

Further Studies on Metaheuristics

- **[Question]** What are the differences between a heuristic and a metaheuristic?

Comparison

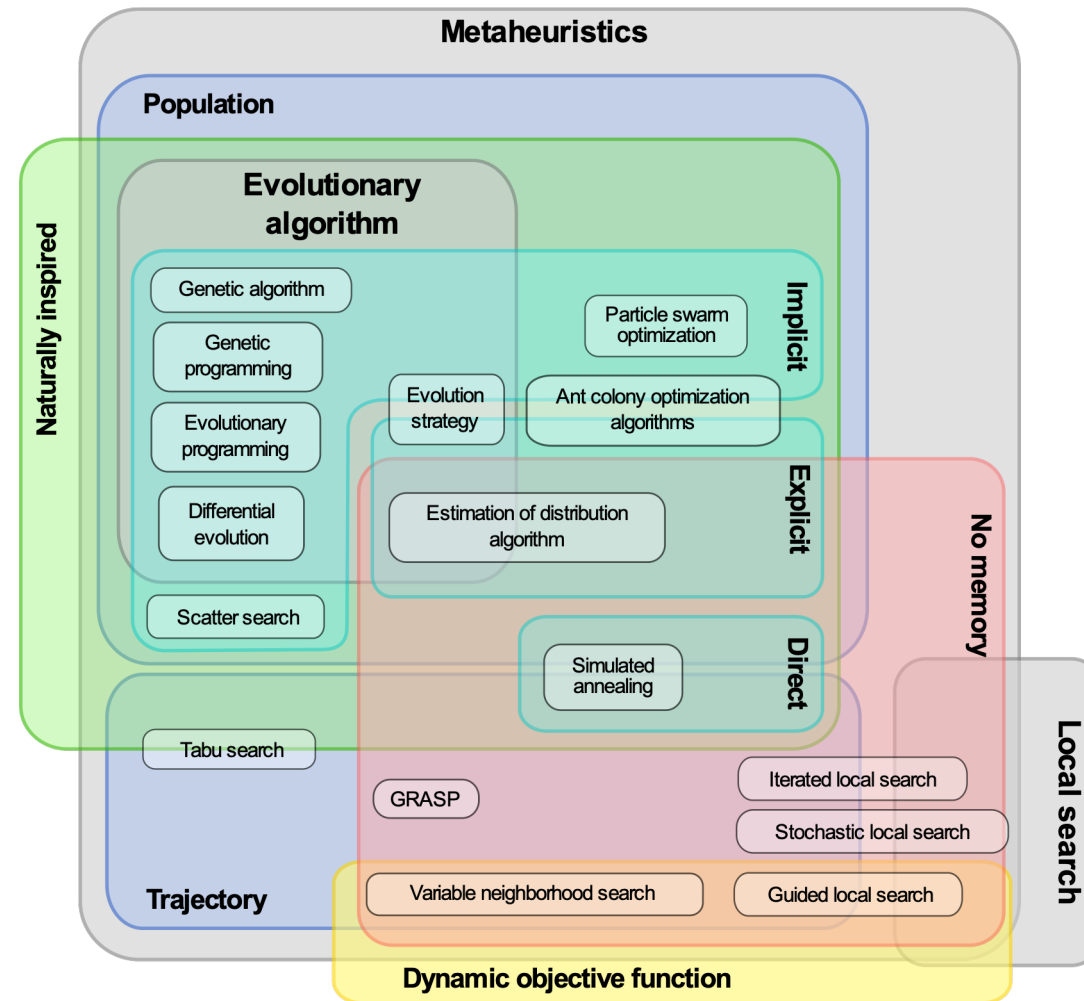
Heuristic

- **Problem-specific**
- Can be used by a metaheuristic

Metaheuristic

- **Problem-independent**
- Can use different heuristics or a combination of heuristics

Metaheuristics



“One general law, leading to the advancement of all organic beings, namely, multiply, vary, let the strongest live and weakest die.”

- Charles Darwin, *The Origin of Species*

Reproduction
(crossover)

Mutation

“One general law, leading to the advancement of all organic beings, namely, **multiply**, **vary**, **let the strongest live and weakest die.**”

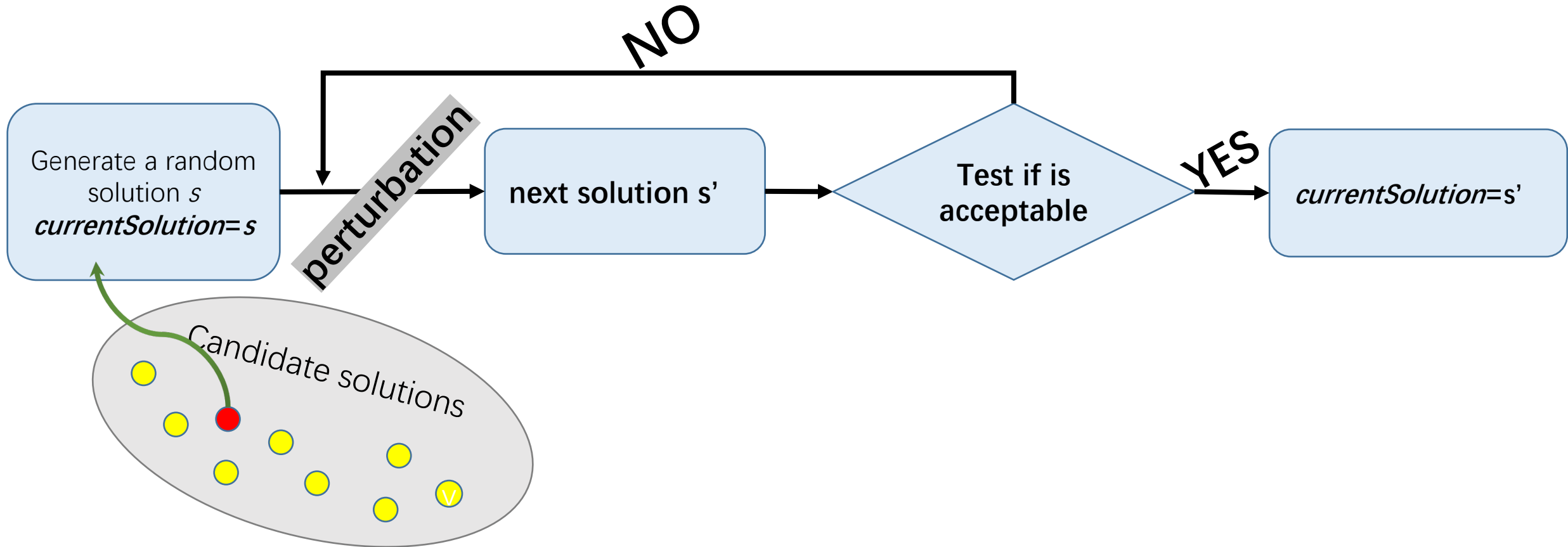
- Charles Darwin, *The Origin of Species*

Selection

Evolutionary Computation

- It is the study of computational systems which use ideas and get inspirations from natural evolution.
- One of the principles borrowed is *survival of the fittest*.
- Evolutionary computation (EC) techniques can be used in optimisation, learning, and design.
- EC techniques do **not** require rich domain knowledge to use. However, domain knowledge can be incorporated into EC techniques.

Generate-and-Test (G&T)

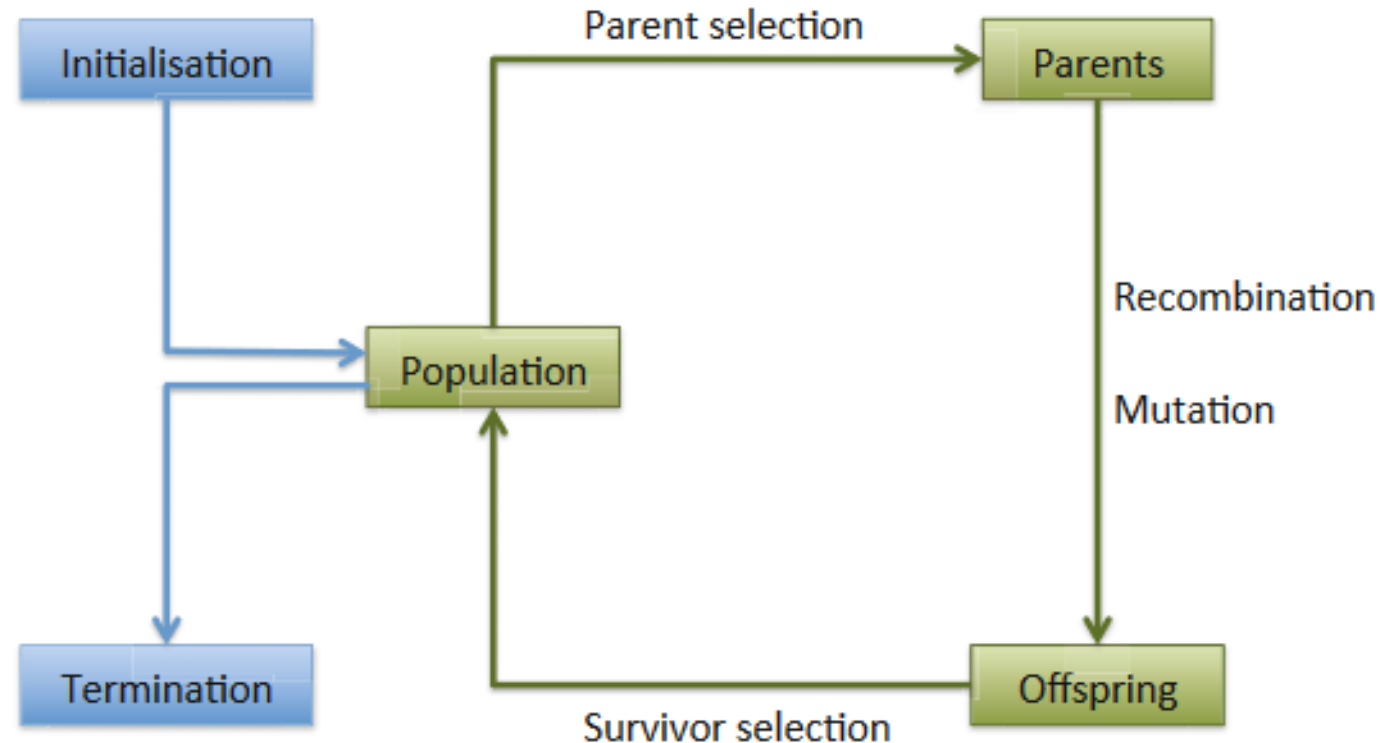


Generate-and-Test: Steps

1. Generate the initial solution at random and denote it as the **current solution**.
2. Generate the **next solution** from the current one by **perturbation**.
3. Test whether the newly generated solution (**next solution**) is acceptable;
 1. Accepted it as the current solution **if yes**;
 2. Keep the current solution unchanged **otherwise**.
4. Go to Step 2 if the current solution is not satisfactory, stop otherwise.

EA: Population-based G&T

- **Generate:** Mutate and/or recombine individuals in a population.
- **Test:** Select the next generation from the parents and offspring.



A Simple Evolutionary Algorithm (EA)

- 1 Generate the initial population $P(0)$ at random
- 2 $i \leftarrow 0$ *// Generation counter*
- 3 **WHILE** halting criteria are not satisfied
- 4 **Evaluate** the fitness of each individual in $P(i)$
- 5 **Select** parents from $P(i)$ based on their fitness in $P(i)$
- 6 **Generate** offspring from the parents using **crossover** and
 mutation to form $P(i + 1)$
- 7 $i \leftarrow i + 1$

So how does this simple EA work?

Illustration Example

Let's use the simple **EA with population size 4** to maximise the function

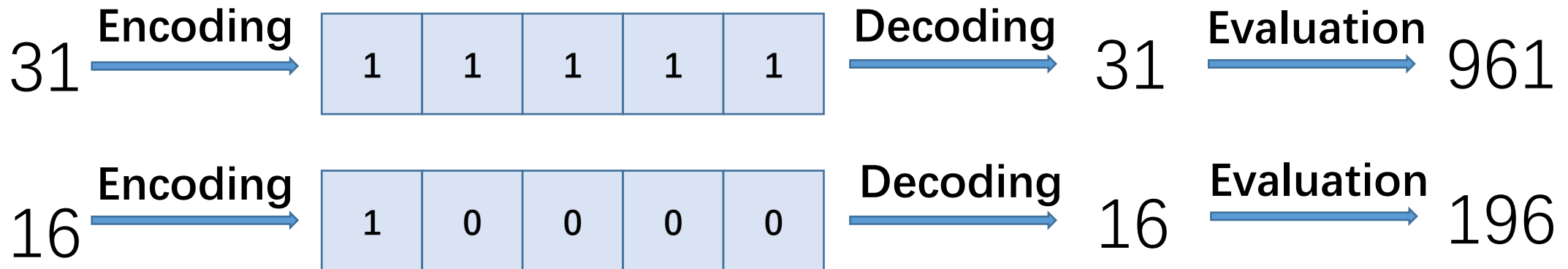
$$f(x) = x^2$$

with x in the *integer* interval $[0, 31]$, i.e., $x = 0, 1, \dots, 30, 31$.

- Population size = 4 \Leftrightarrow 4 individuals/chromosomes
- So, what is an **individual** or **chromosome**?

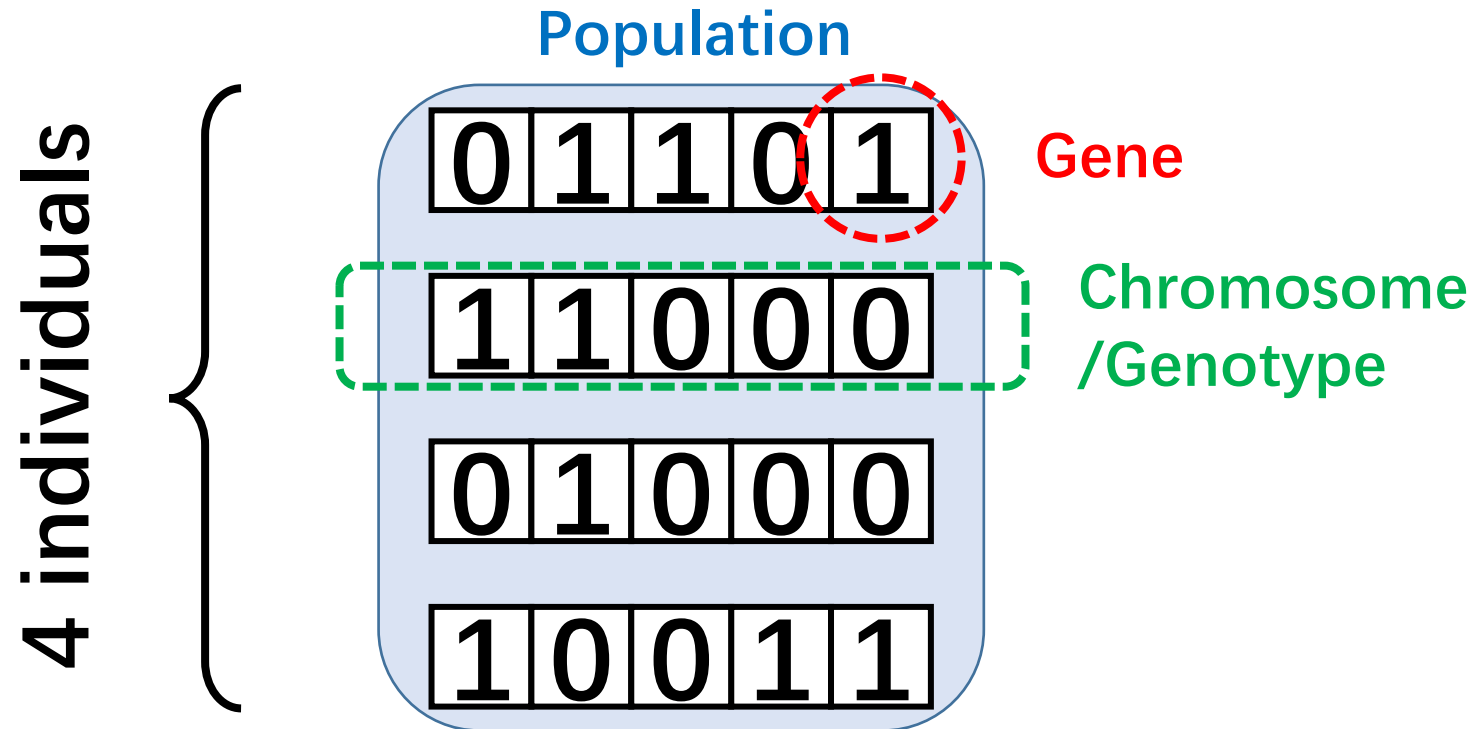
[Example] Encoding and decoding

- **Representation**: The first step of EA applications is *encoding* (i.e., the representation of chromosomes).
 - We adopt binary representation for integers.
 - 5 bits are used to represent integers up to 31.
 - Examples:



[Example] EA: Step 1

1. Initialisation: Generate initial population at random, e.g., 01101, 11000, 01000, 10011. These are *chromosomes* or *genotypes*.



[Example] EA: Step 2

2. Evaluation: Calculate fitness value for each individual.

a) **Decode** the individual into an integer (called *phenotypes*):

01101 -> 13; 11000 -> 24, 01000 -> 8, 10011 -> 19;

b) **Evaluate** the fitness according to $f(x) = x^2$:

$f(13) = 169, f(24) = 576, f(8) = 64, f(19) = 361.$

[Example] EA: Step 3-a

3. Crossover:

- a) Select two individuals for crossover based on their fitness. If **roulette-wheel selection** is used, then

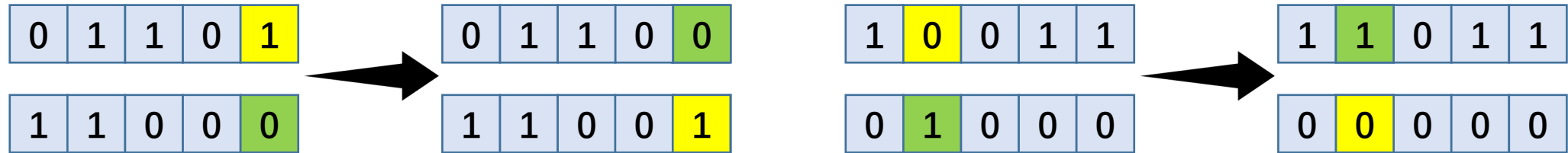
$$P_i = \frac{f_i}{\sum_j f_j}$$

Two offspring are often produced and added to an intermediate population. Repeat this step until the intermediate population is filled.
In our example:

$$P_1(13) = \frac{169}{1170} = 0.14, P_2(24) = \frac{576}{1170} = 0.49, P_3(8) = \frac{64}{1170} = 0.06, P_4(19) = \frac{361}{1170} = 0.31$$

[Example] EA: Step 3-b

b) Examples of crossover



Now the intermediate population is 01100, 11001, 11011, 00000.

EA: Steps 4-5

4. Apply mutation to individuals in the intermediate population with a *small* probability. A simple mutation is bit-flipping. For example, we may have the following new population $P(1)$ after random mutation:

Example:

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

5. Go to step 2 if not stop.

Different Evolutionary Algorithms

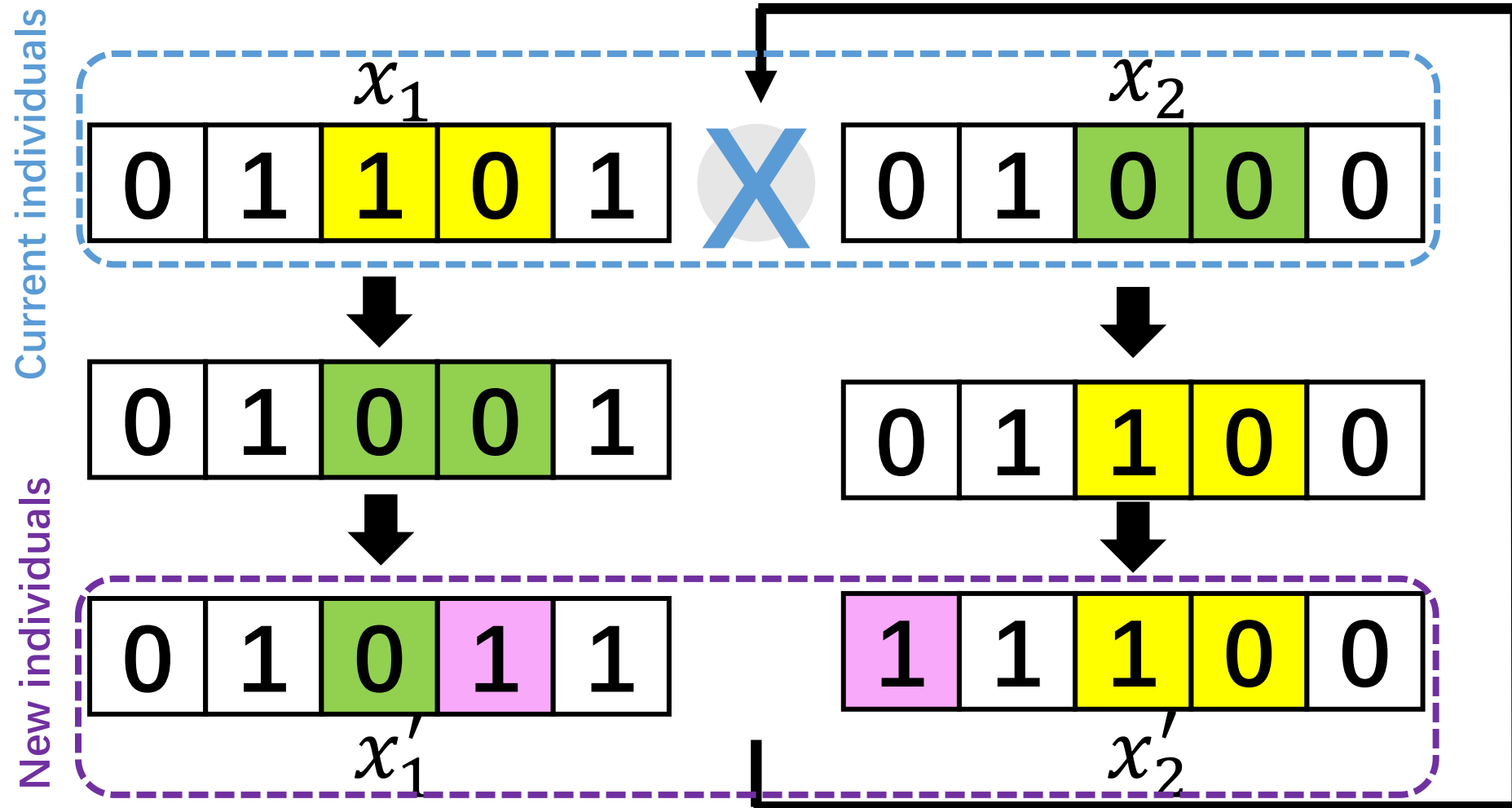
- There are several well-known EAs with different
 - historical backgrounds,
 - representations,
 - variation operators,
 - and selection schemes.

In fact, EAs refer to **a whole family of algorithms**, not a single algorithm.

EA families

- Genetic Algorithms (GAs)
- Evolutionary Programming (EP)
- Evolution Strategies (ES)
- Genetic Programming (GP)
- ...

Genetic Algorithms (GAs)



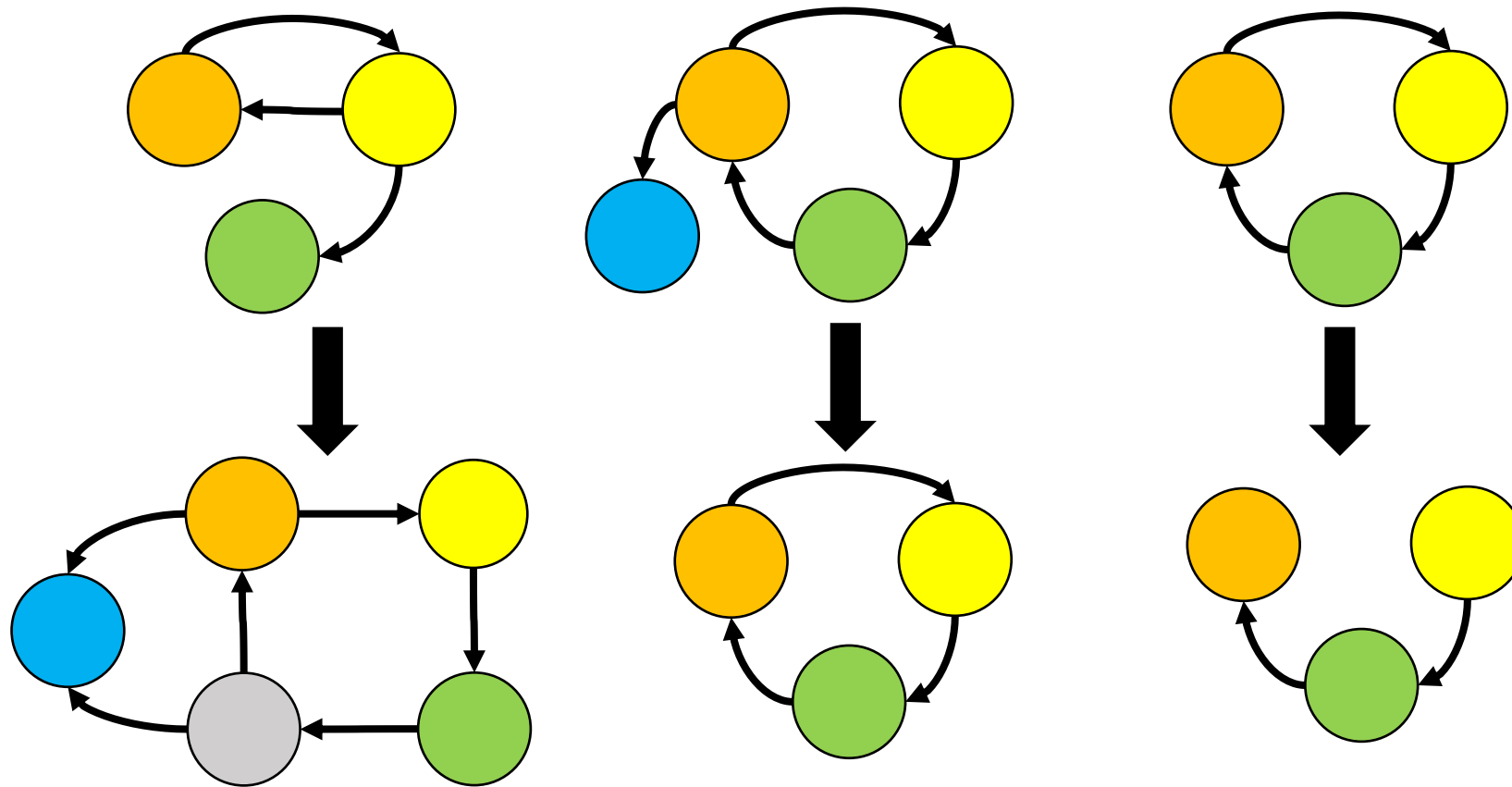
Genetic Algorithms (GAs)

- First formulated by Holland for adaptive search and by his students for optimisation from mid 1960s to mid 1970s.
- Binary strings have been used extensively as individuals (*chromosomes*).
- Simulate **Darwinian evolution**.
- Search operators are only applied to the *genotypic* representation (chromosome) of individuals.
- Emphasise the role of **recombination** (*crossover*). Mutation is only used as a background operator.
- Often use **roulette-wheel** selection.

Sketch of the simple GA

Representation	Bit-strings
Recombination	1-Point crossover
Mutation	Bit flip
Parent selection	Fitness proportional - implemented by Roulette Wheel
Survival selection	Generational

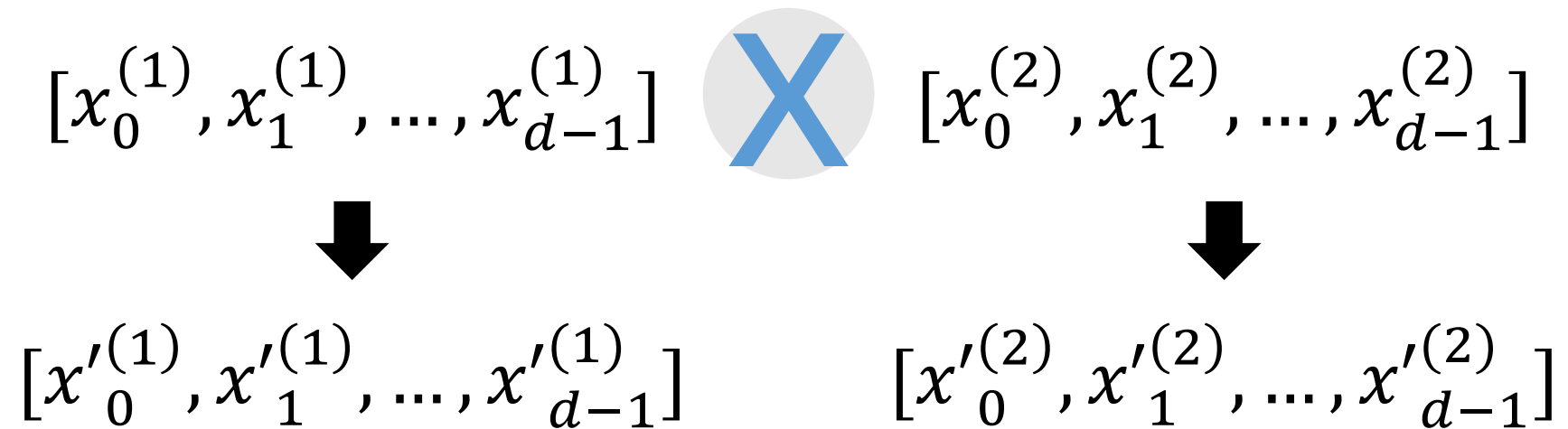
Evolutionary Programming (EP)



Evolutionary Programming (EP)

- First proposed by Fogel *et al.* in mid 1960s for simulating intelligence.
- **Finite state machines** (FSMs) were used to represent individuals, although real-valued vectors have always been used in numerical optimisation.
- It is closer to **Lamarckian evolution**.
- Search operators (mutations only) are applied to the *phenotypic* representation of individuals.
- It does *not* use any recombination.
- Usually use **tournament** selection.

Evolution Strategies (ES)



Evolution Strategies (ES)

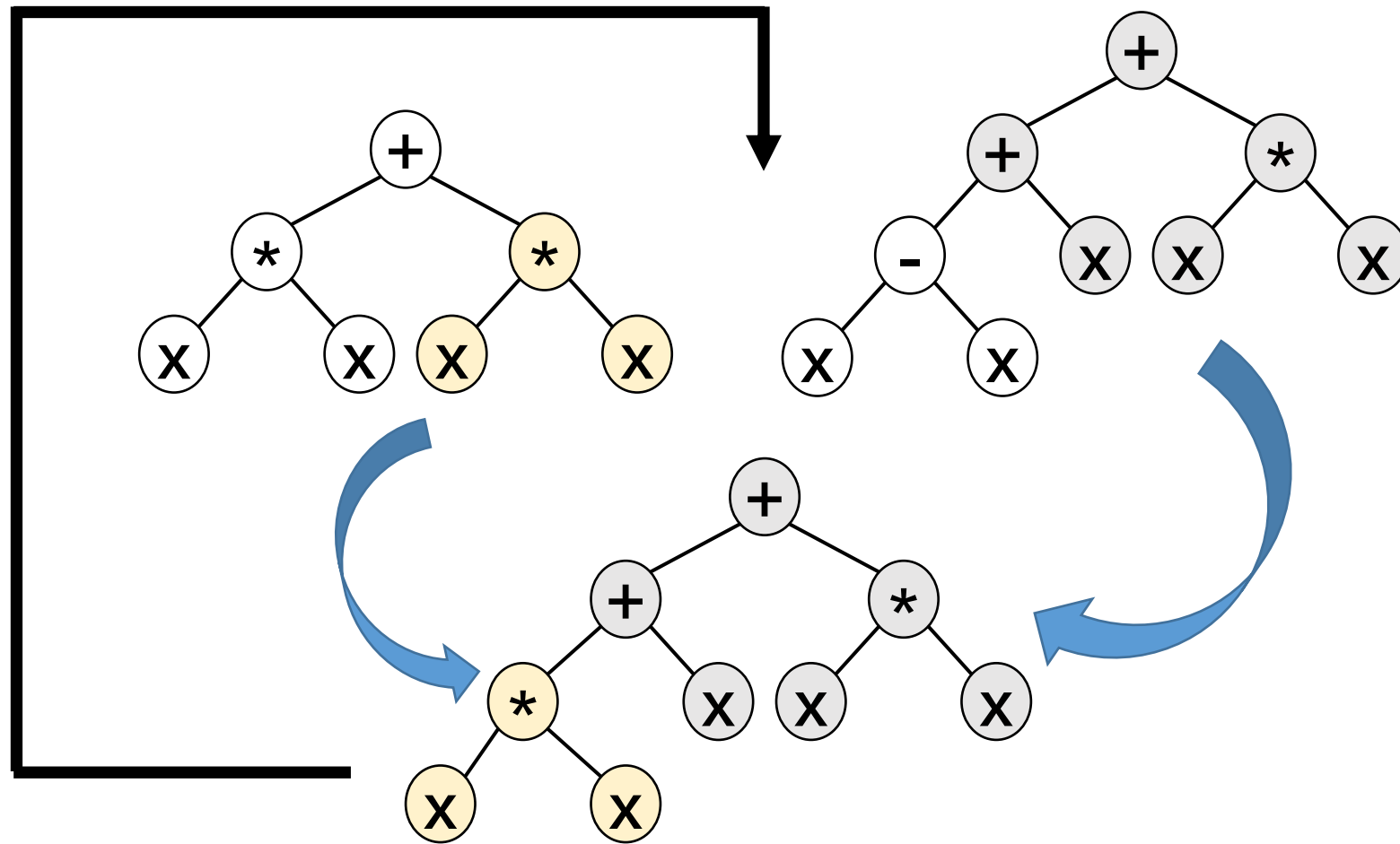
- First proposed by Rechenberg and Schwefel in mid 1960s for numerical optimisation.
- **Real-valued vectors** are used to represent individuals.
- They are closer to **Larmackian evolution**.
- They do have recombination.
- They use *self-adaptive mutations*.

Sketch of the simple ES

Representation	Real-valued vectors
Recombination	Discrete or intermediary
Mutation	Gaussian perturbation
Parent selection	Uniform random
Survivor selection	Deterministic elitist replacement by (μ, λ) or $(\mu + \lambda)$
Speciality	Self-adaptation of mutation step sizes

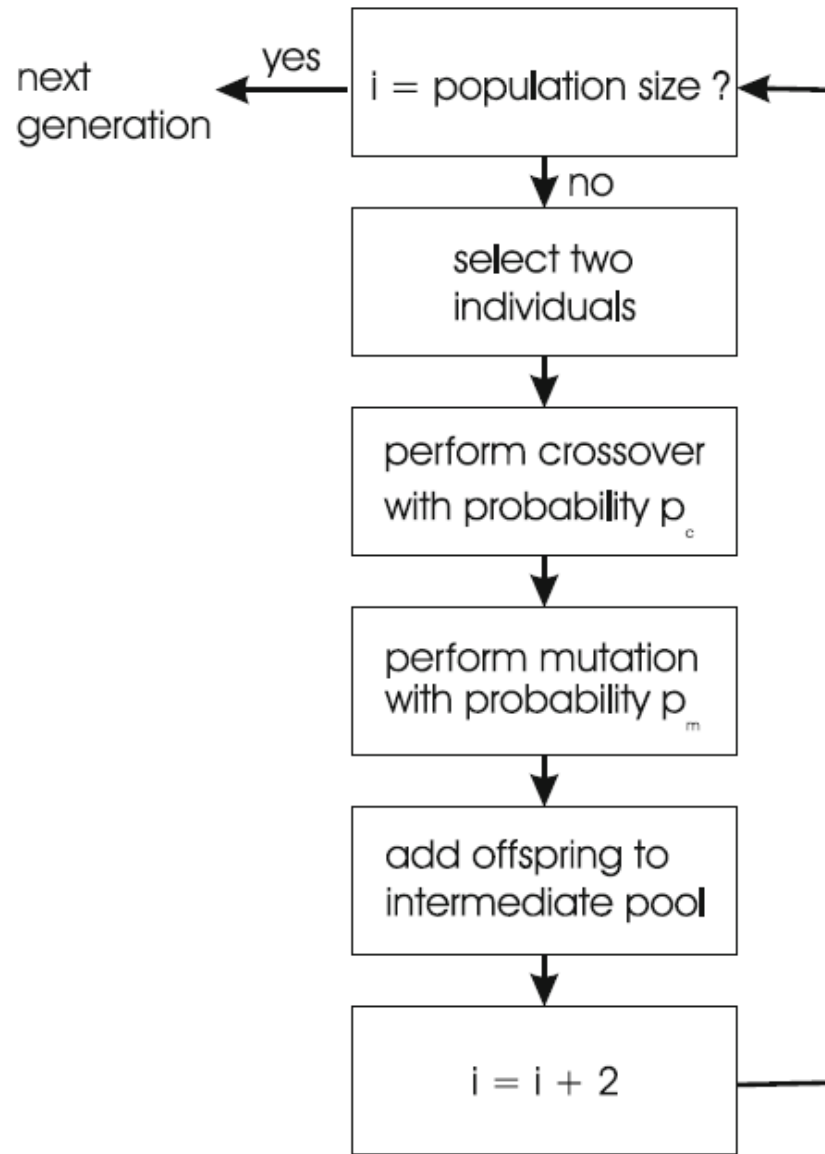
- μ : parents size
- λ : offspring size

Genetic Programming (GP)

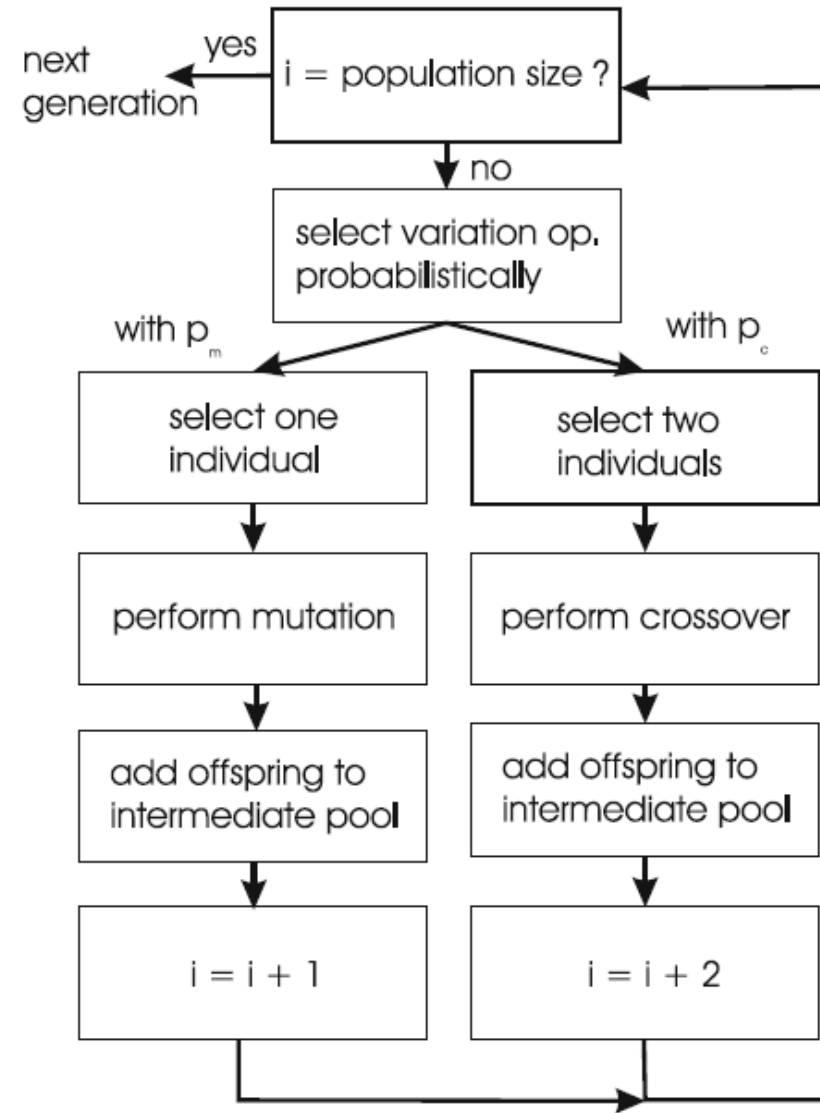


Genetic Programming (GP)

- First used by de Garis to indicate the evolution of artificial neural networks, but used by Koza to indicate the evolution of computer programs.
- **Trees** (especially Lisp expression trees) are often used to represent individuals.
- Both *crossover* and *mutation* are used.



GA loop



GP loop

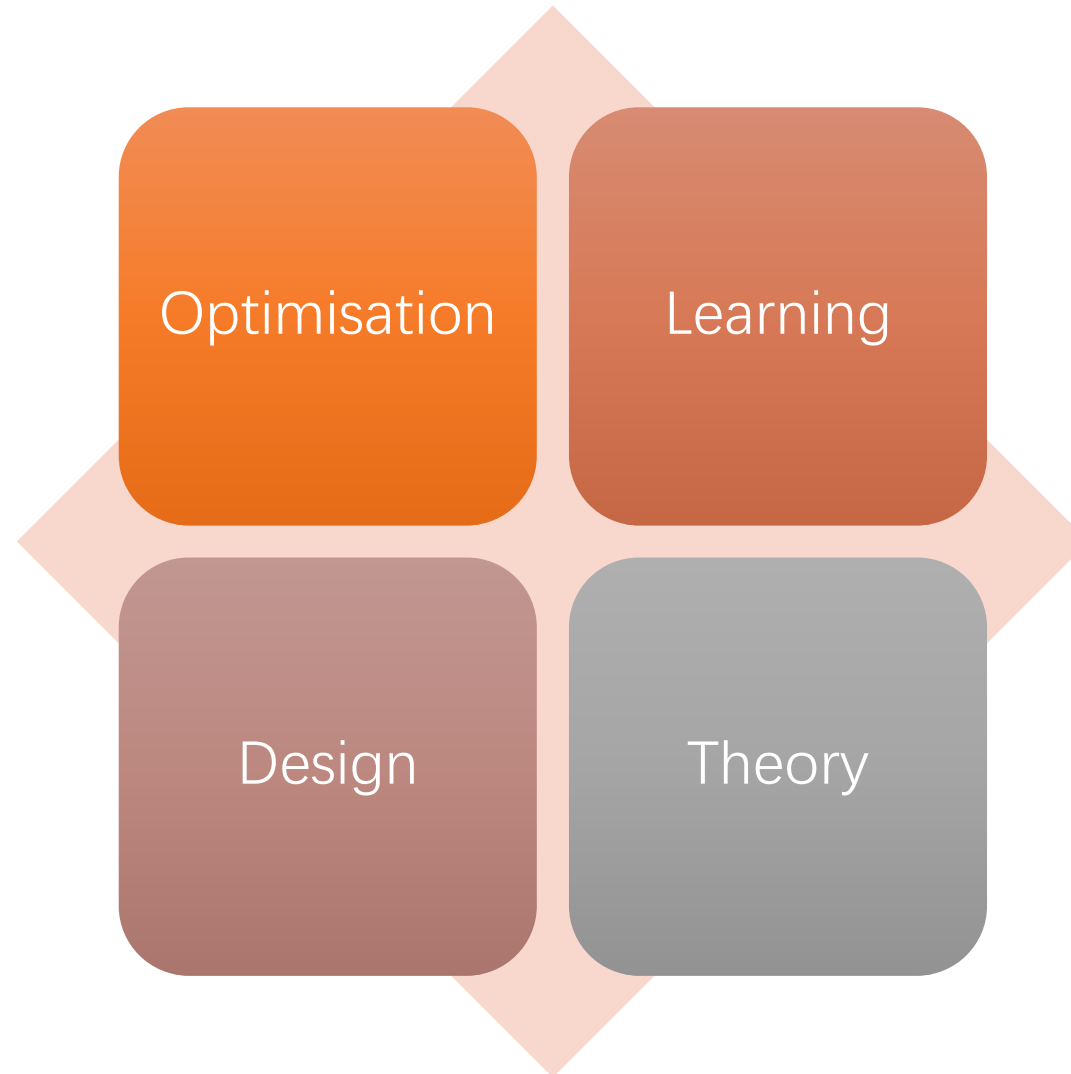
Preferred Term: Evolutionary Algorithms

- EAs face the same fundamental issues as those classical AI faces, i.e., representation, and search.
- Although GAs, EP, ES, and GP are different, they are all different variants of **population-based generate-and-test** algorithms. They share more similarities than differences!
- A better and more general term to use is evolutionary algorithms (EAs).

Variations in Operators

- **Crossover/Recombination:** one-point crossover, two-point crossover, uniform crossover, intermediate crossover, etc.
- **Mutation:** bit-flipping, Gaussian mutation, Cauchy mutation, etc.
- **Selection:** roulette wheel selection (fitness proportional selection), tournament selection, rank-based selection (linear and nonlinear), etc.
- **Replacement Strategy:** generational, steady-state (continuous), etc.
- **Specialised Operators:** multi-parent recombination, inversion, order-based crossover, etc.

Major Areas in EC



Evolutionary Optimisation

- Numerical (global) optimisation.
- Combinatorial optimisation (of NP-hard problems).
- Mixed optimisation.
- Constrained optimisation.
- Multi-objective optimisation.
- Optimisation in a dynamic environment (with a dynamic fitness function).

Evolutionary Learning

Evolutionary learning can be used in supervised, unsupervised and reinforcement learning.

- Learning classifier systems (Rule-based systems).
- Evolutionary artificial neural networks.
- Evolutionary fuzzy logic systems.
- Co-evolutionary learning.

Evolutionary Design

EC techniques are particularly good at exploring unconventional designs which are very difficult to obtain by hand.

- Evolutionary design of artificial neural networks.
- Evolutionary design of electronic circuits.
- Evolvable hardware.
- Evolutionary design of (building) architectures.

Some Applications of EA

- High-speed train head design (Japan)



Series 700 Designed by human

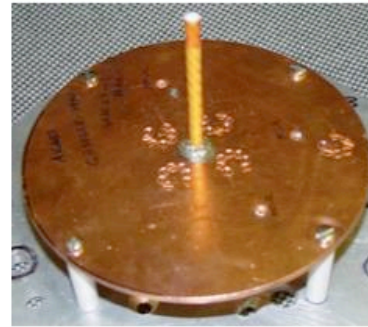
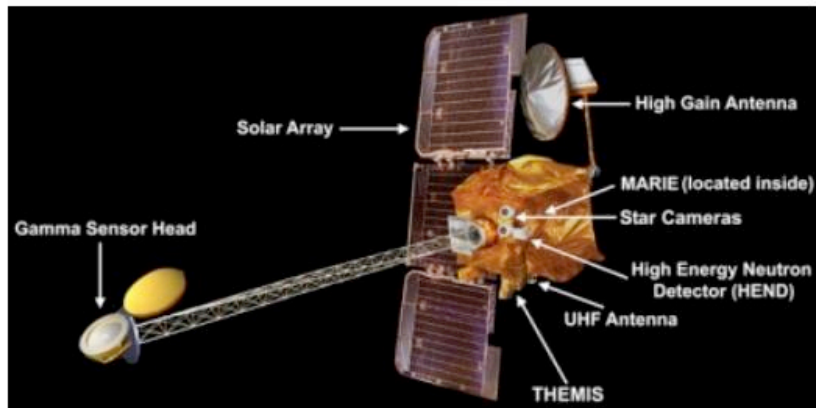


Series N700 Designed by EA

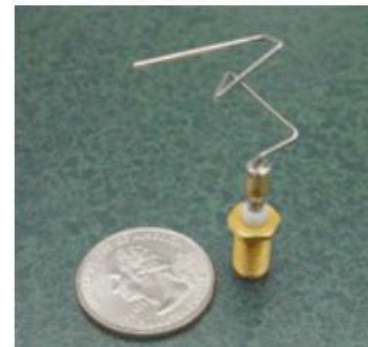
- Save 19% energy...30 increase in the output...

Some Applications of EA

- X-Band Antenna Design (NASA, US)



Human

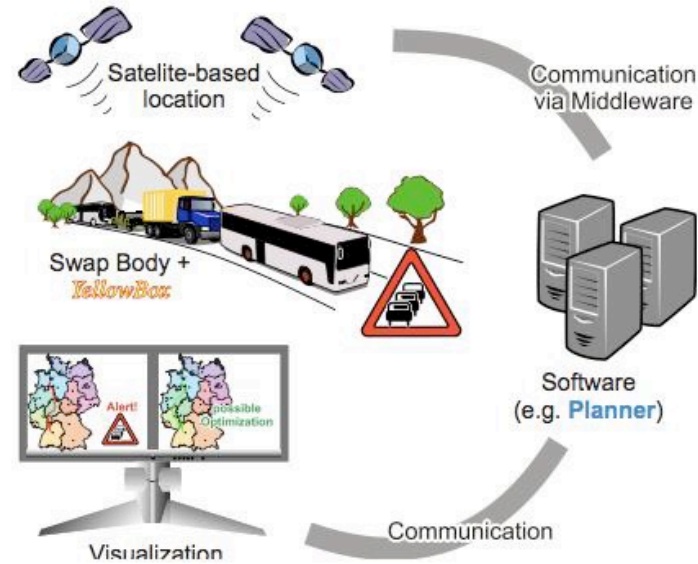


EA

- Increase efficiency from 38% to 93%

Some Applications of EA

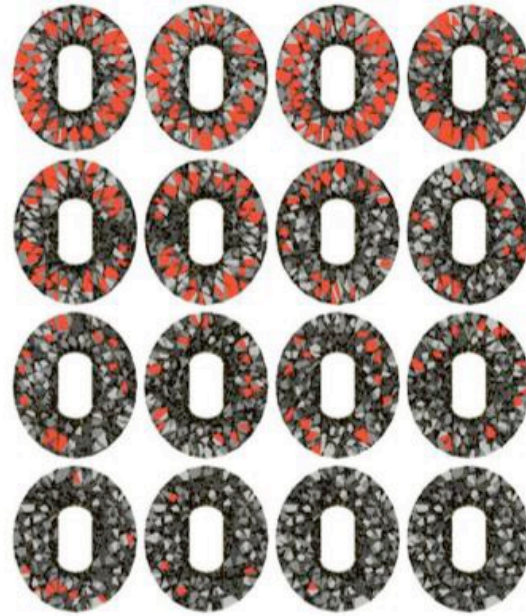
- Transportation Planning System (DHL, Germany)



- Save 9% of the transportation costs.

Some Applications of EA

- Birds Nest (China & Switzerland)



- The irregular ordering of the beams poses an insoluble problem for the then-current CAD tools.

Summary

- Evolutionary algorithms can be regarded as population-based generate-and-test algorithms.
- Evolutionary computation techniques can be used in optimisation, learning and design.
- Evolutionary computation techniques are flexible and robust.
- Evolutionary computation techniques are definitely useful tools in your toolbox, but there are problems for which other techniques might be more suitable.