University of Ljubljana, Faculty of Computer and Information Science

Genetic algorithms and hybrids

Analysis of Algorithms and Heuristic Problem Solving
Version 2024

Contents

- Introduction to evolutionary computation
- Genetic algorithms
- Memetic algorithm

Evolutionary and natural computation

- Many engineering and computational ideas from nature work fantastically!
- Evolution as an algorithm
- Abstraction of the idea:
  - progress, adaptation - learning, optimization
- Survival of the fittest - competition of agents, programs, solutions
- Populations – parallelization
- (Over)specialization – local extremes
- Neuro-evolution, evolution of robots, evolution of novelty
- Revival of interest

Template of evolutionary program

generate a population of agents (objects, data structures)

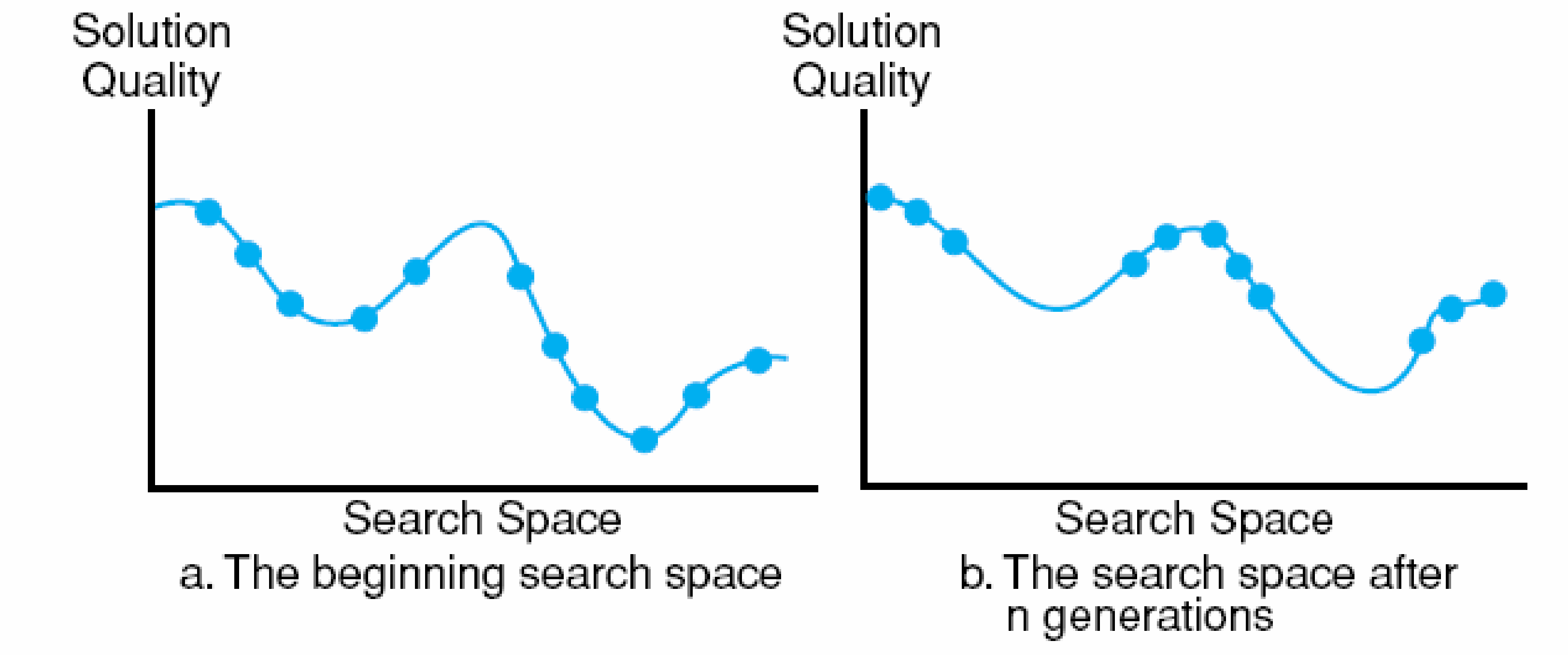
do {

    compute fitness (quality) of the agents
    select candidates for the reproduction using fitness
    create new agents by combining the candidates
    replace old agents with new ones

} while (not satisfied)

- immensely general -> many variants

A result of a successful evolutionary program



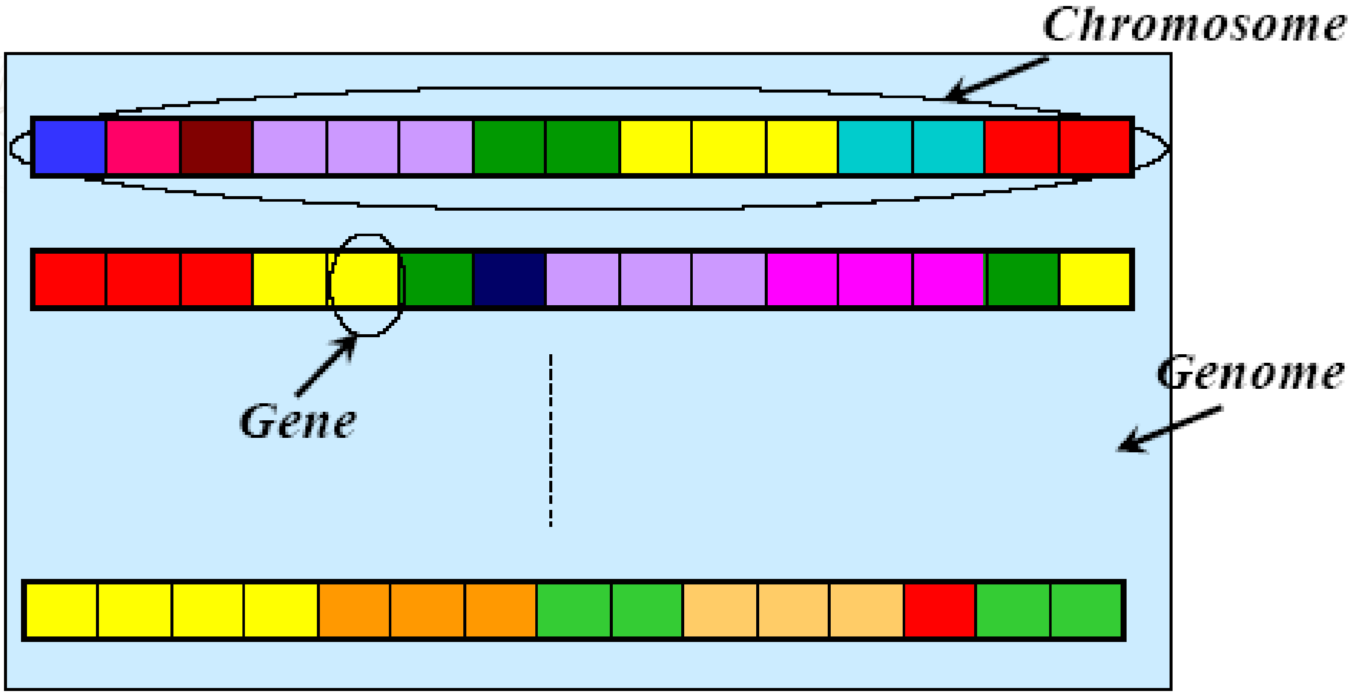
Main evolutional approaches

- Genetic algorithms
- Genetic programming
- Swarm methods (particles, ants, bees, …)
- Self-organized fields
- Differential evolution
- etc.

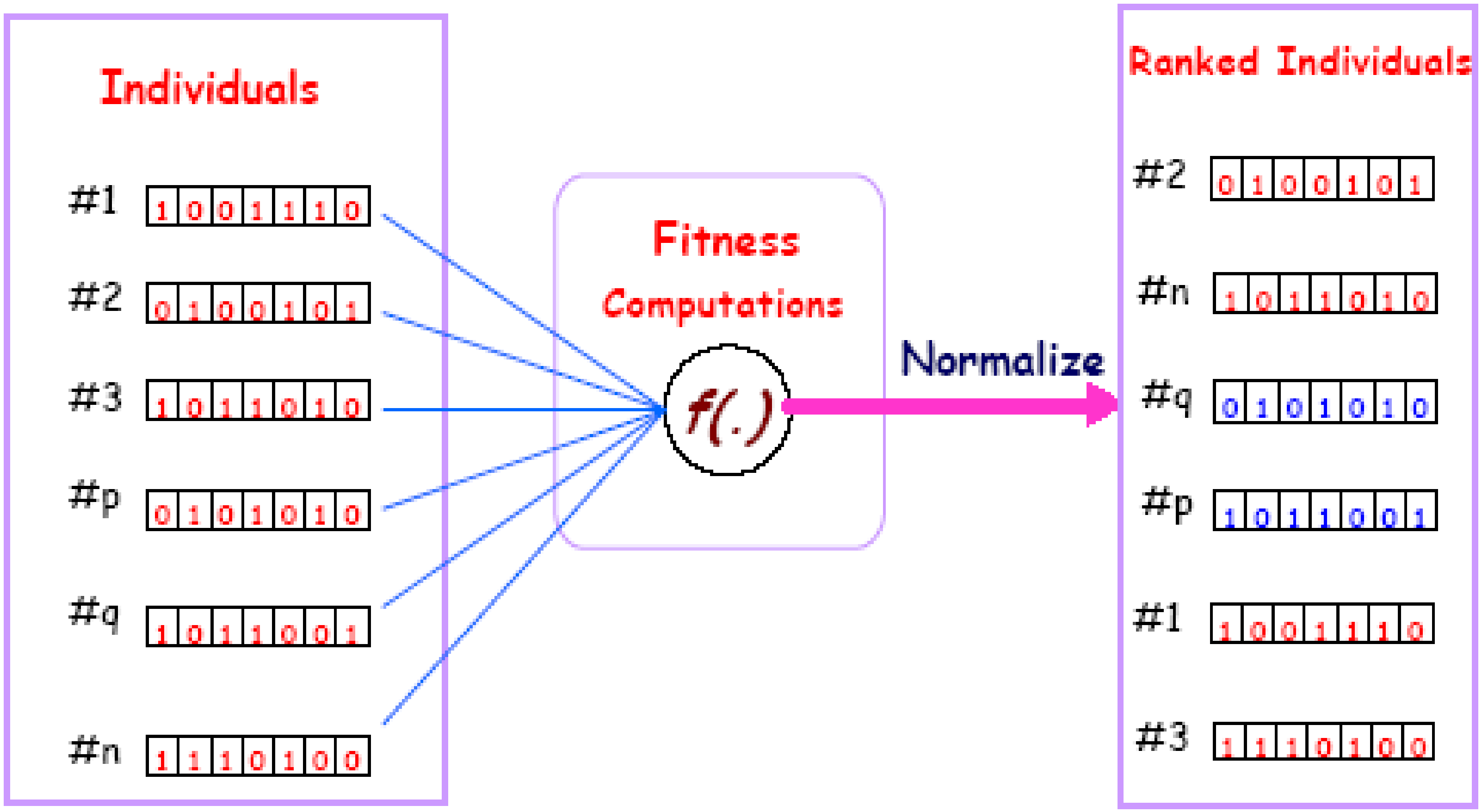
Genetic Algorithms - History

- Pioneered by John Holland in the 1970's
- Got popular in the late 1980's
- Based on ideas from Darwinian evolution
- Can be used to solve a variety of problems that are not easy to solve using other techniques

Chromosome, Genes and Genomes



A fitness function



Gene representation

- Bit vector
- Numeric vectors
- Strings
- Permutations
- Trees: functions, expressions, programs
- …

Crossover

- Single point/multipoint
- Shall preserve individual objects

Crossover: bit representation

Parents: 1101011100 0111000101

Children: 1101010101 0111001100

Crossover: vector representation

Simplest form

Parents: (6.13, 4.89, 17.6, 8.2) (5.3, 22.9, 28.0, 3.9)

Children: (6.13 , 22.9, 28.0, 3.9) (5.3, 4.89, 17.6, 8.2)

In reality: linear combination of parents

Linear crossover

- The linear crossover simply takes a linear combination of the two individuals.
- Let $x = (x_1, \ldots x_N)$ and $y = (y_1, \ldots y_N)$
- Select α in $(0, 1)$
- The results of the crossover is $\alpha x + (1 - \alpha) y$.
- Possible variation: choose a different α for each position.

Linear crossover example

- Let $\alpha = 0.75$ and we have this two individuals:

  $A = (5, 1, 2, 10)$ and $B = (2, 8, 4, 5)$

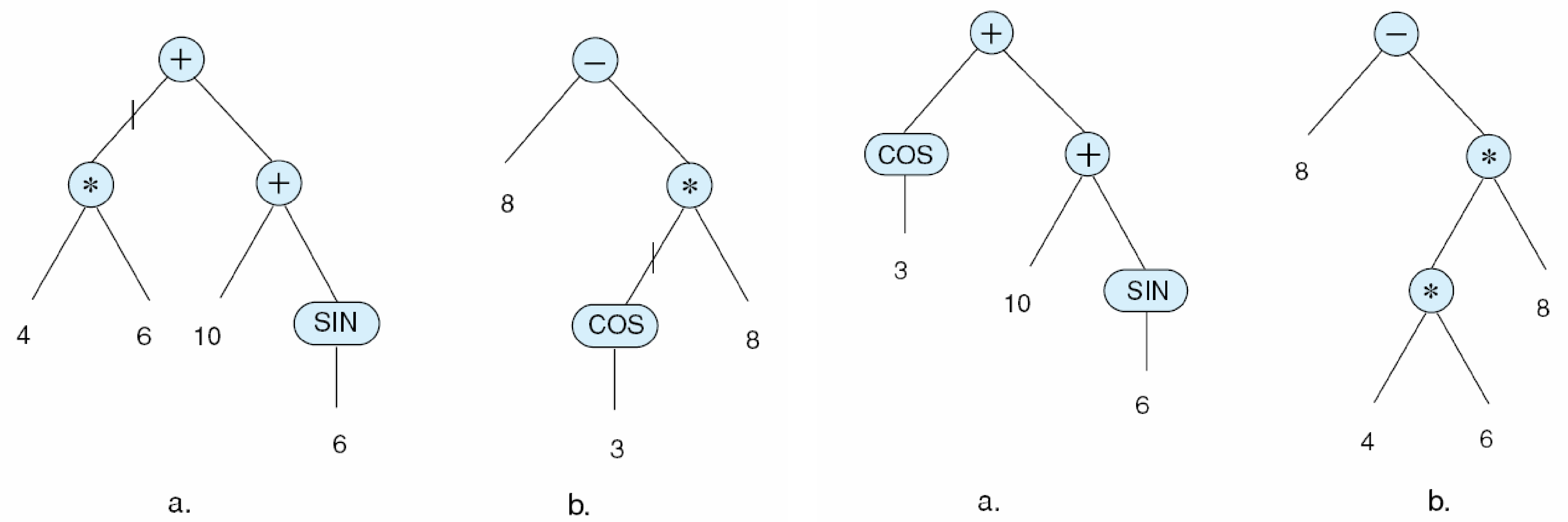
- Then the result of the crossover is:

$(3.75 + 0.5, 0.75 + 2, 1.5 + 1, 7.5 + 1.25) = (4.25, 2.75, 2.5, 8.75)$

- If we use the variation and we have $\alpha = (0.5, 0.25, 0.75, 0.5)$, the result is:

$(2.5 + 1, 0.25 + 6, 1.5 + 1, 5 + 2.5) = (3.5, 6.25, 2.5, 7.5)$

Crossover: trees



Permutations: travelling salesman problem

- 9 cities: 1,2 ..9
- bit representation using 4 bits?
  - 0001 0010 0011 0100 0101 0110 0111 1000 1001
  - crossover would give invalid genes
- permutation and ordered crossover
  - keep (part of) sequences
  - use the sequence from second cut, keep already existing

1 9 2 | 4 6 5 7 | 8 3 → x x x | 4 6 5 7 | x x ↘ 2 3 9 | 4 6 5 7 | 1 8

4 5 9 | 1 8 7 6 | 2 3 → x x x | 1 8 7 6 | x x ↗ 3 9 2 | 1 8 7 6 | 4 5

A demo: Eaters

- Plant eaters are simple organisms, moving around in a simulated world and eating plants
- Fitness function: number of plants eaten
- An eater sees one square in front of its pointed end; it sees 4 possible things: another eater, plant, empty square or the wall
- Actions: move forward, move backward, turn left, turn right
- It is not allowed to move into the wall or another eater
- Internal state: number between 0 and 15
- The behavior is determined by the 64 rules encoded in its chromosome; one rule for each of 16 states x 4 observations; one rule is a pair (action, next state)
- The chromosome therefore consists of length 64 x (4+2) bits = 384 bits
- Crossover and mutation

Mutation

- Adding new information
- Binary representation:
  0111001100 --> 0011001100
- Single point/multipoint
- Random search?
- Lamarckian (searching for locally best mutation)

Gaussian mutation

- When mutating one gene, selecting the new value by choosing uniformly among all the possible values is not the best choice (empirically).
- The mutation selects a position in the vector of floats and mutates it by adding a Gaussian error: a value extracted according to a normal distribution with the mean o and certain variance depending on the problem.

Template of evolutionary program

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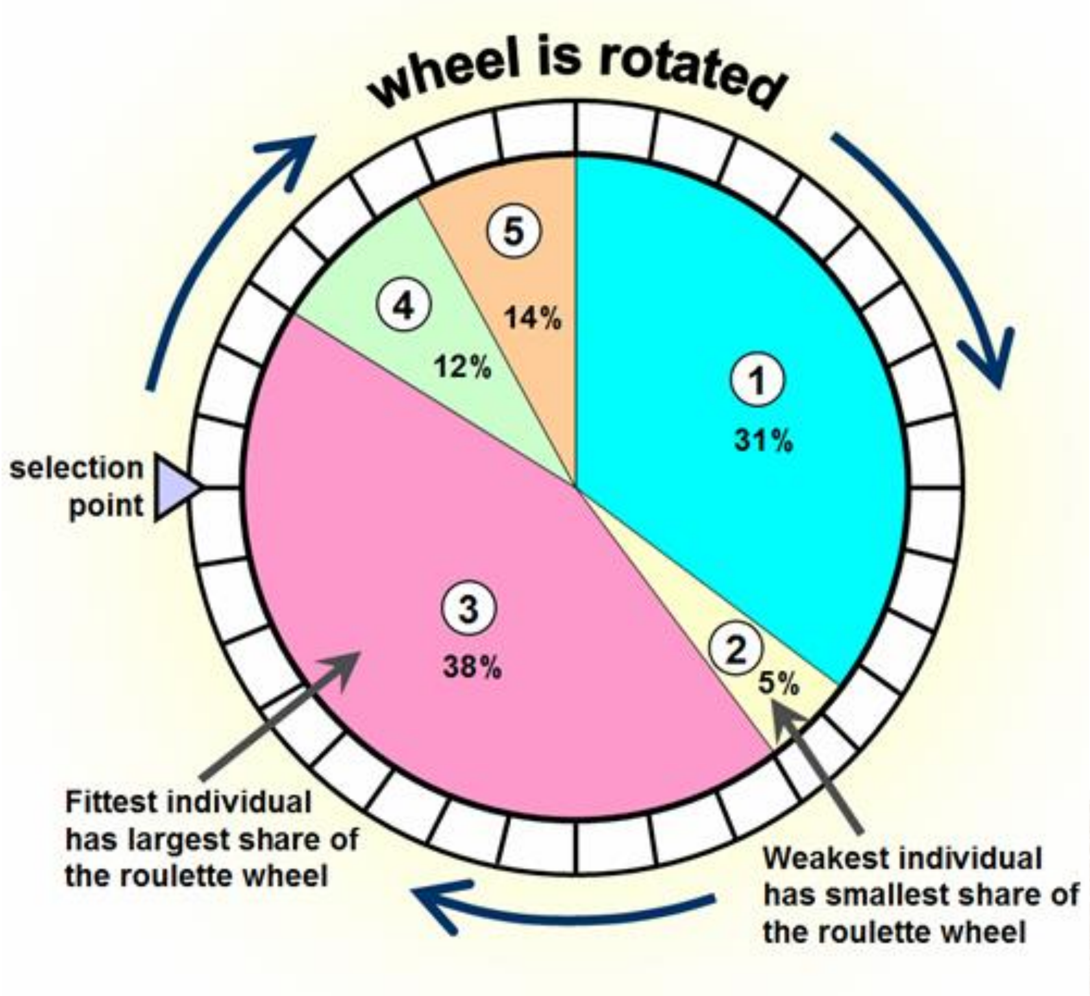
Evolutional model - who will reproduce

- Keeping the good
- Prevent premature convergence
- Assure heterogeneity of population

Selection

- Proportional
- Rank proportional
- Tournament
- Single tournament



Tournament selection

1. set t=size of the tournament,
   p=probability of a choice
2. randomly sample t agents from population forming a tournament
3. select the best with probability p
4. select second best with probability p(1-p)
5. select third best with probability $p(1-p)^2$
6. …

Replacement

- All
- According to the fitness (roulette, rang, tournament, randomly)
- Elitism (keep a portion of the best)
- Local elitism (children replace parents if they are better)

Single tournament selection

1. randomly split the population into small groups
2. apply crossover to two best agents from each group; their offspring replace two worst agents from the group

- advantage: in groups of size *g* the best g-2 progress to next generation (we do not use good agents, maximal quality does not decrease)
- no matter the quality even the best agents have no more than two offspring (we do not loose population diversity)
- computational load?

Population size

- small, large?

Niche specialization

- evolutionary niches are generally undesired
- punish too similar agents

$f'_i = f_i / q(r,i)$

$$q(r,i) = \begin{cases} 1 & ; \mathrm{sim}(i) <= 4, \\ \mathrm{sim}(i)/4 & ; \text{otherwise} \end{cases}$$

Stopping criteria

- number of generations, track progress, availability of computational resources, etc.

Why genetic algorithms work?

- building blocks hypothesis
- … is controversial (mutations)
- sampling based hypothesis

Parameters of GA

- Encoding (into fixed length strings)
- Length of the strings;
- Size of the population;
- Selection method;
- Probability of performing crossover (p_c);
- Probability of performing mutation (p_m);
- Termination criteria (e.g., a number of generations, a leaderboard mutability, a target fitness).

Usual settings of GA parameters

- Population size: from 20–50 to a few thousands individuals;
- Crossover probability: high (around 0.9);
- Mutation probability: low (below 0.1).

Applications

- optimization
- scheduling
- bioinformatics,
- machine learning
- planning
- multicriteria optimization

Where to use evolutionary algorithms?

- Many local extremes
- Just fitness, without derivations
- No specialized methods
- Multiobjective optimization
- Robustness
- Combined approaches

Multiobjective optimization

- Fitness function with several objectives
- Cost, energy, environmental impact, social acceptability, human friendliness
- $\min F(x) = \min (f_1(x), f_2(x), \ldots, f_n(x))$
- Pareto optimal solution: we cannot improve one criteria without getting worse on others
- GA: in reproduction, use all criteria

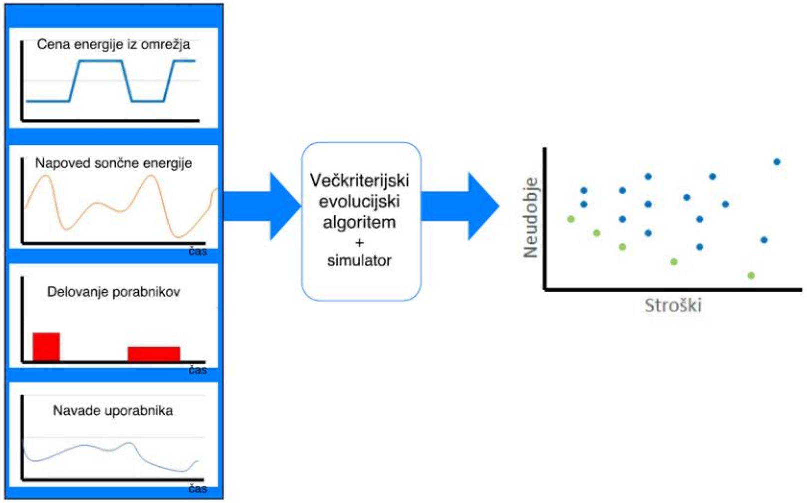
An example: smart buildings

- simple scenario: heater, accumulator, solar panels, electricity from grid
- criteria: price, comfort of users (as the difference in temperature to the desired one)
- chromosome: shall encode schedule of charging and discharging the battery, heating on/off
- operational time is discretized to 15min intervals

Control problem for smart buildings

Parameters:

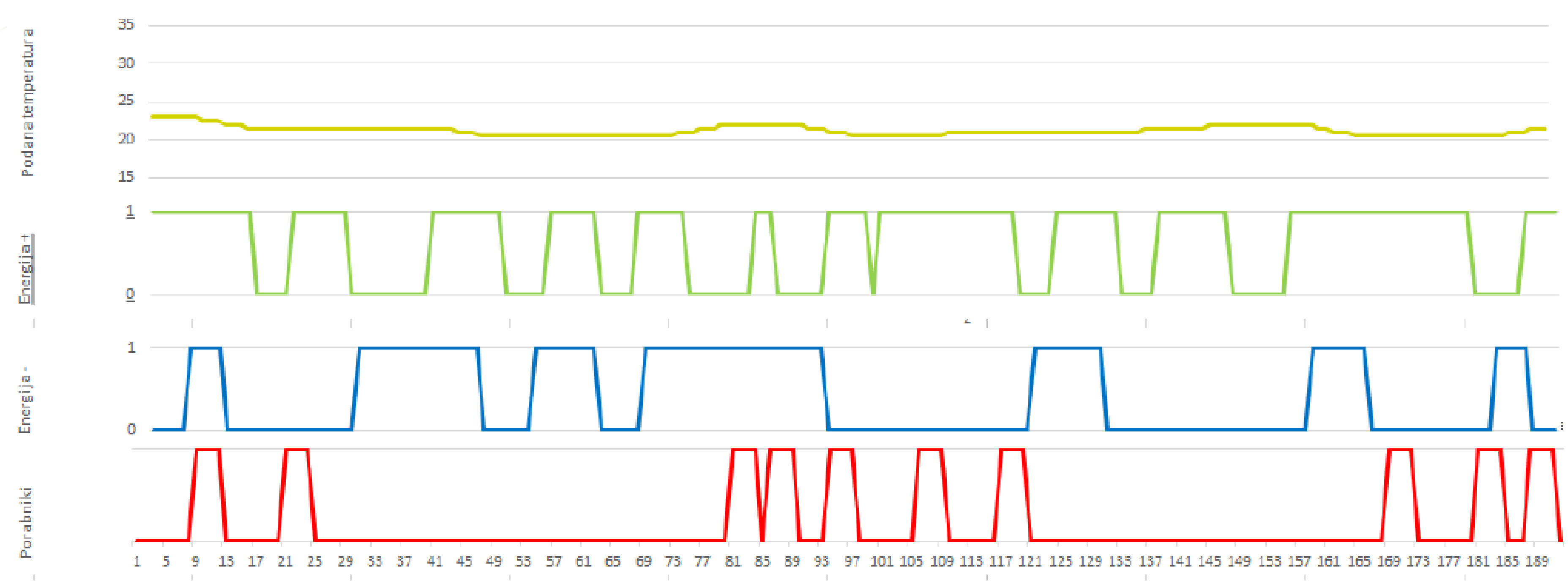
- the price of energy from the grid varies during the day
- the prediction of solar activity
- schedule of heater and battey
- usual activities of a user



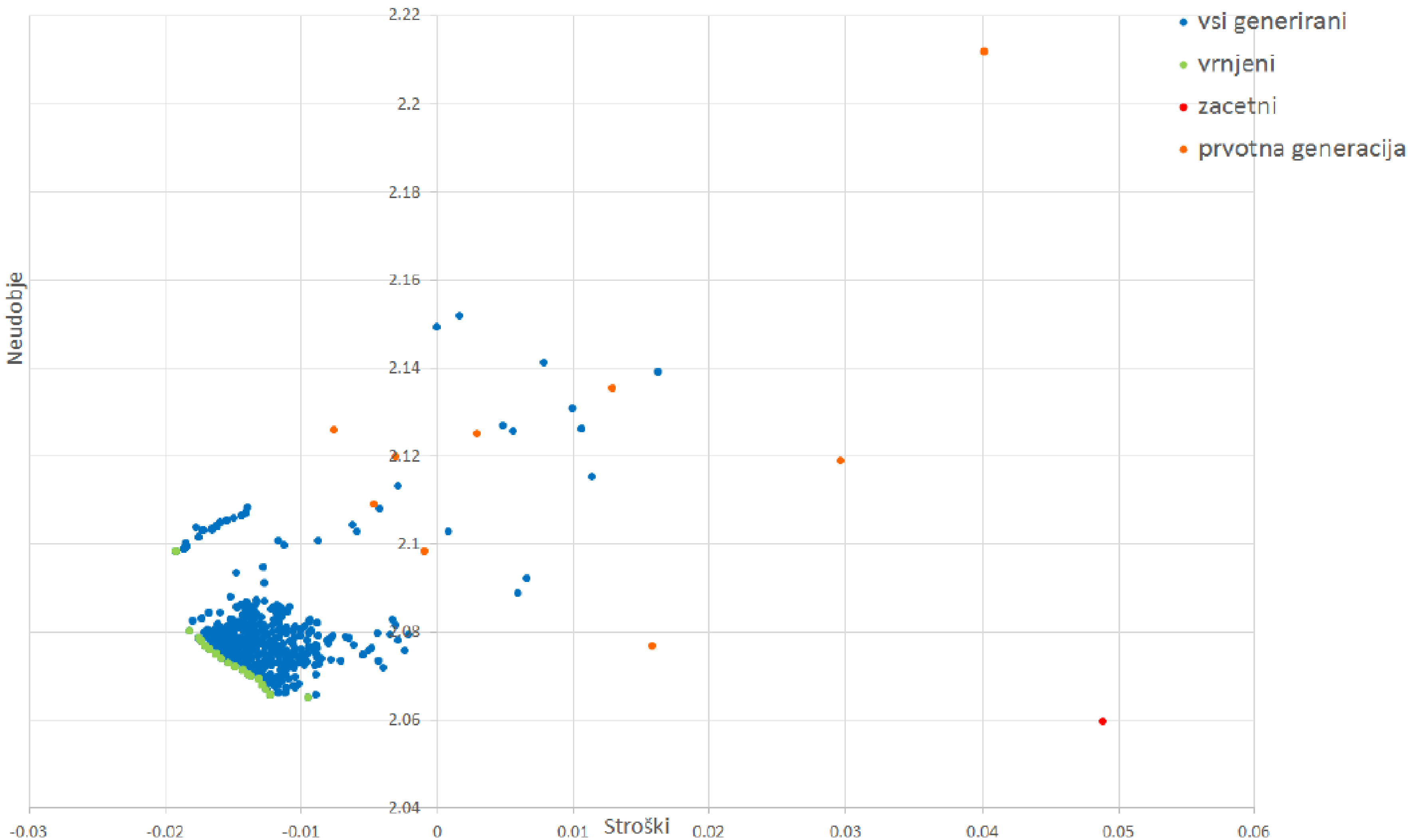
Smart building: structure of the chromosome

- temperature: for each interval we set the desired temperature between Tmin and Tmax interval
- battery+: if photovoltaic panels produce enough energy we set: 1 charging, 0 no charging
- battery-: if photovoltaic panels do not produce enough energy, we set: 1 battery shall discharge, 0 battery is not used
- appliances: each has its schedule when it is used (1) and when it is off (0)

Example of schedule



Example of solutions and optimal front



Pros and Cons of GA

- Pros
  - Faster (and lower memory requirements) than searching a very large search space.
  - Easy, in that if your candidate representation and fitness function are correct, a solution can be found without any explicit analytical work.
- Cons
  - Randomized – not optimal or even complete.
  - Can get stuck on local maxima, though crossover can help mitigate this.
  - It can be hard to work out how best to represent a candidate as a bit string (or otherwise).

Genetic programming

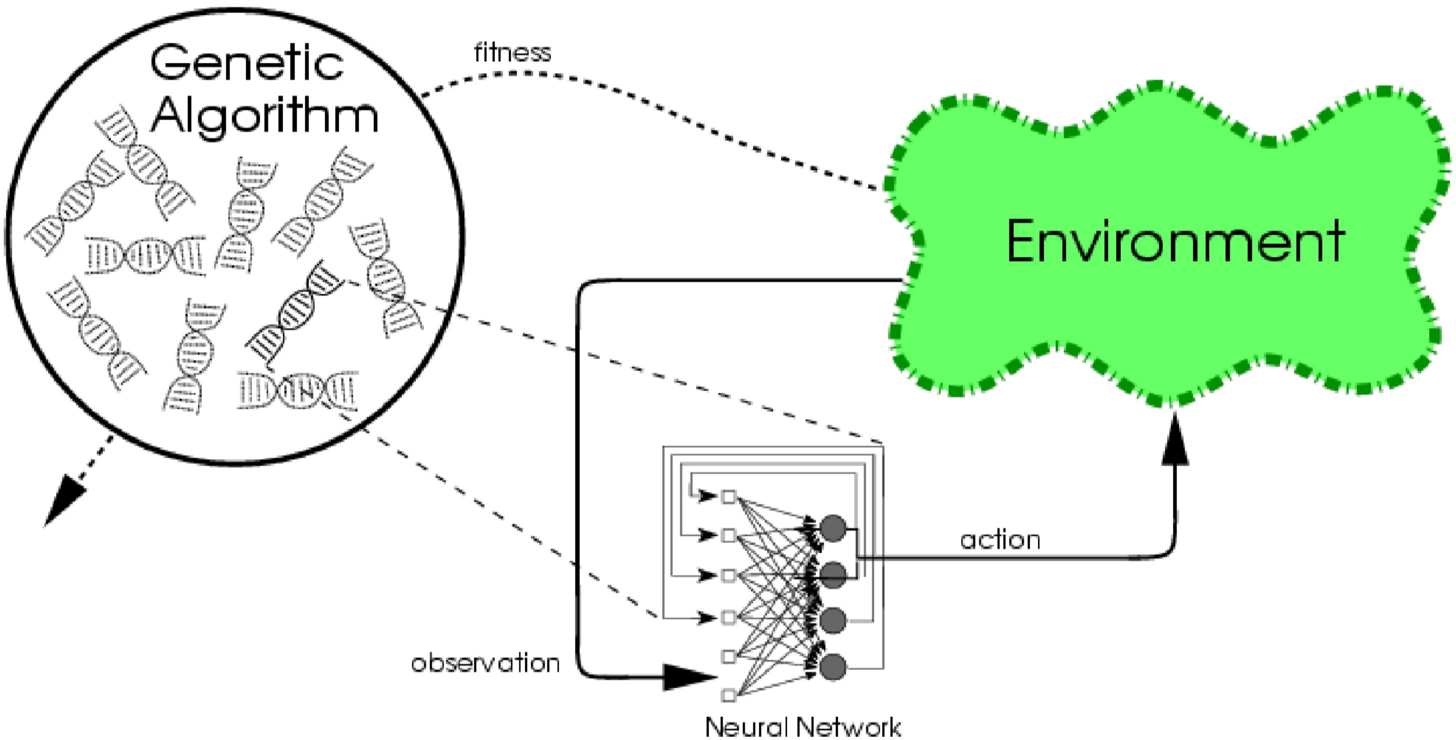
- Functions, programs, expression trees
- Keep the structures valid
- Tree crossover, type closure

GP quick overview

- Developed: USA in the 1990's
- Early names: J. Koza
- Typically applied to:
  - machine learning tasks (prediction, classification…)
  - controller design
  - function fitting
- Attributed features:
  - competes with neural nets and alike
  - needs huge populations (thousands)
  - slow
- Special:
  - non-linear chromosomes: trees, graphs
  - mutation possible but not necessary (disputed!)
- large potential, but so far did not deliver much

Neuroevolution: evolving neural networks

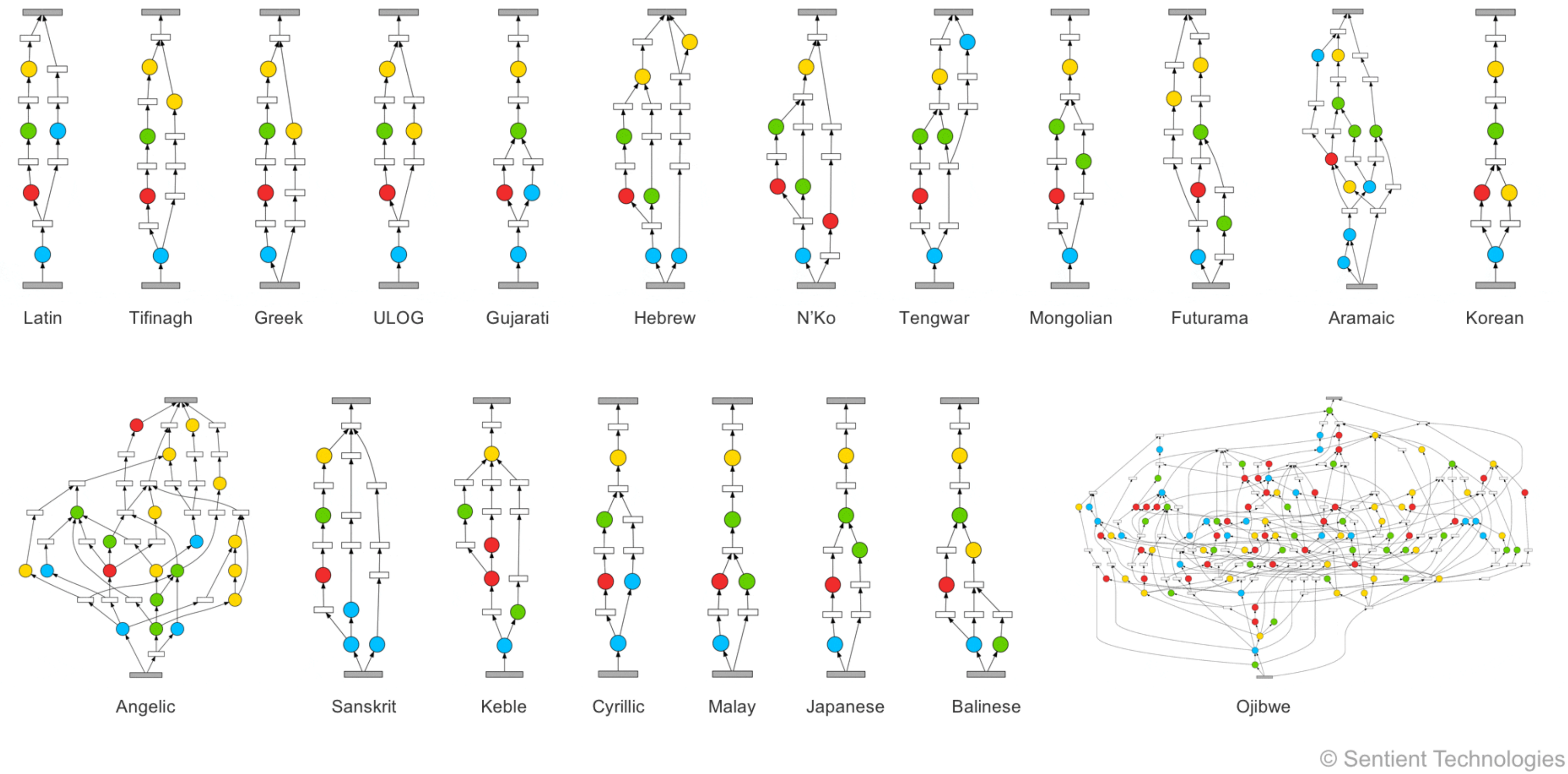
- Evolving neurons and/or topologies



Neuroevolution

- Evolving neurons: not really necessary but attempted
- Evolving weights instead of backpropagation and gradient descent
- Evolving the architecture of neural network
  - For small nets, one uses a simple matrix representing which neuron connects which.
  - This matrix is, in turn, converted into the necessary 'genes', and various combinations of these are evolved.

Example: multialphabet character recognition architectures



https://evolution.ml/demos/cmsr/

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Memetic algorithms

- An attempt to merge several ideas from combinatorial optimization

```
Procedure Population-Based-Search-Engine;
begin
    Initialize pop using GenerateInitialPopulation();
    repeat
        newpop ← GenerateNewPopulation(pop);
        pop ← UpdatePopulation (pop, newpop);
        if pop has converged then
            pop ← RestartPopulation(pop);
        endif
    until TerminationCriterion() ;
end
```

Memetic algorithms initialization

- Using local search

```
Procedure GenerateInitialPopulation;
begin
    Initialize pop using EmptyPopulation();
    for j ← 1 to popsize do
        i ← GenerateRandomConfiguration();
        i ← Local-Search-Engine (i);
        InsertInPopulation individual i to pop;
    endfor
    return pop;
end
```

Memetic algorithms - restart

- elitism and local search

Procedure RestartPopulation (*pop*);
begin
    Initialize *newpop* **using** EmptyPopulation();
    $\#preserved \leftarrow popsize \cdot \%preserve$;
    for $j \leftarrow 1$ **to** $\#preserved$ **do**
        $i \leftarrow$ ExtractBestFromPopulation(*pop*);
        InsertInPopulation individual i **to** *newpop*;
    endfor
    for $j \leftarrow \#preserved + 1$ **to** $popsize$ **do**
        $i \leftarrow$ GenerateRandomConfiguration();
        $i \leftarrow$ Local-Search-Engine (i);
        InsertInPopulation individual i **to** *newpop*;
    endfor
    return *newpop*;
end