Programming the Basics of an Evolutionary Algorithm(EA)

IT3708 - Subsymbolic AI methods

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Abstract

In this report, a general purpose EA solver and framework is presented and applied to the One-Max problem. Further, optimal parent selection strategies, reproduction schemes, and parameters for the evolutionary algorithm are discussed.

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1 Description of the EA program

The EA program consists of the following modules.

1. A Generic EA solver class. Acts as the evolutionary loop, calling the required methods on the EA problem.
2. A generic EA problem class. All functions are sent in as parameters, so this class simply acts as the skeleton which ties the hot-swappable components together.
3. Collections of fitness functions, adult selection functions, parent selection functions and genotype to phenotype converters.
4. A testrunner with logging and statistical capabilities.

Composing an EA problem is as simple as selecting the required functions from each set (parent selection etc), bind them together using the generic EA problem class, and then apply it to the EA solver.

2 Code modularity

A EA problem is composed by providing the functions one might want to use to an implementation of the generic EA problem class 1. The Generic EA solver is initialized with the problem, when to terminate the simulation, and then executed.

Listing 1: *constructing an ea problem*

```
ea_problem = EA_PROBLEM(vector_length=VECTOR_LENGTH,
                            fitness_function=FITNESS_FUNCTION,
                            adult_selection_function=
                                ADULT_SELECTION_FUNCTION,
                            # Some parameters omitted for brevity
                            n_reproducing_couples=N_REPRODUCING_COUPLES,
                            crossover_chance=CROSSOVER_CHANCE,
                            mutation_chance=MUTATION_CHANCE)

generation, winner = generic_ea_solver\
    .GenericEaSolver(ea_problem,
                     GENERATION_LIMIT).start_simulation()
```

Default constants are defined as follows 2. For each step of the evolutionary chain one can pick and chose between multiple functions. The collection of adult selection functions contains both full generational replacement, generational mixing, and over production, for example.

Overrides for values are accepted at runtime, but omitted for brevity.

Listing 2: *Initial values for the EA problem*

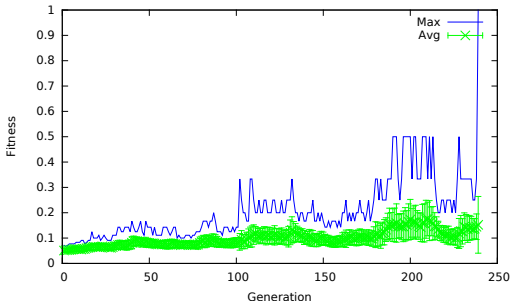
```
EA_PROBLEM = one_max_problem.OneMaxProblem
PHENO_FROM_GENO_FUNCTION = pheno_from_geno_functions\
  .identity_function
# Some assignments omitted for brevity
FITNESS_FUNCTION = fitness_functions\
  .omf_punish

POPULATION_SIZE = 200
N_REPRODUCING_COUPLES = POPULATION_SIZE / 2
VECTOR_LENGTH = 40
GENERATION_LIMIT = 400

CROSSOVER_CHANCE = 1
MUTATION_CHANCE = 0.001
```

3 40-bit One-Max with FGR and FP

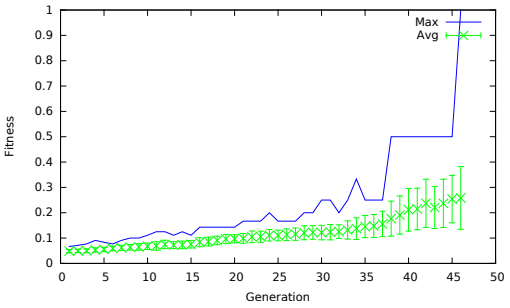
Chosing a good fitness function was paramount in minimizing the needed population size. A punishing one was chosen (fitness proportionate with the inverse of the error), which greatly increased the effectiveness of fitness-proportionate scaling due to greater spacing of good phenotypes.

A population size of 80 was consistently able to terminate in 100 generations or less (52 generations average, standard deviation 12.61, 100 runs sample size).

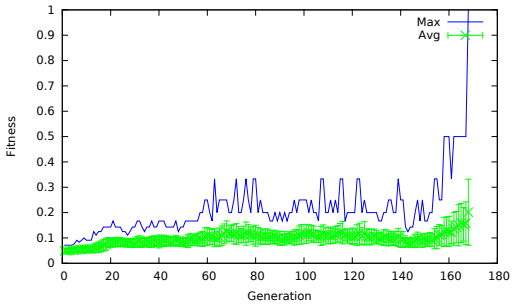
A per bit mutation chance of $(0.01 > \epsilon > 0.001)$ and a crossover rate of $\epsilon > 0.9$ was found to be optimal. Higher mutation chances led to randomized search, the opposite causing stagnation of the gene pool due to cycles and lack of variance. If none of the genomes have bit n set, no amount of crossover can generate a solution. Fitness graphs a to c in figure 2 illustrate these findings.



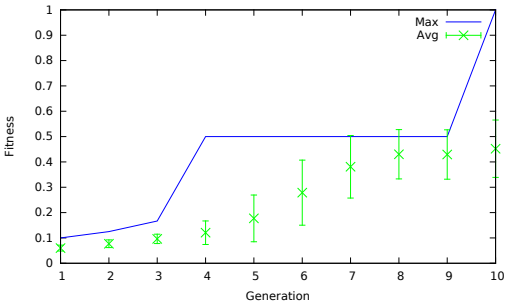
(a) *Generation size 80, crossover chance 0.6, mutation chance 0.03*



(b) *Generation size 80, crossover chance 1, mutation chance 0.01*



(c) *Generation size 80, crossover chance 1, 0.03 mutation chance*



(d) *Finding a random 40-length bit vector with tournament selection*

Figure 1: *Different parameters for FGR and FP (Includes orphaned figure for section 5 due to space issues)*

4 Parent selection functions

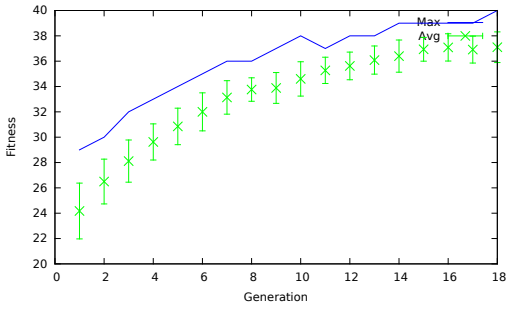
Tournament selection reigned surpreme (fig 2b, epsilon=0.2, tournament size=8), averaging 12.55 generations (2.13 std) before finishing. This is a noticeable improvement from fitness proportionate (fig 2c, 52 generations average, 12.61 std.

Sigma scaling (figure 2a) averaged 18.375 generations (4.37 std), placing itself firmly in the middle. Uniform selection with generational mixing (120 children, 80 adults) fared well (figure 2d 16.3 avg, 1.83 std) but this is due to the selection pressure of generational mixing, without which this selection mechanism devolves to random search.

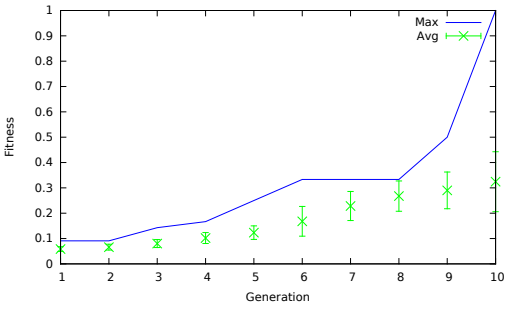
One can see how the parent selection functions extending higher selection

pressure fare much better in the simple One-Max problem. This especially due to the infrequency of local maxima, encouraging the greedy choice in most situations.

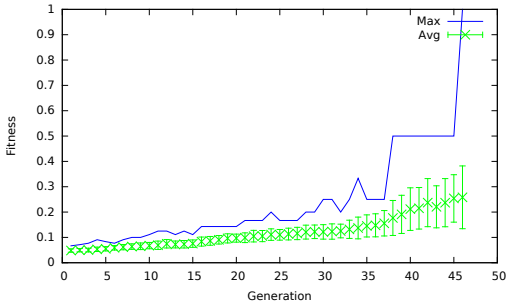
All averages were taken over a set of 100 runs.



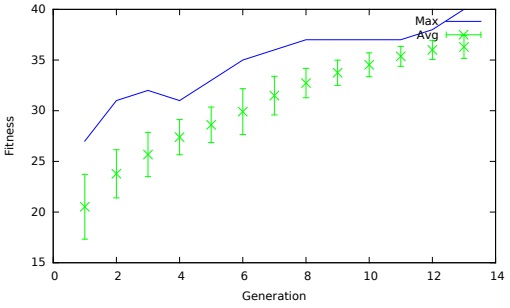
(a) *Sigma-scaling. Using a linearly rewarding fitness function*



(b) *Tournament selection (epsilon=0.2, tournament size=8*



(c) *Fitness proportionate*



(d) *Uniform selection with gen. mixing*

Figure 2: *Different adult selection algorithms, all ran with mutation=0.01, crossover=1, and population size=80*

5 Modified bit vector

Changing the target vector from all ones to a random bitvector poses only a minor jump required computational power. This due to the fact that the fitness function now has to calculate the delta between two vectors, instead of naively summing the ones.

When finding a random bitvector of length 40, tournament selection used 10.96 generations average for 100 runs (1.67 std), in line with results from finding a bit vector of all ones. An example run is included in figure 1d