

# Probabilistic Analysis of QuickSort

**Theorem 1.** *The expected run time of (deterministic) Quicksort on a random input, uniformly chosen from all possible permutation of  $S$  is  $O(n \log n)$ .*

**Proof.**

Set  $X_{i,j}$  as before.

If all permutations have equal probability, all permutations of  $S_i, \dots, S_j$  have equal probability, thus

$$Pr(X_{i,j}) = \frac{2}{j - i + 1}.$$

$$E\left[\sum_{i=1}^n \sum_{j>i} X_{i,j}\right] = O(n \log n).$$

□

## Randomized Algorithms:

- Analysis is true for **any** input.
- The sample space is the space of random choices made by the algorithm.
- Repeated runs are independent.

## Probabilistic Analysis:

- The sample space is the space of all possible inputs.
- If the algorithm is **deterministic** repeated runs give the same output.

# Randomized Algorithm classification

A **Monte Carlo Algorithm** is a randomized algorithm that may produce an incorrect solution.

For decision problems: A **one-side error** Monte Carlo algorithm errs only on one possible output, otherwise it is a **two-side error** algorithm.

A **Las Vegas** algorithm is a randomized algorithm that **always** produces the correct output.

In both types of algorithms the run-time is a random variable.

# Distributed Algorithms

Algorithms that are designed to run on a distributed network of computers.

A distributed algorithm is a **localized** algorithm if it uses only the information of the local nodes (computers/processors).

# Maximal Independent Set Problem

Given an arbitrary (topology) network we want to find a maximal independent set of nodes.

A set of nodes is called an *independent set* if it contains no pair of neighboring nodes, and it is maximal if it cannot be increased to form a larger independent set by the addition of other nodes.

**Applications:** resource allocation, dominating sets, clusterhead selection in ad hoc wireless networks etc.

Given an arbitrary network  $G = (V, E)$ , we want to design a distributed (and local) algorithm which will output a MIS set as follows: every node will know whether it is in the MIS or not.

Let  $\Gamma(v)$  be the set of vertices in  $V$  that are adjacent to  $v$ .

**Basic idea:** The algorithm proceeds in rounds; in every round find an independent set  $S$ , add  $S$  to  $I$  (initially  $I$  is empty) and delete  $S \cup \Gamma(S)$  from the graph.

# Algorithm

1.  $I = \phi$
2. **repeat**
  - 2.1 for all  $v \in V$  do  
if  $d(v) = 0$  then  
add  $v$  to  $I$  and delete  $v$  from  $V$   
else mark  $v$  with probability  $1/(2d(v))$
  - 2.2 for all  $(u, v) \in E$  do  
if both  $u$  and  $v$  are marked then  
unmark the lower degree vertex
  - 2.3 for all  $v \in V$  do  
if  $v$  is marked then add  $v$  to  $S$ .
  - 2.4  $I = I \cup S$
  - 2.5 delete  $S \cup \Gamma(S)$  from  $V$ ,  
and all incident edges from  $E$
3. **until**  $V = \phi$

# Analysis

**Theorem 2.** *The expected number of iterations of the above algorithm is  $O(\log n)$ .*

**Proof:** We show that the expected fraction of edges removed from  $E$  during each iteration is bounded from below by a constant.

A vertex  $v \in V$  is **good** if it has at least  $d(v)/3$  neighbors of degree no more than  $d(v)$ ; otherwise the vertex is **bad**.

An edge is good if at least one of its endpoints is a good vertex, and it is bad if both endpoints are bad vertices.

We show that a good vertex is likely to have one of its lower degree neighbors in  $S$  and thereby deleted from  $V$ .

**Lemma 1.** *Let  $v \in V$  be a good vertex with degree  $d(v) > 0$ . Then, the probability that some vertex  $w \in \Gamma(v)$  gets marked is at least  $1 - e^{-1/6}$ .*

**Proof.** Each vertex  $w \in \Gamma(v)$  is marked independently with probability  $1/(2d(w))$ . The probability that none of the neighbors of  $v$  gets marked is at most

$$\left(1 - \frac{1}{2d(v)}\right)^{d(v)/3} \leq e^{-1/6}$$

□

**Lemma 2.** *During any round, if a vertex  $w$  is marked then it is selected to be in  $S$  with probability at least  $1/2$ .*

**Proof.** The only reason a marked vertex  $w$  becomes unmarked is that one of its neighbors of degree at least  $d(w)$  is also marked. The probability of this happening is at most

$$\sum_{x \in \Gamma(w)} \frac{1}{2d(w)} \leq 1/2$$

□

**Lemma 3.** *The probability that a good vertex belongs to  $S \cup \Gamma(S)$  is at least  $(1 - e^{-1/6})/2$ .*

**Lemma 4.** *In a graph  $G = (V, E)$  the number of good edges is at least  $|E|/2$ .*

**Proof.** Direct the edges in  $E$  from the lower degree end-point to the higher degree end-point breaking ties arbitrarily. Let  $d_i(v)$  and  $d_o(v)$  be the in-degree and out-degree of  $v$ .

For each bad vertex  $v$ ,

$$d_o(v) - d_i(v) \geq d(v)/3 = \frac{d_o(v) + d_i(v)}{3}$$

Let  $E(S, T)$  be the set of edges directed from vertices in  $S$  to vertices in  $T$ ; and  $e(S, T) = |E(S, T)|$ .

The total degree of the bad vertices is given by

$$\begin{aligned} & 2e(V_B, V_B) + e(V_B, V_G) + e(V_G, V_B) \\ &= \sum_{v \in V_B} (d_o(v) + d_i(v)) \\ &\leq 3 \sum_{v \in V_B} (d_o(v) - d_i(v)) \\ &= 3 \sum_{v \in V_G} (d_i(v) - d_o(v)) \\ &= 3[(e(V_B, V_G) + e(V_G, V_G)) - (e(V_G, V_B) + e(V_G, V_G))] \\ &= 3[e(V_B, V_G) - e(V_G, V_B)] \\ &\leq 3[e(V_B, V_G) + e(V_G, V_B)] \end{aligned}$$

Thus,

$$e(V_B, V_B) \leq e(V_B, V_G) + e(V_G, V_B).$$

□

We now argue that the expected number of edges removed at a given iteration is at least a constant fraction of the number of edges present.

Let r.v.  $X$  denote the number of edges deleted in the current iteration and let  $E$  denote the current set of edges.

For each  $e \in E$ , let r.v.  $X_e$  indicate whether  $e$  is deleted or not.

$$X = \sum_{e \in E} X_e$$

$$E[X] = \sum_{e \in E} E[X_e] \geq \sum_{e \text{ is good}} E[X_e]$$

$$\geq \sum_{e \text{ is good}} (1 - e^{-1/6})/2 \geq (1 - e^{-1/6})|E|/4$$

## A Probabilistic Recurrence

Let  $g(x)$  be a monotone non-decreasing function from  $R^+$  to  $R^+$ . Consider a particle whose position changes at discrete time steps and is always at a positive integer. If the particle is currently at position  $m > 1$ , it proceeds at the next step to position  $m - X$ , where  $X$  is a random variable over integers  $1, \dots, m - 1$ . We are only given that  $E[X] \geq g(m)$  and that  $X$  is chosen independently of the past.

Assuming the particle starts at position  $n$ , what is the expected number of steps before it reaches position 1 ?

**Theorem 3.** *Let  $T$  be the random variable denoting the number of steps in which the particle reaches the position 1. Then  $E[T] \leq \int_1^n dx/g(x)$ .*

## Proof

By induction on  $n$ .

Suppose the theorem holds for values of  $m$  smaller than  $n$ . Let  $f(m) = \int_1^m dx/g(x)$  for  $m \geq 1$ .

Consider the first step, during which the particle proceeds from position  $n$  to position  $n - X$ , where  $X$  is chosen from a distribution for which  $E[X] \geq g(n)$ .

We have

$$\begin{aligned} E[T] &\leq 1 + E[f(n - X)] \\ &= 1 + E\left[\int_1^n dy/g(y) - \int_{n-X}^n dy/g(y)\right] \\ &= 1 + f(n) - E\left[\int_{n-X}^n dy/g(y)\right] \\ &\leq 1 + f(n) - E\left[\int_{n-X}^n dy/g(n)\right] \\ &= 1 + f(n) - E[X]/g(n) \leq f(n) \end{aligned}$$