

# Lecture 1:

## Basics of Algorithm Analysis

Course: Algorithms for Big Data

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# Outline

- ▶ Basic Definitions
- ▶ Input Size
- ▶ Time Complexity
- ▶ Space Complexity
- ▶ Randomization
- ▶ Approximation

# Basic Definitions I

An algorithm is a sequence of simple operations (addition, multiplication, comparison, ...) performed on input data to produce desired results.



## Examples for Input Data:

- ▶ A list of  $n$  integers
- ▶ A graph with  $n$  nodes and  $m$  edges
- ▶ A  $n$  by  $m$  matrix
- ▶ A large text

## Some Specific Tasks:

- ▶ Sorting
- ▶ Finding shortest paths
- ▶ Rank of a matrix
- ▶ Most frequent word

# Basic Definitions

- ▶ Size of input (in bits or numbers)
- ▶ Size of output
- ▶ Time complexity (worst-case, average)
- ▶ Space Complexity
- ▶ Deterministic or Randomized?
- ▶ Exact or Approximate

# Input Size

## A few examples:

- ▶ An integer  $a$ :                      Task: Check if  $a$  is a prime.

Input Size:  $n = \log_2 a$  bits

- ▶ A list of  $n$  integers:

Input Size:  $n$  numbers

- ▶ An undirected graph with  $t$  vertices and  $m$  edges:

Input Size: depends on the representation.

Adjacency Matrix:  $n = t^2$  bits

Adjacency list:  $n = t + 2m$  numbers

- ▶ A  $t$  by  $t$  matrix:

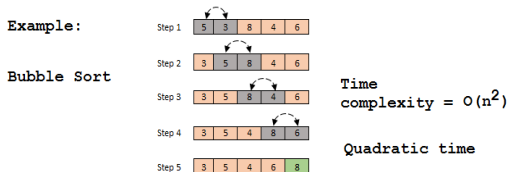
Input Size:  $n = t^2$  numbers

# Time Complexity

**Time complexity of an algorithm:** Maximum number of basic steps (addition, multiplication, comparison, ...) an algorithm takes on a given input of size  $n$

A function of the input size:  $T(n)$

Known as the **worst-case** time complexity.



# Big O Notation

- ▶ (Informally speaking)  $O(f(n))$  includes all functions with the leading term asymptotically smaller than or equal to  $f(n)$  after eliminating the constant coefficient.

$$O(n^2) = \{100n^2, n^2 + 10n, 4n \log n + 2n, \log^2 n - 1, \dots\}$$

$$n^3 \notin O(n^2), n^2 \log n \notin O(n^2), 2^n \notin O(n^2)$$

- ▶  $\Omega(f(n))$  includes all functions with the leading term asymptotically bigger than or equal to  $f(n)$  after eliminating the constant coefficient.

$$\Omega(n^2) = \{100n^2, n^2 + 10n, n^3 + n^2 + 1, 2^n + 1, \dots\}$$

$$2n \notin \Omega(n^2), n^{1.9} \notin \Omega(n^2), n^2 / \log n \notin \Omega(n^2)$$

- ▶  $o(f(n))$  includes all functions with the leading term asymptotically bigger than  $f(n)$  after eliminating the constant coefficient.

$$o(n) = \{100n^{0.99}, 2 \log n + 10, n / \log n + 1, \dots\}$$

$$n \notin o(n), n \log n \in o(n^2), 2^n \in o(3^n)$$

# Typical Running Times

- ▶ Polynomial time:  $O(n^c)$  when  $c$  is a constant.
- ▶ Linear time:  $O(n)$
- ▶ Quadratic time:  $O(n^2)$
- ▶ Cubic time:  $O(n^3)$
- ▶ Exponential time:  $O(2^n)$
- ▶ Sublinear time:  $o(n)$
- ▶ Logarithmic time:  $O(\log n)$
- ▶ Constant time:  $O(1)$



# Running Time Comparison

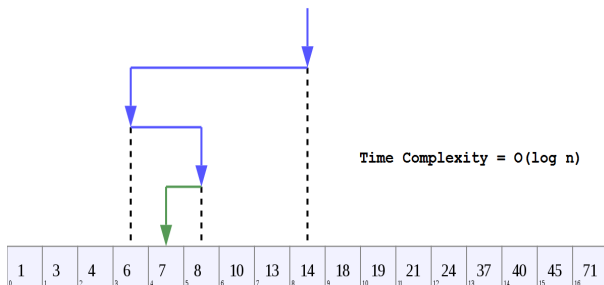
**Table 2.1** The running times (rounded up) of different algorithms on inputs of increasing size, for a processor performing a million high-level instructions per second. In cases where the running time exceeds  $10^{25}$  years, we simply record the algorithm as taking a very long time.

	$n$	$n \log_2 n$	$n^2$	$n^3$	$1.5^n$	$2^n$	$n!$
$n = 10$	< 1 sec	< 1 sec	< 1 sec	< 1 sec	< 1 sec	< 1 sec	4 sec
$n = 30$	< 1 sec	< 1 sec	< 1 sec	< 1 sec	< 1 sec	18 min	$10^{25}$ years
$n = 50$	< 1 sec	< 1 sec	< 1 sec	< 1 sec	11 min	36 years	very long
$n = 100$	< 1 sec	< 1 sec	< 1 sec	1 sec	12,892 years	$10^{17}$ years	very long
$n = 1,000$	< 1 sec	< 1 sec	1 sec	18 min	very long	very long	very long
$n = 10,000$	< 1 sec	< 1 sec	2 min	12 days	very long	very long	very long
$n = 100,000$	< 1 sec	2 sec	3 hours	32 years	very long	very long	very long
$n = 1,000,000$	1 sec	20 sec	12 days	31,710 years	very long	very long	very long

Source: Algorithm Design, Jon Kleinberg, Eva Tardos, 2006.

# Sublinear Time: Example

Searching in a sorted array: **Binary Search**



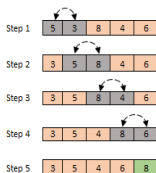
# Space Complexity I

The space complexity of an algorithm is the amount of memory the algorithm uses during its execution (measured in bits or numbers).

A function of the input size:  $S(n)$

**Example:**

**Bubble Sort**



**Time**  
complexity =  $O(n^2)$

**space**  
complexity =  $O(n)$

# Space Complexity II

In the **RAM Model (Random Access Memory)** Model it is assumed the entire input is saved in the memory.

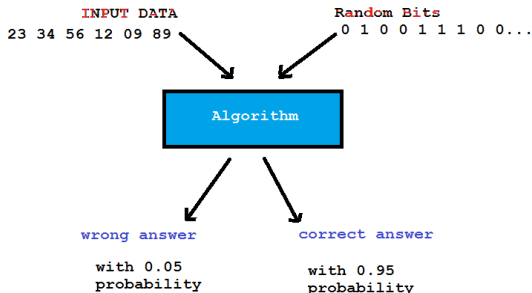
⇒ Space Complexity  $\geq$  Input Size

We shall see in the **Data Stream** Model and the **MPC (Massively Parallel Computation)** Model the entire input is not present in the memory.

Here the Space Complexity could be smaller than the Input Size. **Sublinear Space Complexity**

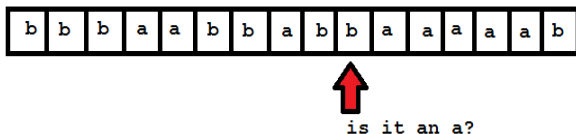
# Deterministic or Randomized?

A **randomized algorithm** in addition to the input uses a series of **random bits** for its computation. The algorithm produces the desired output with a certain **success probability**. It **fails** with a certain probability.



## Randomized algorithm: example

**Problem:** Given an array  $A$  of length  $n$  containing  $n/2$  number of  $a$ 's and  $n/2$  number of  $b$ 's, find the position of an  $a$ .



**Randomized Algorithm I:** Randomly pick a position and check if it is an  $a$ . Do this 3 times. If no  $a$  is found declare failure.

**Analysis:**  $\Pr[\text{failure}] = 1/2 \times 1/2 \times 1/2 = 1/8$ . The algorithm succeeds with probability  $7/8$ . Running time =  $O(1)$ .

**Assumption:** Generating a random number between 0 and  $n$  takes  $O(1)$  time.

# Randomized algorithm: example continued

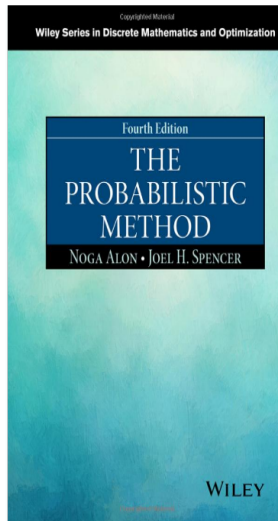
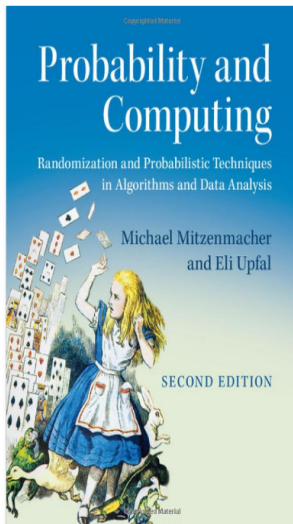
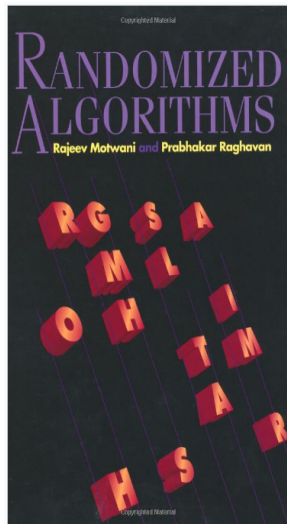
**Randomized Algorithm II:** Randomly pick a position and check if it is an a. Repeat this until an a is found.

**Analysis:**  $\Pr[\text{failure}] = 0$ . The algorithm succeeds with probability 1.

$$\text{Expected running time} = \sum_i^{\infty} \frac{i}{2^i} = 2$$

- ▶ **Las Vegas** Randomized Algorithm: Zero Failure Prob.
- ▶ **Monte Carlo** Randomized Algorithms: Positive Failure Prob.

# Randomized Algorithms: books





# Exact or Approximation

Given data  $A$ , suppose we want to compute the nonzero function  $f(A)$

**Exact Algorithm:** The algorithm outputs  $f(A)$ .

**Additive Error:** Algorithm outputs  $F$  where  $|F - f(A)| \leq E$ . Here  $E$  is called the additive error.

**Multiplicative Error:** Algorithm outputs  $F$  where  $|F - f(A)| \leq \epsilon f(A)$ . Here  $(1 \pm \epsilon)$  is called the approximation factor.

**$(\epsilon, \delta)$  Approximation:** The algorithms with probability  $1 - \delta$  computes  $F$  where  $|F - f(A)| \leq \epsilon f(A)$ .

# Approximate vs Exact: Counting Inversions

**Problem:** Counting inversions in a permutations  $\pi \in S_n$ .

The pair  $(i, j)$  is called an inversion in permutation  $\pi$  iff

$$i < j \text{ and } \pi(i) > \pi(j)$$

$$\pi = 7, 1, 2, 3, 9, 5, 8, 4, 6, 10$$

$$K(\pi) = \text{number of inversions in } \pi$$

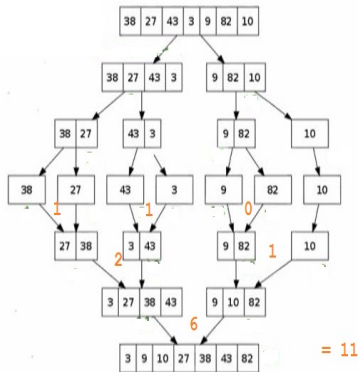
**Brute-Force Strategy:** Check all pairs.

Running time =  $O(n^2)$

# Approximate vs Exact: Counting Inversions

Divide and Conquer Strategy:

```
if list L has one element
  return 0 and the list L
divide the list into two halves A and B
( $r_A$ , A) ← Sort-and-Count(A)
( $r_B$ , B) ← Sort-and-Count(B)
( $r$ , R) ← Merge-and-Count(A, B)
return  $r = r_A + r_B + r$  and the sorted list R
```



Running Time:

$$T(n) = 2T(n/2) + O(n) \Rightarrow T(n) = O(n \log n)$$

# Approximate vs Exact: Counting Inversions

**An Idea:** Compute  $K'(\pi) = \sum_i^n |\pi(i) - i|$

**Lemma:**  $K(\pi) \leq K'(\pi) \leq 2K(\pi)$

**Running Time:**  $O(n)$

**Streaming Space Usage:**  $O(\log n)$  bits

# Next Lecture

Sublinear Time Algorithms: Some Examples

Two Concentration Lemmas: Markov and Chebyshev bounds