### CS 388R: Randomized Algorithms, Fall 2019

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Lecture 1: Introduction to randomized algorithms; min-cut
Prof. Eric Price Scribe: Tongzheng Ren, Garrett Bingham
NOTE: THESE NOTES HAVE NOT BEEN EDITED OR CHECKED FOR CORRECTNESS

# 1 Randomized Algorithms

### Examples of Randomized Algorithms:

- Primality Testing
- Quick Sort
- Factoring
- Hash tables

### Benefits of randomized algorithms:

- Speed
- Simplicity
- Some things only possible with randomization

Keep in mind that randomness is over the choices of algorithms, not the choices of input.

#### Key techniques of randomized algorithms:

- Avoiding adversarial inputs
  - For example, how should one choose the pivot in quicksort? One way is to always choose the first element, but in the adversarial case, this results in  $O(n^2)$  time.
  - In the case of hashing, we might use some modulo function. While it may work well in some cases, for structured input there will likely be many collisions.
- Fingerprinting: compare short, random description of items
- Random sampling
- Load balancing
- Symmetry breaking
- Probabilistic existence proofs

#### Types of randomized algorithms:

- Las Vegas: always correct, but the running time is random
- Monte Carlo: running time is fixed, but the algorithm is only correct with high probability

Las Vegas style algorithms can be converted to Monte Carlo algorithms by designating a fixed stopping time T. Monte Carlo algorithms cannot in general be made into Las Vegas algorithms.

#### 2 Quick Sort

 $\begin{array}{l} \textbf{Algorithm 1} \ \texttt{QuickSort}(X) \\ \hline \textbf{Input: List } X \\ \textbf{Choose random pivot } t \in \texttt{range(len}(X)) \\ \textbf{return } \ \texttt{QuickSort}([X_i|X_i < X_t]) + [X_t] + \texttt{QuickSort}([X_i|X_i > X_t]) \end{array}$ 

#### Expected running time

Define  $Z_{ij}$  := number of times the *i*th smallest element and *j*th smallest element are compared  $\in \{0, 1\}$ .

Time = 
$$O(\text{total comparisons}) = O\left(\sum_{i < j} Z_{i,j}\right)$$

Notice that:

$$\mathbb{P}[Z_{i,j}=1] = \frac{2}{j-i+1}$$

This is because the probability the *i*th and *j*th elements are compared is equal to the probability that either the *i*th or *j*th element is chosen as a pivot before any of the  $i + 1, \ldots, j - 1$  elements are.

Next, we have

$$\mathbb{E}[\text{Time}] \leq \mathbb{E}\left[\sum_{i < j} Z_{i,j}\right] = \sum_{i < j} \frac{2}{j-i+1} = 2\sum_{i < j} \frac{1}{j-i+1} = 2\sum_{i < j} \frac{1}{n+1-i} \leq 2n\sum_{i=2}^{n} \frac{1}{i} \leq 2n\log n$$

where  $f \leq g$  means  $\exists C$  constant that  $f \leq Cg$ . Notice that  $\sum_{i=2}^{n} \frac{1}{i}$  is the harmonic series.

### 3 Karger's min-cut algorithm [Kar93]

**Min-cut definition:** Given some graph G = (V, E) with *n* vertices and *m* edges, a global min-cut is a set  $S \subset V : 1 \leq |S| \leq n-1$  that minimizes the number of edges going from *S* to  $\overline{S}$  (the vertices not in *S*). We define the cut-value of *S* as the number of edges from *S* to  $\overline{S}$ , denoted  $\mathbb{E}(S, \overline{S})$ 

Possible approaches include some traditional deterministic algorithms like the Ford–Fulkerson method with the max-flow min-cut theorem, etc. We will discuss faster algorithms.

Algorithm 2 Karger's min-cut algorithm

**Input:** Graph G = (V, E) with *n* vertices and *m* edges while n > 2 do Contract a random edge e(u, v): merge the vertices and remove self-loops end while return Preimage of the two remaining vertices

Here we allow for multiplicity (there can be multiple edges between one pair of vertices). See here for a single run of Karger's min-cut algorithm.

**Lemma 1.** Algorithm 2 succeeds with probability larger than  $\frac{2}{n^2}$ .

*Proof.* Let d(u) denote the degree of vertex u.

$$\mathbb{P}[\text{fail in the first step}] = \frac{\mathbb{E}(S,\overline{S})}{n} \le \frac{\min d(u)}{m} \le \frac{\frac{1}{n}\sum d(u)}{m} = \frac{2}{n}$$

Similarly,

$$\mathbb{P}[\text{fail in the } i\text{-th step}|\text{succeed in the } i-1\text{-th step}] \leq \frac{2}{n-i}$$

Thus:

$$\mathbb{P}[\text{succeed in the all of steps}] \ge \prod_{i=1}^{n-2} \left( 1 - \frac{2}{n+1-i} \right) = \frac{n-2}{n} \cdot \frac{n-3}{n-1} \cdots \frac{2}{4} \cdot \frac{1}{3} = \frac{2}{n(n-1)} \ge \frac{2}{n^2}$$

When n is large, this guarantee is poor. However, if we repeat  $n^2$  times and return the best result, then the failure probability becomes

$$\left(1-\frac{2}{n^2}\right)^{n^2} \approx \frac{1}{e^2} > \frac{2}{3}$$

The time complexity is  $n^2 m \alpha(n) = n^2 (m \log_{m/n} n)$  by Union-Find/Disjoint-set data structure whose time complexity is  $O(\alpha(n))$ .

# 4 Karger-Stein faster min-cut algorithm [KS96]

Intuition Most of the work is done at the beginning when there is a low chance of failure.

The running time is:

$$T(n) = 2\left(T\left(\frac{n}{\sqrt{2}}\right) + O\left(n^2\right)\right) = O(n^2 \log n)$$

Algorithm 3 Karger-Stein min-cut algorithm
<b>Input:</b> Graph $G = (V, E)$ with <i>n</i> vertices and <i>m</i> edges
for $i=1, 2$ do
Run Algorithm 2 for $\frac{n}{\sqrt{2}}$ steps
Recursively run Algorithm 3
end for
<b>return</b> Better of the two results

since the depth of the search is  $O(\log n)$  and each step takes  $O(n^2)$  time.

Let  $\mathbb{P}(n)$  denote the success probability, then

$$\begin{split} \mathbb{P}(n) &= 1 - (1 - \text{chance one branch succeeds})^2 \qquad \text{i.e. } \mathbb{P}\left(\frac{n}{\sqrt{2}}\right) \text{ by definition} \\ &= 1 - \left(1 - \frac{1}{2}\mathbb{P}\left(\frac{n}{\sqrt{2}}\right)\right)^2 \\ &= \mathbb{P}\left(\frac{n}{\sqrt{2}}\right) - \frac{1}{4}\mathbb{P}\left(\frac{n}{\sqrt{2}}\right)^2 \end{split}$$

We can find that  $\mathbb{P}(n) = \Theta(\frac{1}{\log n})$ . To show this, let  $x = \log_{\sqrt{2}} n$  and  $f(x) = \mathbb{P}(2^{\frac{x}{2}})$ . Then

$$f(x) = f(x-1) - \frac{1}{4}f(x-1)^2$$

We can find the solution  $f(x) = \frac{4}{x}$ , thus  $\mathbb{P}(n) = \Theta(\frac{1}{\log n})$ . Also see [KS96] for another approach.

If we repeat Algorithm 3  $O(\log n)$  times, we get  $O(n^2 \log^2 n)$  time with constant probability of success. To see this, we consider the success probability:

$$1 - (1 - \mathbb{P}(n))^{\log n} = \Theta(1) + O\left(\frac{1}{\log n}\right)$$

is some constant. This method outperforms the  $O(mn^2 \log n)$  time complexity approach mentioned earlier, as in practice m can be on the order of  $O(n^2)$ .

# References

- [Kar93] David R Karger. Global min-cuts in rnc, and other ramifications of a simple min-cut algorithm. In SODA, volume 93, pages 21–30, 1993.
- [KS96] David R Karger and Clifford Stein. A new approach to the minimum cut problem. *Journal* of the ACM (JACM), 43(4):601–640, 1996.