

# Randomised Algorithms

## Winter term 2022/2023, Exercise Sheet No. 4

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### Exercise 1.

(a) Every deterministic algorithm has a predefined list of  $S$  that it checks in the same order, hence is  $s^*$  was the last item in the algorithm's list, it would be forced to try all words in  $S$ . To know this input we can try a naive approach, try all words of  $S$  as input, and collect the time it took the algorithm to break the lock, the input we are looking for would take the longest time.

(b) For  $|S| = 1$  there is only one input and hence,  $\mathbb{P}[T = 1] = 1 = 1/|S|$ . Let's suppose that for some set  $S$  of size  $n \geq 1$  we have  $\mathbb{P}[T = k] = \frac{1}{|S|}$  for all  $1 \leq k \leq n$ .

Let  $S$  be a set of size  $n + 1$ , we have the following for some  $k \in \{1, \dots, n + 1\}$ :

$$\mathbb{P}[T = k] = \mathbb{P}[T = k | T \leq n] \mathbb{P}[T \leq n] + \mathbb{P}[T = k | T = n + 1] \mathbb{P}[T = n + 1]$$

For  $k \leq n$ :

$\mathbb{P}[T = k | T \leq n] = \frac{1}{n}$  (using the hypothesis, knowing that  $T \leq n$ , gives us one less choice and puts us back to the hypothesis  $n$ ), and  $\mathbb{P}[T = k | T = n + 1] = 0$ , which yields,  $\mathbb{P}[T = k] = \frac{1}{n} \mathbb{P}[T \leq n] = \frac{1}{n} \frac{n}{n+1} = \frac{1}{n+1}$

For  $k = n + 1$ :

$$\mathbb{P}[T = k] = \mathbb{P}[T = k | T = n + 1] \mathbb{P}[T = n + 1] = 1 \frac{1}{n+1} = \frac{1}{n+1}$$

Hence, for all  $k \in \{1, \dots, n + 1\}$ :  $\mathbb{P}[T = k] = \frac{1}{n+1}$  which completes our induction.

For  $|S| = n$ , let's compute  $\mathbb{E}[T]$ :

$$\begin{aligned} \mathbb{E}[T] &= \sum_{k=1}^n k \mathbb{P}[T = k] \\ &= \frac{1}{n} \frac{n(n+1)}{2} \\ &= \frac{n+1}{2} \end{aligned}$$

(c) The hardest distribution  $p$  is a uniform one, otherwise (if  $p$  favoured some combinations), then there are always some deterministic algorithms that would check for those combinations first, and hence make the expected numbers of checks smaller in average.

Let  $p$  be the uniform distribution over words of  $S$ , let  $A$  be any optimal deterministic algorithm, hence, for each  $k \in \{1, \dots, |S|\}$ , there is one and only one input  $I_j$  such that  $k = C(I_j, A)$ , this observation justifies the equality [\*] below.

$$\begin{aligned}\mathbb{E}[C(I_p, A)] &= \sum C(I_k, A) \mathbb{P}[I_k] \\ &= \frac{1}{|S|} \sum k \quad [*] \\ &= \frac{|S| + 1}{2}\end{aligned}$$

Now let  $q$  be a probability distribution over the set of deterministic algorithms  $\mathcal{A}$ , using Yao's minmax theorem we get:

$$\frac{|S| + 1}{2} \leq \max_{I \in S} \mathbb{E}[C(I, A_q)]$$

From the last inequality, we can conclude that no randomized algorithm can do better in average than  $\frac{|S|+1}{2}$ , and hence the algorithm in (b) is optimal.

## Exercise 2.

Let  $C = \{x_1, \dots, x_N\}$  be a random cut of the graph, where  $\{x_i\}_{1 \leq i \leq N}$  represents the edges. We are obviously interested in  $\mathbb{E}[N]$ , i.e., the expected number of edges in a cut. Let  $E = \{e_1, \dots, e_{|E|}\}$  and let the RV  $X_i$  be the indicator of edge  $e_i$  in  $C$ , i.e.,  $X_i = \delta(e_i \in C)$ .

$$\text{Clearly } N = \sum_{i=1}^{|E|} X_i, \text{ and hence, } \mathbb{E}[N] = \sum_{i=1}^{|E|} \mathbb{E}[X_i]$$

Now we prove that  $\mathbb{E}(X_i) = 1/2$ . Suppose the edge  $e_i$  connects the vertices  $A$  and  $B$ .

$$\begin{aligned}\mathbb{E}[X_i] &= \mathbb{P}[X_i = 1] \\ &= \mathbb{P}[\{A \text{ random cut } S_1/S_2 \text{ contains } e_i\}] \\ &= \mathbb{P}[\{S_1 \text{ contains } A \text{ alone or } B \text{ alone}\}]\end{aligned}$$

Each cut defines a partition of vertices  $S_1/S_2$ , where  $S_1$  selects  $j \in \{1, \dots, |V| - 1\}$  vertices at random from  $V$ . Each vertex has  $1/2$  probability to be in  $S_1$  (resp.  $S_2$ ), which yields:

$$\begin{aligned}\mathbb{E}[X_i] &= \mathbb{P}[\{(A, B) \in (S_1, S_2) \vee (A, B) \in (S_2, S_1)\}] \\ &= \mathbb{P}[\{(A, B) \in (S_1, S_2)\}] + \mathbb{P}[\{(A, B) \in (S_2, S_1)\}] \\ &= \mathbb{P}[\{A \in S_1 \wedge B \in S_2\}] + \mathbb{P}[\{A \in S_1 \wedge B \in S_1\}] \\ &= \mathbb{P}[\{A \in S_1\}] \mathbb{P}[\{B \in S_2\}] + \mathbb{P}[\{A \in S_1\}] \mathbb{P}[\{B \in S_1\}] \\ &= \frac{1}{2} \frac{1}{2} + \frac{1}{2} \frac{1}{2} = \frac{1}{2}\end{aligned}$$

Now we have:  $\mathbb{E}[N] = \sum_i \mathbb{E}[X_i] = \frac{|E|}{2} \geq \frac{|E|}{2}$ . Hence, there must be a cut that has at least  $\frac{|E|}{2}$  edges.

**Exercise 3.**

(a) The probability that *ModeratelyFastCut* outputs a given minimum cut, is the same as the probability of the contraction algorithm (the while loop of *MODERATELYFASTCUT*) not cutting any edge from the minimum cut, which is, according to the notes:  $\frac{t(t-1)}{n(n-1)}$ . (Assuming the deterministic algorithm always outputs the correct answer)

(b) The running time could be expressed as follows:  $M(t, n) = (n - t)\mathcal{O}(n) + \mathcal{O}(t^3)$

(c) If we run the algorithm  $N$  times, the running time would be:  $T_{\text{Amp}}(t, n, N) = N\mathcal{O}((t^3 - nt + n^2))$

To make it efficient, each run has to be efficient first, we find  $t$  that minimizes the polynomial  $P(t) = t^3 - nt + n^2$  given that  $t \in \{2, \dots, n\}$ . A quick derivation would give the value  $\lfloor \sqrt{\frac{n}{3}} \rfloor$ , assuming  $n$  is large enough ( $n \geq 12$ ). The new runtime: would be  $T(n, N) = N\mathcal{O}(n^2)$

And we would get the following upper bound:

$$\begin{aligned}
 \mathbb{P}[\{\text{Error}\}] &\leq \left(1 - \frac{t(t-1)}{n(n-1)}\right)^N \\
 &\leq e^{-\frac{t(t-1)N}{n(n-1)}} \\
 (\text{for } t = \sqrt{\frac{n}{3}}) \quad &= e^{-\left(\frac{(\sqrt{n}-\sqrt{3})N}{3\sqrt{n}(n-1)}\right)} \\
 &\leq e^{-\frac{N}{\sqrt{n}(\sqrt{n}-\sqrt{3})}} \\
 &\leq e^{-\frac{N}{n}}
 \end{aligned}$$

(d) We have the following results:

- For Fast cut:  $\mathcal{O}(n^2 \log^2(n))$
- For Randomized Contraction:  $\Theta(n^4)$
- *ModeratelyFastCut*: for  $t = \lfloor \sqrt{\frac{n}{3}} \rfloor$  we would need  $\mathcal{O}(n)$  repetitions to guarantee a constant error (using the upper bound we derived in the past equation), plus, each run would take  $\mathcal{O}(n^2)$ , which yields the following:  $\mathcal{O}(n^3)$