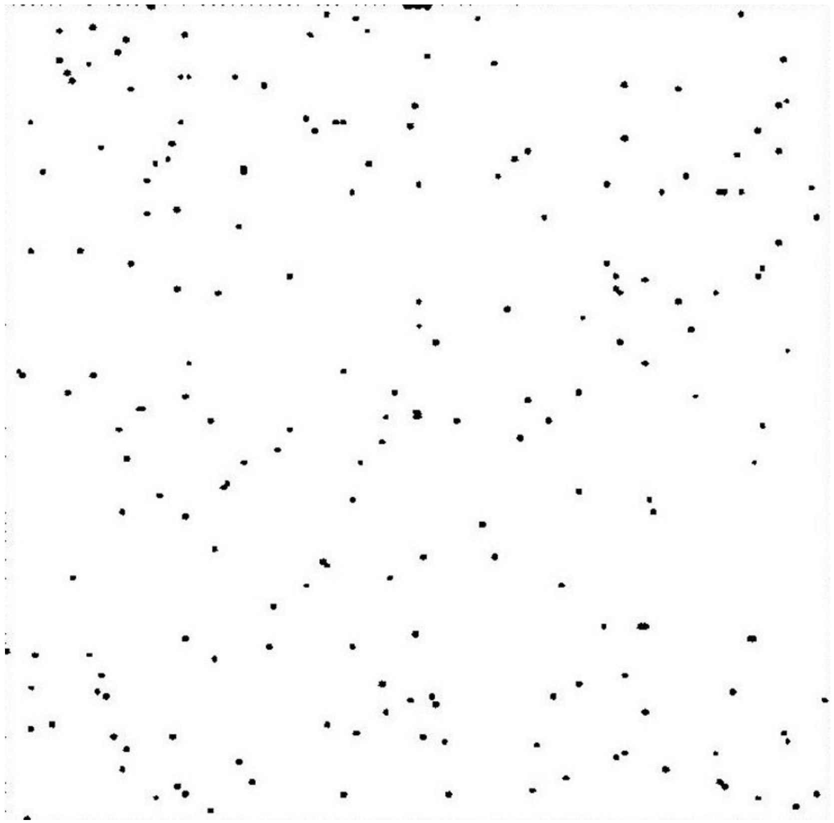
Ant Colony Optimization (ACO): example



Ant Colony Opimization (ACO): Natural ants example



Ant Colony Opimization (ACO): Natural ants example



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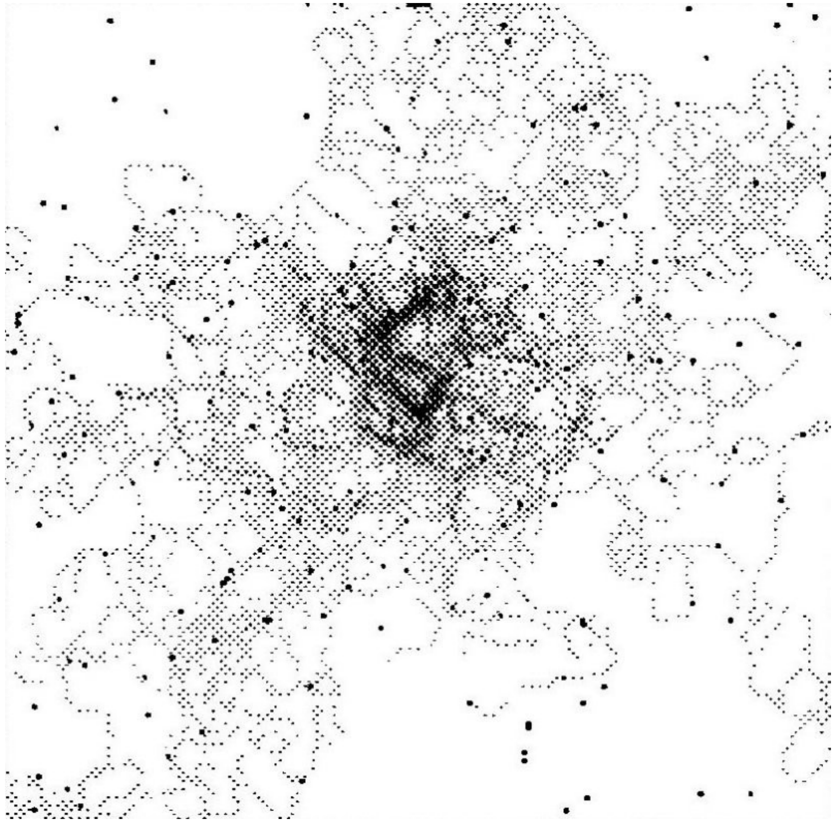

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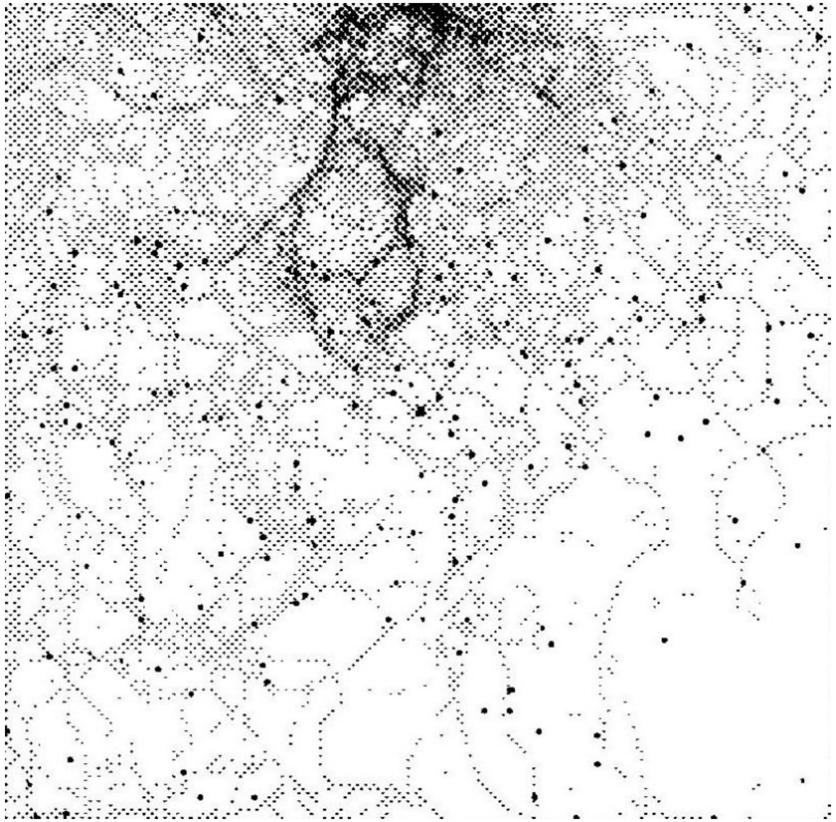

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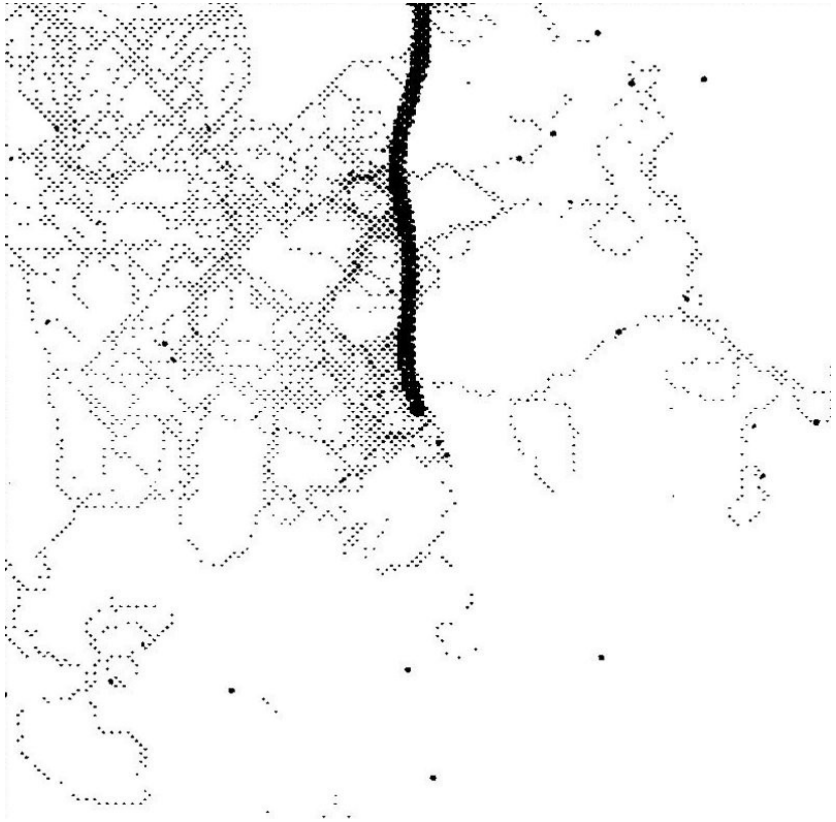

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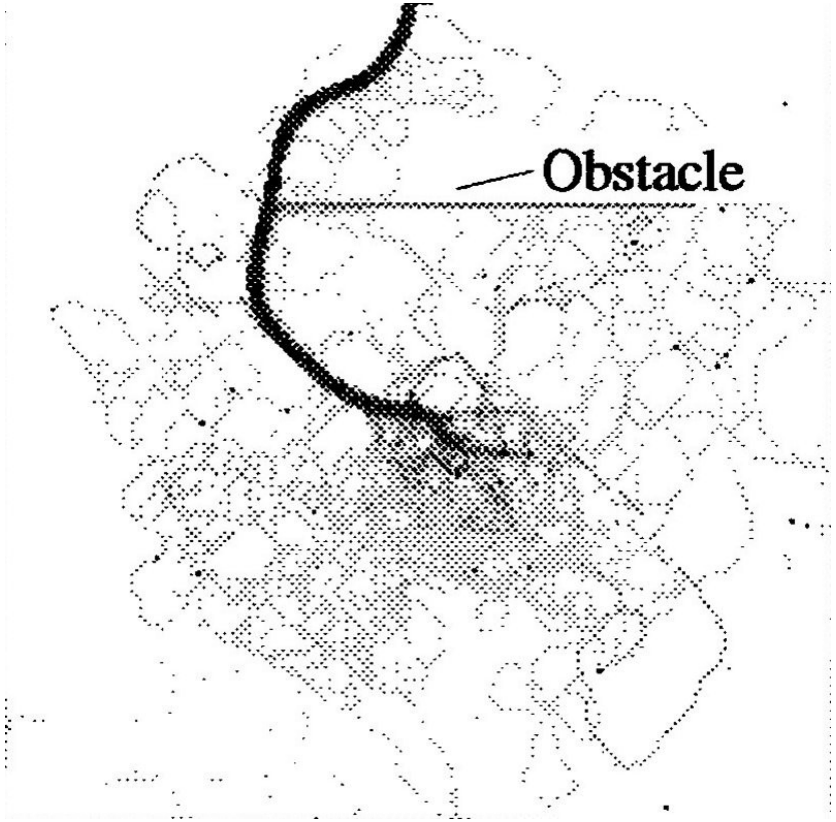
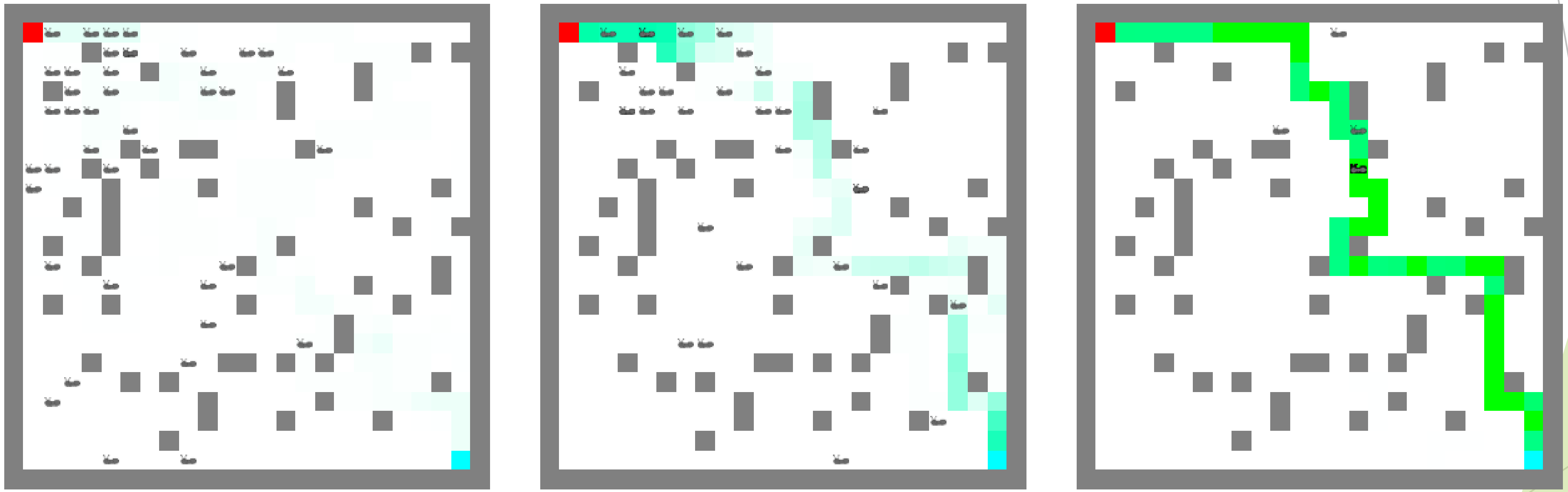
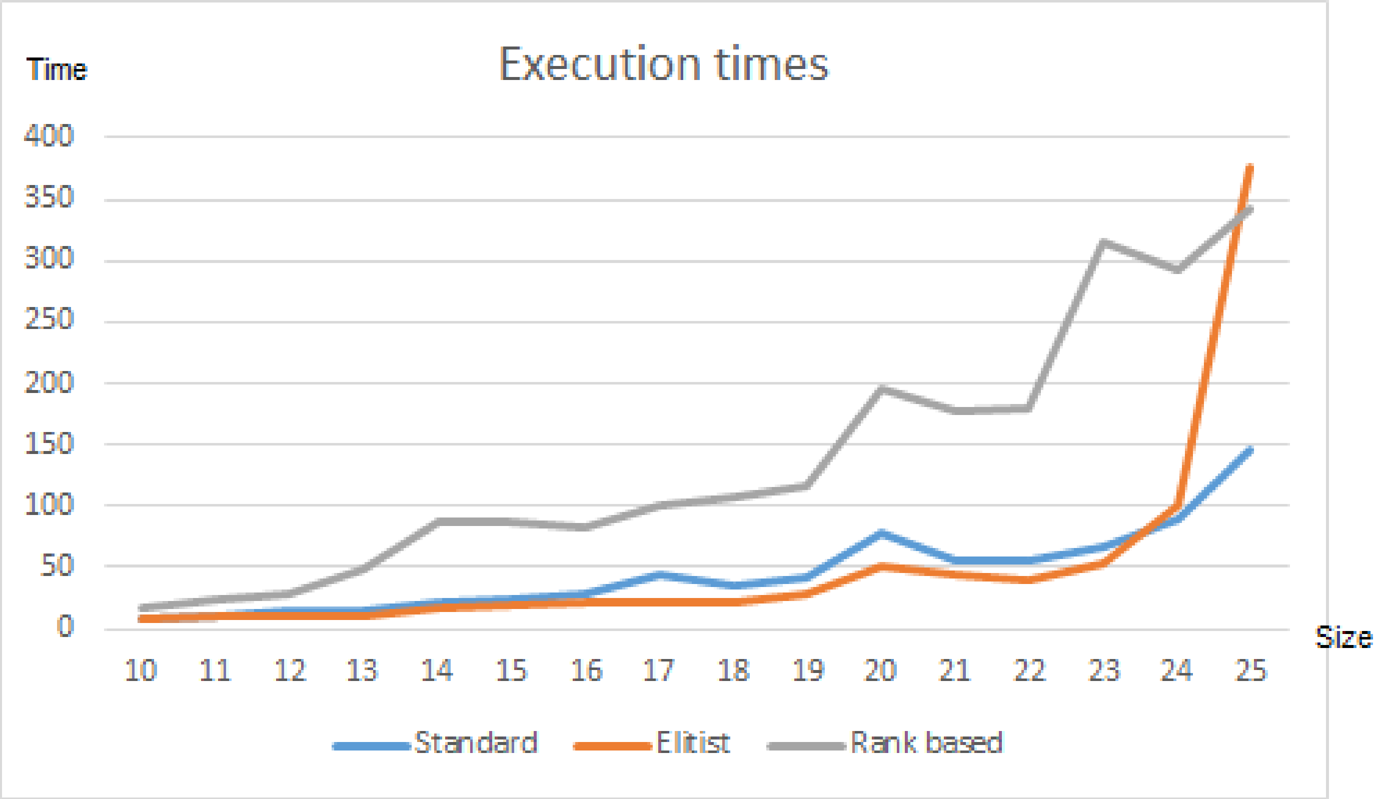


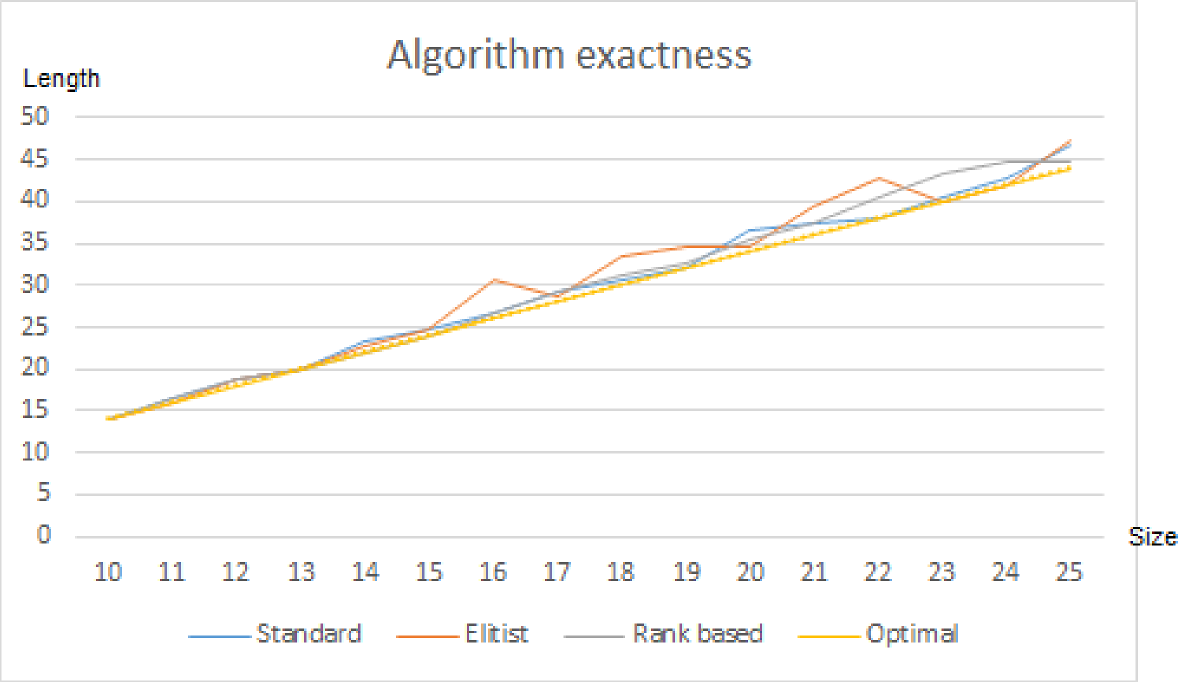
Ant Colony Opimization (ACO): Project Intelligent system 2015



Ant Colony Opimization (ACO): Project Intelligent system 2015



Ant Colony Opimization (ACO): Project Intelligent system 2015




ITS!

Reading Guidance

- It is important to read carefully and understand the content of the slides
- Read the following sections of Chapter of the Machine Learning book of Tom M. Mitchell: 9.1, 9.2, 9.3, 9.5.1

References

- GA and GP:
  - Tom M. Holland. Machine Learning. 1997.
  - Stuart Russell and Peter Norvig. Artificial intelligence: A modern approach. Third version
- DE:
  - Storn, R., & Price, K. (1997). Differential evolution–a simple and efficient heuristic for global optimization over continuous spaces. *Journal of global optimization*, *11*(4), 341-359.
- PSO:
  - Shi, Y. (2001). Particle swarm optimization: developments, applications and resources. In *evolutionary computation, 2001. Proceedings of the 2001 Congress on* (Vol. 1, pp. 81-86). IEEE.
- ACO:
  - M. Dorigo, V. Maniezzo, A. Colorni. Ant system: Optimization by a colony of cooperating agents. IEEE Transactions on Systems, Man and cybernetics, Part B, Vol 26, 29-41