

Summer Term 2017

## Homework 3 – *Nature Inspired Algorithms*

<https://hpi.de/friedrich/teaching/ss17/natinsalg.html>

The goal of this homework is to review some of the basic concepts in the theoretical analysis of nature-inspired algorithms. The lecture slides for lectures 3 and 4 (posted to the Moodle) should be a helpful resource for this assignment. You will also need the concept of *conditional expectation*, which is outlined in the gray box below.

The homework is submitted on Moodle (<https://hpi.de/friedrich/moodle/>) by uploading a PDF file with your solutions. You are welcome to write your solutions out by hand and scan them.

Given two events  $A$  and  $B$  from a probability space with  $\Pr(B) > 0$ , the conditional probability of  $A$  given  $B$  is defined as  $\Pr(A | B) = \Pr(A \cap B) / \Pr(B)$ . Roughly speaking, the *conditional expectation*<sup>a</sup> of a random variable is the expectation *given* that a certain event has occurred. For example, let  $X$  be the random variable that corresponds to the value that comes up on the toss of a six-sided die. The expectation of  $X$  is

$$E(X) = \sum_{\omega \in \Omega} X(\omega) \Pr(\omega) = \sum_{i=1}^6 i/6 = \frac{21}{6} = 3.5.$$

Let  $\mathcal{E}$  be the event that the die comes up with an even number. The expectation of  $X$  *conditioned* on  $\mathcal{E}$  is

$$\begin{aligned} E(X | \mathcal{E}) &= \sum_{\omega \in \Omega} X(\omega) \Pr(\omega | \mathcal{E}) = \sum_{\omega \in \Omega} X(\omega) \frac{\Pr(\{\omega\} \cap \mathcal{E})}{\Pr(\mathcal{E})} \\ &= \frac{(0 + 2/6 + 0 + 4/6 + 0 + 6/6)}{1/2} = 4. \end{aligned}$$

We used the fact that  $\Pr(\emptyset) = 0$ .

<sup>a</sup>[http://en.wikipedia.org/wiki/Conditional\\_expectation](http://en.wikipedia.org/wiki/Conditional_expectation)

**Theorem 1 (Law of Total Expectation)** Let  $\mathcal{E}$  and  $\mathcal{F}$  be mutually disjoint events and  $\mathcal{E} \cup \mathcal{F} = \Omega$ . Denote as  $E(T | \mathcal{E})$  the expectation of  $T$  conditioned on event  $\mathcal{E}$ . Then  $E(T) = E(T | \mathcal{E}) \Pr(\mathcal{E}) + E(T | \mathcal{F}) \Pr(\mathcal{F})$ .

Earlier in the semester, I claimed that there are functions on which the runtime of the (1+1) EA can be worse than the worst-case runtime of blind RANDOMSEARCH.

Define the function  $g: \{0, 1\}^n \rightarrow \mathbb{R}$  as follows

$$g(x) = \begin{cases} 2 & \text{if } |x|_1 = n, \\ 0 & \text{if } 3n/4 \leq |x|_1 < n, \\ 1 & \text{otherwise;} \end{cases}$$

**Exercise 4** *Answer the following.*

- (a) *What is the expected runtime of RANDOMSEARCH to maximize  $g$ ?*
- (b) *Let  $\mathcal{E}$  be the event that the initial solution of the  $(1+1)$  EA has at most  $n/4$  zero bits. Derive an upper bound on  $\Pr(\mathcal{E})$ .*  
***Hint: use one of the methods we discussed in Lecture 4.***
- (c) *Suppose  $\mathcal{E}$  has **not** occurred. Give a lower bound on the expected time for the  $(1+1)$  EA to first generate the all-ones string under this condition.*
- (d) *Conclude that the expected runtime to maximize  $g$  for the  $(1+1)$  EA is worse than the runtime of RANDOMSEARCH on  $g$ .*  
***Hint: use the law in Theorem 1.***