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Genetic Algorithms

~~Genetic algorithms are a class of algorithms that find the solution of a problem, approximately, over a number of generations or iterations.~~

1 A genetic algorithm is a type of searching algorithm that searches the solution space for an optimal solution to a problem. It creates a poppulation of possible solutions and lets them evolve over multiple generations, to find better solutions.

2 Mutation corresponds to exploration in genetic.

3 Crossover corresponds to exploitation in genetics.

4 Selection refers to the process of picking individuals, from a poppulation, that will move to the next generation.

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⑤ Roulette Wheel Selection (RWS)

Each individual is given a space on a roulette wheel, proportional to its fitness.

$$\text{Expected Value of individual 'i' at time 't'} = \frac{\text{Fitness of individual 'i' at time}}{\text{Sum of fitness of all individuals at time 't'}}$$

$$\Rightarrow \text{Expected Value}(i,t) = \frac{fit(i,t)}{F(t)}, \text{ where}$$

$$F(t) = \sum_{1}^{n} fit(i,t)$$

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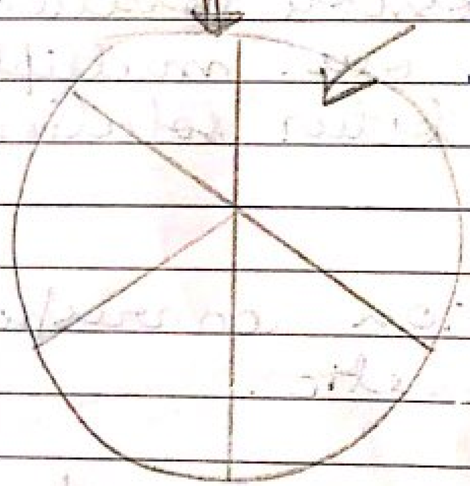
space proportional to fitness.



To obtain a mating pool of size N, the wheel is rotated N times, and the individual pointed to by the header is selected.

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(6) Stochastic Uniform Selection (SUS)

Let $p = \frac{F}{N}$, where F is the sum of fitness of all individuals and N is the number of individuals in the population

Let selector = random(0, p)

Then $P = \{x : x = selector + i * p, \; i \in [0, N-1]\}$

The SUS algorithm states -

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for i in [0, N-1, 1]
    sum = 0; j = 0
    for sum < P[i]
        sum += fit(j, t)
        j++
    add j to the mating pool
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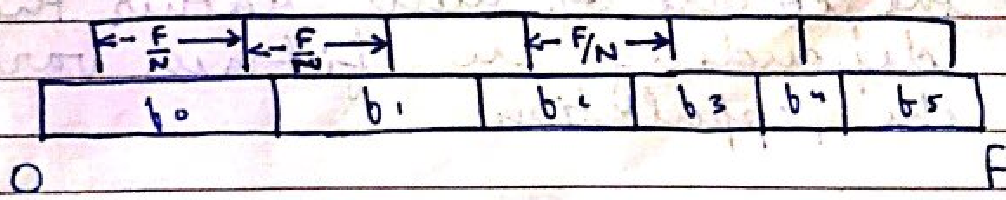

Hence the individuals will be selected based on the proportion of their fitness to the total fitness of the population.

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Under the two previous schemes of selection based on fitness proportional the fit individuals and their descendants will multiply quickly in the popppulation, this prematurely the algorithm from doing further exploration. The new generation will be concentrated in an optimal region rather than searching for an even better solution. This is known as premature convergence.

A solution to the above problem is

(7) Sigma scaling:

Selection pressure is the degree to which highly fit individuals are allowed many offsprings.

Sigma scaling keeps the selection pressure relatively constant ~~at~~ over the course of run rather than depending on fitness variance in the popppulation.

Under sigma scaling the expected value of an individual is ~~the~~ a function of its fitness, the population mean and the population std. deviation.

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For example

$$\text{ExpValue}(i,t) = \begin{cases} 1 + \dfrac{f(i) - \bar{f}(t)}{2\sigma(t)}, & \text{if } \sigma(t) \neq 0 \\ 1.0, & \text{if } \sigma(t) = 0 \end{cases}$$

For individuals with fitness value one std. deviation above mean fitness are allowed 1.5 expected offsprings.

If expval is less than 0, it can be reset to a small positive value, so that even the less fit individuals have a chance to reproduce.

Initially the std. deviation of fitness will be high, thus even the most fit individuals will not be given an unfairly large chance to propagate. Later in the run standard deviation would decrease and the fitter individuals will stand out more.

This way, we can ensure variety.

(8) Boltzman Selection

Often different amount of selection pressure is needed at different times in a run, eg. early on it might be good to ~~be~~ liberal but in later

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stages it might be good to allow only the strong individuals to reproduce.

We control the selection pressure using a parameter 'temperature' (T)

$$\text{ExpVal}(i,t) = \frac{e^{f(i)/T}}{\langle e^{f(i)/T} \rangle_t}$$

where T is the temperature and $\langle e^{f(i)/T} \rangle_t$ is the average of $e^{f(i)/T}$ of all the individuals at time t.

As T decreases, the difference in expected values of strong and weak individuals increases.

(9) Genetic Algorithms are heavily used in optimization of weights.

(10) ExpVal can never be negative.

(11) In sigma scaling $1 + \frac{f(i,t) - \overline{f(t)}}{2\sigma(t)}$ near convergence $\overline{f(t)}$ starts increasing and $\sigma(t)$ starts decreasing.

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(12) When do we stop the evolution?
⇒ We stop evolution when either the best fitness or average fitness remains almost same for a number of generations.

(13) Due to undefined termination times GAs cannot be used in real time systems.

(14) Elitism : A selection method where the few most fit solutions are preserved over to the next generation.

(15) Rank Selection : Solutions are ranked corresponding to their fitness.

$$ExpVal(i, t) = min + (max - min) * \frac{Rank(i,t) -}{N - 1}$$

(16) Schema Theory — Why GAs work?

(17) Tournament Selection: Two solutions are chosen at random, we choose a random number between 0 and 1, called 'K'. Then we calculate r = rand(0, 1). If 'r > K' then we choose the less fit individual and vice versa. The individuals are then replaced in the population.

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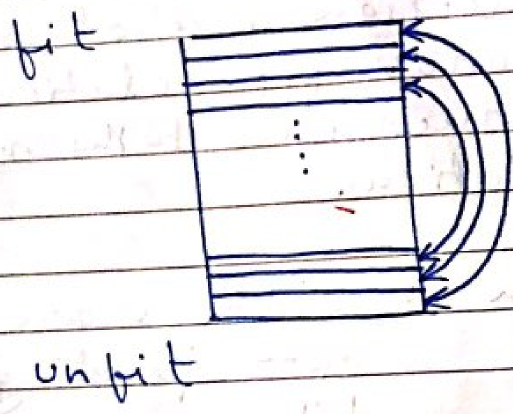
(18) Steady state selection: It is usually used along with elitism (almost all heuristics can be applied alongside elitism). A fit individual is made to mate with a less fit individual. Thus the crossover gives rise to exploitation but there will be an element of exploration.



(19) Cuckoo Search: It is a meta heuristic. A solution is an egg in the nest. A cuckoo comes and picks a random nest containing an egg (i.e. a solution). If the cuckoo's egg (solution) is more fit than the selected egg the cuckoo replaces the previous egg (solution) with its own egg (solution). When the crow returns it identifies some foreign eggs and replace them again with its own eggs.

(20) Heavy tailed and Long tailed distributions must be used to generate random numbers