Biologically-inspired algorithms and models

1. Evolutionary algorithms and their mechanisms

Maciej Komosinski

Reminder from earlier studies (and, possibly, a supplement) #1

- What are the differences between *random search* and *random walk*?
- What two variants of the local search algorithm do you know?
- Is it known that one of them is better (ultimately produces better results – this question concerns quality, not running time)?
- What are the ways of intensification and diversification in *Tabu Search* and *Simulated Annealing*?

Reminder from earlier studies (and, possibly, a supplement) #2

- What crossover operators do you know in evolutionary/genetic algorithms?
- What selection techniques in evolutionary algorithms do you know?
- What methods do you know of increasing the diversity of solutions during evolution?
- What is the difference between the *steady state* and the *generational replacement* architectures?
- What ways do you know to deal with constraints?

Two scenarios of using optimization algorithms

Applications of optimization algorithms can be roughly divided into interactive ones (*on-line*) and batch ones (*off-line*).

In the off-line approach, we are interested in the best solution found during the entire running time of the algorithm. In the interactive ("on-line") approach, we are interested in making a given optimization algorithm yield results as good as possible all the time. To evaluate the behavior of the optimization algorithm in the *on-line* and *off-line* scenarios, De Jong proposed specific indicators [Gol02, pp. 107, 110]; come up with the two simple ones.

Variants of evolutionary algorithms

- Genetic algorithms (GA)
- Evolutionary strategies (ES)
- Evolutionary programming (EP)
- Genetic programming (GP)
- Classifier systems (CFS) and genetics-based machine learning (GBML)
- Coevolutionary architectures
- ...

GA: John Holland (1973, 1975), David Goldberg (1989)
EP: Lawrence Fogel (1963), David Fogel (1992)
ES: Ingo Rechenberg (1973), Thomas Bäck (1996)
GP: John Koza (1992)

Reminder: algorithm structure and parameters

Main loop:

$t := 0$
initialize $P(t)$
evaluate $P(t)$
while (**not** stopping-condition)
{
    $t := t + 1$
    select $P(t)$ from $P(t-1)$
    modify $P(t)$
    evaluate $P(t)$
}

Reminder: algorithm structure and parameters

Parameters:

- population size *POPSIZE*
- probability of crossing-over *PXOVER*
- probability of mutation *PMUT*

- choosing the stopping criterion
- choosing the selection mechanism (positive and possibly negative)
- adjusting parameter values of the selection mechanism

The role of selection

- What is selection needed for in an evolutionary algorithm?
- What would happen if selection were purely random?
- What would happen if selection were deterministic and gave every individual an equal chance?
- Can the strength of the selection pressure be expressed as a number?

Discussion on the types of nondeterminism and the role of nondeterminism in algorithms and in computer science.

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The role of nondeterminism in algorithmics

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```
int random1(int n)
    static int c=-1
    c++
    c=c%n
    return c

int random2(int n)
    static int c=0
    c=(c·...+...)%n
    return c

int random3(int n)
    //very
    //complicated
    //logic
    return ...

int random4(int n)
    return %n
```

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- an example of supplementation (e.g., 4 substances every 2 days each, interactions are unknown)
- an example of giving gifts
- an example of signal dithering (audio, video, . . .) and rounding
- and finally, an example of an algorithm. . .

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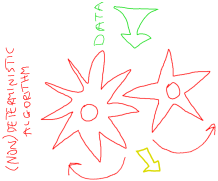
- when is true randomness preferable to good pseudo-randomness?



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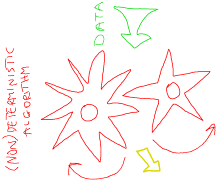

- when is true randomness preferable to good pseudo-randomness?
- and finally: should he get this funding and why??

Selection – popular techniques

f_i – the fitness of i-th individual ($i = 1..POPSIZE$)
e_i – the number of its expected copies in the new (consecutive) population,
$e_i = POPSIZE \cdot f_i / \sum f_j$

- Fitness proportionate random selection with replacement, commonly called the roulette wheel technique: individuals are assigned fields on the roulette wheel, the sizes of which are proportional to their fitness f_i. Then the roulette wheel is spun *POPSIZE* times, selecting the drawn individual. The same principle, but better properties: *stochastic universal sampling* method*.
- Stochastic remainder selection without replacement: each individual gets as many copies in the new population as the integer part of its e_i. The remaining free places are filled by randomly deciding, for each individual with the probability being the fractional part of its e_i, whether it should go to the new population. Example: 4 individuals, $\boldsymbol{f} = [1,3,5,6]$.
- Selection according to random tournaments (parameter: k – tournament size). A more careful variant of this technique ensures that each individual participates in the same number of tournaments.

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*https://en.wikipedia.org/wiki/Stochastic_universal_sampling

Selection – other techniques

- Deterministic remainder-based selection: each individual gets as many copies in the new population as the integer part of its e_i, and the remaining free places in the population are filled in order of decreasing fractional parts of individual e_i.
- Stochastic remainder selection with replacement: each individual gets as many copies in the new population as the integer part of its expected number of copies (e_i). The remaining places are filled according to the roulette principle proportionally to the fractional part of e_i.
- Ordinal selection: individuals are assigned integer ranks that correspond to their position in ranking, from best to worst. The selection is based on the probability function that depends not on raw fitness values, but on individual positions in the ranking. Various probability functions are used – linear and non-linear, and the parameters of these functions allow one to adjust selective pressure.

Exercise: classify these 6 techniques into two categories – depending on how they use the values of the fitness function.

Selection – additional properties

- Elitism (elitist model): fulfills the expectation that the selection process should not cause the loss of the best individual found so far. If such an individual does not find its way to the next population in a natural way (resulting from the selection method used), it is included in it and thus the information about the best solution so far is always preserved.
- Crowding factor model: similar to nature, where species filling the ecological niche must fight for limited resources – in the crowding model, new individuals replace old individuals (from the previous population) taking into account their similarities, i.e., new individuals take the place of the old individuals most similar to them. The crowding factor (a parameter) affects the way individuals are replaced [DJ75; Mah92].

Meta-schemes of selection

In the following selection methods, parts of the population (subpopulations) can be independently processed – these methods can therefore also act as a distribution and parallelization scheme for evolution.

- Island model: a population is split into subpopulations in which the chosen selection scheme operates (for example tournament, roulette or other). Evolution proceeds on each island independently, with periodic migration of some genotypes between islands. What effects does this have?
- Convection selection: unlike in the traditional island model, the division into subpopulations follows the similarity of the value of the objective function of solutions. What effects does this have?

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- Island model: a population is split into subpopulations in which the chosen selection scheme operates (for example tournament, roulette or other). Evolution proceeds on each island independently, with periodic migration of some genotypes between islands. This model increases exploration capabilities.
- Convection selection: unlike in the traditional island model, the division into subpopulations follows the similarity of the value of the objective function of solutions. Convection selection improves the exploration ability of an EA by properly balancing selective pressure [KU17; KM18]. The way this selection method works is illustrated in animations here.
  Discussion: how will this meta-scheme perform in *EqualNumber* and *EqualWidth* variants [KM18, Fig. 3] when the selection in subpopulations is random (e.g., tournament size $= 1$), compared to the island model and to the standard, single-population EA with random selection?

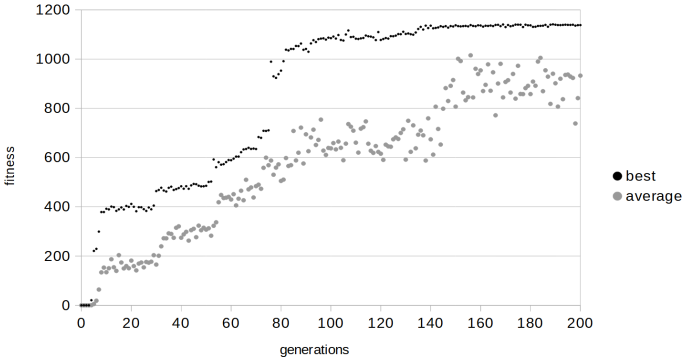
Negative selection

Sometimes (depending on the adopted GA architecture), in addition to using a positive selection, it is also necessary to employ a negative selection.

Its role is to make room in the population for new genotypes – negative selection decides which genotypes to remove from the population. Similar mechanisms as for the positive selection can be used; two examples of naive methods are deleting the worst genotype and a random one.

You ran an evolutionary algorithm with roulette selection

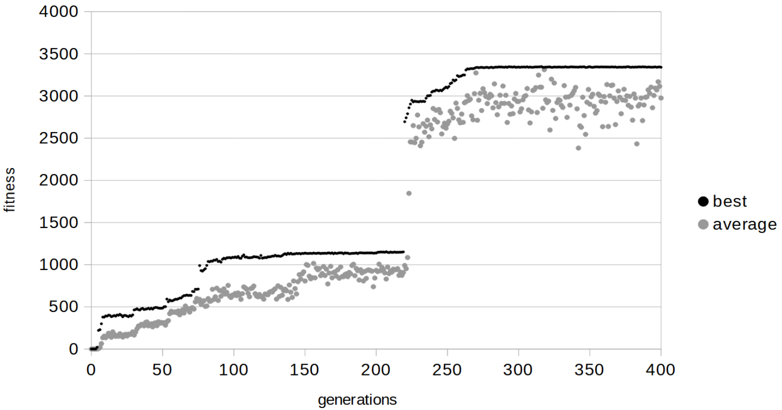
and got this outcome:



Question 1: Is it a good moment to stop optimization?

Question 2. Is it correct to conclude from this run that the diminishing (and eventually zero) improvements are due to the fact that it is becoming increasingly difficult to find better solutions in the surroundings of the population?

Answering question 1: the future is unknown!



What other criteria (apart from stabilized fitness) can be used to develop a better stopping condition and avoid the situation above?

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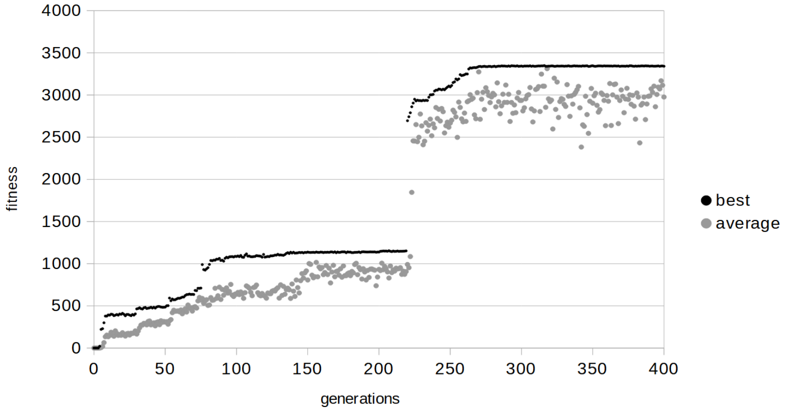

Measures of solution diversity in the population and the relationship with selection pressure and with the potential for operators to change solutions. Possibly also some knowledge (even a cursory one) of the fitness landscape.

Scaling

Discussion: where does the need for scaling come from? Analysis of the behavior of roulette selection at the beginning of evolution and in later stages (cf. previous plot).

- Linear scaling: $f' = af + b$. The coefficients a and b are adjusted so that the fitness f' of the best individual is a given multiple (for example $2\times$) of the fitness of the "average" individual. After scaling, negative fitness values may appear – you can then reset them to zero or perform another linear transformation.
- Power law scaling: $f' = f^k$. The coefficient k depends on the specific optimization task, and thus this method is not particularly useful.
- σ-truncation scaling (truncation at the level dependent on the standard deviation). Fitness values depend not only on the values of the original fitness of individuals, but also on the distribution of fitness in the population. The average fitness of the population μ and the standard deviation of the fitness in the population σ are determined, and the fitness (in the case of maximization) becomes $f' = f - (\mu - c \cdot \sigma)$. Negative values of f' are replaced by zero. The coefficient c determines the selection pressure: the larger the c, the lower the pressure.

σ-truncation scaling – example

For example 10 individuals with fitness 57, 57, 58, 58, 59, 59, 61, 62, 62, 65. The average, μ, is 59.8, and the standard deviation $\sigma = 2.6$.

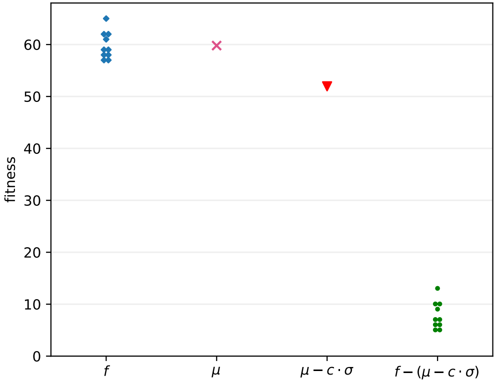

Figure: Scaling plot (truncation at the level dependent on the standard deviation) for coefficient $c = 3$.

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