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Nature Inspired Search and Optimisation

22 – Runtime Analysis

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Evolutionary Algorithms

$(\mu+\lambda)$ EA

Initialise P_0 with μ individuals chosen uniformly a random from $\{0,1\}^n$
for $t = 0, 1, 2, \dots$ until stopping condition met **do**
 Create λ new individuals by

- choosing $x \in P_t$ uniformly at random
- flipping each bit in x with probability p

 Create the new population P_{t+1} by
 choosing the best μ individuals out of $\mu + \lambda$.
end for

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- If $\mu = \lambda = 1$, then we get the $(1+1)$ EA;
- $p = 1/n$ is generally considered a good parameter setting [Bäck, 1993, Droste et al., 1998];
- By introducing stochastic selection and crossover we obtain a **Genetic Algorithm** (GA)

(1+1) Evolutionary Algorithm

(1+1) EA

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repeat

 Create x' by flipping each bit in x with $p = 1/n$.

if $f(x') \geq f(x)$ **then**

$x \leftarrow x'$.

end if

until stopping condition met.

If only one bit is flipped per iteration: Random Local Search (RLS).

How does it work?

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$$= \sum_{i=1}^n 1 \cdot 1/n = n/n = 1$$

$(1+1)$ EA: 2

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$$\begin{aligned} \Pr(X = 2) &= \binom{n}{2} \left(\frac{1}{n}\right)^2 \left(1 - \frac{1}{n}\right)^{n-2} \\ &= \frac{n(n-1)}{2} \left(\frac{1}{n}\right)^2 \left(1 - \frac{1}{n}\right)^{n-2} \\ &= \frac{1}{2} \left(1 - \frac{1}{n}\right)^{n-1} \approx 1/(2e) \end{aligned}$$

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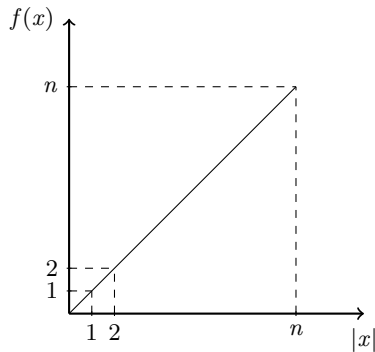
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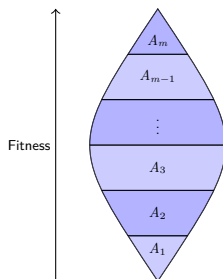
$$\Pr(X = 0) = \binom{n}{0} (1/n)^0 \cdot (1 - 1/n)^n \approx 1/e$$

ONEMAX

$$\text{ONEMAX}(x) := x_1 + x_2 + \cdots + x_n = \sum_{i=1}^n x_i$$



Fitness-based Partitions



Definition

A tuple (A_1, A_2, \dots, A_m) is an **f -based partition** of $f : \mathcal{X} \rightarrow \mathbb{R}$ if

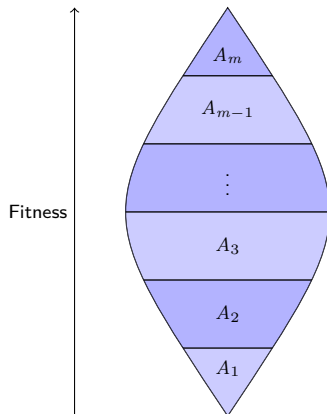
- ① $A_1 \cup A_2 \cup \dots \cup A_m = \mathcal{X}$
- ② $A_i \cap A_j = \emptyset$ for $i \neq j$
- ③ $f(A_1) < f(A_2) < \dots < f(A_m)$
- ④ $f(A_m) = \max_x f(x)$

Example

Partition of ONEMAX into $n + 1$ levels

$$A_j := \{x \in \{0, 1\}^n \mid \text{ONEMAX}(x) = j\}$$

Artificial Fitness Levels - Upper bounds



s_i : prob. of starting in A_i

u_i : prob. of jumping from A_i to any A_j , $i < j$.

T_i : Time to jump from A_i to any A_j , $i < j$.

Expected runtime

$$\begin{aligned} \mathbb{E}[T] &\leq \sum_{i=1}^{m-1} s_i \mathbb{E} \left[\sum_{j=i}^{m-1} T_j \right] \\ &= \sum_{i=1}^{m-1} s_i \sum_{j=i}^{m-1} \mathbb{E}[T_j] \\ &= \sum_{i=1}^{m-1} s_i \sum_{j=i}^{m-1} 1/u_j \leq \sum_{j=1}^{m-1} 1/u_j. \end{aligned}$$

(1+1) EA on ONEMAX

Theorem

The expected runtime of (1+1) EA on ONEMAX is $O(n \ln n)$.

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- To reach a higher fitness level it is sufficient to flip a zero into a one and leave the other bits unchanged, which occurs with probability

$$u_j \geq (n - j) \frac{1}{n} \left(1 - \frac{1}{n}\right)^{n-1} \geq \frac{n - j}{en}$$

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- Then by Artificial Fitness Levels

$$\mathbb{E}[T] \leq \sum_{j=0}^{m-1} 1/u_j \leq \sum_{j=0}^{n-1} \frac{en}{n-j} = en \sum_{i=1}^n \frac{1}{i} \leq en(\ln n + 1) = O(n \ln n)$$