

CS4618 Artificial Intelligence I

Today: Analysing Mutation
Applying RSH

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Plans for Today

- 1 Analysing Mutation
Motivation
- 2 Global Mutations Excel
Shortcuts
- 3 Local Mutations Excel
Traps
- 4 Research
Intuition and Counterexample
- 5 Applying RSH
Problem Modelling
- 6 Summary
Summary & Take Home Message

Comparing Mutation Operators

Remember (1+1) EA and RLS are algorithmically similar they only differ in the mutation operator

RLS 1-bit flips

(1+1) EA flip each bit with probability $1/n$

\rightsquigarrow in expectation 1 bit flipped for both

We have seen

- on ONEMAX both algorithms in time $O(n \log n)$
- on $f_1(x) = \begin{cases} \text{ONEMAX}(x) & \text{if } |x| \neq n - 1 \\ 0 & \text{otherwise} \end{cases}$

(1+1) EA in time $O(n^2)$

RLS in finite time only with probability 2^{-n+1}

- useful proof method: f -based partitions
- useful visualisation of functions
 - plotted over number of 1-bits (not always possible)
 - as 'map' over search space

On Comparing Mutation Operators

So we have compare local mutations (RLS)
with global mutations ((1+1) EA)
and proved that global mutations **outperform** local mutations
when local optima a involved

Observation **completely pointless** and **completely obvious**

More useful question **Can global mutations outperform local mutations
on functions without local optima?**

Interlude: A Useful Tool

Long k -Paths (introduced by Horn, Goldberg, and Deb (1994))

Definition

- long k -path of dimension 1

$$P_k^1 = (0, 1)$$

- long k -path of dimension n

$$P_k^n = (0^k v_1, 0^k v_2, \dots, 0^k v_l, 10^{k-1} v_l, 1^2 0^{k-2} v_l, \dots, 1^k v_l, 1^k v_{l-1}, \dots, 1^k v_1)$$

$$\text{if } P_k^{n-k} = (v_1, v_2, \dots, v_l)$$

Properties

- length $(k + 1) \cdot 2^{(n-1)/k} - k + 1$
- $\forall p \in P_k^n: \forall i \in \{1, 2, \dots, k-1\}: \exists_1 \text{successor } y \in P_k^n: H(p, y) = i$

Long Path Function

Example

$$f_2(x) := \begin{cases} n^2 + p & \text{if } x = v_p \in P_2^n \\ n^2 - n \cdot \left(\sum_{i=1}^2 x[i] \right) - \sum_{i=3}^n x[i] & \text{otherwise} \end{cases}$$

Easy to prove $E(T_{\text{RLS}, f_2}) = \Omega(n \cdot |P_2^n|) = \Omega(n \cdot 2^{n/2})$
Idea Prob (hit path in first half) $\geq 1/2 = \Omega(1)$
 after that specific 1-bit mutations needed ✓

Observe $E(T_{(1+1)\text{ EA}, f_2}) = O(n^3)$ (due to Rudolph (1996))
Idea taking $\leq n$ shortcuts suffices
 for each **shortcut** 2-bit mutation suffices
 (formal proof with f_2 -based partition) ✓

What we have so far

- global and local mutations can result in almost equal performance

on **ONEMAX**

(1+1) EA in time $O(n \log n)$, RLS in time $O(n \log n)$

- global mutations outperform local mutations when local optima are involved

on $f_1(x) = \begin{cases} \text{ONEMAX}(x) & \text{if } |x| \neq n - 1 \\ 0 & \text{otherwise} \end{cases}$

(1+1) EA in time $O(n^2)$

RLS in finite time only with probability 2^{-n+1}

- global mutations can exploit shortcuts that are not available to local mutations

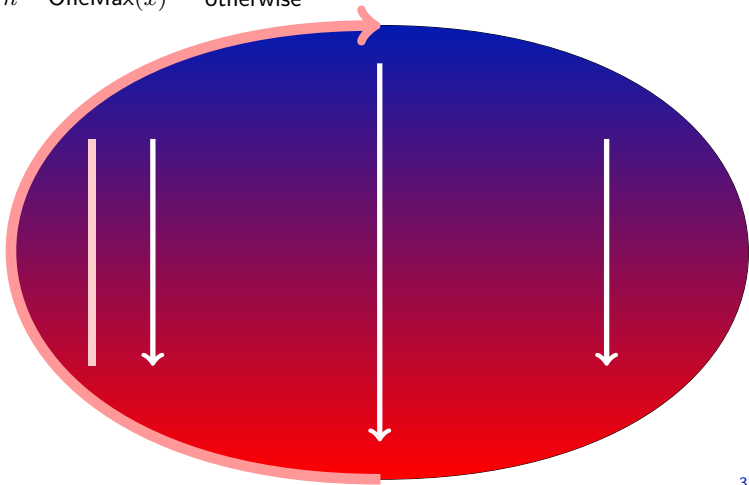
on a long path function

(1+1) EA in time $O(n^3)$, RLS in time $\Omega(n \cdot 2^{n/2})$

Can global mutations be very much slower than local mutations?

Trapping Global Mutations

$$f_3(x) := \begin{cases} n + 2i & \text{if } x = 1^i 0^{n-i} \\ 3n - 1 & \text{if } x = 1^i 0^j 10^k 10^{n-i-j-k-2} \\ & \text{with } n/4 \leq i \leq 3n/4 \text{ and } j > 0 \\ n - \text{OneMax}(x) & \text{otherwise} \end{cases}$$



RLS on f_3

$$f_3(x) := \begin{cases} n + 2i & \text{if } x = 1^i 0^{n-i} \\ 3n - 1 & \text{if } x = 1^i 0^j 10^k 10^{n-i-j-k-2} \\ & \text{with } n/4 \leq i \leq 3n/4 \text{ and } j > 0 \\ n - \text{OneMax}(x) & \text{otherwise} \end{cases}$$

Theorem

$$\text{Prob}(T_{\text{RLS}, f_3} = O(n^2)) = 1 - 2^{-\Omega(n)}$$

Proof

Observation $\text{Prob}(\text{trap not found}) = 1 - 2^{-\Omega(n)}$ ✓

Observation

$$\mathbb{E}(T_{\text{RLS}, f_3} \mid \text{trap not found}) = O(n \log n) + \mathbb{E}(\text{time on ridge})$$

RLS on the Ridge

$$f_3(x) := \begin{cases} n + 2i & \text{if } x = 1^i 0^{n-i} \\ 3n - 1 & \text{if } x = 1^i 0^j 10^k 10^{n-i-j-k-2} \\ & \text{with } n/4 \leq i \leq 3n/4 \text{ and } j > 0 \\ n - \text{OneMax}(x) & \text{otherwise} \end{cases}$$

$$\begin{aligned} \mathbb{E}(\text{time on ridge}) &= \sum_{i=0}^{n-1} \mathbb{E}(\text{time with } |x| = i) \\ &\leq \sum_{i=0}^{n-1} \left(\frac{1}{n}\right)^{-1} = n \cdot \sum_{i=0}^{n-1} 1 = n^2 \end{aligned}$$

Thus $\mathbb{E}(T_{\text{RLS}, f_3} \mid \text{trap not found})$
 $= O(n \log n) + \mathbb{E}(\text{time on ridge})$
 $= O(n \log n) + O(n^2) = O(n^2)$



(1+1) EA on f_3

$$f_3(x) := \begin{cases} n + 2i & \text{if } x = 1^i 0^{n-i} \\ 3n - 1 & \text{if } x = 1^i 0^j 10^k 10^{n-i-j-k-2} \\ & \text{with } n/4 \leq i \leq 3n/4 \text{ and } j > 0 \\ n - \text{OneMax}(x) & \text{otherwise} \end{cases}$$

Theorem

$$\text{Prob} \left(T_{(1+1) \text{ EA}, f_3} \geq n^{n/4} \right) = 1 - 2^{-\Omega(n)}$$

Proof

Observation $E \left(T_{(1+1) \text{ EA}, f_3} \mid \text{trapped} \right) \geq \left(\left(\frac{1}{n} \right)^{n/4} \right)^{-1} = n^{n/4}$

Needed $\text{Prob}(\text{enter trap})$

On Entering the Trap

$$f_3(x) := \begin{cases} n + 2i & \text{if } x = 1^i 0^{n-i} \\ 3n - 1 & \text{if } x = 1^i 0^j 10^k 10^{n-i-j-k-2} \\ & \text{with } n/4 \leq i \leq 3n/4 \text{ and } j > 0 \\ n - \text{OneMax}(x) & \text{otherwise} \end{cases}$$

Prob ((1+1) EA enters trap)

= Prob ((1+1) EA enters trap 'in the beginning')

+ Prob ((1+1) EA enters trap 'when on the ridge')

like for RLS

Prob ((1+1) EA enters trap 'in the beginning') = $2^{-\Omega(n)}$ negligible

Observation Prob (improve on ridge) = $\Theta\left(\frac{1}{n}\right)$

$$\begin{aligned} \text{Prob (enter trap)} &\geq \binom{n/4}{2} \left(\frac{1}{n}\right)^2 \cdot \left(1 - \frac{1}{n}\right)^{n-2} \\ &\geq \frac{(n/4) \cdot (n/4 - 1)}{2} \cdot \frac{1}{n^2} \cdot \frac{1}{e} = \Theta(1) \end{aligned}$$

Thus in each step on the ridge Prob (enter trap) = $1 - O(1/n)$

Thus Prob (don't enter trap) = $1 - 2^{-\Omega(n)}$ □

One Word on Research

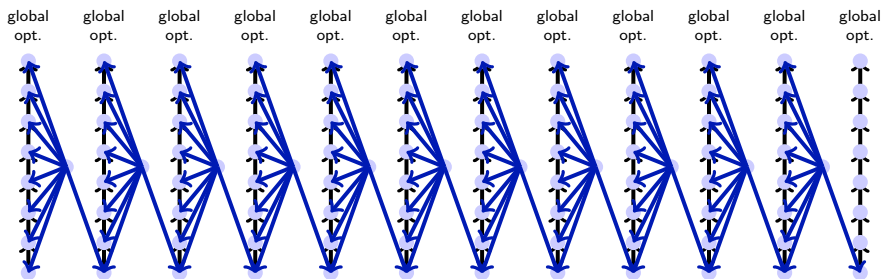
When do local and global mutations perform similar?

Idea when there are no local optima and no traps

Fact **wrong**

Idea for proving this wrong

Think random walk on graph with
single steps for RLS, double steps for $(1+1)$ EA



Embedding the Counter-Example in $\{0, 1\}^n$

Definition

For $n \in \mathbb{N}$ with $n \geq 16$

$$n_1 := 4 \cdot \lfloor n/8 \rfloor, k := \lfloor \sqrt{n_1 - 1} \rfloor, n_2 := k^2 + 1, n_3 := n - n_1 - n_2.$$

For $x = x_1 x_2 x_3 \in \{0, 1\}^n$ (with $\forall i \in \{1, 2, 3\}: x_i \in \{0, 1\}^{n_i}$)

$$f_4(x) := \begin{cases} 2^n \cdot n^2 & \text{if } x_1 = 1^{n_1} \text{ or } x_2 = v_l \\ i \cdot n^2 + j & \text{if } x_1 = 1^j 0^{n_1-j}, x_2 = v_i \\ i \cdot n^2 + n + n_1 - j_1 & \text{if } x_1 = 1^{j_1} 0^{j_2} 10^{j_3} 10^{n_1-j_1-j_2-j_3-2}, x_2 = v_i, \\ & n_1/4 \leq j_1 + j_2 \leq n_1/2, j_1 + j_2 + j_3 \geq (3/4)n_1 \\ i \cdot n^2 + 2n & \text{if } x_1 = 0^j 10^{n_1-j-1}, n_1/4 \leq j \leq n_1/2, \\ & x_2 = v_i, i \text{ odd} \\ i \cdot n^2 - 1 & \text{if } x_1 = 0^j 10^{n_1-j-1}, n_1/4 \leq j \leq n_1/2, \\ & x_2 = v_i, i \text{ even} \\ i \cdot n^2 + 2n & \text{if } x_1 = 0^j 10^{n_1-j-1}, j > n_1/2, \\ & x_2 = v_i, i \text{ even} \\ i \cdot n^2 - 1 & \text{if } x_1 = 0^j 10^{n_1-j-1}, j > n_1/2, \\ & x_2 = v_i, i \text{ odd} \\ n - |x| & \text{otherwise} \end{cases}$$

Result and Open Problem

Theorem

$$\forall x \in \{0, 1\}^n : \mathbb{E}(T_{\text{RLS}, f_4} \mid x_0 = x) = O(n^2)$$

$$\text{Prob}(T_{(1+1)\text{EA}, f_4} = 2^{\Omega(\sqrt{n})}) = 1 - 2^{-\Omega(\sqrt{n})}$$

For a proof see B. Doerr, T. Jansen, C. Klein (GECCO 2008):
Comparing global and local mutations on bit strings.

Still open For what class of functions do RLS and (1+1) EA
have similar performance?

More precisely 'Find X such that Y '

Instantiations of X

- sufficient conditions
- necessary and sufficient conditions
- interesting function classes
- relevant function classes

Instantiations of Y

- $\mathbb{E}(T_{\text{RLS}, f}) = \Theta(t(n))$
 $\Rightarrow \mathbb{E}(T_{(1+1)\text{EA}, f}) = \Theta(t(n))$
- $\mathbb{E}(T_{\text{RLS}, f}) = O(t(n))$
 $\Rightarrow \mathbb{E}(T_{(1+1)\text{EA}, f}) = O(t(n))$
- $\mathbb{E}(T_{\text{RLS}, f}) = O(t(n))$
 $\Rightarrow \mathbb{E}(T_{(1+1)\text{EA}, f}) = O(p(t(n))), p \text{ poly.}$

Applying Randomised Search Heuristics

Situation have difficult optimisation problem
 have no good problem-specific algorithm
 have desire to apply standard randomised search heuristic

Observation **encoding** of the problem required
 so that it matches the standard setting
 of the randomised search heuristics

Main Ingredients

- **problem-wise**
 - set of potential solutions P
 - quality measure $g: P \rightarrow \mathbb{R}$
- **RSH-wise**
 - standard search space S (e. g., $S = \{0, 1\}^n$)
 - fitness function $f: S \rightarrow \mathbb{R}$

Observation one way of solving this gap
 design mapping $m: S \rightarrow P$
 delivers $f(s) = g(m(s))$

More Freedom in the Design

We have one way of solving this gap
 design mapping $m: S \rightarrow P$
delivers $f(s) = g(m(s))$

Observation more freedom in design by
 designing mapping $m: S \rightarrow P \cup I$
 (I set of invalid solutions)
delivers $f(s) = g(m(s))$ if $m(s) \in P$

Remark optimisation problems with constraints
 introduce I naturally

often specific optimisation problem
 easier to represent as constrained case of more general problem

Design Guidelines

Setting **have** problem by means of
 potential solutions P and quality measure $g: P \rightarrow \mathbb{R}$
have standard RSH
 with search space S and fitness $f: S \rightarrow \mathbb{R}$
design encoding by
 mapping $m: S \rightarrow P \cup I$ gives $f(s) = g(m(s))$ for $m(s) \in P$

Design Guidelines

- $m(s)$ must be computable efficiently, for all $s \in S$
- ideally, m should be **bijective**
- if not possible, try to make m **surjective**
- if not possible, have $s \in S$ with $m(s) = p$ for all important p
- make m 'even': $|m^{-1}(p)|$ roughly equal for all $p \in P$
- $s \approx s'$ should imply $m(s) \approx m(s')$ (and vice versa)
- make finding P from I as easy as possible

Summary & Take Home Message

Things to remember

- Local mutations may systematically miss shortcuts.
- Global mutations can get trapped.
- Telling when local and global mutations are equal is an open problem.
- Applying standard RSH to optimisation problems requires modelling.

Take Home Message

- Equal expected behaviour is very much different from equal behaviour.
- Be careful when something is intuitively clear.