Linear Function with Harmonic Weights Problem F3

The F3 problem is intened to maximise value of the linear function, but this can deduce to the OneMax problem, as for the definition of the linear function of $i \cdot x_i + \ldots + n \cdot x_n$, the value of the function only incease when there is increasing in the number of ones. Given $\mathbf{x} \in \{0,1\}^n$ thus we have that,

$$\underset{\mathbf{x} \in \{0,1\}^n}{\arg \max} \, \mathsf{F}(\mathbf{x}) \text{ where } \mathsf{F}(\mathbf{x}) = \sum_{i=1}^n i x_i$$

RLS Setup

RLS

- 1. Choose $\mathbf{x} \in \{0,1\}^n$ randomly.
- 2. Produce \mathbf{x}' from \mathbf{x} by flipping **one** randomly chosen bit.
- 3. Replace \mathbf{x} by \mathbf{x}' if $\mathsf{F}(\mathbf{x}) \geq \mathsf{F}(\mathbf{x})$.
- 4. Repeat Steps 2 and 3 forever.

Problem

Prove that Random Local Search with fitness evaluations to reach an optimal search point for the function F3 is

$$\mathcal{O}(n \log n)$$
 with probability of $\Omega(1)$

Proof. From the Put the link here: Chernoff Bound Initialisation, we know that the tuple \mathbf{x} will expect to have 2n/3 ones after initialisation with a high probability. Thus now we care for m = n/3 0-bits to be flipped. Let t_i be the number of times to flip each 0-bit where $i = k, k + 1, \ldots, m$ $t_i \sim \text{Geo}(p_i)$, where p_i is defined as

$$p_i = \frac{m - (i - 1)}{n}$$

And the expected number of times to flipped the i^{th} to 1 is

$$\mathbb{E}[t_i] = \frac{n}{m - (i - 1)}$$

Let $T = \sum_{i=k}^{m-1} t_i$ be the total time to get to optimum. Then, from the note, put link here using the Coupon Theorem,

$$\mathbb{E}[T] = n \ln(n - k + 1) + \mathcal{C}, \quad \text{where } \mathcal{C} > 0$$

Recall that for upper bound,

$$\mathcal{O}(n\log n) = \{g(n) : \exists c > 0 : \exists n_0 \in \mathbb{N}^+ : \forall n \ge n_0 : g(n) \le c \cdot n\log n\}$$

Given that $g(n) = n \ln(n - k + 1) + C$, thus:

$$n \ln(n - k + 1) + \mathcal{C} \le cn$$

 $\Rightarrow c > \ln(n - k + 1) + \mathcal{C}$

Therefore there exists such c > 0, hence

$$\mathbb{E}[T] = \mathcal{O}(n \log n)$$

Recall the Markov's inequality

$$P(X \ge s \cdot \mathbb{E}[X]) \le \frac{1}{s}$$
, where $s > 0$

Then,

$$P(T \ge \mathbb{E}[T]) \le 1$$

$$\Rightarrow P(T < \mathbb{E}[T]) \ge 0 = \Omega(1)$$

Thus the probability of having at least one successful flip to 1-bit in less than the expected time, = is neglectible for large time is $P(T < \mathbb{E}[T]) = \Omega(1)$

(1+1) EA Setup

(1+1) EA

- 1. Choose $\mathbf{x} \in \{0,1\}^n$ randomly.
- 2. Produce \mathbf{x}' from flipping each bit of \mathbf{x} with probability 1/n
- 3. Replace \mathbf{x} by \mathbf{x}' if $\mathsf{F}(\mathbf{x}') \geq \mathsf{F}(\mathbf{x})$.
- 4. Repeat Steps 2 and 3 forever.

Problem

Prove that (1+1) EA with fitness evaluations to reach an optimal search point for the function F3 is

$$\mathcal{O}(n \log n)$$
 with probability of $\Omega(1)$

Proof. Given that the (1+1) EA and (1+1) EA_b is similar from the pseudo-code of [1, p.42]. From [1, p.44]

Assume that we are working in a search space S and consider w.l.o.g. a function $f: S \to \mathbb{R}$ that should be maximized. S is partitioned into disjoint sets A_1, \ldots, A_m such that $A_1 <_f A_2 <_f \cdots <_f A_m$ holds, where $A_i <_f A_j$ means that f(a) < f(b) holds for all $a \in A_i$ and all $b \in A_j$. In addition, A_m contains only optimal search points. An illustration is given in Figure 4.1. We denote for a search point $x \in A_i$ by p(x) the probability that in the next step a solution $x' \in A_{i+1} \cup \cdots \cup A_m$ is produced. Let $p_i = \min_{a \in A_i} p(a)$ be the smallest probability of producing a solution with a higher partition number. [1, p. 44]

There are n = m, as similar problem to OneMax, levels. Each level are defined as $A_i = \{1\}^i$ for i = 1, 2, ..., m. Suppose that the algorithm is currently in A_{m-k} level. There are k 0-bits left.

$$\frac{1}{n}, \quad \text{A specific bit is flipped to 1}$$

$$1 - \frac{1}{n}, \quad \text{A specific bit is not flipped to 1}$$

$$\left(1 - \frac{1}{n}\right)^{(n-1)}, \quad \text{All } n - 1 \text{ bits are not flipped to 1}$$

$$\frac{1}{n} \cdot \left(1 - \frac{1}{n}\right)^{(n-1)}, \quad \text{All } n - 1 \text{ bits are not flipped to 1, except for a bit to be flipped to 1}$$

$$\frac{k}{n} \cdot \left(1 - \frac{1}{n}\right)^{(n-1)}, \quad \text{All } n - 1 \text{ bits are not flipped to 1, except for the } k \text{ bits to be flipped to 1}$$

We have that,

$$\left(1 - \frac{1}{n}\right)^{(n-1)} \ge \frac{1}{e}$$

Thus,

$$\frac{k}{n} \cdot \left(1 - \frac{1}{n}\right)^{(n-1)} \ge \frac{k}{ne}$$

Then the transition probability to move to the next level for a better result is.

$$p_{n-k} \ge \frac{k}{en}$$

From Lemma 4.1[1, p.45] we have that $A_{n-k} \leq \frac{1}{p_{n-k}} \leq \frac{en}{k}$. The algorithm must move up all the levels until to reach level m for the optimum. Thus we have that,

$$\mathbb{E}[T] \le \sum_{k=1}^{m-1} \frac{en}{k}$$

$$\mathbb{E}[T] \le en \sum_{k=1}^{m-1} \frac{1}{k}$$

$$\mathbb{E}[T] \le en \cdot H_{m-1}$$

Using the proof from above note we have that

$$en \cdot H_{m-1} = \mathcal{O}(n \log n)$$

Thus

$$\mathbb{E}[T] = \mathcal{O}(n \log n)$$

References

[1] Frank Neumann and Carsten Witt. Bioinspired Computation in Combinatorial Optimization: Algorithms and Their Computational Complexity. Natural Computing Series. Springer, 2010. DOI: 10.1007/978-3-642-16544-3.