

Chapter 2 analysis

Analyse Algorithm's performance

Completeness: all case take into considering

Optimality: it's an optimal solution

Time complexity: It takes not long to execute it

space complexity: How much memory is needed to perform such task

Polynomial-time

1. brute force:

there is a natural brute force to search algorithm ==> to check all the possible solution

typically takes 2^n time ==> unacceptable

2. desirable scaling property

algorithm should only **slow down** by some constant factor **C**, we defaultly say that it should be bound by cN^d steps

3. definition

an algorithm is *poly-time* if the above scaling property hold

worst-case analysis

1. worst-case running time:

largest possible running time of algorithm on input of a given size N

2. average case running time:

algorithm tuned for a certain distribution may perform poorly on toher inputs

3. worst-case polynomial-time

definition: an alforithm is *efficient* if its running time is polynomail-time

Asymptotic order of growth

1. Asymptotic Order of Growth

upperbound:

$T(n)$ is $O(f(n))$ if there exist constants $c > 0$ and $n_0 \geq 0$ such that
for all $n \geq n_0$ we have $T(n) \leq c \cdot f(n)$.

lowerbound:

$T(n)$ is $\Omega(f(n))$ if there exist constants $c > 0$ and $n_0 \geq 0$ such that
for all $n \geq n_0$ we have $T(n) \geq c \cdot f(n)$.

tight bounds:

$T(n)$ is $\Theta(f(n))$ if $T(n)$ is $O(f(n))$ and $T(n)$ is $\Omega(f(n))$

2. Notation

Slight abuse of notation. $T(n) = O(f(n))$

Better notation: $T(n) \in O(f(n))$.

3. transitivity

If $f = O(g)$ and $g = O(h)$ then $f = O(h)$

If $f = \Omega(g)$ and $g = \Omega(h)$ then $f = \Omega(h)$

If $f = \Theta(g)$ and $g = \Theta(h)$ then $f = \Theta(h)$

4. additivity

If $f = O(h)$ and $g = O(h)$ then $f + g = O(h)$

If $f = \Omega(h)$ and $g = \Omega(h)$ then $f + g = \Omega(h)$

If $f = \Theta(h)$ and $g = \Theta(h)$ then $f + g = \Theta(h)$

5. polynomials

$a_0 + a_1n + \dots + a_d n^d$ is $\Theta(n^d)$ if $a_d > 0$.

logarithms

$O(\log_a n) = O(\log_b n)$, $\forall a, b > 0$

$\forall x > 0$, $\log n = O(n^x)$

exponentials

$\forall r > 1$, $n^d = O(r^n)$

A Survey of Common Running Times

1. Linear time: $O(n)$

1. *Computing the maximum* :

Computing the maximum of n numbers a_1, \dots, a_n

2. *Merge* :

combine two sorted list $A = a_1, \dots, a_n$ with $B = b_1, \dots, b_n$ into a sorted whole.

2. $O(\log n)$ time: arise in divide-and-conquer algorithm

1. *sorting* :

Mergesort and heapsort are sorting algorithms that perform $O(\log n)$ comparisons.

2. *Largest empty interval* :

Given n time-stamps x_1, \dots, x_n on which copies of a file arrive at a server, what is largest interval of time when no copies of the file arrive?

Sort the time-stamps. Scan the sorted list in order, identifying the maximum gap between successive time-stamps.

3. Quadratic time: $O(n^2)$

Closest pair of points

Given a list of n points in the plane $(x_1, y_1), \dots, (x_n, y_n)$, find the pair that is closest

solution: Try all pairs of points.

Remark: $O(n^2)$ seems inevitable, but this is just an illusion.

4. Cubic time: $O(n^3)$

Set disjointness :

Given n sets S_1, \dots, S_n each of which is a subset of $1, 2, \dots, n$, is there some pair of these which are disjoint?

solution: For each pairs of sets, determine if they are disjoint.

5. polynomial time: $O(n^k)$

Independent set of size k :

Given a graph, are there k nodes such that no two are joined by an edge

solution: Enumerate all subsets of k nodes.

check whether S is an independent set: $O(k^2)$

number of k element subsets: $O(n^k)$

$$\binom{n}{k} = \frac{n(n-1)\dots(n-k+1)}{k(k-1)\dots 1} \leq \frac{n^k}{k!}$$

total complexity: $O(n^k)$

6. exponential time

maximum independent set :

Given a graph, what is maximum size of an independent set?

solution: Enumerate all subsets. Then check any subset whether independent

time complexity: $O(n^2 2^n)$