

Basics of Modern Computer Science

Evolutionary Algorithms

Selected Basic Topics and Terms

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Topics

- Population.
- Individual and its structure in general.
- The Gray code.
- Common attributes of evolutionary algorithms.
- Problems solvable by evolutionary algorithms.



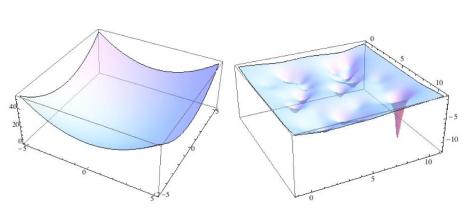
Objectives

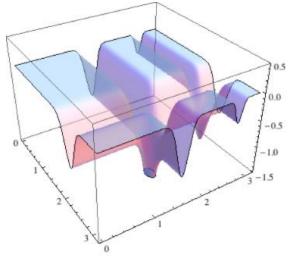
The objectives of the lesson are:

- What is the population, individual and structure in general.
- What is the Gray code and what impact does it have on evolution performance.
- Common attributes of evolutionary algorithms.
- What kind of problems can be solved by evolutionary algorithms.



- Almost every optimization problem can be seen as a geometric problem in which the objective is to find the
 - Lowest (minimum) or
 - Highest (maximum)
 point in N dimensional surface.

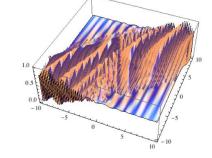






• Those areas, usually given by some functional regulation, may suffer from various pathologies in the

mathematical sense.



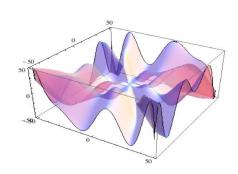
• Due to the tests carried out on test functions, the attributes are listed on the next slide, can be said that evolutionary algorithms are very powerful and usually suitable for global optimization.

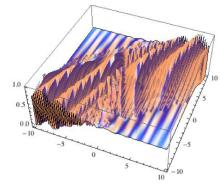


- On this set of test functions can be viewed as a field application of evolutionary algorithms. For the above mentioned test function applies:
 - Graph has fractal character.
 - Are defined on the real, integer or discrete arguments.
 - Are multimodal (one or more extremes).
 - Have different restrictions (placed on the arguments and the value of objective function).
 - Are strongly nonlinear.
 - Problems represent a "needle in a haystack".
 - Finding the global extreme evolutionary algorithms is NP complex.



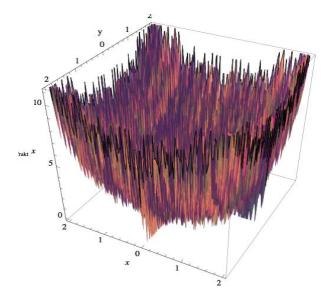
- Also may be true that:
 - Function is separable (non separable), which means that it can (not) be decomposed into several simpler functions that can be optimized independently.
 - The number of variables is high.
 - The space of possible solutions can be extensive and incoherent.







• The fractal function – Weierstrass non-differentiable function added on the 1st De Jong.





Common Features

Evolutionary algorithms have several common features:

- Simplicity because these algorithms usually can be programmed easily.
- **Hybridization** of numbers with which algorithms work. Without any problem, you can combine numbers of type integer, real, or only a selected set of numbers (usually known as discrete), such as {-5, 2, 8, 55, 3, 100}.
- The use of decimal numbers. For example. numbers 15, 16 and 17 are represented by 01111, 10000 and 10001 The transition from 15 to 16 indicates inversion of the five bits, ie 100% mutation. The transition from 16 to 17, however, requires only a single bit mutation.



Common Features

- **Speed**. Due to its relative simplicity, especially when compared with conventional methods, we can say that a solution will find a lot faster.
- The ability to find even in extreme functions that are in a graphical sense, flat and extreme is the "hole" in this plane. With a little exaggeration, you can search for such an extreme position described as a problem of "finding a needle in a haystack." Unfortunately for these problems is the efficiency of any algorithm, including evolutionary, low. If the area around the extreme plane, then find the extreme usually a matter of chance.
- The ability to give multiple solutions. The result is the best (selected *n* individuals representing one (*n*) solutions. The quality of graded course.



Common Features

In other words, evolutionary algorithms are suitable for finding extreme of functions suffer from such pathologies, such as noise, a high number of dimensions, "multimodality" (multiple local extremes).



- A typical feature of evolutionary algorithms is that they are based on the work with a population of individuals.
- Population can be represented as $N \times M$ matrix where the columns represent each individual.

	l ₁	l ₂	I ₃	I ₄		I _M
CV	55,2	68,3	5,36	9,5	•••	0,89
P_1	2,55	549,3	-55,36	896,5		1,89
P ₂	0,25	66,2	2	-10		-2,2
P_3	-66,3	56	4	15,001		-83,66
•••						
P_N	259,3	-10	22,22	536,22		-42,22



- Each individual represents a timely solution to the problem. It is basically a set of arguments of the objective function, the optimal numerical combination is gradually being sought.
- With each individual is also associated with objective function value (sometimes fitness fitness), which tells how the individual is suitable for further development of the population.
- This value is not participating in their own evolutionary process. It carries only information about the quality of the individual.



• To create the population is needed to define the pattern (specimen).

Specimen =
$$\{\{\text{Real}, \{\text{Lo}, \text{Hi}\}\}, \{\text{Integer}, \{\text{Lo}, \text{Hi}\}\}, \dots, \{\text{Real}, \{\text{Lo}, \text{Hi}\}\}\}$$

which is generated by the entire initial population. The individual sample is also used to correct the parameters of individuals who cross the border search space.

• The population is based on the model generated by an individual. $P^{(0)}$ is a primordial population, $x_{i,j}$ is the j_{th} parameter of the i_{th} individual.

$$P_{i,j}^{(0)} = x_{i,j}^{(0)} = rnd[0.1] \cdot (x_{i,j}^{(Hi)} - x_{i,j}^{(Lo)}) + x_{i,j}^{(Lo)}$$

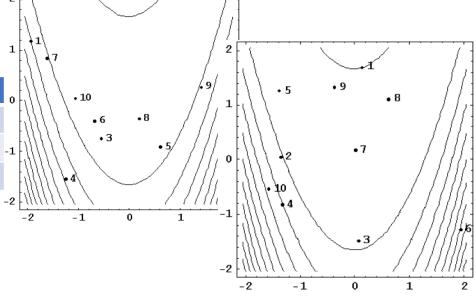
$$i = 1, \dots, M , j = 1, \dots, N$$



• This relationship ensures that all parameters of individuals are randomly generated within the permitted limits the space of possible solutions.

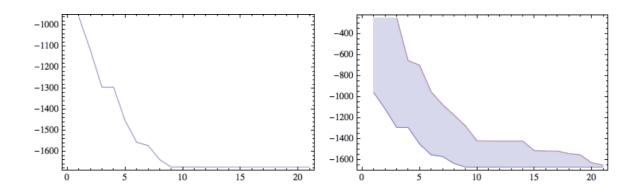
A sample of the population is an example in figures here.

J ₁	J ₂	J ₃	J ₄		J ₁₀
424	104	53,3	942.9	•••	178
-1,8	-1	0,7	-1,25		-1,19
1,2	2	1,2	-1,5		0,1





- History of the best individual (or best individuals in repeated simulations).
- History of the worst individual.
- Overall view of the convergence of the population.





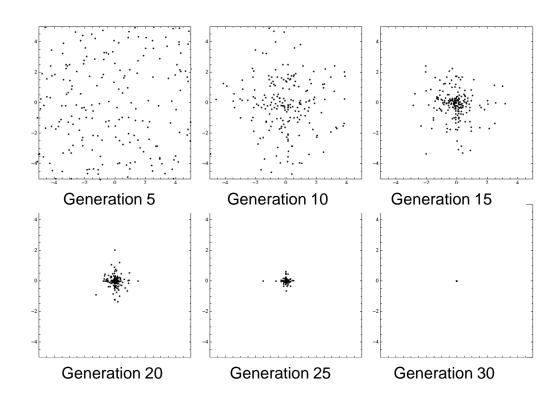
- When the best and worst individual have the same objective function value, then there are only **two** possible explanations, namely:
 - The population is spread out in more extremes of the same value of objective function.
 - The whole population at one extreme, more likely, because most problems are represented by functions with a single global extreme.
- Development of the population **must always be convergent** to better values, which means it can never show divergence. In the event that seeks a minimum (maximum), the development must decline to lower (higher) values.



- If it were not, so the algorithm is somehow violated the "elitism", which serves as a sort of one-way filter, which transmits the new population, only those solutions that are better or as good as the old population.
- In case of malfunction would be the evolutionary algorithm relegated to mere random search.

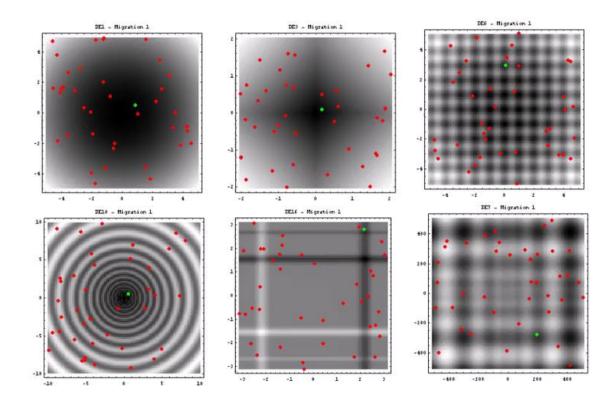


Population Dynamics





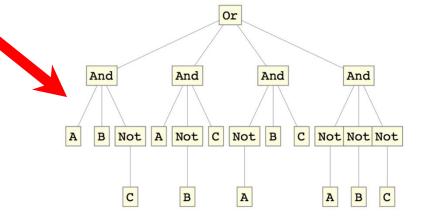
Population Dynamics





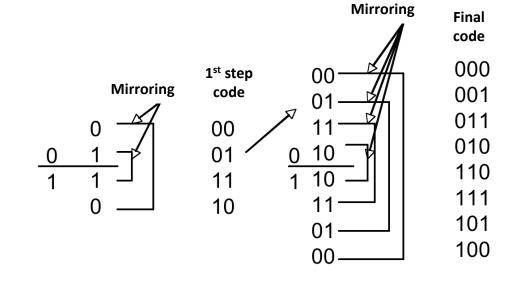
Individuals, their Structure and Representation

- Binary: 010,011,101th ...
- Real: 2.54, -4.44, ...
- Integer: 1, 6, 20, -33, ...
- Symbolic: True, False, UserFunction, ...
- So called "Tree":





- Gray code.
- Methods of construction
 - Mirroring.





- Methods of construction
 - Another computer, and easily implementable method is to use the XOR operation.

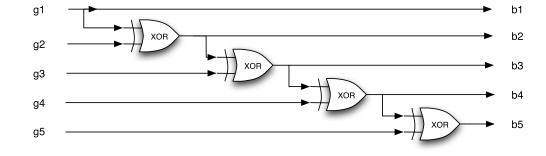
$$b1 = g1$$

$$b2 = g1 \oplus g2 = b1 \oplus g2$$

$$b3 = g1 \oplus g2 \oplus g3 = b2 \oplus g3$$

$$b4 = g1 \oplus g2 \oplus g3 \oplus g4 = b3 \oplus g4$$

$$b5 = g1 \oplus g2 \oplus g3 \oplus g4 \oplus g5 = b4 \oplus g5$$





- Methods of construction
 - Another computer, and easily implementable method is to use the XOR operation.

$$g1 = b1$$

$$g2 = b1 \oplus b2$$

$$g3 = b2 \oplus b3$$

$$g4 = b3 \oplus b4$$

$$g5 = b4 \oplus b5$$

$$g1 \longrightarrow b1$$

$$g2 \longrightarrow xOR \longrightarrow b2$$

$$g3 \longrightarrow xOR \longrightarrow b3$$

$$g4 \longrightarrow xOR \longrightarrow b4$$

$$g5 \longrightarrow b4 \oplus b5$$



- The advantage of Gray coding is reflected in the uniform mutation, and individuals generally faster convergence of the algorithm to the global optimum.
- Opinions differ, however. Some argue rather that the Gray code genetic algorithm (GA) slows down due to the conversion process (Haupt, 2004). Others are, however, advocates the use of Gray code (Carulana 1988, Hinterding, 1989).
- The genetic algorithms for mutation or crossing standard binary individuals may experience large changes argument (gene), whereas in subjects in Gray coding for the major are not.



- Difference between Gray and Binary code.
- Hamming distance.
- Uniform mutations.

Decimal value	Gray code	Binary code
0	000	000
1	001	001
2	011	010
3	010	011
4	110	100
5	111	101
6	101	110
7	100	111

Gray code	Binary code
000	000
001	001
011	010
010	011
110	100
111	101
101	110
100	111
	000 001 011 010 110 111 101



Want to Know More?

- More can be read in (Back, Fogel, Michalewicz, 1997).
- The representation of individuals, ETV basic concepts and properties of test functions can be read also in the (Back, 1996).
- Monographs and Internet resources providing such information is of course more, but two publications listed in this direction we consider to be representative.



Conclusions

- Population structure.
- Individual and its structure in general.
- The Gray code and its impact on evolution performance.
- Methods of construction.
- Common attributes of evolutionary algorithms like simplicity, hybridization, speed, ...



Thank you for your attention

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