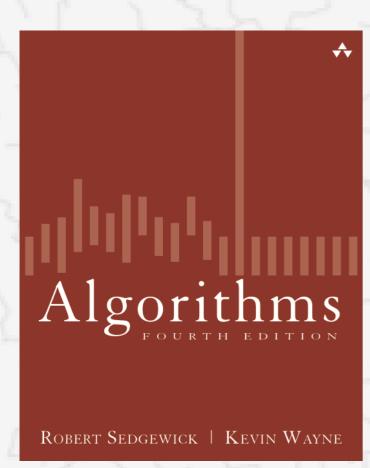


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1.4 ANALYSIS OF ALGORITHMS

- Asymptotic analysis
- Analyzing recursive algorithms
- ► The Master Theorem



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Big O Notation – Upper Bounds

Let f(n) and g(n) be running time functions. ($\geq 0 \ \forall n \geq 0$)

Definition.

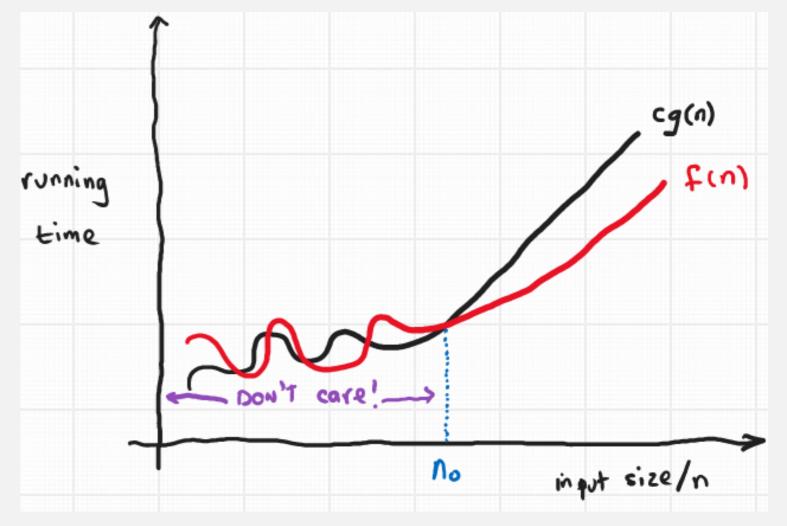
f(n) is O(g(n)) if there exists a constant c>0 and $n_0\geq 0$ such that $f(n)\leq 0$

$$cg(n)$$
, $\forall n \geq n_0$

Ex.
$$f(n) = 3n^3 + 2n^2 - n$$

• $f(n)$ is $O(n^3)$
choose $c = 6, n_0 = 0$

We use it to provide an upper bound on the time Complexity of an algorithm.



We say, algorithm A takes $O(n^3)$ time to solve problem P.

- Q. If $f(n) = 32n^2 + 17n + 1$, which of the following is true?
- A. f(n) is O(n)

- *B.* f(n) is $O(n^2)$
- *C.* f(n) is $O(n^3)$
- D. Both B and C
- E. Both A and B
- F. Both A and C
- G. All of A, B, and C

Big O Properties

Let f(n) and g(n) be running time functions. ($\geq 0 \ \forall n \geq 0$)

Reflexivity. f(n) is O(f(n))

Constants. If f(n) is O(g(n)) and c > 0, then cf(n) is O(g(n)).

Products. If f(n) is $O(g_1(n))$ and h(n) is $O(g_2(n))$, then f(n)h(n) is $O(g_1(n)g_2(n))$.

Sums. If f(n) is $O(g_1(n))$ and h(n) is $O(g_2(n))$, then f(n) + h(n) is $O(\max\{g_1(n), g_2(n)\})$.

Transitivity. If f(n) is $O(g_1(n))$ and $g_1(n)$ is $O(g_2(n))$, then f(n) is $O(g_2(n))$.

Big Omega Notation – Lower Bounds

Let f(n) and g(n) be running time functions. ($\geq 0 \ \forall n \geq 0$)

Definition.

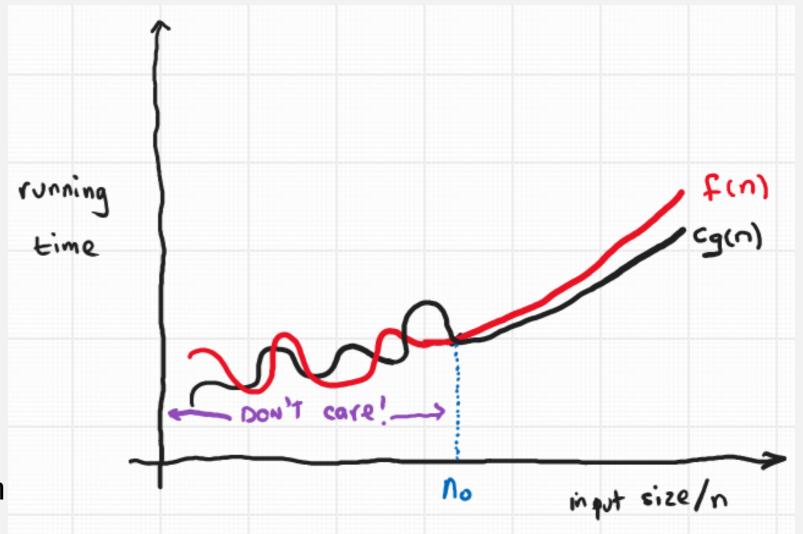
f(n) is $\Omega(g(n))$ if there exists a constant c>0 and $n_0\geq 0$ such that $f(n)\geq 0$

$$cg(n)$$
, $\forall n \geq n_0$

Ex.
$$f(n) = 3n^3 + 2n^2 - n$$

• $f(n)$ is $\Omega(n^3)$
choose $c = 3, n_0 = 0$

We use it to provide a lower bound on the time Complexity for solving a problem



We say, any algorithm requires $\Omega(n^3)$ operations to solve problem P in the worst case. (on some computational model)

Big Theta Notation – Tight bounds

Let f(n) and g(n) be running time functions. ($\geq 0 \ \forall n \geq 0$)

Definition.

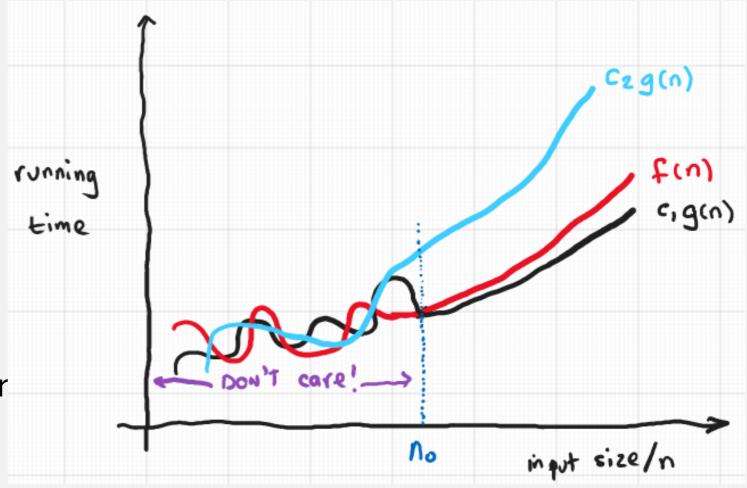
f(n) is $\Theta(g(n))$ if there exists constants $c_1 > 0, c_2 > 0$ and $n_0 \ge 0$ such that $c_1g(n) \le 0$

$$f(n) \le c_2 g(n), \forall n \ge n_0$$

Ex.
$$f(n) = 3n^3 + 2n^2 - n$$

• $f(n)$ is $\Theta(n^3)$
choose $c_1 = 3$, $c_2 = 6$, $n_0 = 0$

We use it to provide tight bounds or Complexity of an algorithm solving problem P.



We say, merge-sort makes $\Theta(n \lg n)$ comparisons to sort n elements.

Big O Properties

Let f(n) and g(n) be running time functions. ($\geq 0 \ \forall n \geq 0$)

Proposition. f(n) is $\Theta(g(n))$ if and only if f(n) is $\Omega(g(n))$ and f(n) is O(g(n)).

Proposition. If $\lim_{n\to\infty}\frac{f(n)}{g(n)}=c$ for some constant c>0, then f(n) is $\Theta(g(n))$.

Proposition. If $\lim_{n\to\infty}\frac{f(n)}{g(n)}=0$ then f(n) is O(g(n)).

Proposition. If $\lim_{n\to\infty}\frac{f(n)}{g(n)}=\infty$ then f(n) is $\Omega(g(n))$.

Proposition. If $f(n) = a_d n^d + a_{d-1} n^{d-1} + \dots + a_1 n + a_0$, with $a_d > 0$, then f(n) is $\Theta(n^d)$.

Proposition. $\log_a n$ is $O(n^d)$ for every a > 1 and every d > 0.

Proposition. n^d is $O(r^n)$ for every d > 0 and every r > 1.

Q. In each of the following, indicate whether f(n) is O(g(n)), or f(n) is $\Omega(g(n))$, or both.

A.
$$f(n) = n - 100$$
, $g(n) = n - 200$

B.
$$f(n) = 2^n$$
, $g(n) = 2^{n+1}$

C.
$$f(n) = 10 \log n$$
, $g(n) = \log n^2$

Q. For each of the following algorithms, give an analysis of their running time. Big O will do.

QUAD(a, b, c)

1. d =
$$a^2 - 4bc$$

- 2. if $d \ge 0$
- 3. return true
- 4. return false

SUM1(n)

1.
$$x = 0$$

- 2. for i = 1 to n
- 3. x = x + 1
- 4. return x

Q. For each of the following algorithms, give an analysis of their running time. Big O will do.

SUM2(n)

- 1. x = 0
- 2. for i = 1 to n
- 3. for j = 1 to i
- 4. x = x + 1
- 5. return x

SUM3(n)

- 1. x = 0
- 2. for i = 1 to n
- 3. x = x + SUM1(n)
- 4. return x

Q. How many times, asymptotically (Big O), is the statement x = x + 1 executed?

```
SUM4(n);
                             SUM5(n);
1. j = n
                             1. j = n
2. x = 0
                             2. x = 0
3. while j \ge 1
                             3. while j \ge 1
4. x = x + 1
                             4. for i = 1 to j
5. j = j/2
                             5. x = x + 1
                             6. j = j/2
6. return x
                             7. return x
```

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Q. What is the running time of the following algorithms?

ALGO1(A[1:n], n) 1. if n == 1 2. return 3. for i = 1 to n 4. A[i] = n 5. ALGO1(A[0:n-1], n) 1. if n == 0 2. return A[0] 3. return A[n] + ALGO2(A, n-1) 4. A[i] = n 5. ALGO1(A, n/2)

Recurrences

A **recurrence** is a recursive definition of a function. It has a **base case(s)** and one or more **recursive cases**.

Example.

$$f(n) = \begin{cases} 0, & n = 0 \\ f(n-1) + 1, & n > 0 \end{cases}$$

$$f(n) = \begin{cases} 1, & n = 1\\ f\left(\frac{n}{3}\right) + f\left(\frac{2n}{3}\right) + n, & n > 1 \end{cases}$$

These recurrences often arise when analyzing recursive algorithms. We seek closed form solutions to these kinds of relations.

General Recurrence Formula

$$T(n) = \begin{cases} c, if \ n = n_0 \\ aT\left(\frac{n}{b}\right) + D(n) + C(n), otherwise \end{cases}$$

- D(n) is the time for dividing the input
- C(n) is the time to combine solutions
- a is the number of subproblems, each of size $\frac{1}{b}$
- n_0 is the base case(s) and c is a constant

Example #1

```
ALGO2(A[0:n-1], n)
```

- 1. if n == 0
- 2. return A[0]
- 3. return A[n] + ALGO2(A, n-1)

- D(n) = 1 is the time for dividing the input --- at line 3, subtract 1 from n
- C(n) = 1 is the time to combine solutions --- at line 3, addition
- $n_0 = 0$ is the base case and c = 3
- General formula is T(n) = T(n-1) + 2, T(0) = 3

Solving recurrences by iteration/subtitution

Pause...

Solve the recurrences.

1.
$$T(n) = T(n-1) + n$$
, $T(0) = 0$

2.
$$T(n) = 2T(n-1) + 1$$
, $T(1) = 1$

Example #2

```
ALGO1(A[1:n], n)
1. if n == 1
2. return
3. for i = 1 to n
4. A[i] = n
5. ALGO1(A, n/2)
```

- D(n) = 1 is the time for dividing the input --- at line 3, division by 2
- C(n) = n we don't combine solutions, however, when n > 1, we execute lines 3 and 4 which takes O(n) time.
- $n_0 = 1$ is the base case and c = 2
- General formula is T(n) = T(n/2) + n, T(1) = 2

The Master Theorem

Let $T(n) = aT\left(\frac{n}{b}\right) + O(n^d)$ for some constants a > 0, b > 1, and $d \ge 0$, then

$$T(n) = \begin{cases} O(n^d), & \text{if } d > \log_b a \\ O(n^d \log n), & \text{if } d = \log_b a \\ O(n^{\log_b a}), & \text{if } d < \log_b a \end{cases}$$

Solving recurrences by iteration/subtitution

$$T(n) = T(n/2) + n$$
 $T(1) = 2$

Note that we could have used iteration \Rightarrow then have to deal with summations!!

By Master Theorem,

 $a=1, b=2, d=1$
 $d \supseteq log_a$
 $log_a = 0$
 $T(n) = O(n)$

Pause...

Solve the recurrences.

1.
$$T(n) = 2T(n/2) + n$$

2.
$$T(n) = 4T(n/2) + n^2$$

2.
$$T(n) = 4T(n/2) + n^2$$

3. $T(n) = 4T(\frac{n}{3}) + n$

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