



CLRS Notes

MIT 6.046J

Author: Haopeng Li

Date: July 27, 2022



Contents

Chapter 1	Analysis of Algorithms	1
1.1	The problem of sorting	1
1.2	Insertion Sort	1
1.3	Running time	1
1.4	Merge Sort	3
Chapter 2	Asymptotic Notation & Recurrences	5
2.1	Asymptotic notation	5
2.2	Solving recurrences	6

Chapter 1 Analysis of Algorithms

Introduction

❑ Insertion sort

❑ Asymptotic analysis

❑ Merge sort

❑ Recurrences

Definition 1.1 (Algorithms)

The theoretical study of computer-program performance and resource usage.



Note Why study algorithms and performance?

- Algorithms help us to understand scalability.
- Performance often draws the line between what is feasible and what is impossible.
- Algorithmic mathematics provides a language for talking about program behavior.
- Performance is the currency of computing.
- The lessons of program performance generalize to other computing resources.
- Speed is fun!

1.1 The problem of sorting

Problem 1.1(The problem of sorting)

- Input: sequence $\langle a_1, a_2, \dots, a_n \rangle$ of numbers.
- Output: permutation $\langle a'_1, a'_2, \dots, a'_n \rangle$ such that $a'_1 \leq a'_2 \leq \dots \leq a'_n$

1.2 Insertion Sort

```
Insertion-Sort(A,n)
  for j <- 2 to n
    do key <- A[j]
      i <- j - 1
      while i > 0 and A[i] > key
        do A[i+1] <- A[i]
          i <- i-1
      A[i+1] = key
```

1.3 Running time

- The running time depends on the input: an already sorted sequence is easier to sort.
- Parameterize the running time by the size of the input, since short sequences are easier to sort than long ones.
- Generally, we seek upper bounds on the running time, because everybody likes a guarantee.

1.3.1 Kinds of Analysis

Definition 1.2 (Worst-Case(usually))

$T(n)$ = maximum time of algorithm on any input of size n .



Definition 1.3 (Average-Case(Sometimes))

- $T(n)$ = expected time of algorithm over all inputs of size n .
- Need assumption of statistical distribution of inputs.



Definition 1.4 (Best-case: (bogus))

Cheat with a slow algorithm that works fast on some input.



Note What is insertion sort's worst-case time?

It depends on the speed of our computer:

- relative speed (on the same machine),
- absolute speed (on different machines).



Note BIG IDEA:

1. Ignore machine-dependent constants.
2. look at the growth of $T(n)$ as $n \rightarrow \infty$
3. "Asymptotic Analysis"

1.3.2 Θ -Notation

Definition 1.5 (Θ -Notation)

$\Theta(g(n)) = \{f(n) : \text{there exist positive constants } c_1, c_2, \text{ and } n_0 \text{ such that } 0 \leq c_1g(n) \leq f(n) \leq c_2g(n) \text{ for all } n \geq n_0\}$



Note Engineering: Drop low-order terms; Ignore leading constants.

Example 1.1

$$3n^3 + 90n^2 - 5n + 6046 = \Theta(n^3)$$

1.3.3 Asymptotic performance



Note When n gets large enough, a $\Theta(n^2)$ algorithm always beats a $\Theta(n^3)$ algorithm.



Note

- We shouldn't ignore asymptotically slower algorithms, however.
- Real-world design situations often call for a careful balancing of engineering objectives.
- Asymptotic analysis is a useful tool to help to structure our thinking.

1.3.4 Insertion sort analysis

Worst case

Input reverse sorted

$$T(n) = \sum_{j=2}^n \Theta(j) = \Theta(n^2)$$

Average case

All permutations equally likely.

$$T(n) = \sum_{j=2}^n \Theta(j/2) = \Theta(n^2)$$



Note Is insertion sort a fast sorting algorithm?

- Moderately so, for small n
- Not at all, for large n

1.4 Merge Sort

Merge-Sort $A[1..n]$

1. If $n = 1$, done
2. Recursively sort $A[1 \dots \lceil n/2 \rceil]$ and $A[\lceil n/2 \rceil + 1 \dots n]$
3. Merge the 2 sorted lists.



Note Key subroutine: MERGE

1.4.1 Analyzing Merge Sort

Time = $\Theta(n)$ to merge a total of n elements (linear time).

$T(n)$	MERGE-SORT $A[1 \dots n]$
$\Theta(1)$	1. If $n = 1$, done.
$2T(n/2)$	2. Recursively sort $A[1 \dots \lceil n/2 \rceil]$ and $A[\lceil n/2 \rceil + 1 \dots n]$.
$\Theta(n)$	3. "Merge" the 2 sorted lists



Note Sloppiness: $2T(n/2)$ should be $T(\lceil n/2 \rceil) + T(\lfloor n/2 \rfloor)$, but it turns out not to matter asymptotically.

1.4.2 Recurrence for merge sort

$$T(n) = \begin{cases} \Theta(1) & \text{if } n = 1 \\ 2T(n/2) + \Theta(n) & \text{if } n > 1 \end{cases}$$



Note

- We shall usually omit stating the base case when $T(n) = \Theta(1)$ for sufficiently small n , but only when it has no effect on the asymptotic solution to the recurrence.
- CLRS and Lecture 2 provide several ways to find a good upper bound on $T(n)$.

1.4.3 Recursion tree

Example 1.2 Solve $T(n) = 2T(n/2) + cn$, where $c > 0$ is constant.

1.4.4 Conclusions

- $\Theta(n \lg n)$ grows more slowly than $\Theta(n^2)$
- Therefore, merge sort asymptotically beats insertion sort in the worst case.
- In practice, merge sort beats insertion sort for $n > 30$ or so.

Chapter 2 Asymptotic Notation & Recurrences

Introduction

- ☐ O -, Ω -, and Θ - notation
- ☐ Substitution method
- ☐ Iterating the recurrence

- ☐ Recursion tree
- ☐ Master method

2.1 Asymptotic notation

2.1.1 O -notation (upper bounds)


Definition 2.1 (O -notation (upper bounds))

We write $f(n) = O(g(n))$ if there exist constants $c > 0, n_0 > 0$ such that $0 \leq f(n) \leq cg(n)$ for all $n \geq n_0$



Example 2.1

$$2n^2 = O(n^3) \quad (c = 1, n_0 = 2)$$

 **Note** Notice that in this equation, $2n^2$ are functions not values and the equal sign is just "one-way" equality. Actually, it can be denoted more precisely:

$$2n^2 \in O(n^3)$$

 **Note** Convention: A set in a formula represents an anonymous function in the set.

Example 2.2

$$n^2 + O(n) = O(n^2)$$

means for any $f(n) \in O(n), n^2 + f(n) = h(n)$ for some $h(n) \in O(n^2)$

2.1.2 Ω -notation (lower bounds)

O -notation is an upper-bound notation. It makes no sense to say $f(n)$ is at least $O(n^2)$.

Definition 2.2 (Ω -notation (lower bounds))

$\Omega(g(n)) = \{f(n) : \text{there exist constants } c > 0, n_0 > 0 \text{ such that } 0 \leq cg(n) \leq f(n) \text{ for all } n \geq n_0\}$



Example 2.3

$$\sqrt{n} = \Omega(\lg n) \quad (c = 1, n_0 = 16)$$

2.1.3 Θ -notation (tight bounds)

Definition 2.3 (Θ -notation (tight bounds))

$$\Theta(g(n)) = O(g(n)) \cap \Omega(g(n))$$



Example 2.4

$$\frac{1}{2}n^2 - 2n = \Theta(n^2)$$

2.1.4 o -notation and ω -notation

O -notation and Ω -notation are like \leq and \geq . o -notation and ω -notation are like $<$ and $>$.

Definition 2.4 (o -notation)

$o(g(n)) = \{f(n) : \text{for any constant } c > 0, \text{ there is a constant } n_0 > 0 \text{ such that } 0 \leq f(n) < cg(n) \text{ for all } n \geq n_0\}$

**Example 2.5**

$$2n^2 = o(n^3) \quad (n_0 = 2/c)$$

Definition 2.5 (ω -notation)

$\omega(g(n)) = \{f(n) : \text{for any constant } c > 0, \text{ there is a constant } n_0 > 0 \text{ such that } 0 \leq f(n) < cg(n) \text{ for all } n \geq n_0\}$

**Example 2.6**

$$\sqrt{n} = \omega(\lg n) \quad (n_0 = 1 + 1/c)$$

2.2 Solving recurrences

The analysis of merge sort from Lecture 1 required us to solve a recurrence. Recurrences are like solving integrals, differential equations, etc. Learn a few tricks.

2.2.1 Substitution method**Definition 2.6 (Substitution method)**

The most general method:

1. Guess the form of the solution.
2. Verify by induction.
3. Solve for constants.

**Example 2.7**


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

- Assume that $T(1) = \Theta(1)$.
- Guess $O(n^3)$. (Prove O and Ω separately.)
- Assume that $T(k) \leq ck^3$ for $k < n$
- Prove $T(n) \leq cn^3$ by induction.

Solution


$$\begin{aligned}
T(n) &= 4T(n/2) + n \\
&\leq 4c(n/2)^3 + n \\
&= (c/2)n^3 + n \\
&= cn^3 - ((c/2)n^3 - n) \leftarrow \text{desired - residual} \\
&\leq cn^3 \leftarrow \text{desired}
\end{aligned}$$

whenever $(c/2)n^3 - n \geq 0$, for example, if $c \geq 2$ and $n \geq 1$

 **Note** We must also handle the initial conditions, that is, ground the induction with base cases.

1. **Base:** $T(n) = \Theta(1)$ for all $n < n_0$, where n_0 is a suitable constant.
2. For $1 \leq n < n_0$, we have " $\Theta(1)$ " $\leq cn^3$, if we pick c big enough.

This bound is not tight!

 **Note** A tighter upper bound? We shall prove that $T(n) = O(n^2)$


Assume that $T(k) \leq ck^2$ for $k < n$:

$$\begin{aligned}
T(n) &= 4T(n/2) + n \\
&\leq 4c(n/2)^2 + n \\
&= cn^2 + n \\
&= O(n^2)
\end{aligned}$$

Wrong! We must prove the I.H. ($T(k) \leq ck^2$)

$$= cn^2 - (-n)$$

for no choice of $c > 0$. Lose!

 **Note** **IDEA:** Strengthen the inductive hypothesis. (Subtract a low-order term.)

Inductive hypothesis: $T(k) \leq c_1k^2 - c_2k$ for $k < n$.

Solution

$$\begin{aligned}
T(n) &= 4T(n/2) + n \\
&= 4(c_1(n/2)^2 - c_2(n/2)) + n \\
&= c_1n^2 - 2c_2n + n \\
&= c_1n^2 - c_2n - (c_2n - n) \\
&\leq c_1n^2 - c_2n \text{ if } c_2 \geq 1.
\end{aligned}$$

Pick c_1 big enough to handle the initial conditions.

2.2.2 Recursion-tree method

- A recursion tree models the costs(time) of a recursive execution of an algorithm.
- The recursion-tree method can be unreliable, just like any method that uses ellipses (...)
- The recursion-tree method promotes intuition, however.
- The recursion tree method is good for generating guesses for the substitution method.

Example 2.8 Solve

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

2.2.3 The master method

The master method applies to recurrences of the form

$$T(n) = aT(n/b) + f(n)$$

where $a \geq 1, b > 1$ and f is asymptotically positive.

Theorem 2.1 (Three common cases)

Compare $f(n)$ with $n^{\log_b a}$:

1. $f(n) = O(n^{\log_b a - \varepsilon})$ for some constant $\varepsilon > 0$
 - $f(n)$ grows polynomially slower than $n^{\log_b a}$ (by an n^ε factor).

Solution:

$$T(n) = \Theta(n^{\log_b a})$$

2. $f(n) = \Theta(n^{\log_b a} \lg^k n)$ for some constant $k \geq 0$
 - $f(n)$ and $n^{\log_b a}$ grow at similar rates.

Solution:

$$T(n) = \Theta(n^{\log_b a} \lg^{k+1} n)$$

3. $f(n) = \Omega(n^{\log_b a + \varepsilon})$ for some constant $\varepsilon > 0$
 - $f(n)$ grows polynomially faster than $n^{\log_b a}$ (by an n^ε factor), and $f(n)$ satisfies the regularity condition that $af(n/b) \leq cf(n)$ for some constant $c < 1$

Solution:

$$T(n) = \Theta(f(n))$$



Example 2.9

$$T(n) = 4T(n/2) + n^3$$

Solution

$$a = 4, b = 2 \Rightarrow n^{\log_b a} = n^2; f(n) = n^3$$

CASE 3: $f(n) = \Omega(n^{2+\varepsilon})$ for $\varepsilon = 1$ and $4(n/2)^3 \leq cn^3$ (reg. cond.) for $c = 1/2$.

$$\therefore T(n) = \Theta(n^3)$$

Example 2.10

$$T(n) = 4T(n/2) + n^2/\lg n$$

Solution

$$a = 4, b = 2 \Rightarrow n^{\log_b a} = n^2; f(n) = n^2/\lg n$$

Master method does not apply. In particular, for every constant $\varepsilon > 0$, we have $n^\varepsilon = \omega(\lg n)$.

2.2.3.1 Idea of master theorem