

Lecture II RECURRENCES

Recurrences arise naturally in the complexity analysis of recursive algorithms and in probabilistic analysis. We introduce some basic techniques for solving recurrences. A recurrence is a recursive relation for a complexity function $T(n)$. Here are two examples:

$$F(n) = F(n-1) + F(n-2) \quad (1)$$

and

$$T(n) = n + 2T(n/2). \quad (2)$$

Looks familiar?

The reader may recognize the first as the recurrence for Fibonacci numbers, and the second as the complexity of the Mergesort, described in Lecture 1. These recurrences have¹ the following “separable form”:

$$T(n) = G(n, T(n_1), \dots, T(n_k)) \quad (3)$$

where $G(x_0, x_1, \dots, x_k)$ is a function in $k+1$ variables and each n_i ($i = 1, \dots, k$) is a function of n that is strictly less than n . E.g., in (1), we have $k = 2$ and $n_1 = n-1, n_2 = n-2$ while in (2), we have $k = 1$ and $n_1 = n/2$.

What does it mean to “solve” recurrences such as equations (1) and (2)? The Fibonacci and Mergesort recurrences have the following well-known solutions:

$$F(n) = \Theta(\phi^n)$$

where $\phi = (1 + \sqrt{5})/2 = 1.618\dots$ is the golden ratio, and

Solve up to Θ -order

$$T(n) = \Theta(n \log n).$$

In this book, we generally estimate complexity functions $T(n)$ only up to its Θ -order. If only an upper bound or lower bound is needed, and we determine $T(n)$ up to its O -order or to Ω -order. In rare cases, we may be able to derive the exact solution (in fact, this is possible for $T(n)$ and $F(n)$ above). One benefit of Θ -order solutions is this — most of the recurrences we treat in this book can be solved by only elementary methods, without assuming differentiability or using calculus tools.

The variable “ n ” is called the **designated variable** of the recurrence (3). If there are non-designated variables, they are supposed to be held constant. In mathematics, we usually reserve “ n ” for natural numbers or perhaps integers. In the above examples, this is the natural interpretation for n . But one of the first steps we take in solving recurrences is to re-interpret n (or whatever is the designated variable) to range over the real numbers. The corresponding recurrence equation (3) is then called a **real recurrence**. For this reason, we may prefer the symbol “ x ” as our designated variable, since x is normally viewed as a real variable.

All recurrences are real

What does an extension to real numbers mean? In the Fibonacci recurrence (1), what is $F(2.5)$? In Mergesort (2), what does $T(\pi) = T(3.14159\dots)$ represent? The short answer is, we don’t really care.

In addition to the recurrence (3), we generally need the **boundary conditions** or **initial values** of the function $T(n)$. They give us the values of $T(n)$ *before* the recurrence (3) becomes valid. Without initial values, $T(n)$ is generally under-determined. For our example (1), if n ranges over natural numbers, then the initial conditions

$$F(0) = 0, \quad F(1) = 1$$

give rise to the standard Fibonacci numbers, i.e., $F(n)$ is the n th Fibonacci number. Thus $F(2) = 1, F(3) =$

Some initial conditions lead to trivial solutions

¹Non-separable recurrences looks like $G(n, T(n), T(n_1), \dots, T(n_k)) = 0$, but these are rare.

2, $F(4) = 3$, etc. On the other hand, if we use the initial conditions $F(0) = F(1) = 0$, then the solution is trivial: $F(n) = 0$ for all $n \geq 0$. Thus, our assertion earlier that $F(n) = \Theta(\phi^n)$ is the solution to (1) is not² really true without knowing the initial conditions. On the other hand, $T(n) = \mathcal{O}(n \log n)$ can be shown to hold for (2) regardless of the initial conditions. For the typical recurrence from complexity analysis, this will be the case.

EXERCISES

Exercise 0.1: Consider the non-homogeneous version of Fibonacci recurrence $F(n) = F(n-1) + F(n-2) + f(n)$ for some function $f(n)$. If $f(n) = 1$, show that $F(n) = \Omega(c^n)$ for some $c > 1$, regardless of the initial conditions. Try to find the largest value for c . Does your bound hold if we have $f(n) = n$ instead? \diamond

Exercise 0.2: Let $T(n) = aT(n/b) + n$, where $a > 0$ and $b > 1$. How sensitive is this recurrence to the initial conditions? More precisely, if $T_1(n)$ and $T_2(n)$ are two solutions corresponding to two initial conditions, what is the strongest relation you can infer between T_1 and T_2 ? \diamond

Exercise 0.3: Consider recurrences of the form

$$T(n) = (T(n-1))^2 + g(n). \quad (4)$$

In this exercise, we restrict n to natural numbers and use explicit boundary conditions.

(a) Show that the number of binary trees of height at most n is given by this recurrence with $g(n) = 1$ and the boundary condition $T(1) = 1$. Show that this particular case of (4) has solution

$$T(n) = \left\lfloor k^{2^n} \right\rfloor. \quad (5)$$

(b) Show that the number of Boolean functions on n variables is given by (4) with $g(n) = 0$ and $T(1) = 2$. Solve this.

NOTE: Aho and Sloane (1973) investigate the recurrence (4). \diamond

Exercise 0.4: Let T, T' be binary trees and $|T|$ denote the number of nodes in T . Define the relation $T \sim T'$ recursively as follows: (BASIS) If $|T| = 0$ or 1 then $|T| = |T'|$. (INDUCTION) If $|T| > 1$ then $|T'| > 1$ and either (i) $T_L \sim T'_L$ and $T_R \sim T'_R$, or (ii) $T_L \sim T'_R$ and $T_R \sim T'_L$. Here T_L and T_R denote the left and right subtrees of T .

(a) Use this to give a recursive algorithm for checking if $T \sim T'$.

(b) Give the recurrence satisfied by the running time $t(n)$ of your algorithm.

(c) Give asymptotic bounds on $t(n)$. \diamond

END EXERCISES

§1. Simplification

In the real world, when faced with an actual recurrence to be solved, there are usually some simplifications steps to be taken. Here are three general simplifications that should be automatically taken:

- **Initial Condition.** In this book, we normally state recurrence without any initial conditions. This is deliberate: we expect the student to supply the initial conditions, based on the following assumption:

how convenient!!

Default Initial Condition (DIC): *There is some $n_1 > 0$ such that for all $n < n_1$, $T(n)$ is assigned arbitrary values. The recurrence for $T(n)$ holds for all $n \geq n_1$.*

The intent is for the student to make convenient choices for n_1 and the initial values of $T(n)$. Normally, we make choices so that the resulting solution has a simple form. Our favorite version of DIC is $T(n) = C$ for all $n < n_1$ and some constant C . To use DIC, we need not specify n_1 or the initial values of $T(n)$ before hand. We just proceed to solve the recurrence, and at the appropriate moments, introduce these values.

What is the justification for this approach? It allows us to focus on the recurrence itself rather than the initial conditions. In many cases, this arbitrariness does not affect the asymptotic behavior of the solution. Even if this simplification is not valid, we might have learned something about the recurrence.

- **Extension to Real Functions.** Even if the function $T(n)$ is originally defined for natural numbers n , we will now treat $T(n)$ as a real function (*i.e.*, n is viewed as a real variable), and defined for n sufficiently large. See the Exercise for an alternative approach (“ample domain”) that avoids extensions to real functions. It is important to realize that even if we have no interest in real recurrences, some solution techniques below will transform our recurrences into non-integer recurrences. So we might as well take the plunge from the start.
- **Converting Recurrence Inequality into a Recurrence Equation.** If we begin with a recurrence inequality such as $T(n) \leq G(n, T(n_1), \dots, T(n_k))$, we simply rewrite this as an equality relation: $T(n) = G(T(n_1), \dots, T(n_k))$. Because of this change, our eventual solution for $T(n)$ is only an upper bound on the original function. Similarly, if we had started with $T(n) \geq G(n, T(n_1), \dots, T(n_k))$, the eventual solution is only a lower bound.

¶1. **Special Simplifications.** Suppose the running time of an algorithm satisfies the following inequality:

$$T(n) \leq T(\lceil n/2 \rceil) + T(\lfloor n/2 \rfloor) + 6n + \lg n - 4, \quad (6)$$

for integer $n > 100$, with boundary condition

$$T(n) = 3n^2 - 4n + 2 \quad (7)$$

for $0 \leq n \leq 100$. Such a **recurrence in-equation** may arise in some imagined implementation of Mergesort, with special treatment for $n \leq 100$. Our general simplification steps tells us to (a) discard the specific boundary conditions (7) in favor of DIC, (b) treat $T(n)$ as a real function, and (c) write the recurrence as an equation.

What other simplifications might apply here? Let us convert (6) into the following

$$T(n) = 2T(n/2) + n. \quad (8)$$

This represents two additional simplifications: (i) We replaced the term “ $+6n + \lg n - 4$ ” by some simple expression (“ $+n$ ”) with same Θ -order. (ii) We have removed the ceiling and floor functions. Step (i) is justified because this does not affect the Θ -order (if this is not clear, then you can always come back to verify this claim). Step (ii) exploits the fact that we now treat $T(n)$ as a real function, so we need not worry about non-integral arguments when we remove the ceiling or floor functions. Also, it does not affect the asymptotic value of $T(n)$ here.

The justifications for these steps are certainly not obvious, but they should seem reasonable. Ultimately, one ought to return to such simplifications to justify them.

²The reason behind this is that (1) is a homogeneous recurrence while (2) is non-homogeneous. For instance, $F(n) = F(n-1) + F(n-2) + 1$ would be non-homogeneous and its Θ -solution would not depend on the initial conditions.

EXERCISES

Exercise 1.1: Show that our above simplifications of the recurrence (6) (with its initial conditions) cannot affect the asymptotic order of the solution. [Show this for ANY choice of a Default Boundary Condition.]

◇

Exercise 1.2: We seek counterexamples to the claim that we can replace $\lceil n/2 \rceil$ by $n/2$ in a recurrence without changing the Θ -order of the solution.

(a) Construct a function $g(n)$ that provides a counter example for the following recurrence: $T(n) = T(\lceil n/2 \rceil) + g(n)$. HINT: make $g(n)$ depend on the parity of n .

(b) Construct a different counter example of the form $T(n) = h(n)T(\lceil \frac{n}{2} \rceil)$ for a suitable function $h(n)$.

◇

Exercise 1.3: Show examples where the choice of initial conditions can change the Θ -order of the solution $T(n)$. HINT: Choose $T(n)$ to increase exponentially.

◇

Exercise 1.4: Suppose x, n are positive numbers satisfying the following “recurrence” equation,

$$2^x = x^{2n}.$$

Solve for x as a function of n , showing

$$x(n) = [1 + o(1)]2n \log_2(2n).$$

HINT: take logarithms. This is an example of a bootstrapping argument where we use an approximation of $x(n)$ to derive yet a better approximation. See, e.g., Purdom and Brown [14].

◇

Exercise 1.5: [Ample Domains] Our approach of considering real functions is non-standard. The standard approach to solving recurrences in the algorithms literature is the following. Consider the simplification of (6) to (8). Suppose, instead of assuming $T(n)$ to be a real function (so that (8) makes sense for all values of n), we continue to assume n is a natural number. It is easy to see that $T(n)$ is completely defined by (8) iff n is a power of 2. We say that (8) is closed over the set $D_0 := \{2^k : k \in \mathbb{N}\}$ of powers of 2. In general, we say a recurrence is “closed over a set $D \subseteq \mathbb{R}$ ” if for all $n \in D$, the recurrence for $T(n)$ depends only on smaller values n_i that also belong in D (unless n_i lies within the boundary condition).

(a) Let us call a set $D \subseteq \mathbb{R}$ an “ample set” if, for some $\alpha > 1$, the set $D \cap [n, \alpha \cdot n]$ is non-empty for all $n \in \mathbb{N}$. Here $[n, \alpha n]$ is closed real interval between n and αn . If the solution $T(n)$ is sufficiently “smooth”, then knowing the values of $T(n)$ at an ample set D gives us a good approximation to values where $n \notin D$. In this question, our “smoothness assumption” is simply: $T(n)$ is *monotonic non-decreasing*. Suppose that $T(n) = n^k$ for n ranging over an ample set D . What can you say about $T(n)$ for $n \notin D$? What if $T(n) = c^n$ over D ? What if $T(n) = 2^{2^n}$ over D ?

(b) Suppose $T(n)$ is recursively expressed in terms of $T(n_1)$ where $n_1 < n$ is the largest prime smaller than n . Is this recurrence defined over an ample set?

◇

Exercise 1.6: Consider inversions in a sequence of numbers.

(a) The sequence $S_0 = (1, 2, 3, 4)$ has no inversions, but sequence $S_1 = (2, 1, 4, 3)$ has two inversions, namely the pairs $\{1, 2\}$ and $\{3, 4\}$. Now, the sequence $S_2 = (2, 3, 1, 4)$ also has two inversions, namely the pairs $\{1, 2\}$ and $\{1, 3\}$. Let $I(S)$ be the number of inversions in S . Give an $O(n \lg n)$ algorithm to compute $I(S)$. Hint: this is a generalization of Mergesort.

(b) We next distinguish between the quality of the inversions of S_1 and S_2 . The inversions $\{1, 2\}$ and $\{3, 4\}$

in S_1 are said to have weight of 1 each, so the **weighted inversion** of S_1 is $W(S_1) = 2 = 1 + 1$. But for S_2 , the inversion $\{1, 2\}$ has weight 2 while inversion $\{1, 3\}$ has weight 1. So the weighted inversion is $W(S_2) = 3 = 2 + 1$. Thus the “weight” measures how far apart the two numbers are. In general, if $S = (a_1, \dots, a_n)$ then a pair $\{a_i, a_j\}$ is an **inversion** if $i < j$ and $a_i > a_j$. The weight of this inversion is $j - i$. Let $W(S)$ be the sum of the weights of all inversions. Give an $O(n \lg n)$ algorithm for weighted inversions. \diamond

Exercise 1.7: We might consider following form of DIC where we assume that there exists $0 < n_0 < n_1$, and constants $0 < C_0 \leq C_1$ such that

$$(\forall n_0 \leq n < n_1)[C_0 \leq T(n) \leq C_1]. \quad (9)$$

Solve the Fibonacci and mergesort recurrences using this version of DIC. Your solutions should be stated in terms of the parameters C_1, C_2 . \diamond

END EXERCISES

§2. Divide-and-Conquer Algorithms

In this section, we see some other interesting recurrences that arise in a divide-and-conquer algorithms. First, we look at Karatsuba’s classic algorithm for multiplying integers [8]. Then we consider a modern problem arising in searching for key words.

¶2. Example from Arithmetic. To motivate Karatsuba’s algorithm, let us recall the classic “high-school algorithm” for multiplying integers. Given positive integers X, Y , we want to compute their product $Z = XY$. This algorithm assumes you know how to do single-digit multiplication and multi-digit additions (“pre-high school”). The algorithm multiplies X by each digit of Y . If X and Y have n digits each, then we now have n products, each having at most $n + 1$ digits. After appropriate left-shifts of these n products, we add them all up. It is not hard to see that this algorithm takes $\Theta(n^2)$ time. Can we improve on this?

OK, you learned it in grade school

Usually we think of X, Y in decimal notation, but the algorithm works equally well in any base. We shall assume base 2 for simplicity. For instance, if $X = 19$ then in binary $X = 10011$. To avoid the ambiguity from different bases, we indicate³ the base using a subscript, $X = (10011)_2$. The standard convention is that decimal base is assumed when no base is indicated. Thus a plain “100” without any base represents one hundred, and not four.

If we wanted four, we have to write “(100)₂”

Assume X and Y has length exactly n where n is a power of 2 (we can pad with 0’s if necessary). Let us split up X into a high-order half X_1 and low-order half X_0 . Thus

$$X = X_0 + 2^{n/2}X_1$$

where X_0, X_1 are $n/2$ -bit numbers. Similarly,

$$Y = Y_0 + 2^{n/2}Y_1.$$

³By the same token, we may write $X = (19)_{10}$ for base 10. But now the base “10” itself may be ambiguous — after all “10” in binary is equal to two. The convention is to write the base in decimal.

Then

$$\begin{aligned} Z &= (X_0 + 2^{n/2} X_1)(Y_0 + 2^{n/2} Y_1) \\ &= X_0 Y_0 + 2^{n/2} (X_1 Y_0 + X_0 Y_1) + 2^n X_1 Y_1 \\ &= Z_0 + 2^{n/2} Z_1 + 2^n Z_2, \end{aligned}$$

where $Z_0 = X_0 Y_0$, etc. Clearly, each of these Z_i 's have at most $2n$ bits. Now, if we compute the 4 products

$$X_0 Y_0, X_1 Y_0, X_0 Y_1, X_1 Y_1$$

recursively, then we can put them together (“conquer step”) in $\mathcal{O}(n)$ time. To see this, we must make an observation: in binary notation, multiplying any number X by 2^k (for any positive integer k) takes $\mathcal{O}(k)$ time, independent of X . We can view this as a matter of shifting left by k , or by appending a string of k zeros to X .

Hence, if $T(n)$ is the time to multiply two n -bit numbers, we obtain the recurrence

$$T(n) \leq 4T(n/2) + Cn \quad (10)$$

for some $C > 1$. Given our simplification suggestions, we immediately rewrite this as

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

As we will see, this recurrence has solution $T(n) = \Theta(n^2)$, so we have not really improved on the high-school method.

Karatsuba observed that we can proceed as follows: we can compute $Z_0 = X_0 Y_0$ and $Z_2 = X_1 Y_1$ first. Then we can compute Z_1 using the formula

$$Z_1 = (X_0 + X_1)(Y_0 + Y_1) - Z_0 - Z_2.$$

Thus Z_1 can be computed with one recursive multiplication plus some additional $\mathcal{O}(n)$ work. From Z_0, Z_1, Z_2 , we can again obtain Z in $\mathcal{O}(n)$ time. This gives us the **Karatsuba recurrence**,

$$T(n) = 3T(n/2) + n. \quad (11)$$

We shall show that $T(n) = \Theta(n^\alpha)$ where $\alpha = \lg 3 = 1.58\dots$. This is clearly an improvement of the high school method.

There is an even faster algorithm from Schönhage and Strassen (1971) that runs in $\mathcal{O}(n \log n \log \log n)$ time. This has withstood improvements for almost 20 years, but in recent years, the $\log \log n$ factor has begun to be breached (they can be replaced by $\log^* n$). Many theoretical computer scientists believe that an $\mathcal{O}(n \log n)$ algorithm should be possible. There is an increasing need for multiplication of arbitrarily large integers. In cryptography or computational number theory, for example. These are typically implemented in software in a “big integer” package. For instance, Java has a `BigInteger` class. A well-engineered big integer multiplication algorithm will typically implement the High-School algorithm for $n \leq n_0$, and use Karatsuba for $n_0 < n \leq n_1$, and use Schönhage-Strassen for $n > n_1$. Typical values for n_0, n_1 are 30, 200.

first improvement in 1000 years? According to Wikipedia, high school multiplication is equivalent to the “lattice method” which is at least 1000 years old.

¶3. A Google Problem. The Google Phenomenon is possible because of efficient algorithms: every files on the web can be searched and indexed. Searching is by keywords. Let us suppose that Google pre-processes every file in its database for keywords. However, a user may ask to search files for two or more keywords. We will reduce this multi-keyword search to a precomputed single-keyword index.

Let F be a file, viewed as a sequence of words (ignoring punctuations, capitalization, etc). We first preprocess F for the occurrences of keywords. For each keyword w , we precompute an **index** which amounts a sorted sequence $P(w)$ of positions indicating where w occurs in F . E.g.,

$$P(\text{divide}) = (11, 16, 42, 101, 125, 767)$$

means that the keyword *divide* occurs 6 times in F , at positions 11, 16, etc. Suppose we want to search the file using a conjunction of k keywords, w_1, \dots, w_k . An interval $J = [s, t]$ is called a **cover** for w_1, \dots, w_k if each w_i occurs at least once within the positions in J . The size of a cover $[s, t]$ is just $t - s$. A cover is **minimal** if it is not contained in some larger cover; it is **minimum** if its size is smallest among all covers. Note that if $[s_i, t_i]$ are minimal covers for $i = 1, 2, \dots$, and if $s_i < s_{i+1}$ then $t_i < t_{i+1}$. The **keyword cover problem** is this: given the indices $P(w_1), \dots, P(w_k)$ for a set $W = \{w_1, \dots, w_k\}$ of keywords in a file, to compute a minimum cover for W .

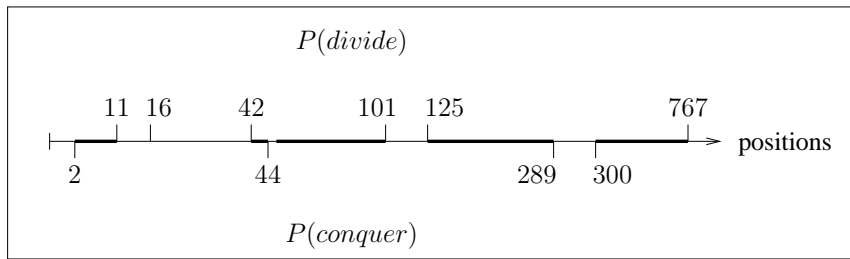


Figure 1: Minimal Covers

E.g., let $k = 2$ with $w_1 = \text{divide}$ and $w_2 = \text{conquer}$. With $P(\text{divide})$ as before, let $P(\text{conquer}) = (2, 44, 289, 300)$. Then the minimal covers are $[2, 11]$, $[42, 44]$, $[44, 101]$, $[125, 289]$, $[289, 767]$. This is illustrated in Figure 1. The minimum cover is $[42, 44]$.

Before attempting to solve this problem, consider how Google might use the minimum cover solutions: suppose a user wants to search for a set $W = \{w_1, \dots, w_k\}$ of key words. For each file f_j ($j = 1, 2, \dots$) we use the algorithm to compute a minimum cover $[c_j, d_j]$ (if one exists) for W in f_j . The indices $P(w_i)$ for each key word w_i are assumed to have been precomputed. The search results will be a list of all files for which covers exist, but we order these files in order of non-decreasing cover size $d_j - c_j$. The actual cover $[c_j, d_j]$ can be used by Google to display a snippet of the file f_j .

Let us now consider algorithms. Let n_i be the length of list $P(w_i)$ ($i = 1, \dots, k$) and $n = n_1 + \dots + n_k$. The case $k = 2$ is relatively straightforward, and we leave it for an exercise. Consider the case $k = 3$. First, merge $P(w_1), P(w_2), P(w_3)$ into the array $A[1..n]$. Recall that in Lecture I, we discussed the merging of sorted lists. Merging takes time $O(n_1 + n_2 + n_3) = O(n)$. To keep track of the origin of each number in A , we may also construct an array $B[1..n]$ such that $B[i] = j \in \{1, 2, 3\}$ iff $A[i]$ comes from the list $P(w_j)$.

We use a divide-and-conquer approach. Recursively, compute a minimum cover of $A[1..(n/2)]$ and $A[(n/2) + 1..n]$ (for simplicity, assume n is a power of 2). Let $C_{1,n/2}$ and $C_{(n/2)+1,n}$ be these minimum covers. We now need to find a minimal cover that straddles $A[(n/2)]$ and $A[(n/2) + 1]$. Let $C = [A[i], A[j]]$ be such a minimal cover, where $i \leq (n/2)$ and $j \geq (n/2) + 1$. There are 6 cases. One case is when $C = C' \cup C''$, where $C' = [A[i], A[n/2]]$ is the rightmost cover for w_1 in $A[1..(n/2)]$, and $C'' = [A[(n/2) + 1], A[j]]$ is the leftmost cover for w_2, w_3 in $A[(n/2) + 1, n]$. We can find C' and C'' in $O(n)$ time. The remaining 5 cases can similarly be found in $O(n)$ time. Then C is the cover that has minimum size among these 6 cases. Hence, the overall complexity of the algorithm satisfies

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

We have seen this recurrence before, as the Mergesort recurrence (2). The solution is $T(n) = \Theta(n \log n)$. See exercise for a general solution in $O(n \log k)$ time.

¶4. **Master Recurrence and Divide-and-Conquer Algorithms.** The recurrences (2) and (11) are instances of the **Master Recurrence** which has the form:

$$T(n) = aT(n/b) + d(n) \quad (12)$$

where $a > 0$ and $b > 1$ are constants and d is any function, usually called the **driving function**. Below, we shall solve this recurrence under fairly general conditions.

The idea of solving a problem by reducing it to smaller subproblems is a very general one. In this chapter, we mainly focus on reductions from problems of size n to subproblems of size $\leq cn$ for some fixed $c < 1$. If there are a finite number of such subproblems, the running times can be bounded using solutions to the Master recurrence (12). In other problems, we reduce a problem of size n to several subproblems that of size $\leq n - c$ for some fixed $c \geq 1$. Such solutions would be exponential time without additional properties; we study these under the topic of dynamic programming (Chapter 7). In applications, we have $d(n) > 0$, representing the cost of merging solutions of subproblems in divide-and-conquer algorithms.

EXERCISES

Exercise 2.1: Carry out Karatsuba's algorithm for $X = 6 = (0110)_2$ and $Y = 11 = (1011)_2$. It is enough to display the recursion tree with the correct arguments for each recursive call, and the returned values. ◇

Exercise 2.2: Suppose an implementation of Karatsuba's algorithm achieves $T(n) \leq Cn^{1.58}$ where $C = 1000$. Moreover, the High School multiplication is $T(n) = 30n^2$. At what value of n does Karatsuba become competitive with the High School method? ◇

Exercise 2.3: Consider the recurrence $T(n) = 3T(n/2) + n$ and $T'(n) = 3T'(\lceil n/2 \rceil) + 2n$. Show that $T(n) = \Theta(T'(n))$. ◇

Exercise 2.4: The following is a programming exercise. It is best done using a programming language such as Java that has a readily available library of big integers.

(a) Implement Karatsuba's algorithm using such a programming language and using its big integer data structures and related facilities. The only restriction is that you must not use the multiplication, squaring, division or reciprocal facility of the library. But you are free to use its addition/subtraction operations, and any ability to perform left/right shifts (multiplication by powers of 2).

(b) Let us measure the running time of your implementation of Karatsuba's algorithm. For input numbers, use a random number generator to produce numbers of any desired bit length. If $T(n) \leq Cn^\alpha$ then $\lg T(n) \leq \lg C + \alpha \lg n$. The **exponent** α is thus the slope of the curve obtained by plotting $\lg T(n)$ against $\lg n$, we should get a slope of at most α . Plot the running time of your implementation to verify that its exponent is < 1.58 .

(c) What is the exponent in Java's native implementation? Explain your data.

(d) My 1999 undergraduate class in algorithms did the preceding exercise, using the `java.math.BigInteger` package. One timing from this class is shown in Table 2. The "exponent" in this table is computing with a crude formula $\frac{\lg(\text{avgTime}) - \text{avgTime}_0}{\lg(\text{numBits}) - \text{numBits}_0}$ where $\text{numBits}_0 = 4000$ and $\text{avgTime}_0 = 4.358$ (the initial trial). This crude exponent hovers around 1.9. What would be the empirical exponent if you do a proper regression analysis? This data suggests that in 1999, the library only implemented the High School algorithm. By 2001, the situation appeared to have improved. ◇

Exercise 2.5: Suppose the running time of an algorithm is an unknown function of the form $T(n) = An^a + Bn^b$ where $a > b$ and A, B are arbitrary positive constants. You want to discover the exponent a by

NumBits	AvgTime	Exponent	NumBits	AvgTime	Exponent
4000	4.358	0.0	9600	23.034	1.9017905239616146
4200	4.696	1.531002145103799	9800	24.055	1.9064306092855452
4400	5.194	1.841260577604784	10000	24.986	1.905838802838669
4600	5.517	1.6873048110254347	10200	25.987	1.9074840762036238
4800	5.983	1.7381865504999572	10400	26.948	1.9067232067781992
5000	6.51	1.7985113947251763	10600	28.108	1.912700793571853
5200	6.988	1.7997159663026001	10800	29.111	1.9120055203582398
5400	7.509	1.812998128928515	11000	30.221	1.9143159996069712
5600	8.01	1.8089977665618309	11200	31.534	1.922120988851413
5800	8.684	1.85558837393382	11400	31.542	1.8898795547030012
6000	9.183	1.838236378924439	11600	32.67	1.8920105894497778
6200	9.769	1.8418523402197153	11800	33.703	1.8908891117429292
6400	10.365	1.8434357852847953	12000	34.67	1.8877101089855162
6600	11.088	1.864808884276074	12200	36.082	1.8955269064390694
6800	11.717	1.8638802969571109	12400	37.218	1.8956825843907563
7000	12.413	1.8704459319724756	12600	38.049	1.8884930574030907
7200	13.092	1.8714070696035303	12800	39.242	1.8894663931349043
7400	13.843	1.8787279477010768	13000	40.553	1.892493164635265
7600	14.532	1.8763458534440565	13200	41.696	1.8915733844170872
7800	15.297	1.8801860861195574	13400	42.951	1.8925738155123988
8000	16.054	1.8811947011507577	13600	44.159	1.8923271871808227
8200	16.905	1.8884383570994894	13800	45.533	1.8947617307075215
8400	17.644	1.8847717474449632	14000	46.816	1.8951803717241376
8600	18.498	1.8885827751677746	14200	48.1	1.8953182704475686
8800	19.283	1.8862283707110576	14400	49.401	1.8954588786790316
9000	20.225	1.8927722703240168	14600	50.873	1.8979435636574864
9200	21.17	1.8976522229154338	14800	52.364	1.9002856600816482
9400	22.063	1.8982439890258536	15000	53.537	1.8977482007273088

Figure 2: Timing as a function of number of bits

measurement. How can you, by plotting the running time of the algorithm for various n , find a with an error of at most ϵ ? Assume that you can do least squares line fitting. \diamond

Exercise 2.6: Try to generalize Karatsuba's algorithm by breaking up each n -bit number into 3 parts. What recurrence can you achieve in your approach? Does your recurrence improve upon Karatsuba's exponent of $\lg 3 = 1.58 \dots$? \diamond

Exercise 2.7: To generalize Karatsuba's algorithm, consider splitting an n -bit integer X into m equal parts (assuming m divides n). Let the parts be X_0, X_1, \dots, X_{m-1} where $X = \sum_{i=0}^{m-1} X_i 2^{in/m}$. Similarly, let $Y = \sum_{i=0}^{m-1} Y_i 2^{in/m}$. Let us define $Z_i = \sum_{j=0}^i X_j Y_{i-j}$ for $i = 0, 1, \dots, 2m-2$. In the formula for Z_i , assume $X_\ell = Y_\ell = 0$ when $\ell \geq m$.

(i) Determine the Θ -order of $f(m, n)$, defined to be the time to compute the product $Z = XY$ when you are given $Z_0, Z_1, \dots, Z_{2m-2}$. Remember that $f(m, n)$ is the number of bit operations.

(ii) It is known that we can compute $\{Z_0, Z_1, \dots, Z_{2m-2}\}$ from the X_i 's and Y_j 's using $\mathcal{O}(m \log m)$ multiplications and $\mathcal{O}(m \log m)$ additions, all involving (n/m) -bit integers. Using this fact with part (i), give a recurrence relations for the time $T(n)$ to multiply two n -bit integers.

(iii) Conclude that for every $\epsilon > 0$, there is an algorithm for multiplying any two n -bit integers in time $T(n) = \Theta(n^{1+\epsilon})$. NOTE: part (iii) is best attempted after you have studied the Master Theorem in the subsequent sections. \diamond

Exercise 2.8: In the Google problem, we need to merge several sorted lists. Recall from Lecture I that we can merge a two lists of sizes m and n in time $\Theta(m + n)$. Suppose X_1, \dots, X_n are $n \geq 1$ sorted lists, each with $k \geq 1$ elements. Here, n and k are independent parameters.

(a) We want to analyze the complexity $T(n, k)$ of sorting the set $X = \bigcup_{i=1}^n X_i$. At each phase, we merge pairs of lists. With n lists of size k , we take $\mathcal{O}(nk)$ time to merge, and produce $n/2$ lists each of size $2k$. Set up the recurrence for $T(n, k)$ based on this repeated merging algorithm.

(b) Show that $T(n, k) = \mathcal{O}(nk \lg(1 + n))$ (we say " $1 + n$ " to ensure that the logarithm does not vanish

when $n = 1$). HINT: you could use domain transformation (see §7) but this is not necessary.

(c) Use the Information Theoretic Lower Bound from Lecture I to show a lower bound of $\Omega(nk \lg(1+n))$. \diamond

Exercise 2.9: Recall the Google⁴ multi-keyword search. This was reduced to computing a minimum cover for a set $W = \{w_1, \dots, w_k\}$ of key words in a file. For each key word $w \in W$, we are given an index $P(w)$ which is just a sorted list of positions where w occurs in the file.

(a) Solve the minimum cover for $k = 2$ in linear time.

(b) Suppose $P(w_i) = (s_i, t_i)$ for each $i = 1, \dots, k$, i.e., each keyword has just two positions. Give an $O(k \log k)$ algorithm to find the minimum cover C for w_1, \dots, w_k . HINT: suppose the minimal covers are C_1, \dots, C_m for some $m \geq 1$. Give an algorithm to list all the minimal covers. If $C_i = [c_i, d_i]$ and assuming $c_1 < c_2 < \dots < c_m$, how do you find C_1 ? How do you find C_{i+1} given C_i ?

(c) Solve the general Google problem (k is arbitrary and each word can have arbitrarily many occurrences in the file). HINT: if you used the hint from (b), it should be possible to generalize your solution. \diamond

Exercise 2.10: Write a program to solve the Google multi-keyword for the case $k = 3$ as described in the text. Use your favorite programming language (C or Java without any Object-Oriented fanfare is recommended). Initially, assume n is a power of 2. Indicate how to adapt your algorithm when n is not a power of 2. \diamond

Exercise 2.11: Consider the following problem: we are given an array $A[1..n]$ of numbers, possibly with duplicates. Let $f(x)$ be the number of times (“frequency”) a number x occurs. Given a number $k \geq 1$, we want to know whether there are k distinct numbers x_1, \dots, x_k such that $\sum_{i=1}^k f(x_i) > n/2$. Call $\{x_1, \dots, x_k\}$ a **k -majority set**.

(a) Solve this decision problem for $k = 1$.

(b) Solve this decision problem for $k = 2$.

(c) Instead of the previous decision problem, we consider the optimization version: find the smallest k such that there are k numbers x_1, \dots, x_k with $\sum_{i=1}^k f(x_i) > n/2$. \diamond

END EXERCISES

§3. EGVS Method

We are going to introduce two “direct methods” for solving recurrences: rote method and induction. They are “direct” as opposed to other transformational methods which we will introduce later. Although fairly straightforward, these direct methods may call for some creativity (educated guesses). We begin with the rote method, as it appears to require somewhat less guess work.

¶5. What is rote? The “rote method” refers to the idea of solving a recurrence by repeated expansion of a recurrence. Since such expansions can be done mechanically, this method has been characterized as rote.

⁴This problem was adapted from a Google interview question (the interviewed student was hired).

Let us illustrate this method using the merge-sort recurrence (8):

$$\begin{aligned}
 T(n) &= 2 \boxed{T(n/2)} + n && \text{(first expansion)} \\
 &= 2 \boxed{2T(n/4) + (n/2)} + n && \text{(second expansion)} \\
 &= 4 \boxed{T(n/4)} + 2n && \text{(simplify)} \\
 &= 4 \boxed{2T(n/8) + (n/4)} + 2n && \text{(third expansion)} \\
 &= 8T(n/8) + 3n && \text{(simplify)}
 \end{aligned} \quad \left. \vphantom{\begin{aligned} T(n) &= 2 \boxed{T(n/2)} + n \\ &= 2 \boxed{2T(n/4) + (n/2)} + n \\ &= 4 \boxed{T(n/4)} + 2n \\ &= 4 \boxed{2T(n/8) + (n/4)} + 2n \\ &= 8T(n/8) + 3n \end{aligned}} \right\} \quad (13)$$

This is the expansion step. At this point, we may guess that the i th expansion, the formula is

$$(G)_i : \quad T(n) = 2^i T(n/2^i) + in. \quad (14)$$

To verify our guess, we use natural induction. Note that the formula (14) is true for $i = 1$ (it also holds for $i = 2$ and 3, but this is not logically necessary). We need an induction step: This amounts to expanding the formula once more:

$$\begin{aligned}
 T(n) &= 2^i \boxed{2T(n/2^{i+1})} + in && \text{(guessed } i\text{th expansion)} \\
 &= 2^i \boxed{2T(n/2^{i+1}) + n/2^i} + in && (i+1\text{st expansion)} \\
 &= 2^{i+1}T(n/2^{i+1}) + (i+1)n, && \text{(simplify)}
 \end{aligned} \quad \left. \vphantom{\begin{aligned} T(n) &= 2^i \boxed{2T(n/2^{i+1})} + in \\ &= 2^i \boxed{2T(n/2^{i+1}) + n/2^i} + in \\ &= 2^{i+1}T(n/2^{i+1}) + (i+1)n \end{aligned}} \right\} \quad (15)$$

and noting that this confirms that the formula holds for $i + 1$ (cf. formula $(G)_{i+1}$ in (14)).

Finally, we must choose a value of i at which to stop this expansion. First consider the ideal situation where n is a power of 2 and we choose $i = \lg n$. Then (14) yields $T(n) = 2^i T(n/2^i) + in = nT(1) + (\lg n)n$. Invoking DIC to make $T(1) = 0$, we obtain the solution $T(n) = n \lg n$. This is a beautiful solution, except for one problem: i must be an integer, and it will not work when n is not a power of 2. It makes no sense to pretend that i is a real variable (as we did for n). In general, we may choose an integer close to $\lg n$: $\lceil \lg n \rceil$ or $\lfloor \lg n \rfloor$ will do. Let us choose

$$i = \lfloor \lg n \rfloor \quad (16)$$

as our stopping value. With this choice, we obtain $1 \leq n/2^i < 2$. Under DIC, we can choose the initial condition to be

$$T(n) = 0, \quad \text{for } n < 2. \quad (17)$$

This yields the *exact* solution that for $n \geq 2$,

$$T(n) = n \lfloor \lg n \rfloor. \quad (18)$$

¶6. Is is really rote? To recap, there are four distinct stages in the rote method:

- (E) Expansion steps as in (13). This is the rote part. You can expand as many times as you like until you see the general pattern.
- (G) Guessing of a formula for the i th expansion, as in (14). This guess may require some creativity. Indeed, if we had not re-arranged the terms in our example in the suggestive manner, you might see the pattern.
- (V) Verification of the formula as in (15). This step should be mechanical, and amounts to one more expansion step and re-arranging the terms into the desired form. One problem is that students sometimes do not do this step “honestly”.
- (S) Stopping criteria choice as in (16). You need to know when to stop expansion! Note you must choose i to be a natural number. Thus, you cannot pick “ $i = \lg n$ ” in (16), but need something like $i = \lceil \lg n \rceil$ or $i = \lfloor \lg n \rfloor$. Now you can invoke DIC to finish off the derivation.

Child’s dilemma: *I can’t spell banana because I don’t know when to stop!*

In summary, you must expand, then guess, then verify and finally stop. Even if you get the correct form in the form of a summation, you do need to know how to replace it by a closed form expression. But when the method works, it gives you the exact solution. How can this method fail? It is clear that you can always perform expansions, but you may be stuck at the next step. For instance, try to expand the recurrence $T(n) = 2T(\lceil n/2 \rceil) + n$ in an exact form. The only way out is to give up exact solution, and guess reasonable upper and/or lower bounds.

The appearance of the floor function in the solution (18) makes $T(n)$ discontinuous whenever n is a power of 2. We can make the solution continuous if we fully exploit our freedom in specifying boundary conditions. Let us now assume that $T(n) = n \lg n$ for $1 \leq n < 2$. Then the above proof gives the solution

$$T(n) = n \lg n \quad (19)$$

for $n \geq 1$. This solution is the “ultimate” in simplicity for the recurrence (8). In the exercises, we see more examples of the influence of DIC (17) on our solution.

EXERCISES

Exercise 3.1: No credit work: Rote is discredited word in pedagogy, so we would like a more dignified name for this method. We could call this the “4-Fold Path” or the “EGVS Method”. Suggest your own name for this method. In a humorous vein, what can EGVS stand for? ◇

Pronounce “EGVS” as “egg-us” (like the Romans, treat V as U).

Exercise 3.2: Use the Rote Method to solve the following recurrences

(a) $T(n) = n + 8T(n/2)$.

(b) $T(n) = n + 16T(n/4)$.

(c) Can you generalize your results in (a) and (b) to recurrences of the form $T(n) = n + aT(n/b)$ where a, b are in some special relation? ◇

Exercise 3.3: Solve the Karatsuba recurrence (11) using the Rote Method. ◇

Exercise 3.4: Give the exact solution for $T(n) = 2T(n/2) + n$ for $n \geq 1$ under the initial condition $T(n) = 0$ for $n < 1$. ◇

Exercise 3.5: Solve (37) assuming that $d(n) = n^\beta$ for some real β . NOTE: there will be three different cases, depending on the relationships between β, a, b . ◇

Exercise 3.6: Let us consider the following form of DIC, where we assume that

$$C_0 \leq T(n) \leq C_1$$

for $0 < n \leq n_1$, with the recurrence operative for $n > n_1$. Here, C_0, C_1, n_1 are positive constants. Solve the Mergesort Recurrence under this initial condition, and show how the solution depends on n_1, C_0, C_1 . ◇

END EXERCISES

§4. Real Induction

The rote method, when it works, is a very sharp tool in the sense that as it gives us the exact solution to recurrences. Unfortunately, it does not work for many recurrences: while you can always expand, you may not be able to guess the general formula for the i -th expansion. We now introduce a more widely applicable method, based on the idea of “real induction”.

To illustrate this idea, we use a simple example: consider the recurrence

$$T(x) = T(x/2) + T(x/3) + x. \quad (20)$$

The student is encouraged to attempt the rote method on this recurrence. Let us use real induction to prove an upper bound: suppose we guess that $T(x) \leq Kx$ (ev.), for some $K > 1$. Then we verify it “inductively”:

$$\begin{aligned} T(x) &= T(x/2) + T(x/3) + x && \text{(By definition)} \\ &\leq K\frac{x}{2} + K\frac{x}{3} + x && \text{(Inductive hypothesis)} \\ &= Kx\left(\frac{1}{2} + \frac{1}{3} + \frac{1}{K}\right) \\ &= Kx && \text{(Provided } K > 6/5) \end{aligned}$$

In the following, we will rigorously justify this method of proof.

How did we guess the upper bound $T(x) \leq Kx$? What if we had guessed $T(x) \leq Kx^2$? Well, we would have succeeded as well. In other words, this argument confirms a particular guess; it does not tell us anything about the optimality of the guess (in reality, the proof yields hints how tight an inequality is). We could likewise use real induction to confirm a guessed lower bound. The combined upper and lower bound can often lead to optimal bounds.

¶7. Natural Induction. Real induction is not a familiar in computing or even mathematics, so let us begin by recalling the related but well-known method of **natural induction**. The latter is a proof method based on induction over natural numbers. In brief, suppose $P(\cdot)$ is a natural number predicate, i.e., for each $n \in \mathbb{N}$, $P(n)$ is a proposition.

For example, $P(n)$ might be “There is a prime number between n and $n + 10$ inclusive”. A proposition is either true or false. Thus, we may verify⁵ that $P(100)$ is true because 101 is prime, but $P(200)$ is false because 211 is the smallest prime larger than 200. A similar predicate is $P(n) \equiv$ “there is prime between n and $2n - 1$ ”, called Bertrand’s Postulate (1845).

We simply write “ $P(n)$ ” or, for emphasis, “ $P(n)$ holds” when we want to assert that “proposition $P(n)$ is true”. Natural induction is aimed at proving propositions of the form

$$(\forall n \in \mathbb{N})[P(n) \text{ holds}]. \quad (21)$$

When (21) holds, we say the predicate $P(\cdot)$ is **valid**. For instance, Chebyshev proved in 1850 that Bertrand’s Postulate $P(n)$ is valid. A “proof by natural induction” has three steps:

- (i) [Natural Basis Step] Show that $P(0)$ holds.
- (ii) [Natural Induction Step] Show that if $n \geq 1$ and $P(n - 1)$ holds then $P(n)$ holds:

$$(n \geq 1) \wedge P(n - 1) \Rightarrow P(n). \quad (22)$$

- (iii) [Principle of Natural Induction] Invoke the principle of natural induction, which simply says that (i) and (ii) imply the validity of $P(\cdot)$, i.e., (21).

⁵The smallest n such that $P(n)$ is false is $n = 114$.

Since step (iii) is independent of the predicate $P(\cdot)$, we only need to show the first two steps. A variation of natural induction is the following: for any natural number predicate $P(\cdot)$, introduce a new predicate (the “star version of P ”) denoted $P^*(\cdot)$, defined via

$$P^*(n) : (\forall m \in \mathbb{N})[m < n \Rightarrow P(m)]. \quad (23)$$

The “Strong Natural Induction Step” replaces (22) in step (ii) by

$$(n \geq 1) \wedge P^*(n) \Rightarrow P(n). \quad (24)$$

It is easy to see that if we carry out the Natural Basis Step and the Strong Natural Induction Step, we have shown the validity of $P^*(n)$. Moreover, $P^*(\cdot)$ is valid iff $P(\cdot)$ is valid. Hence, a proof of the validity of $P^*(\cdot)$ is called a **strong natural induction proof** of the validity of $P(\cdot)$.

¶8. Real Induction. Now we introduce the real analogue of strong natural induction. Unlike natural induction, real induction is rarely discussed in standard mathematical literature, except possibly as a form of transfinite induction. Nevertheless, this topic holds interest in areas such as program verification [2], timed logic [11], and real computational models [3]. We regard it is an important technique for analysis of algorithms.

Real induction is applicable to **real predicates**, i.e., a predicate $P(\cdot)$ such that for each $x \in \mathbb{R}$, we have a proposition denoted $P(x)$. For example, suppose $T(x)$ is a total complexity function that satisfies the Karatsuba recurrence (11) subject to the initial condition $T(x) = 1$ for $x \leq 10$. Let us define the real predicate

$$P(x) : [x \geq 10 \Rightarrow T(x) \leq x^2]. \quad (25)$$

As in (21), we want to prove the **validity** of the real predicate $P(\cdot)$, i.e.,

$$(\forall x \in \mathbb{R})[P(x) \text{ holds}]. \quad (26)$$

In analogy to (23), we transform $P(\cdot)$ into a “star-version of P ”, defined as follows:

$$P_\delta^*(x) : (\forall y \in \mathbb{R})[y \leq x - \delta \Rightarrow P(y)] \quad (27)$$

where δ is any positive real number. The predicate $P_\delta^*(x)$ is called the **Real Induction Hypothesis (RIH)**. When δ is understood, we may simply write $P^*(x)$ instead of $P_\delta^*(x)$.

THEOREM 1 (Principle of Real Induction). *Let $P(x)$ be a real predicate. Suppose there exist real numbers $\delta > 0$ (gap constant) and x_1 (cutoff constant) such that*

(I) [Real Basis Step] *For all $x < x_1$, $P(x)$ holds.*

(II) [Real Induction Step] *For all $x \geq x_1$, $P_\delta^*(x) \Rightarrow P(x)$.*

Then $P(x)$ is valid: for all $x \in \mathbb{R}$, $P(x)$ holds.

The proof of this principle is left as an exercise. It amounts to a reduction to Natural Induction. The principle behind this reduction is a very intuitive property of real numbers: *Given any $\delta > 0$, for every real number x there is a smallest natural number $n(x)$ such that $x \leq n(x)\delta$.* This is also known as the **Archimedean Property** of the reals. We can divide \mathbb{R} into the set $\{Q(k) : k \in \mathbb{N}\}$ of intervals where each interval $Q(i)$ comprises all those x with $n(x) = k$. This is illustrated in Figure 3. We can then prove that the Principle of Real Induction holds over each $Q(k)$ for k , using natural induction.

“Give me a lever long enough and I can move the earth” – Archimedes

Let us apply real induction to real recurrences. Note that its application requires the existence of two constants, x_1 and δ , making it somewhat harder to use than natural induction.

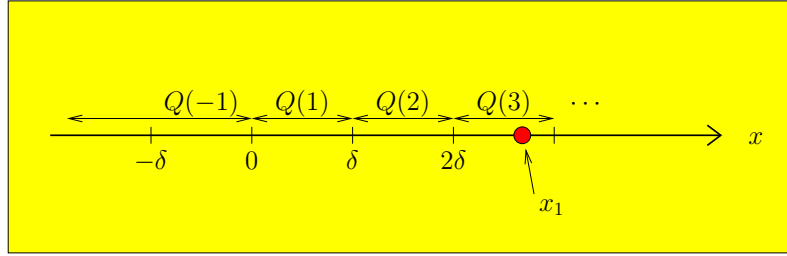


Figure 3: Discrete steps in real induction

¶9. **Example.** Suppose $T(x)$ satisfies the recurrence

$$T(x) = x^5 + T(x/a) + T(x/b) \quad (28)$$

where $a \geq b > 1$. Given $x_0 \geq 1$ and $K > 0$, let $P(x)$ be the proposition

$$x \geq x_0 \Rightarrow T(x) \leq Kx^5. \quad (29)$$

Define the constant $k_0 = a^{-5} + b^{-5}$. **CLAIM:** If $k_0 < 1$ then for all $x_0 \geq 1$, there is a $K > 0$ such that $P(x)$ is valid.

Proof: Now for any x_1 , if $x_1 > x_0$ then our Default Initial Condition says that there is a $C > 0$ such that

$$T(x) \leq C$$

for all $x_0 \leq x < x_1$. If we choose K such that $K \geq C/x_0^5$ then for all $x_0 \leq x < x_1$, we have $T(x) \leq C \leq Kx_0^5 \leq Kx^5$ (since $x \geq x_0 \geq 1$). Hence $P(x)$ holds. This establishes the Real Basis Step (I) for $P(x)$ relative to x_1 .

To establish the Real Induction Step (II), we need more properties for x_1 and must choose a suitable δ . First choose

$$x_1 = ax_0. \quad (30)$$

Thus for $x \geq x_1$, we have $x_0 \leq x/a \leq x/b$. Next choose

$$\delta = x_1 - (x_1/b) = x_1 \frac{b-1}{b}. \quad (31)$$

This ensures that for $x \geq x_1$, we have $x/a \leq x/b \leq x - \delta$. The Real Induction Hypothesis $P_\delta^*(x)$ says that for all $y \geq x - \delta$, $P(y)$ holds, i.e., $y \geq x_0 \Rightarrow P(y)$. Suppose $x \geq x_1$ and $P_\delta^*(x)$ holds. We need to show that $P(x)$ holds:

$$\begin{aligned} T(x) &= x^5 + T(x/a) + T(x/b) \\ &\leq x^5 + K \cdot (x/a)^5 + K \cdot (x/b)^5, \quad (\text{by } P_\delta^*(x) \text{ and } x_0 \leq x/a \leq x/b \leq x - \delta) \end{aligned} \quad (32)$$

$$\begin{aligned} &= x^5(1 + K \cdot k_0) \\ &\leq Kx^5 \end{aligned} \quad (33)$$

where the last inequality is true provided our choice of K above further satisfies $1 + K \cdot k_0 \leq K$ or $K \geq 1/(1 - k_0)$. This proves the Real Induction Step (II). Invoking the Principle of Real Induction, we conclude that $P(\cdot)$ is valid. ■

In a similar vein, we can use real induction to prove a lower bound: there is a constant $k > 0$ such that $T(x) \geq kx^5$ (ev.). Hence, we have shown $T(x) = \Theta(n^5)$ for the recurrence (28).

¶10. **Default Real Basis.** The last example shows that the direct application of the Principle of Real Induction can be tedious, as we have to track constants such as δ , x_1 and K . But this tedium is only associated with justifying the Real Basis (RB); the proof of the Real Induction (RI) is actually not tedious and highly instructive. Our goal in this subsection is to seek ways to avoid RB, so that you can focus on the interesting part (RI).

There is a simple way out, by fiat! Let $f(x)$ be a complexity function and T satisfies some recurrence. Suppose we want to show that

$$T(x) \prec f(x)$$

by real induction. This amounts to showing that there exists $K > 0$ and x_1 such that

$$(\forall x \geq x_1) T(x) \leq K f(x). \quad (34)$$

We ask you to assume (34) holds provided K and x_1 is sufficiently large. Call this the **Default Real Basis** (DRB). In the next subsection, we will formally justify this for a large class of situations (surely enough to cover all your applications).

¶11. **Growth Functions.** We will now show that under some general conditions, the Real Basis (RB) of Real Induction Principle is automatic. The idea is to exploit the following property that most natural complexity functions satisfy.

SKIP this on first reading!

A real function $f : \mathbb{R}^k \rightarrow \mathbb{R}$ is said to be a **growth function** if f is eventually defined, eventually non-decreasing and is unbounded in each of its variables. For instance, $f(x) = x^2 - 3x$ and $f(x, y) = x^y + x/\log x$ are growth functions, but $f(x) = -x$ and $f(x, y, z) = xy/z$ are not.

THEOREM 2. Assume $T(x)$ satisfies the real recurrence

$$T(x) = G(x, T(g_1(x)), \dots, T(g_k(x)))$$

and

- $G(x, t_1, \dots, t_k)$ and each $g_i(x)$ ($i = 1, \dots, k$) are growth functions.
- There is a constant $\delta > 0$ such that each $g_i(x) \leq x - \delta$ (ev. x).

Suppose $f(x)$ is a growth function such that

$$G(x, K f(g_1(x)), \dots, K f(g_k(x))) \leq K f(x) \text{ (ev. } K, x). \quad (35)$$

Under the Default Initial Condition, we conclude

$$T(x) = \mathcal{O}(f(x)).$$

Proof. Pick $x_0 > 0$ and $K > 0$ large enough so that all the “eventual premises” of the theorem are satisfied. In particular, $f(x)$, $G(x, t_1, \dots, t_k)$ and $g_i(x)$ are all defined, non-decreasing and positive when their arguments are $\geq x_0$. Also, $g_i(x_0) \leq x_0 - \delta$ for each i . Let $P(x)$ be the predicate

$$P(x) : x \geq x_0 \Rightarrow T(x) \leq K f(x).$$

Pick

$$x_1 = \max\{g_i^{-1}(x_0) : i = 1, \dots, k\}. \quad (36)$$

The inverse g_i^{-1} of g_i is undefined at x_0 if there does not exist y_i such that $g_i(y_i) = x_0$, or if there exists more than one such y_i . In this case, take $g_i^{-1}(x_0)$ in (36) to be any y_i such that $g_i(y_i) \geq x_0$. We then conclude that for all $x \geq x_1$,

$$x_0 \leq g_i(x) \leq x - \delta.$$

By the Default Initial Condition (DIC), we conclude that for all $x \in [x_0, x_1]$, $P(x)$ holds. Thus, the Real Basis Step is verified. We now verify the Real Induction Step. Assume $x \geq x_1$ and $P_\delta^*(x)$. Then,

$$\begin{aligned} T(x) &= G(x, T(g_1(x)), \dots, T(g_k(x))) \\ &\leq G(x, Kf(g_1(x)), \dots, Kf(g_k(x))) \quad (\text{by } P_\delta^*(x)) \\ &\leq Kf(x) \quad (\text{by (35)}). \end{aligned}$$

Thus $P(x)$ holds. By the Principle of Real Induction, $P(x)$ is valid. This implies $T(x) = \mathcal{O}(f(x))$. **Q.E.D.**

To apply this theorem, the main property to verify is the inequality (35), since the other properties are usually routine to check. Let us see this in action on the example (28). We basically need to verify that

1. $f(x) = x^5$, $G(x, t_1, t_2) = x^5 + t_1 + t_2$, $g_1(x) = x/a$ and $g_2(x) = x/b$ are growth functions
2. $g_1(x) \leq x - 1$ and $g_2(x) \leq x - 1$ when x is large enough.
3. The inequality (35) holds when $K \geq 1/(1 - k_0)$. This is just the derivation of (33) from (32).

From theorem 2 we conclude that $T(x) = \mathcal{O}(f(x))$. The step (35) is the most interesting step of this derivation.

It is clear that we can give an analogous theorem which can be used to easily establish lower bounds on $T(x)$. We leave this as an Exercise.

- One phenomenon that arises is that one often has to introduce a stronger induction hypothesis than the actual result aimed for. For instance, to prove that $T(x) = \mathcal{O}(x \log x)$, we may need to guess that $T(x) = Cx \log x + Dx$ for some $C, D > 0$. See the Exercises below.
- A real predicate P can be identified with a subset S_P of \mathbb{R} comprising those x such that $P(x)$ holds. The statement $P(x)$ can be generically viewed as asserting membership of x in S_P , viz., “ $x \in S_P$ ”. Then a principle of real induction is just one that gives necessary conditions for a set S_P to be equal to \mathbb{R} . Similarly, a natural number predicate is just a subset of \mathbb{N} .

In the rest of this chapter, we indicate other systematic pathways; similar ideas are in lecture notes of Mishra and Siegel [12], the books of Knuth [9], Greene and Knuth [6]. See also Purdom and Brown [14] and the survey of Lueker [10].

EXERCISES

Exercise 4.1: Prove theorem 1, by reduction to natural induction. You can also use a proof by contradiction. \diamond

Exercise 4.2: Suppose $T(x) = 3T(x/2) + x$. Show by real induction that $T(x) = \Theta(x^{\lg 3})$. \diamond

Exercise 4.3: Consider equation (8), $T(n) = 2T(n/3) + n$. Fix any $k > 1$. Show by induction that $T(n) = \mathcal{O}(n^k)$. Which part of your argument suggests to you that this solution is not tight? \diamond

Exercise 4.4: Consider the recurrence $T(n) = n + 10T(n/3)$. Suppose we want to show $T(n) = \mathcal{O}(n^3)$.
 (a) Attempting to prove by real induction, students often begin with a statement such as “Using the Default Initial Condition, we may assume that there is some $C > 0$ and $n_0 > 0$ such that $T(n) \leq Cn^3$ for all $n < n_0$ ”. What is wrong with this statement?
 (b) Give a correct proof by real induction.
 (c) Suppose $T(n) = n + 10T((n + K)/2)$ for some constant K . How does your proof in (b) change? \diamond

Exercise 4.5: Let $T(n) = 2T(\frac{n}{2} + c) + n$ for some $c > 0$.
 (a) By choosing suitable initial conditions, prove the following bounds on $T(n)$ by induction, and *not* by any other method:
 (a.1) $T(n) \leq D(n - 2c) \lg(n - 2c)$ for some $D > 1$. Is there a smallest D that depends only on c ? Explain. Similarly, show $T(n) \geq D'(n - 2c) \lg(n - 2c)$ for some $D' > 0$.
 (a.2) $T(n) = n \lg n - o(n)$.
 (a.3) $T(n) = n \lg n + \Theta(n)$.
 (b) Obtain the exact solution to $T(n)$.
 (c) Use your solution to (b) to explain your answers to (a). \diamond

Exercise 4.6: Generalize our principle of real induction so that the constant δ is replaced by a real function $\delta : \mathbb{R} \rightarrow \mathbb{R}_{>0}$. \diamond

Exercise 4.7: (Gilles Dowek, “Preliminary Investigations on Induction over Real Numbers”, manuscript 2002).
 (a) A set $S \subseteq \mathbb{R}$ is closed if every limit point of S belongs to S . Let $P(x)$ be a real predicate $P(x)$. Assume $\{x \in \mathbb{R} : P(x) \text{ holds}\}$ is a closed set. Suppose

$$P(a) \wedge (\forall c \geq a)[P(c) \Rightarrow (\exists \varepsilon)(\forall y)[c \leq y \leq c + \varepsilon \Rightarrow P(y)]]$$

Conclude that $(\forall x \geq a)P(x)$.

(b) Let $a, b \in \mathbb{R}$ and $\alpha, \beta : \mathbb{R} \rightarrow \mathbb{R}$ such that for all x , $\alpha(x) \geq 0$ and $\alpha(x) > 0$. Suppose f is a differentiable function satisfying

$$f(a) = b, f'(x) = -\alpha(x)f(x) + \beta(x)$$

then for all $x \geq a$, $f(x) > 0$. Intuition: If $f(x)$ is the height of an object at time x , then the object will never reach the ground, i.e., $f(x) > 0$. \diamond

END EXERCISES

§5. Basic Sums

In this section, we discuss some well-known basic sums and their role in solving recurrences.

¶12. **Rote expansion of the Master Recurrence.** As motivataton, let us return to the rote or EGVs method. We have used it for the Mergesort recurrence (8). We now try to see if the technique extends to the more general Master Recurrence (12) which is

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

for $a > 0$ and $b > 1$. Expanding, guessing and verifying yields:

$$\begin{aligned} T(n) &= a \boxed{T(n/b)} + d(n) \\ &= a^2 \boxed{T(n/b^2)} + ad(n/b) + f(n) \\ &= \dots \\ &= a^i \boxed{T(n/b^i)} + \sum_{j=0}^{i-1} a^j d(n/b^j). \end{aligned} \quad (37)$$

The general i -th expansion, unlike in the Mergesort case, is an **open sum**, i.e., a sum with an unbounded number of summands depending on n . This open sum remains after we stop in EGVs. We generally do not regard an open sum as a satisfactory solution. This calls for techniques to convert open sums into closed form solutions. That is the topic of this section.

¶13. **The Standard Recurrence and Descending Sums.** Basically, the EGVs method has transformed the Master Recurrence into a recurrence of the form

$$T(n) = T(n-1) + f(n). \quad (38)$$

We shall call this the **standard recurrence**. Our goal in the following sections is to show systematic ways to reduce many recurrences into this standard form. Trivially, (38) has the following open sum as solution

$$T(n) = \sum_{i=1}^n f(i), \quad (39)$$

assuming $T(0) = 0$ and n is integer.

In the solution (39) we have assumed that n is integer. But what if n is an arbitrary real value? Let us introduce some general notations that befits our intention of “going totally real”. In general, for any real numbers a, b , we define two kinds of sums of f -values over this real interval $[a, b]$:

$$\left. \begin{aligned} \sum_{i \geq a}^b f(i) &= f(b) + f(b-1) + f(b-2) + \dots + f(b - \lfloor b-a \rfloor) \quad (\text{descending}) \\ \sum_{i=a}^b f(i) &= f(a) + f(a+1) + f(a+2) + \dots + f(a + \lfloor b-a \rfloor) \quad (\text{ascending}) \end{aligned} \right\} \quad (40)$$

We call these the **descending** and **ascending f -summations**. Such sums are defined to be 0 if $a > b$. Note that the difference between these two sums is indicated by the way we write the initial value of the summation variable i : “ $\sum_{i \geq a}^b$ ” instead “ $\sum_{i=a}^b$ ”. We shall mainly focus on the descending sums, but sometimes we need to use ascending sums as well. There is a simple connection between these two sums:

$$\sum_{i \geq a}^b f(i) = \sum_{i=a}^b f(b-i). \quad (41)$$

Even when $f(x)$ is a partial function, these sums are well-defined using the convention that undefined summands are replaced by 0. In recognition of our interest in descending sums, we introduce a convenient notation:

$$S_f(n) := \sum_{i \geq 1}^n f(i). \quad (42)$$

Hey, $\sum_{x \geq 1}^{\pi} x = \frac{3\pi^2}{6} = \frac{\pi^2}{2}$ where $\pi = 3.1415\dots$

Henceforth, pay close attention to this minute detail!

¶14. **What Does It Mean to Solve a Recurrence?** The RHS in (39) is an **open sum**, meaning a summation in which the number of summands is unbounded as a function of n . We do not regard open sums as a satisfactory final answer. But what is a satisfactory answer?

Suppose $f(n) = n$ in (39). Then we know how to convert the open sum into a **closed sum**:

$$T(n) = \sum_{i=1}^n f(i) = \sum_{i=1}^n i = \binom{n+1}{2} = \frac{n(n+1)}{2} = \Theta(n^2).$$

Indeed, we would be perfectly happy with the answer “ $T(n) = \Theta(n^2)$ ” even though the answer is really $\binom{n+1}{2}$ — remember that we are generally interested in Θ -order answers in this book. The reason we are happy with the answer $\Theta(n^2)$ is because n^2 is a “familiar function”. So this section is about how we can write some “basic sums” in terms of similar familiar functions. These are the ones you must know. You will not be responsible for summations outside this small repertoire of basic sums.

¶15. **Familiar Functions.** So we conclude that “solving a recurrence” is relative to the form of solution we allow. This we interpret to mean a finite sum or finite product involving only “familiar” functions. For our purposes, the functions considered familiar include

polynomials $f(n) = n^k$, logarithms $f(n) = \log n$, and exponentials $f(n) = c^n$ ($c > 0$).

I see! Solving means to relate to known functions

Functions such as factorials $n!$, binomial coefficients $\binom{n}{k}$ and harmonic numbers H_n (see below) are tightly bounded by familiar functions, and are therefore considered familiar. Finally, we have a rule saying that *the sum, product and functional composition of familiar functions are considered familiar*. Thus $\log^k n$, $\log \log n$, $n + 2 \log n$ and $n^n \log n$ are familiar. For instance, let $f(n)$ be the number of ways an integer n can be written as the sum of two integers. Number theorists have shown that $f(n)$ is $(\log n)^{O(\log n)}$, which is familiar by our definition.

In addition to the above functions, two very slow growing functions arise naturally in algorithmic analysis. These are the log-star function $\log^* x$ and the inverse Ackermann function $\alpha(n)$ (see Lecture XII). We will consider them familiar, although functional compositions involving them are only familiar in our technical sense!

We refer the reader to the Appendix A in this lecture for basic properties of the exponential and logarithm function. In this section, we present some basic closed form summations.

Here are some basic facts that you should know of basic functions:

LEMMA 3.

- (i) For all $k < k'$, $n^k = \mathcal{O}(n^{k'})$ and $n^k \neq \Omega(n^{k'})$.
- (ii) For all $k > 0$, $\lg n = \mathcal{O}(n^k)$ and $\lg n \neq \Omega(n^k)$.
- (iii) For all k and all $c > 1$, $n^k = \mathcal{O}(c^n)$ and $n^k \neq \Omega(c^k)$.

We ask you to prove these in the exercises.

¶16. **Arithmetic series.** The basic arithmetic series is

$$S_n := \sum_{i=1}^n i = \binom{n+1}{2}. \quad (43)$$

In proof,

$$2S_n = \sum_{i=1}^n i + \sum_{i=1}^n (n+1-i) = \sum_{i=1}^n (n+1) = n(n+1).$$

There is a well-known “proof by picture” where you draw two congruent staircases, each representing the desired sum; you can put these two staircases together to get a rectangle of area $2S_n = n(n+1)$.

More generally, for fixed $k \geq 1$, we have the “arithmetic series of order k ”,

$$S_n^k := \sum_{i=1}^n i^k = \Theta(n^{k+1}). \quad (44)$$

In proof, we have

$$n^{k+1} > S_n^k > \sum_{i=\lceil n/2 \rceil}^n (n/2)^k \geq (n/2)^{k+1}.$$

For more precise bounds, we bound S_n^k by integrals,

$$\frac{n^{k+1}}{k+1} = \int_0^n x^k dx < S_n^k < \int_1^{n+1} x^k dx = \frac{(n+1)^{k+1} - 1}{k+1},$$

yielding

$$S_n^k = \frac{n^{k+1}}{k+1} + \mathcal{O}_k(n^k). \quad (45)$$

¶17. Geometric series. For $x \neq 1$ and $n \geq 1$,

$$\begin{aligned} S_n(x) &:= \sum_{i=0}^{n-1} x^i \\ &= \frac{x^n - 1}{x - 1}. \end{aligned} \quad (46)$$

In proof, note that $xS_n(x) - S_n(x) = x^n - 1$. Next, letting $n \rightarrow \infty$, we get the series

$$\begin{aligned} S_\infty(x) &:= \sum_{i=0}^{\infty} x^i \\ &= \begin{cases} \infty & \text{if } x \geq 1 \\ \uparrow \text{ (undefined)} & \text{if } x \leq -1 \\ \frac{1}{1-x} & \text{if } |x| < 1. \end{cases} \end{aligned}$$

Why is $S_\infty(-1)$ (say) considered undefined? For instance, writing

$$\begin{aligned} S_\infty(-1) &= 1 - 1 + 1 - 1 + 1 - 1 + \cdots \\ &= (1 - 1) + (1 - 1) + (1 - 1) + \cdots \\ &= 0 + 0 + 0 + \cdots, \end{aligned}$$

we conclude $S_\infty(-1) = 0$. But writing

$$\begin{aligned} S_\infty(-1) &= 1 - 1 + 1 - 1 + 1 - \cdots \\ &= 1 - (1 - 1) + (1 - 1) - \cdots \\ &= 1 + 0 + 0 + \cdots, \end{aligned}$$

Don't worry about our use of integrals — they are not essential for this book at all. We will show elementary ways to get these bounds, up to Θ -order, without any calculus! Yay? Yay!

we conclude $S_\infty(-1) = 1$. So that we must consider this sum as having no definite value, i.e., undefined. Again,

$$\begin{aligned} S_\infty(-1) &= 1 - 1 + 1 - 1 + 1 - \cdots \\ &= 1 - S_\infty(-1), \end{aligned}$$

and we conclude that $S_\infty(-1) = 1/2$. In fact, $S_\infty(-1)$ can take infinitely many possible values in this way. This provides a strong case why $S_\infty(-1)$ should be regarded as undefined.

Mathematical analysts learned this lesson in the 19th century: treat infinite sums with great care.

Viewing x as a formal⁶ variable, the simplest infinite series is $S_\infty(x) = \sum_{i=0}^{\infty} x^i$. It has a very simple closed form solution,

$$\sum_{i=0}^{\infty} x^i = \frac{1}{1-x}. \quad (47)$$

Viewed numerically, we may regard this solution as a special case of (46) when $n \rightarrow \infty$; but avoiding numerical arguments, it can be directly derived from the formal identity $S_\infty(x) = 1 + xS_\infty(x)$. We suggest calling $\sum_{i=0}^{\infty} x^i$ the “mother of series” because, from the formal solution to this series, we can derive solutions for many related series, including finite series. In fact, for $|x| < 1$, we can derive equation (46) by plugging equation (47) into

The one infinite series to know!

$$S_n(x) = S_\infty(x) - x^n S_\infty(x) = (1 - x^n) S_\infty(x).$$

By differentiating both sides of the mother series with respect to x , we get:

$$\begin{aligned} \frac{1}{(1-x)^2} &= \sum_{i=1}^{\infty} i x^{i-1} \\ \frac{x}{(1-x)^2} &= \sum_{i=1}^{\infty} i x^i \end{aligned} \quad (48)$$

This process can be repeated to yield formulas for $\sum_{i=0}^{\infty} i^k x^i$, for any integer $k \geq 2$. Differentiating both sides of equation (46), we obtain the finite summation analogue:

$$\begin{aligned} \sum_{i=1}^{n-1} i x^{i-1} &= \frac{(n-1)x^n - nx^{n-1} + 1}{(x-1)^2}, \\ \sum_{i=1}^{n-1} i x^i &= \frac{(n-1)x^{n+1} - nx^n + x}{(x-1)^2}, \end{aligned} \quad (49)$$

$$(50)$$

Combining the infinite and finite summation formulas, equations (48) and (49), we also obtain

$$\sum_{i=n}^{\infty} i x^i = \frac{nx^n - (n-1)x^{n+1}}{(1-x)^2}. \quad (51)$$

We may verify by induction that these formulas actually hold for all $x \neq 1$ when the series are finite. In general, for any $k \geq 0$, we obtain formulas for the **geometric series of order k** :

$$\sum_{i=1}^{n-1} i^k x^i. \quad (52)$$

The infinite series have finite values only when $|x| < 1$.

⁶I.e., as an uninterpreted symbol rather than as a numerical value. Thereby, we avoid questions about the sum converging to some unique numerical value.

¶18. **Harmonic series.** For natural numbers $n \geq 1$, the n th **harmonic number** is defined as

$$H_n := 1 + \frac{1}{2} + \frac{1}{3} + \cdots + \frac{1}{n}. \quad (53)$$

We can give some easy estimates of H_n using calculus:

$$H_n < 1 + \int_1^n \frac{dx}{x} < 1 + H_n.$$

But $\int_1^n \frac{dx}{x} = \ln n$. This proves that

$$H_n = \ln n + g(n), \quad \text{where } 0 < g(n) < 1. \quad (54)$$

Note that \ln is the natural logarithm (appendix A).

Claim: $\ln x$ is identically 1:

$$\frac{d(\ln x)}{dx} = \frac{1}{x}$$

and

$$\begin{aligned} \frac{d(1)}{dx} &= \frac{d(x^0)}{dx} \\ &= x^{0-1} = \frac{1}{x}. \end{aligned}$$

So $\ln x = 1$.

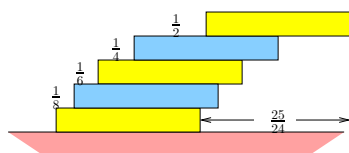


Figure 4: Stacking bricks with maximum overhang: $n = 5$

Harmonic numbers arise naturally in the analysis of algorithms. But here is a “physical” application of harmonic numbers: Suppose you have a set of $n \geq 2$ bricks. The bricks are identical and have unit length. We want to stack the bricks so that the overhang is as large as possible. For instance, if $n = 2$, the overhang is $1/2$ since we can put one brick over the other such that the center of gravity of the top brick is above the edge of the bottom brick. This is illustrated in Figure 4(a). The case of $n = 3$ is shown in Figure 4(b). An obvious question is whether we can make the overhang arbitrarily large (provided n is large enough)? Somewhat surprisingly, the answer is ‘yes’. See Figure 4(c) for the case $n = 5$: we see that in this case, the overhang is $25/24$, already exceeding the length of a single brick! In general, the overhang is $\frac{1}{2}H_{n-1}$ (Exercise). As H_n is about $\ln n$, the overhang goes to infinity (albeit very slowly) as $n \rightarrow \infty$.

We can view (54) as a special case of our descending sums $S_f(n)$ where $f(n) = 1/n$. Then for all real n , $H_n = S_f(n) = \sum_{i=1}^n \frac{1}{i}$. There are more precise estimates for $g(n)$:

$$g(n) = \gamma + (2n)^{-1} + \mathcal{O}(n^{-2}) \quad (55)$$

where $\gamma = 0.577\dots$ is **Euler’s constant**. We can also deduce asymptotic properties of H_n without calculus: if $n = 2^N$, then

$$H_n = \sum_1 + \sum_2 + \cdots + \sum_N$$

where \sum_k is defined as $\sum_{i=2^{k-1}}^{2^k-1} \frac{1}{i}$. Clearly,

$$1/2 = 2^{k-1} \frac{1}{2^k} < \sum_k \leq 2^{k-1} \frac{1}{2^{k-1}} = 1.$$

This proves that

$$\frac{1}{2}N \leq H_n \leq N$$

for n a power of 2. Extrapolating to all values of n , we conclude that $H_n = \Theta(N) = \Theta(\log n)$. This result also shows that H_n and $\lg(n)$ are unbounded (we may choose N as big as we like). This idea can be greatly extended (Exercises).

For any real α , we can define the sum

$$H_n^{(\alpha)} := \sum_{i=1}^n \frac{1}{i^\alpha}.$$

Thus $H_n^{(1)}$ is just H_n . When $\alpha > 1$, $H_n^{(\alpha)}$ is bounded as $n \rightarrow \infty$ (below). The infinite sum $H_\infty^{(\alpha)}$ is then the value of the Riemann zeta function at α : $\zeta(\alpha) := \sum_{i=1}^{\infty} n^{-\alpha}$. For instance, $\zeta(2) = H_\infty^{(2)} = \pi^2/6$. An exercise below estimates the sum $H_n^{(2)}$: we will see that a constant analogous to Euler's γ arises. Below, we shall generalize $H_n^{(\alpha)}$ to all real n .

Application: to solve the recurrence $T(n) = 2T(n/2) + (n/\lg n)$, we convert it to the standard form

$$t(N) = t(N-1) + 1/N \quad (56)$$

using the substitution $t(N) = T(2^N)/2^N$, where $N = \lg n$ is a real variable. According to (??), $t(N) = H^{-1}(N)$. Back solving, the original recurrence has solution $T(n) = nH^{-1}(\lg n) = n(\ln \lg n + \mathcal{O}(1))$.

¶19. **Stirling's Approximation.** So far, we have treated open sums. If we have an open product such as the factorial function $n!$, we can convert it into an open sum by taking logarithms. This method of estimating an open product may not give as tight a bound as we wish (why?). For the factorial function, there is a family of more direct bounds that are collectively called **Stirling's approximation**. The following Stirling approximation is from Robbins (1955) and it may be committed to memory:

$$n! = \left(\frac{n}{e}\right)^n \sqrt{2\pi n} e^{\alpha_n}$$

where

$$\frac{1}{12n+1} < \alpha_n < \frac{1}{12n}.$$

Sometimes, the bound $\alpha_n > (12n)^{-1} - (360n^3)^{-1}$ is useful [4]. Up to Θ -order, we may prefer to simplify the above bound to

$$n! = \Theta\left(\left(\frac{n}{e}\right)^{n+\frac{1}{2}}\right).$$

¶20. **Binomial theorem.**

$$\begin{aligned} (1+x)^n &= 1 + nx + \frac{n(n-1)}{2}x^2 + \cdots + x^n \\ &= \sum_{i=0}^n \binom{n}{i} x^i. \end{aligned}$$

For solving real recurrences, it is useful to generalize this theorem to $(1+x)^p$ for any real number p . In general, the binomial function $\binom{x}{i}$ may be extended to all real x and integer i :

$$\binom{x}{i} = \begin{cases} 0 & \text{if } i < 0 \\ 1 & \text{if } i = 0 \\ \frac{x(x-1)\cdots(x-i+1)}{i(i-1)\cdots 2\cdots 1} & \text{if } i > 0. \end{cases}$$

We use Taylor's expansion for a function $f(x)$ at $x = a$:

$$f(x) = f(a) + \frac{f'(a)}{1!}(x-a) + \frac{f''(a)}{2!}(x-a)^2 + \cdots + \frac{f^{(n)}(a)}{n!}(x-a)^n + \cdots$$

where $f^{(n)}(x) = \frac{d^n f}{dx^n}$. This expansion is defined provided all derivatives of f exist and the series converges. Applied to $f(x) = (1+x)^p$ for any real p at $x = 0$, we get the desired binomial theorem for real exponents:

$$\begin{aligned} (1+x)^p &= 1 + px + \frac{p(p-1)}{2!}x^2 + \frac{p(p-1)(p-2)}{3!}x^3 + \cdots \\ &= \sum_{i \geq 0} \binom{p}{i} x^i. \end{aligned}$$

See [9, p. 56] for Abel's generalization of the binomial theorem.

EXERCISES

Exercise 5.1: Show Lemma 3. For logarithms, we want you to use direct inequalities (no calculus). ◇

Exercise 5.2: Solve the recurrence $T(x) = \frac{1}{x} + T(x-1)$ for all $x > 1$. ◇

Exercise 5.3: Let $h(n)$ denote the maximum overhang for n bricks. Prove that $h(n) = \sum_{i=1}^{n-1} \frac{1}{2i} = \frac{1}{2}H_{n-1}$. Thus, $h(2) = 1/2$, $h(3) = h(2) + 1/4 = 3/4$, $h(4) = h(3) + 1/6 = 11/12$, and $h(5) = h(4) + 1/8 = 25/24$. **HINT:** Let the right edge of the i th brick be at position x_i where the i th brick is stacked on the $i+1$ st brick with $x_i > x_{i+1}$. Inductively, assume that the optimal configuration for $h(n)$ is (x_1, x_2, \dots, x_n) where $x_i - x_{i+1} = 1/2i$. Moreover, the C.G. of the optimal configuration for $h(n-1)$ is at x_n . Extend this induction hypothesis to $h(n+1)$. ◇

Exercise 5.4: Let $c > 0$ be any real constant.

- (a) Show that $\ln(n+c) - \ln n = \mathcal{O}(c/n)$.
- (b) Show that $|H_{n+c} - H_n| = \mathcal{O}(c/n)$ where H_x is the generalized Harmonic function.
- (c) Bound the sum $\sum_{i=1+\lfloor c \rfloor}^n \frac{1}{i(i-c)}$. ◇

Exercise 5.5: Consider $S_\infty(x)$ as a numerical sum.

- (a) Prove that there is a unique value for $S_\infty(x)$ when $|x| < 1$.
- (b) Prove that there are infinitely many possible values for $S_\infty(x)$ when $x \leq -1$.
- (c) Are all real values possible as a solution to $S_\infty(-1)$? ◇

Exercise 5.6: Show the following useful estimate:

$$\ln(n) - (2/n) < \ln(n-1) < (\ln n) - (1/n).$$

◇

Exercise 5.7:

- (a) Give the exact value of $\sum_{i=2}^n \frac{1}{i(i-1)}$. **HINT:** use partial fraction decomposition of $\frac{1}{i(i-1)}$.
- (b) Conclude that $H_\infty^{(2)} \leq 2$. ◇

Exercise 5.8: The goal is to give tight bounds for $H_n^{(2)} := \sum_{i=1}^n \frac{1}{i^2}$ (cf. previous exercise).

(a) Let $S(n) = \sum_{i=2}^n \frac{1}{(i-1)(i+1)}$. Find the exact bound for $S(n)$.

(b) Let $G(n) = S(n) - H_n^{(2)} + 1$. Now $\gamma' = G(\infty)$ is a real constant,

$$\gamma' = \frac{1}{1 \cdot 3 \cdot 4} + \frac{1}{2 \cdot 4 \cdot 9} + \frac{1}{3 \cdot 5 \cdot 16} + \cdots + \frac{1}{(i-1) \cdot (i+1) \cdot i^2} + \cdots.$$

Show that $G(n) = \gamma' - \theta(n^{-3})$.

(c) Give an approximate expression for $H_n^{(2)}$ (involving γ') that is accurate to $\mathcal{O}(n^{-3})$. Note that γ' plays a role similar to Euler's constant γ for harmonic numbers.

(d) What can you say about γ' , given that $H_\infty^{(2)} = \pi^2/6$? Use a calculator (and a suitable approximation for π) to compute γ' to 6 significant digits. \diamond

Exercise 5.9: Solve the recurrence $T(n) = 5T(n-1) + n$. \diamond

Exercise 5.10: Solve exactly (choose your own initial conditions):

(a) $T(n) = 1 + \frac{n+1}{n}T(n-1)$.

(b) $T(n) = 1 + \frac{n+2}{n}T(n-1)$. \diamond

Exercise 5.11: Show that $\sum_{i=1}^n H_i = (n+1)H_n - n$. More generally,

$$\sum_{i=1}^n \binom{i}{m} H_i = \binom{n+1}{m+1} \left[H_{n+1} - \frac{1}{m+1} \right].$$

\diamond

Exercise 5.12: (J. van de Lune, 1980) Above, we defined $H_n := \sum_{i \geq 1}^n 1/i$ (descending sum). A variant that is neither a descending nor an ascending sum is to define $H(a, b) := \sum_{a \leq i \leq b} 1/i$ where the summation is over all integer values of i in the range $[a, b]$. Then this sum is bounded by

$$\sum_{a \leq x \leq b} \frac{1}{x} \leq \ln(y/x) + \min\{1, 1/x\}$$

\diamond

Exercise 5.13: Give a recurrence for S_n^k (see (44)) in terms of S_n^i , for $i < k$. Solve exactly for S_n^4 . \diamond

Exercise 5.14: Derive the formula for the “geometric series of order 2”, $k = 2$ in (52). \diamond

Exercise 5.15: (a) Use Stirling's approximation to give an estimate of the exponent E in the expression $2^E = \binom{2n}{n}$.

(b) (Feller) Show $\binom{2n}{n} = \sum_{k=0}^n \binom{n}{k}^2$. \diamond

END EXERCISES

§6. Standard Form and Summation Techniques

Recall that our goal is to reduce all recurrences to the **standard form**:

$$t(n) = t(n-1) + f(n). \quad (57)$$

Assuming the recurrence is valid for all $n \geq 1$, we have

$$t(n-i+1) - t(n-i) = f(n-i+1), \quad (i = 1, \dots, \lfloor n \rfloor).$$

Adding these $\lfloor n \rfloor$ equations together, all but two terms on the left-hand side cancel, leaving us

$$t(n) - t(n - \lfloor n - 1 \rfloor) = \sum_{i \geq 1}^n f(i).$$

(We say the left-hand side is a “telescoping sum”, and this trick is known as “telescoping”.) Assuming DIC with $t(n) = 0$ for $n < 1$, we obtain

$$t(n) = \sum_{i \geq 1}^n f(i). \quad (58)$$

The summation on the right is just our descending sum $S_f(n)$. If this open sum has the form of one of the basic sums in the previous section, we are done. For instance, in the analysis of bubble sort, we obtain a standard form recurrence:

$$t(n) = t(n-1) + n.$$

Choosing the initial condition $t(0) = 0$, we obtain the exact solution $t(n) = \sum_{i=1}^n i = \binom{n+1}{2}$.

¶21. Polynomial-type and Exponential-type Sums. Let us consider what is to be done if the open sum (58) does not readily reduce to one of the basic sums we have discussed in the previous section. Traditionally, the sum $S_f(n)$ (for $n \in \mathbb{N}$) is solved using the Euler-Maclaurin summation formula,

$$\sum_{i=1}^{n-1} f(i) = \int_1^n f(x) dx + \left(\sum_{i=1}^{\infty} \frac{B_i f^{(i-1)}(x)}{i!} \right)_{x=1}^{x=n}$$

where B_i is the i th Bernoulli number. See [5, p. 217]. But throughout this chapter, we have emphasized the solution of recurrences using elementary arguments, avoiding calculus or limits. Moreover, we seek solutions only up to Θ -order. We now introduce two elementary summation techniques for this purpose. They are based on the following “growth classification” of real functions: it is assumed that the function f in these definitions satisfy $f \geq 0$ (when defined), and $f > 0$ (ev.).

No calculus please!

Polynomial Type: A real function f is **polynomial-type** if f is non-decreasing (ev.) and there is some $C > 0$ such that

$$f(x) \leq C \cdot f(x/2) \text{ (ev.)}.$$

E.g.,

$$f_0(x) = x, \quad f_1(x) = \log x, \quad f_2(x) = f_0(x)f_1(x), \quad f_3(x) = (f_0(x))^a \ (a > 0).$$

Exponential Type: The function f is **exponential-type** if it increases exponentially or it decreases exponentially:

(a) f **increases exponentially** if there exists real numbers $C > 1$ and $k > 0$ such that

$$f(x) \geq C \cdot f(x-k) \text{ (ev.)}.$$

E.g.,

$$g_0(x) = 2^x, \quad g_1(x) = x!, \quad g_2(x) = g_0(x)g_1(x), \quad g_3(x) = 2^{g_0(x)}$$

(b) f **decreases exponentially** if there exists real numbers $0 < c < 1$ and $k > 0$ such that

$$f(x) \leq c \cdot f(x - k) \text{ (ev.)}.$$

E.g.,

$$h_0(x) = 2^{-x}, \quad h_1(x) = x^{-x}, \quad h_2(x) = h_0(x)h_1(x), \quad h_3(x) = 2^{h_0(x)}$$

In proofs, we usually assume $k = 1$ in the above definition of exponential-types: i.e., if $g(n)$ is increasing exponentially, $g(n) \geq Cg(n-1)$ and if $h(n)$ is decreasing exponentially, $h(n) \leq ch(n-1)$. It should be clear that these arguments generalize to the more general $k > 0$.

We also say that the sum $S(n) = S_f(n) := \sum_{x \geq 1}^n f(x)$ is polynomial-type or exponential-type, according to the above classification of f . The following theorem gives a simple rule for bounding such sums.

THEOREM 4 (Summation Rules). *Consider the sum $S_f(n)$:*

(i) *If f is polynomial-type, $S(n) = \Theta(nf(n))$.*

(ii) *If f is exponential-type,*

$$S_f(n) = \begin{cases} \Theta(f(n)) & \text{if } f \text{ is increasing exponentially,} \\ \Theta(1) & \text{if } f \text{ is decreasing exponentially.} \end{cases}$$

Proof. (i) For a polynomial-type sum, using the fact that f is non-decreasing, we get the upper bound $S_f(n) \leq \sum_{x=1}^n f(n) = nf(n)$. For lower bound, we also need that $f(x) \leq Cf(x/2)$ (ev.) for some $C > 0$:

$$\begin{aligned} S_f(n) &\geq \sum_{x \geq n/2}^n f(x) \\ &\geq \sum_{x \geq n/2}^n f(n/2) \geq \lfloor n/2 \rfloor f(n/2) \\ &\geq \lfloor n/2 \rfloor \frac{f(n)}{C} = \Omega(nf(n)). \end{aligned}$$

(ii-a) For an increasing exponential sum, there is some $C > 1$, $k > 0$ and $m > 0$ such that for all $n \geq m+1$, we have $f(n) \geq Cf(n-k)$. By increasing k, m, n if necessary, we may assume wlog that $k, n-m \in \mathbb{N}$ and $n \geq m+1$. We can even assume $n-m$ is divisible by k . Thus,

$$S_f(n) = f(n) + f(n-1) + \cdots + f(m+1) + S_f(m)$$

We can subdivide the sum $f(n) + f(n-1) + f(n-2) + \cdots + f(m+1)$ into k different subsums, each of the form

$$f(n-\kappa) + f(n-\kappa-k) + f(n-\kappa-2k) + \cdots + f(m-\kappa+k) \quad (59)$$

for each $\kappa = 0, 1, \dots, k-1$. The lemma then follows since each subsum satisfies

$$\begin{aligned} &f(n-\kappa) + f(n-\kappa-k) + f(n-\kappa-2k) + \cdots + f(m-\kappa+k) \\ &< f(n-\kappa) \left[1 + \frac{1}{C} + \frac{1}{C^2} + \cdots \right] \\ &= f(n-\kappa) \frac{C}{C-1} \\ &= \mathcal{O}(f(n-\kappa)) = \mathcal{O}(f(n)). \end{aligned}$$

(ii-b) For a decreasing exponential sum, there is some $c < 1$, $k > 0$ and $m > 0$ such that for all $n \geq m + 1$, we have $f(n + k) \leq cf(n)$ and $f(m) \geq f(n)$. Again wlog, $k, n - m \in \mathbb{N}$ and k divides $n - m$. Then

$$S_f(n) = S_f(m) + f(m + 1) + f(m + 2) + \cdots + f(n)$$

where $f(m + 1) + f(m + 2) + \cdots + f(n)$ can be broken up into k subsums, as in (59). The result follows since each subsum is bounded as

$$\begin{aligned} & f(m - \kappa + k) + f(m - \kappa + 2k) + f(m - \kappa + 3k) + \cdots + f(n - \kappa) \\ & < f(m - \kappa + k) [1 + c + c^2 + \cdots] \\ & \leq f(m) \frac{1}{1 - c}. \end{aligned}$$

Q.E.D.

This theorem tells us to upper bound a polynomial-type sum $S_f(n)$ by replacing *each term* in the sum by its largest term $f(n)$. Similarly, to upper bound an exponential-type sum $S_f(n)$, replace *the entire sum* by its largest term. So we shift the burden of estimating sums to the simpler task of identifying the growth-type of the function f .

Let us illustrate applications of this theorem:

- Polynomial Sums.

$$\sum_{i \geq 1}^n i \log i = \Theta(n^2 \log n), \quad \sum_{i \geq 1}^n \log i = \Theta(n \log n) \quad \sum_{i \geq 1}^n i^a = \Theta(n^{a+1}) \text{ (where } a > 0). \quad (60)$$

- Exponentially Increasing Sums.

$$\sum_{i \geq 1}^n 2^i = \Theta(2^n), \quad \sum_{i \geq 1}^n i^{-5} 2^{2^i} = \Theta(n^{-5} 2^{2^n}), \quad \sum_{i \geq 1}^n i! = \Theta(n!) \quad . \quad (61)$$

- Exponentially Decreasing Sums.

$$\sum_{i \geq 1}^n 2^{-i} = \Theta(1), \quad \sum_{i \geq 1}^n i^2 2^{-i} = \Theta(1), \quad \sum_{i \geq 1}^n i^{-i} = \Theta(1) \quad . \quad (62)$$

Summation that does not fit the framework of Theorem 4 can sometimes be reduced to one that does. A trivial case is where summation we are interested in does not begin with $i = 1$. As another example, consider

$$S := \sum_{i \geq 1}^n \frac{i!}{\lg^i n}, \quad (63)$$

which has terms depending on i as well as on the limit n . Write $S = \sum_{i \geq 1}^n f(i, n)$ where

$$f(i, n) = \frac{i!}{\lg^i n}.$$

We note that $f(i, n)$ is increasing exponentially for $i \geq 2 \lg n$ (ev. n), since $f(i, n) = \frac{i}{\lg n} f(i - 1, n) \geq 2f(i - 1, n)$. Hence we may split the summation into two parts, $S = A + B$ where A comprise the terms for which $i \geq 2 \lg n$ and B comprising the rest. Since B is an exponential sum, we have $B = \Theta(f(n, n))$. We can easily use Stirling's estimate for A to see that $A = \mathcal{O}(\log^{3/2} n) = \mathcal{O}(f(n, n))$. Thus $S = \Theta(f(n, n))$.

¶22. **A Counter Example.** Most common functions we encounter will be either polynomial-type or exponential-type. But the function $f(n) = n^{\ln n}$ is neither. Showing that $f(n)$ is not polynomial-type is easy. The box below proves it is not exponential-type. How do we estimate the sum $S_f(n) := \sum_{x \geq 0}^n f(x)$ without the benefit of Theorem 4? In this case, techniques similar to polynomial and exponential sums still give reasonably tight bounds (but not Θ -order): $f(n) \leq S(n) \leq n f(n) \leq f(n)^{1+\varepsilon}$ for any $\varepsilon > 0$.

CLAIM: $f(n) = n^{\ln n}$ is not exponential-type. By way of contradiction, suppose there exists $C_0 > 1$ such that

$$f(n) \geq C_0 f(n-1) \text{ (ev.)}. \quad (64)$$

A well-known bound (see Appendix A) says that for $|x| < 1$,

$$\ln(1+x) < x. \quad (65)$$

Also from (54) and (55), we conclude that

$$\ln n + \gamma \leq H_n \leq \ln n + \gamma + (1/n) \text{ (ev.)}. \quad (66)$$

All the following inequalities are to hold eventually:

$$\begin{aligned} \ln n &\leq H_n - \gamma \\ &\leq (1/n) + \ln(n-1) + (1/n) \\ &= \ln(n-1) + (2/n), \end{aligned} \quad (67)$$

We now get a contradiction:

$$\begin{aligned} f(n) &= \left[(n-1) \left(1 + \frac{1}{n-1} \right) \right]^{\ln n} \\ &\leq (n-1)^{\ln(n-1) + (2/n)} \left(1 + \frac{1}{n-1} \right)^{\ln n} \quad (\text{by (67)}) \\ &= f(n-1) \cdot (n-1)^{2/n} \cdot 2^{\ln(1 + \frac{1}{n-1}) \ln n} \\ &\leq f(n-1) \cdot 2^{2 \ln(n-1)/n} \cdot 2^{\frac{\ln n}{n-1}} \quad (\text{by (65)}) \\ &= f(n-1) \cdot C_1(n) \end{aligned}$$

where $C_1(n) := 2^{2 \ln(n-1)/n} \cdot 2^{\frac{\ln n}{n-1}}$. Since $\ln C_1(n) = (2 \ln(n-1)/n) + (\ln n/(n-1)) \rightarrow 0$ as $n \rightarrow \infty$, we conclude that $C_1(n) \leq C_0$ (ev.). This show $f(n) \leq f(n-1)C_0$ (ev.), contradicting (64).

To apply the summation rules Theorem 4, we want to rapidly classify functions according to their growth types:

LEMMA 5. Let $a \in \mathbb{R}$.

- (a) Polynomial-type functions are closed under addition, multiplication, and raising to any positive power $a > 0$.
- (b) Exponential-type functions f are closed under addition, multiplication and raising to any power a . In case $a > 0$, the function f^a will not change its subtype (increasing or decreasing). In case $a < 0$, the function f^a will change its subtype.
- (c) If f is polynomial-type and $f > 1$ (ev.) then $\lg f$ is also polynomial-type. If f is exponential-type and $a > 1$ then so is a^f .

Proof. All the inequalities in the following proofs are assumed to hold eventually:

- (a) Assume $f(n) \leq C f(n/2)$ and $g(n) \leq C g(n/2)$ for some $C > 1$. Then $f(n) + g(n) \leq C(f(n/2) + g(n/2))$, $f(n)g(n) \leq C^2 f(n/2)g(n/2)$, and for any $e > 0$, $f(n)^e \leq C^e f(n/2)^e$.

(b) Assume $g_i(n) \geq Cg_i(n-1)$ and $h_i(n) \leq ch_i(n-1)$, for some $C > 1, c < 1$, and for $i = 0, 1$. Also, let $g = g_0, h = h_0$. Closure under addition: $g_0(n) + g_1(n) \geq C(g_0(n-1) + g_1(n-1))$ and $h_0(n) + h_1(n) \leq c(h_0(n-1) + h_1(n-1))$. Closure under product: $g_0(n)g_1(n) \geq C^2g_0(n-1)g_1(n-1)$ and $h_0(n)h_1(n) \leq c^2h_0(n-1)h_1(n-1)$. Closure under raising to power e : If $e > 0$, then $g^e(n) \geq C^e g^e(n-1)$ and $h^e(n) \leq c^e h^e(n-1)$ where $C^e > 1$ and $c^e < 1$. If $e < 0$, then $g^e(n) \leq C^e g^e(n-1)$ and $h^e(n) \geq c^e h^e(n-1)$ where $C^e < 1$ and $c^e > 1$.

(c) If f is polynomial-type, then $\log(f(n)) \leq (\log C) + \log(f(n/2)) \leq (1 + (\log C)/c) \log(f(n/2))$, where $\log(f(n/2)) \geq c > 0$ for some constant c . This proves $\log f$ to be polynomial-type.

If g, h is exponential type as in (b), then note that $Cg(n) \geq (C-1) + g(n)$ since $g(n) \geq 1$. Thus

$$\begin{aligned} b^{g(n)} &\geq b^{Cg(n-1)} \geq b^{(C-1)+f(n-1)} \\ &\geq b^{C-1} 2^{f(n-1)}. \end{aligned}$$

Q.E.D.

¶23. Generalized Harmonic Numbers. Let us determine the Θ -order of $H_n^{(\alpha)}$. But first, we extend $H_n^{(\alpha)}$ to real values of n .

For all $n, \alpha \in \mathbb{R}$, define the **generalized Harmonic number**

$$\begin{aligned} H^\alpha(n) &:= n^\alpha + (n-1)^\alpha + (n-2)^\alpha + \cdots + (\{n\} + 1)^\alpha \\ &= \sum_{x=1}^n x^\alpha, \end{aligned} \tag{68}$$

using our summation notation (??) for real limits. The original harmonic numbers in our new notation becomes

$$H_n^{(\alpha)} = H^{-\alpha}(n).$$

Also, $H^\alpha(n) = 0$ for $n < 1$.

THEOREM 6. For all $\alpha \in \mathbb{R}$,

$$H^\alpha(n) = \Theta \begin{cases} 1 & \text{if } \alpha < -1 \\ \lg n & \text{if } \alpha = -1 \\ n^{\alpha+1} & \text{if } \alpha > -1 \end{cases}$$

Proof. It is best to initially assume $n+1$ is a power of 2. Then

$$\begin{aligned} H^\alpha(n) &= \sum_{k=1}^{\lg(n+1)} \left(\sum_{i=2^{k-1}}^{2^k-1} i^\alpha \right) \\ &= \sum_{k=1}^{\lg(n+1)} 2^k \cdot \Theta(2^{k\alpha}) \\ &= \sum_{k=1}^{\lg(n+1)} \Theta(2^{k(1+\alpha)}). \end{aligned}$$

Note that the slick use of Θ in this derivation is capturing upper and lower bounds simultaneously. If explicitly spelled out, you would need to consider the cases $\alpha \geq 0$ and $\alpha < 0$ separately. Now we notice that if $1 + \alpha = 0$ then the sum

Exercise: spell it out!

$$\sum_{k=1}^{\lg(n+1)} \Theta(2^{k(1+\alpha)}) = \Theta(\lg(n+1)).$$

If $1 + \alpha < 0$, then the sum is decreasing exponentially and Theorem 4 yields

$$\sum_{k=1}^{\lg(n+1)} = \Theta(1).$$

If $1 + \alpha > 0$, then the sum is increasing exponentially and Theorem 4 yields

$$\sum_{k=1}^{\lg(n+1)} = \Theta\left(2^{\lg(n+1)(1+\alpha)}\right) = \Theta(n^{1+\alpha}).$$

When $n + 1$ is not a power of 2, we can replace n by $\bar{n} = 2^{\lceil \lg(n+1) \rceil} - 1$ and $\underline{n} = 2^{\lfloor \lg(n+1) \rfloor} - 1$ for upper and lower bounds (Exercise). **Q.E.D.**

Up to Θ -order, the result unifies the standard bounds for (a) the arithmetic series (44), (b) harmonic numbers (54), and (c) geometric sums (46). Our proof is completely elementary; its basic method of splitting up the sum into a “geometric sequence” of groups is applicable to many other estimates involving logarithms.

¶24. Grouping: Breaking Up into Big and Small Parts. The above example (63) illustrates the technique of breaking up a sum into two parts, one containing the “small terms” and the other containing the “big terms”. This is motivated by the wish to apply different summation techniques for the 2 parts, and this in turn determines the cutoff point between small and big terms. Suppose we want to show

$$H_n = \sum_{i=1}^n \frac{1}{i} = O(\sqrt{n}).$$

Break H_n into two summations, $H_n = A_n + B_n$ where

$$A_n = \sum_{i=1}^{\lfloor \sqrt{n} \rfloor} \frac{1}{i}$$

comprises the “big terms” and B_n contains the remaining $n - \lfloor \sqrt{n} \rfloor$ “small terms”. Then

$$A_n \leq \sum_{i=1}^{\lfloor \sqrt{n} \rfloor} \frac{1}{i} \leq \sqrt{n}$$

and

$$B_n = \sum_{i=\lfloor \sqrt{n} \rfloor + 1}^n \frac{1}{i} \leq \sum_{i=1}^n \frac{1}{\sqrt{n}} = \sqrt{n}.$$

Thus $S_n \leq 2\sqrt{n}$ as desired.

We can generalize the grouping idea to prove the following:

$$H_n < kn^{1/k} \tag{69}$$

for any integer $k \geq 2$. We break the n term of H_n k subsums, $H_n = A_n(1) + A_n(2) + \cdots + A_n(k)$ where $A_n(1)$ comprises the first $\lceil n^{1/k} \rceil$ terms of H_n , $A_n(2)$ comprises the next $\lceil n^{2/k} \rceil - \lceil n^{1/k} \rceil$ terms, etc, where in general, $A_n(j)$ comprises the next $\lceil n^{j/k} \rceil - \lceil n^{(j-1)/k} \rceil$ terms. It is easy to see that each $A_n(j)$ is bounded by $n^{1/k}$ and this proves (69).

This gives an elementary proof that H_n is $O(n^c)$ for any $c > 0$. This also imply

$$H_n = o(n^c), \quad \log_b n = o(n^c)$$

for any $c > 0$.

EXERCISES

Exercise 6.1: (a) Verify that the examples in (60), (61) and (62) are, indeed, as claimed, polynomial type or exponential type.

(b) Is the summation $\sum_{i=1}^n i^{\lg i}$ an exponential type or polynomial type? Give bounds for the summation. \diamond

Exercise 6.2: Let T_n be a complete binary tree with $n \geq 1$ nodes. So $n = 2^{h+1} - 1$ where h is the height of T_n .

Suppose an algorithm has to visit all the nodes of T_n and at each node of height $i \geq 0$, expend $(i + 1)^2$ units of work. Let $T(n)$ denote the total work expended by the algorithm at all the nodes. Give a tight upper and lower bounds on $T(n)$. \diamond

Exercise 6.3: (a) Show that the summation $\sum_{i=2}^n (\lg n)^{\lg n}$ is neither polynomial-type nor exponential-type.

(b) Estimate this sum. \diamond

Exercise 6.4: For this problem, please use arguments from first principles. Do not use calculus, properties of $\log x$ such as $x/\log x \rightarrow \infty$, etc. (a) Show that $H_n = o(n^\alpha)$ for any $\alpha > 0$. HINT: Generalize the argument in the text.

(b) Likewise, show that $H_n \rightarrow \infty$ as $n \rightarrow \infty$. \diamond

Exercise 6.5: Let $n = 2^k$. Show that $H_n = \theta(k)$ by grouping. Conclude that for all n , $H_n = \Theta(\lg n)$. \diamond

Exercise 6.6: Use the method of grouping to show that $S(n) = \sum_{i=1}^n \frac{\lg i}{i}$ is $\Omega(\lg^2 n)$. \diamond

Exercise 6.7: Give the Θ -order of the following sums:

(a) $S = \sum_{i=1}^n \sqrt{i}$.

(b) $S = \sum_{i=1}^n \lg(n/i)$. \diamond

Exercise 6.8: Let $f(i) = f_n(i) = \frac{i-1}{n-i+1}$. The sum $F(n) = \sum_{i=1}^n f_n(i)$ is neither polynomial-type nor exponential-type. Give a Θ -order bound on $F(n)$. HINT: transform this into something familiar. \diamond

Exercise 6.9: Can our summation rules for $S(n) = \sum_{i=1}^n f(i)$ be extended to the case where $f(i)$ is “decreasing polynomially”, suitably defined? NOTE: such a definition must somehow distinguish between $f(i) = 1/i$ and $f(i) = 1/(i^2)$, since in one case $S(n)$ diverges and in the other it converges as $n \rightarrow \infty$. \diamond

END EXERCISES

§7. Domain Transformation

So our goal for a general recurrence is to transform it into the standard form. You may think of change of domain as a “change of scale”. Transforming the domain of a recurrence equation may sometimes bring it into standard form. Consider

$$T(N) = T(N/2) + N. \quad (70)$$

We define

$$t(n) := T(2^n), \quad N = 2^n.$$

This transforms the original N -domain into the n -domain. The new recurrence is now in standard form,

$$t(n) = t(n-1) + 2^n.$$

Choosing the boundary condition $t(0) = 1$, we get $t(n) = \sum_{i=0}^n 2^i$. This is a geometric series which we know how to sum, $t(n) = 2^{n+1} - 1$; hence, $T(N) = 2N - 1$.

Omit in a first reading

¶25. **Logarithmic transform.** More generally, consider the recurrence

$$T(N) = T\left(\frac{N}{c} - d\right) + F(N), \quad c > 1, \quad (71)$$

and d is an arbitrary constant. It is instructive to begin with the case $d = 0$. Then it is easy to see that the “logarithmic transformation” of the argument N to the new argument $n := \log_c(N)$ converts this to the new recurrence

$$t(n) = t(n-1) + F(c^n)$$

where we define

$$t(n) := T(c^n) = T(N).$$

There is possible confusion in such manipulations where we have used some implicit conventions. So let us state the connection between t and T more explicit. Let τ denote the **domain transformation function**,

$$\tau(N) = \log_c(N)$$

(so “ n ” is only a short-hand for “ $\tau(N)$ ”). Then $t(\tau(N))$ is defined to be $T(N)$, valid for large enough N . In order for this to be well-defined, we need τ to have an inverse for large enough n . Then we can write

$$t(n) := T(\tau^{-1}(n)).$$

We now return to the general case where d is an arbitrary constant. Note that if $d < 0$ then we must assume that N is sufficiently large (how large?) so that the recurrence (71) is meaningful (i.e., $(N/c) - d < N$). The following transformation

$$n := \tau(N) = \log_c\left(N + \frac{cd}{c-1}\right)$$

will reduce the recurrence to standard form. To see this, note that the “inverse transformation” is

$$\begin{aligned} N &:= c^n - \frac{cd}{c-1} \\ &= \tau^{-1}(n) \\ (N/c) - d &= c^{n-1} - \frac{cd}{c-1} \\ &= \tau^{-1}(n-1). \end{aligned}$$

Writing $t(n)$ for $T(\tau^{-1}(n))$ and $f(n)$ for $F(\tau^{-1}(n))$, we convert equation (71) to

$$\begin{aligned} t(n) &= t(n-1) + F\left(c^n - \frac{cd}{c-1}\right) \\ &= t(n-1) + f(n) \\ &= \sum_{i=1}^n f(i). \end{aligned}$$

To finally “solve” for $t(n)$ we need to know more about the function $F(N)$. For example, if $F(N)$ is a polynomially bounded function, then $f(n) = F(c^n + \frac{cd}{c-1})$ would be $\Theta(F(c^n))$. This is the justification for ignoring the additive term “ d ” in the equation (71).

¶26. Division transform. Notice that the logarithmic transform case does not quite capture the following closely related recurrence

$$T(N) = T(N-d) + F(N), d > 0. \quad (72)$$

It is easy to concoct the necessary domain transformation: replace N by $n = N/d$ and substituting

$$t(n) = T(dn)$$

will transform it to the standard form,

$$t(n) = t(n-1) + F(dn).$$

Again, to be formal, we can explicitly introduce the transform function $\tau(N) = N/d$, etc. This may be called the “division transform”.

¶27. General Pattern. In general, we consider $T(N) = T(r(N)) + F(N)$ where $r(N) < N$ is some function. We want a domain transform $n = \tau(N)$ so that

$$\tau(r(N)) = \tau(N) - 1. \quad (73)$$

For instance, if $r(N) = \sqrt{N}$ we may choose

$$\tau(N) = \lg \lg(N). \quad (74)$$

Then we see that

$$\tau(\sqrt{N}) = \lg(\lg(\sqrt{N})) = \lg(\lg(N)/2) = \lg \lg N - 1 = \tau(N) - 1.$$

Applying this transformation to the recurrence

$$T(N) = T(\sqrt{N}) + N, \quad (75)$$

we may define $t(n) := T(\tau^{-1}(n)) = T(2^{2^n}) = T(N)$, thereby transforming the recurrence (75) to $t(n) = t(n-1) + 2^{2^n}$.

REMARKS:

1. The transformation (74) may be regarded as two applications of the logarithmic transform.
2. Domain transformation can be confusing because of the difficulty of keeping straight the similar-looking symbols, ‘ n ’ versus ‘ N ’ and ‘ t ’ versus ‘ T ’. Of course, these symbols are mnemonically chosen. When properly used, these conventions reduce clutter in our formulas. But if they are confusing, you can always fall back to the use of the explicit transformation functions such as τ .

Exercise 7.1: Justify the simplification step (iv) in §1 (where we replace $\lceil n/2 \rceil$ by $n/2$). \diamond

Exercise 7.2: Solve recurrence (71) in these cases:

(a) $F(N) = N^k$.

(b) $F(N) = \log N$. \diamond

Exercise 7.3: Construct examples where you need to compose two or more of the above domain transformations. \diamond

END EXERCISES

§8. Range Transformation

A transformation of the range is sometimes called for. For instance, consider

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

To put this into standard form, we could define

$$t(n) := \frac{T(n)}{2^n}$$

and get the standard form recurrence

$$t(n) = t(n-1) + \frac{n}{2^n}.$$

Telescoping gives us a series of the type in equation (48), which we know how to sum. Specifically, $t(n) = \sum_{\{n\}}^n \frac{n}{2^n} = \Theta(1)$. Hence $T(n) = \Theta(2^n)$.

We have transformed the range of $T(n)$ by introducing a multiplicative factor 2^n : this factor is called the **summation factor**. The reader familiar with linear differential equations will see an analogy with “integrating factor”. (In the same spirit, the previous trick of domain transformation is simply a “change of variable”.)

In general, a range transformation converts a recurrence of the form

$$T(n) = c_n T(n-1) + F(n) \tag{76}$$

into standard form. Here c_n is a constant depending on n . Let us discover which summation factor will work. If $C(n)$ is the summation factor, we get

$$t(n) := \frac{T(n)}{C(n)},$$

and hence

$$\begin{aligned} t(n) &= \frac{T(n)}{C(n)} \\ &= \frac{c_n}{C(n)} T(n-1) + \frac{F(n)}{C(n)} \\ &= \frac{T(n-1)}{C(n-1)} + \frac{F(n)}{C(n)}, \quad (\text{provided } C(n) = c_n C(n-1)) \\ &= t(n-1) + \frac{F(n)}{C(n)}. \end{aligned}$$

Thus we need $C(n) = c_n C(n-1)$ which expands into

$$C(n) = c_n c_{n-1} \cdots c_1.$$

EXERCISES

Exercise 8.1: Solve the recurrence (76) in the case where $c_n = 1/n$ and $F(n) = 1$. ◇

Exercise 8.2: (a) Reduce the following recurrence

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

to standard form. Then solve it exactly when n is a power of 2.

(b) Extend the solution of part(a) to general n using our generalized Harmonic numbers H_x for real $x \geq 2$ (see §2). You may choose any suitable initial conditions, but please state it explicitly.

(c) Solve the variations

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

and

$$T(n) = 4T(n/2) + \frac{n^2}{\sqrt{\lg n}}.$$

◇

Exercise 8.3: Repeat the previous question with the following recurrences:

(a) $T(n) = 4T(n/2) + \frac{n^2}{\lg^2 n}$

(b) $T(n) = 4T(n/2) + \frac{n^2}{\sqrt{\lg n}}.$ ◇

END EXERCISES

§9. Differencing and Quicksort

Summation is the discrete analogue of integration. Extending this analogy, we introduce the **differencing** as the discrete analogue of differentiation. As expected, differencing is the inverse of summation. The differencing operation ∇ applied to any complexity function $T(n)$ yields another function ∇T defined by

$$(\nabla T)(n) = T(n) - T(n-1).$$

Differentiation often simplifies an equation: thus, $f(x) = x^2$ is simplified to the linear equation $(Df)(x) = 2x$, using the differential operator D . Similarly, differencing a recurrence equation for $T(n)$ may lead to a simpler recurrence for $(\nabla T)(n)$.

Indeed, the “standard form” (57) can be rewritten as

$$\nabla t(n) = f(n).$$

This is just an equation involving a difference operator — the discrete analogue of a differential equation.

For example, consider the recurrence

$$T(n) = n + \sum_{i=1}^{n-1} T(i).$$

This recurrence does not immediately yield to the previous techniques. But note that

$$(\nabla T)(n) = 1 + T(n-1).$$

Hence $T(n) - T(n-1) = 1 + T(n-1)$ and $T(n) = 2T(n-1) + 1$, which can be solved by the method of range transformation. (Solve it!)

¶28. QuickSort. A well-known application of differencing is the analysis of the QuickSort algorithm of Hoare. In QuickSort, we randomly pick a “pivot” element p . If p is the i th largest element, this subdivides the n input elements into $i-1$ elements less than p and $n-i$ elements greater than p . Then we recursively sort the subsets of size $i-1$ and $n-i$. For a detailed description of QuickSort, including a different analysis, see Lecture VIII. The recurrence is

$$T(n) = n + \frac{1}{n} \sum_{i=0}^{n-1} (T(i+1) + T(n-i)), \quad (77)$$

since for each i , the probability that the two recursive subproblems in QuickSort are of sizes i and $n-i$ is $1/n$. The additive factor of “ n ” indicates the cost (up to a constant factor) to subdivide the subproblems, and there is no cost in “merging” the solutions to the subproblems. The recurrence (77) is an example of a **full-history recurrence**, so-called because $T(n)$ depends on $T(m)$ for all smaller values of m .

Simplifying (77),

$$\begin{aligned} T(n) &= n + \frac{2}{n} \sum_{i=0}^{n-1} T(i) \\ nT(n) &= n^2 + 2 \sum_{i=0}^{n-1} T(i) && \text{[Multiply by } n\text{]} \\ (n-1)T(n-1) &= (n-1)^2 + 2 \sum_{i=0}^{n-2} T(i) && \text{[Substitute } n \text{ by } n-1\text{]} \\ nT(n) - (n-1)T(n-1) &= 2n-1 + 2T(n-1) && \text{[Differencing operator for } nT(n)\text{]} \\ nT(n) &= 2n-1 + (n+1)T(n-1) && \text{[Simplify]} \\ \frac{T(n)}{n+1} &= \frac{2}{n+1} - \frac{1}{n(n+1)} + \frac{T(n-1)}{n} && \text{[Divide by } n(n+1) \text{ (range transform)]} \\ t(n) &= \frac{2}{n+1} - \frac{1}{n(n+1)} + t(n-1) && \text{[Define } t(n) = T(n)/(n+1)\text{]} \\ &= 2(H_{n+1} - 1) - \sum_{i=1}^n \frac{1}{i(i+1)} + t(0) && \text{[Telescoping a standard form]} \end{aligned}$$

Thus we see that $t(n) \leq 2H_{n+1}$ (assuming $t(0) = 0$) and hence we conclude

$$T(n) = 2n \ln n + \mathcal{O}(n).$$

It is also easy to get the exact solution for $t(n)$, by evaluating the sum $\sum_{i=1}^n \frac{1}{i(i+1)}$ (in a previous Exercise).

¶29. QuickSelect. The following recurrence is a variant of the QuickSort recurrence, and arises in the average case analysis of the QuickSelect algorithm:

$$T(n) = n + \frac{T(1) + T(2) + \cdots + T(n-1)}{n} \quad (78)$$

In the selection problem we need to “select the k th largest” where k is given (This problem is studied in more detail in Lecture XXX). Recursively, after splitting the input set into subsets of sizes $i-1$ and $n-i$ (as in

QuickSort), we only need to continue one one of the two subsets (unless the pivot element is already the k th largest that we seek). This explains why, compared to (78), the only change in (78) is to replace the constant factor of 2 to 1. To solve this, let us first multiply the equation by n (a range transform!). Then, on differencing, we obtain

$$\begin{aligned} nT(n) - (n-1)T(n-1) &= 2n-1 + T(n-1) \\ nT(n) - nT(n-1) &= 2n-1 \\ T(n) - T(n-1) &= 2 - \frac{1}{n} \\ T(n) &= 2n - \ln n + \Theta(1). \end{aligned}$$

Again, note that we essentially obtain an exact solution.

¶30. Improved QuickSort. We further improve the constants in QuickSort by first randomly choosing three elements, and picking the median of these three to be our pivot. The resulting recurrence is slightly more involved:

$$T(n) = n + \sum_{i=2}^{n-1} p_i [T(i-1) + T(n-i)] \quad (79)$$

where

$$p_i = \frac{(i-1)(n-i)}{\binom{n}{3}}$$

is the probability that the pivot element gives rise to subproblems of sizes $i-1$ and $n-i$.

See Lecture 8 on Probabilistic Analysis where we discuss QuickSort

EXERCISES

Exercise 9.1: Solve the following recurrences to Θ -order:

$$T(n) = n + \frac{2}{n} \sum_{i=\lfloor n/2 \rfloor}^{n-1} T(i).$$

HINT: Because of the upper bound $\lfloor n/2 \rfloor$, the function $\nabla T(n)$ has different behavior depending on whether n is even or odd. Simple differencing does not seem to work well here. Instead, we suggest the guess and verify-by-induction approach. \diamond

Exercise 9.2: Generalize the previous question. Consider the recurrence

$$T(n) = n + \frac{c}{n} \sum_{i=1+\lfloor \alpha n \rfloor}^{n-1} T(i)$$

where $c > 0$ and $0 \leq \alpha < 1$ are constants.

(a) Solve the recurrence for $c = 2$.

(b) Solve $T(n)$ when $c = 4$ and $\alpha = 0$.

(c) Fix $c = 4$. Determine the range of α such that $T(n) = \Theta(n)$. You need to argue why $T(n)$ is not $\Theta(n)$ for α outside this range.

(d) Determine the solution of this recurrence for general c, α . \diamond

- Exercise 9.3:** (a) Suppose that in the base case of QuickSort, we do nothing whenever the size of the subarray to be sorted has 10 or less keys. Call this “QuirkSort”.
 (i) Describe the nature of the output from QuirkSort.
 (ii) Describe a linear time method to take the output of QuirkSort and make it into a sorted array.
 (iii) Explain why your method in (ii) takes linear time. \diamond

Exercise 9.4:

- (a) Show that every polynomial $p(X)$ of degree d can be written as a sum of binomial coefficients with suitable coefficients c_i :

$$p(X) = c_d \binom{X}{d} + c_{d-1} \binom{X}{d-1} + \cdots + c_1 \binom{X}{1} + c_0.$$

- (b) Assume the above form for $p(X)$, express $(\nabla p)(X)$ as a sum of binomial coefficients. HINT: what is $\nabla \binom{m}{n}$? \diamond

END EXERCISES

§10. Generalized Master Theorem

§10.1. The Master Theorem

We first look at a recurrence that does fall under our transformation techniques: the **master recurrence** is

$$T(n) = aT(n/b) + f(n) \quad (80)$$

where $a > 0$, $b > 1$ are constants and $f(n)$ is some function.

We have already seen several instances of this recurrence. Another famous one is Strassen’s algorithm for multiplying two $n \times n$ matrices in subcubic time. Strassen’s recurrence is $T(n) = 7T(n/2) + n^2$, which has solution $T(n) = \Theta(n^{\lg 7})$. Evidently, the Master recurrence is the recurrence to solve if we manage to solve a problem of size n by breaking it up into a subproblems each of size n/b , and merging these a sub-solutions in time $f(n)$. The recurrence was systematically studied by Bentley, Haken and Saxe [1]. Solving it requires a combination of domain and range transformation.

First apply a domain transformation by defining a new function $t(k)$ from $T(n)$, where $k = \log_b(n)$:

$$t(k) := T(b^k) \quad (\text{for all } k \in \mathbb{R}).$$

Then (80) transforms into

$$t(k) = a t(k-1) + f(b^k).$$

Next, transform the range by using the summation factor $1/a^k$. This defines the function $s(k)$ from $t(k)$:

$$s(k) := t(k)/a^k.$$

Now $s(k)$ satisfies a recurrence in standard form:

$$\begin{aligned} s(k) &= \frac{t(k)}{a^k} \\ &= \frac{t(k-1)}{a^{k-1}} + \frac{f(b^k)}{a^k} \\ &= s(k-1) + \frac{f(b^k)}{a^k} \end{aligned}$$

Telescoping, we get

$$s(k) - s(\{k\}) = \sum_{i=\{k\}+1}^k \frac{f(b^i)}{a^i},$$

where $\{k\}$ is the fractional part of k (recall that k is real). Using the DIC, we chose the boundary condition

$$s(x) = f(b^x)/a^x, \quad \text{for } x < 1$$

in order to end up with the simple formula,

$$s(k) = \sum_{i=\{k\}}^k \frac{f(b^i)}{a^i}. \quad (81)$$

If we like, we can back substitute to get this solution in terms of the original function $T(n)$:

$$\begin{aligned} T(n) &= t(\log_b n) \\ &= a^{\log_b n} s(\log_b n) \\ &= n^{\log_b a} \sum_{i=\{\log_b n\}} \frac{f(b^i)}{a^i}. \end{aligned}$$

This is the general solution to the master recurrence. But it is an open sum, and we need a closed formula. *Now, we cannot proceed any further without knowing the nature of the function f .*

Let us call the function

$$W(n) = n^{\log_b a} \quad (82)$$

the **watershed function** for our recurrence, and $\log_b a$ the **watershed exponent**. The Master Theorem considers three cases for f . These cases are obtained by comparing f to $W(n)$. The easiest case is where f and W have the same Θ -order (CASE (0)). The other two cases are where f grows “polynomially slower” (CASE (-1)) or “polynomially faster” (CASE $(+1)$) than the watershed function.

CASE (0) This is when $f(n)$ satisfies

$$f(n) = \Theta(n^{\log_b a}). \quad (83)$$

Then $f(b^i) = \Theta(a^i)$ and hence

$$s(k) = \sum_{i=1}^k f(b^i)/a^i = \Theta(k). \quad (84)$$

CASE (-1) This is when $f(n)$ **grows polynomially slower** than the watershed function:

$$f(n) = \mathcal{O}(n^{-\epsilon + \log_b a}), \quad (85)$$

for some $\epsilon > 0$. Then $f(b^i) = \mathcal{O}(b^{i(\log_b a - \epsilon)})$. Let $f(b^i) = \mathcal{O}_1(a^i b^{-i\epsilon})$ (using the subscripting notation for \mathcal{O}). So $s(k) = \sum_{i=1}^k f(b^i)/a^i = \sum \mathcal{O}_1(b^{-i\epsilon}) = \mathcal{O}_2(1)$, since $b > 1$ implies $b^{-\epsilon} < 1$. Hence

$$s(k) = \Theta(1). \quad (86)$$

CASE $(+1)$ This is when $f(n)$ satisfies the **regularity condition**

$$af(n/b) \leq cf(n) \text{ (ev.)} \quad (87)$$

for some $c < 1$. Expanding this,

$$\begin{aligned} f(n) &\geq \frac{a}{c} f\left(\frac{n}{b}\right) \\ &\geq \left(\frac{a}{c}\right)^{\log_b n} f(1) \\ &= \Omega(n^{\epsilon + \log_b a}), \end{aligned}$$

where $\epsilon = -\log_b c > 0$. Thus the regularity condition implies that $f(n)$ **grows polynomially faster** than the watershed function,

$$f(n) = \Omega(n^{\epsilon + \log_b a}). \quad (88)$$

It follows from (87) that $f(b^{k-i}) \leq (c/a)^i f(b^k)$. So

$$\begin{aligned} s(k) &= \sum_{i=1}^k f(b^i)/a^i \\ &= \sum_{i=0}^{k-1} f(b^{k-i})/a^{k-i} \\ &\leq \sum_{i=0}^{k-1} (c/a)^i f(b^k)/a^{k-i} \\ &= f(b^k)/a^k \left(\sum_{i=0}^{k-1} c^{k-i} \right) \\ &= \mathcal{O}\left(\frac{f(b^k)}{a^k}\right), \end{aligned}$$

since $c < 1$. But clearly, $s(k) \geq f(b^k)/a^k$. Hence we have

$$s(k) = \Theta(f(b^k)/a^k). \quad (89)$$

Summarizing,

$$s(k) = \begin{cases} \Theta(1), & \text{CASE } (-1), \text{ see (86),} \\ \Theta(k), & \text{CASE } (0), \text{ see (84),} \\ \Theta(f(b^k)/a^k), & \text{CASE } (+1), \text{ see (89).} \end{cases}$$

Back substituting using $s(k) = t(k)/a^k$, we get

$$t(k) = a^k s(k) = \begin{cases} \Theta(a^k), & \text{CASE } (-1) \\ \Theta(a^k k), & \text{CASE } (0) \\ \Theta(f(b^k)), & \text{CASE } (+1). \end{cases}$$

Further back substitution using $T(n) = t(\log_b n)$, we conclude:

THEOREM 7 (Master Theorem). *The master recurrence (80) has solution:*

$$T(n) = \begin{cases} \Theta(n^{\log_b a}), & \text{if } f(n) = \mathcal{O}(n^{-\epsilon + \log_b a}), \text{ for some } \epsilon > 0, \\ \Theta(n^{\log_b a} \log n), & \text{if } f(n) = \Theta(n^{\log_b a}), \\ \Theta(f(n)), & \text{if } af(n/b) \leq cf(n) \text{ for some } c < 1. \end{cases}$$

Informally, we describe CASE (+) as the case when the driving function $f(n)$ is polynomially faster than $W(n)$. But the actual requirement is somewhat stronger, namely the regularity condition (87). In applications of the Master Theorem, this case is usually the least convenient to check.

We can take advantage of the fact that checking if a function $f(n)$ is polynomially faster (or slower) than $W(n)$ is usually easier to check (just by “inspection”). Hence we normally begin by first verifying the polynomially faster condition, equation (88). If so, we then check the stronger regularity condition (87). To illustrate this process, consider the recurrence

$$T(n) = 3T(n/10) + \sqrt{n}/\lg n.$$

We note that $\alpha = \log_{10} 3 < \log_9 3 = 1/2$ and so $n^\alpha \leq \sqrt{n}/\lg n$ (ev.), confirming equation (88). We now suspect that CASE (+) holds, and must verify that

$$cf(n) \geq 3f(n/10)$$

The Master Theorem is powerful but unfortunately, there are gaps between its 3 cases. For instance, $f(n) = n^{\log_b a} \log n$ grows faster than the watershed function, but not polynomially faster. Thus the Master Theorem is inapplicable for this $f(n)$. Yet it is just as easy to solve this case using the transformation techniques (see Exercise).

In practice, the polynomial version of the theorem is most useful:

COROLLARY 8. *Let $a > 0, b > 1$ and k be constants. The solution to $T(n) = aT(n/b) + n^k$ is given by*

$$T(n) = \begin{cases} \Theta(n^{\log_b a}), & \text{if } \log_b a > k \\ \Theta(n^k), & \text{if } \log_b a < k \\ \Theta(n^k \lg n), & \text{if } \log_b a = k \end{cases}$$

What if the values a, b in the master recurrence are not constants but depends on n ? For instance, attempting to apply this theorem to the recurrence

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

(with $a = 2^n$ and $b = 2$), we obtain the false conclusion that $T(n) = \Theta(n^n \log n)$. See Exercises. The paper [17] treats the case $T(n) = a(n)T(b(n)) + f(n)$. For other generalizations of the master recurrence, see [16].

¶31. Graphic Interpretation of the Master Recurrence. We imagine a recursion tree with branching factor of a at each node, and every leaf of the tree is at level $\log_b a$. We further associate a “size” of n/b^i and “cost” of $f(n/b^i)$ to each node at level i (root is at level $i = 0$). Then $T(n)$ is just the sum of the costs at all the nodes. The Master Theorem says this: In case (0), the total cost associated with nodes at any level is $\Theta(n^{\log_b a})$ and there are $\log_b n$ levels giving an overall cost of $\Theta(n^{\log_b a} \log n)$. In case (+1), the cost associated with the root is $\Theta(T(n))$. In case (−1), the total cost associated with the leaves is $\Theta(T(n))$. Of course, this “recursion tree” is not realizable unless a and $\log_b a$ are integers. Hence the student should view this as a heuristic aid to remembering how the Master Theorem works.

EXERCISES

Exercise 10.1: Which is the faster growing function: $T_1(n)$ or $T_2(n)$ where

$$T_1(n) = 6T_1(n/2) + n^3, \quad T_2(n) = 8T_2(n/2) + n^2.$$

◇

Exercise 10.2: State the solution, up to Θ -order of the following recurrences:

$$\begin{aligned} T(n) &= 10T(n/10) + \log^{10} n. \\ T(n) &= 100T(n/10) + n^{10}. \\ T(n) &= 10T(n/100) + (\log n)^{\log \log n}. \\ T(n) &= 16T(n/4) + 4^{\lg n}. \end{aligned}$$

◇

Exercise 10.3: Solve the following using the Master's theorem.

- (a) $T(n) = 3T(n/25) + \log^3 n$
- (b) $T(n) = 25T(n/3) + (n/\log n)^3$
- (c) $T(n) = T(\sqrt{n}) + n$.

HINT: in the third problem, the Master theorem is applicable after a simple transformation. \diamond

Exercise 10.4: Sometimes the Master Theorem is not applicable directly. But it can still be used to yield useful information. Use the Master Theorem to give as tight an upper and lower bound you can for the following recurrences:

- (a) $T(n) = n^3 \log^3 n + 8T(n/2)$
- (b) $T(n) = n^2 / \log \log n + 9T(n/3)$
- (c) $T(n) = 4T(n/2) + 3T(n/3) + n$.

\diamond

Exercise 10.5: Suppose $T(n) = n + 3T(n/2) + 2T(n/3)$. Joe claims that $T(n) = O(n)$, Jane claims that $T(n) = O(n^2)$, John claims that $T(n) = O(n^3)$. Who is closest to the truth? \diamond

Exercise 10.6: We want to improve on Karatsuba's multiplication algorithm. We managed to subdivide a problem of size n into $a \geq 2$ subproblems of size $n/4$. After solving these a subproblems, we could combine their solutions in $O(n)$ time to get the solution to the original problem of size n . To beat Karatsuba, what is the maximum value a can have? \diamond

Exercise 10.7: Suppose algorithm A_1 has running time satisfying the recurrence

$$T_1(n) = aT(n/2) + n$$

and algorithm A_2 has running time satisfying the recurrence

$$T_2(n) = 2aT(n/4) + n.$$

Here, $a > 0$ is a parameter which the designer of the algorithm can choose. Compare these two running times for various values of a . \diamond

Exercise 10.8: Suppose

$$T_0(n) = 18T_0(n/6) + n^{1.5}$$

and

$$T_1(n) = 32T_1(n/8) + n^{1.5}.$$

Which is the correct relation: $T_0(n) = \Omega(T_1(n))$ or $T_0(n) = \mathcal{O}(T_1(n))$? We want you to do this exercise without using a calculator or its equivalent; instead, use inequalities such as $\log_8(x) < \log_6(x)$ (for $x > 1$) and $\log_6(2) < 1/2$. \diamond

Exercise 10.9: How is the regularity condition on $f(n)$ and the condition that $f(n)$ increase polynomially related? What can you say about the sum $\sum_{i=1}^n f(i)$ when f satisfies the regularity condition for some a, b, c ? \diamond

Exercise 10.10: Solve the master recurrence when $f(n) = n^{\log_b a} \log^k n$, for any $k \geq 1$. \diamond

Exercise 10.11: Show that the master theorem applies to the following variation of the master recurrence:

$$T(n) = a \cdot T\left(\frac{n+c}{b}\right) + f(n)$$

where $a > 0$, $b > 1$ and c is arbitrary. ◇

Exercise 10.12:

(a) Solve $T(n) = 2^n T(n/2) + n^n$ by direct expansion.

(b) To what extent can you generalize the Master theorem to handle some cases of $T(n) = a_n T(n/b_n) + f(n)$ where a_n, b_n are both functions of n ? ◇

Exercise 10.13: Let $W(n)$ be the watershed function of the master recurrence. In what sense is the “watershed function” of the next order equal to $W(n)/\ln n$? ◇

Exercise 10.14:

(a) Let

$$s(n) = \sum_{i=1}^n \frac{\lg i}{i}$$

Prove that $s(n) = \Theta(\lg^2 n)$. For the lower bound, we want you to use real induction, and the fact that for $n \geq 2$, we have

$$\ln(n) - (2/n) < \ln(n-1) < (\ln n) - (1/n).$$

(b) Using the domain/range transformations to solve the following recurrence:

$$T(n) = 2T(n/2) + n \frac{\lg \lg n}{\lg n}.$$

◇

Exercise 10.15: Consider the recurrence $T(n) = aT(n/b) + \frac{n^4}{\log n}$ where $a > 0$ and $b > 1$. Describe the set S of all pairs (a, b) for which the Master Theorem gives a solution for this recurrence. Do not describe the solutions. You must describe the set S in the simplest possible terms. ◇

Exercise 10.16: The following recurrences arises in the analysis of a parallel algorithm for hidden-surface removal (Reif and Sen, Proc. ACM Symp. on Comp. Geometry, 1988):

$$T(n) = T(2n/3) + \lg n \lg \lg n$$

Another version of the algorithm [17] leads to

$$T(n) = T(2n/3) + (\lg n)/\lg \lg n.$$

Solve for $T(n)$ in both cases. ◇

END EXERCISES

§10.2. The Multiterm Master Theorem

The Master recurrence (80) can be generalized to the following **multiterm master recurrence**:

$$T(n) = f(n) + \sum_{i=1}^k a_i T\left(\frac{n}{b_i}\right) \quad (90)$$

where $k \geq 1$, $a_i > 0$ (for all $i = 1, \dots, k$) and $b_1 > b_2 > \dots > b_k > 1$. We give two examples:

$$T(n) = T(c_1 n) + T(c_2 n) + n, \quad (c_1 + c_2 < 1), \quad (91)$$

$$T(n) = T(n/2) + T(n/4) + \log^7 n. \quad (92)$$

The first recurrence (91) arise in linear time selection algorithms (see Chapter XI). There are many versions of this algorithm with different choices for the constants c_1, c_2 . E.g., $c_1 = 7/10, c_2 = 1/5$. The second recurrence (92) arise in the so-called conjugate search trees in computational geometry (see Exercise 8.7).

Before we give the multiterm analogue of the Master Theorem, we generalize two concepts from the Master Theorem:

(a) Associated with the recurrence (90) is the **watershed constant**, a real number α such that

$$\sum_{i=1}^k \frac{a_i}{b_i^\alpha} = 1. \quad (93)$$

Clearly α exists and is unique since the summation tends to 0 as $\alpha \rightarrow \infty$, and tends to ∞ as $\alpha \rightarrow -\infty$. As usual, let $W(n) = n^\alpha$ denote the watershed function.

(b) The recurrence (90) gives rise to a **generalized regularity condition** on the driving function $f(n)$, namely,

$$\sum_{i=1}^k a_i f(n/b_i) \leq c f(n) \quad (94)$$

for some $0 < c < 1$.

THEOREM 9 (Multiterm Master Theorem).

$$T(n) = \begin{cases} \Theta(n^\alpha \log n) & \text{if } f(n) = \Theta(n^\alpha) \\ \Theta(n^\alpha) & \text{if } f(n) = O(n^{\alpha-\varepsilon}), \text{ for some } \varepsilon > 0, \\ \Theta(f(n)) & \text{if } f \text{ satisfies the regularity condition (94).} \end{cases}$$

Proof. The proof uses real induction.

CASE (0): Assume that $f(n) = \Theta_1(W(n))$. We will show that $T(n) = \Theta_2(W(n) \log n)$. We have

$$\begin{aligned} T(n) &= f(n) + \sum_{i=1}^k a_i T\left(\frac{n}{b_i}\right) \\ &= \Theta_1(n^\alpha) + \sum_{i=1}^k a_i \Theta_2\left(\left(\frac{n}{b_i}\right)^\alpha \log\left(\frac{n}{b_i}\right)\right) \quad (\text{by induction}) \\ &= \Theta_1(n^\alpha) + \Theta_2(n^\alpha) \left[\sum_{i=1}^k \frac{a_i}{b_i^\alpha} \log\left(\frac{n}{b_i}\right) \right] \\ &= \Theta_1(n^\alpha) + \Theta_2(n^\alpha) [\log n - D], \quad (\text{where } D = \sum_{i=1}^k \frac{a_i}{b_i^\alpha} \log(b_i) \text{ and using (93)}) \\ &= \Theta_2(n^\alpha \log n). \end{aligned}$$

Let us elaborate on the last equality. Suppose $f(n) = \Theta_1(n^\alpha)$ amounts to the inequalities $c_1 W(n) \leq f(n) \leq C_1 W(n)$ (ev.). We must choose c_2, C_2 such that $c_2 W(n) \log n \leq T(n) \leq C_2 W(n) \log n$ (ev.). The following choice suffices:

$$C_2 = C_1/D, \quad c_2 = c_1/D.$$

CASE (−1): Assume $0 \leq f(n) \leq D_1 n^{\alpha-\varepsilon}$ for some $\varepsilon > 0$. The lower bound is easy: assume $T(n/b_i) \geq c_1(n/b_i)^\alpha$ (ev.) for each i . Then⁷

$$\begin{aligned} T(n) &= f(n) + \sum_{i=1}^k a_i T\left(\frac{n}{b_i}\right) \\ &\geq \sum_{i=1}^k a_i c_1 \left(\frac{n}{b_i}\right)^\alpha \quad (\text{since } f(n) \geq 0 \text{ and by induction}) \\ &= c_1 n^\alpha. \end{aligned}$$

The upper bound needs a slightly stronger hypothesis: assume $T(n/b_i) \leq C_1 n^\alpha (1 - n^{-\varepsilon})$ (ev.). Then

$$\begin{aligned} T(n) &= f(n) + \sum_{i=1}^k a_i T\left(\frac{n}{b_i}\right) \\ &\leq D_1 n^{\alpha-\varepsilon} + \sum_{i=1}^k a_i C_1 \left(\frac{n}{b_i}\right)^\alpha \left[1 - \left(\frac{n}{b_i}\right)^{-\varepsilon}\right] \quad (\text{by induction}) \\ &= C_1 n^\alpha - C_1 n^{\alpha-\varepsilon} \left[\sum_{i=1}^k \frac{a_i}{b_i^{\alpha-\varepsilon}} - D_1/C_1\right] \\ &\leq C_1 n^\alpha - C_1 n^{\alpha-\varepsilon} \end{aligned}$$

provided $\sum_{i=1}^k a_i/b_i^{\alpha-\varepsilon} \geq 1 + (D_1/C_1)$. Since $\sum_{i=1}^k a_i/b_i^{\alpha-\varepsilon} > 1$, we can certainly choose a large enough C_1 to satisfy this.

CASE (+1): The lower bound $T(n) = \Omega(f(n))$ is trivial. As for upper bound, assuming $T(m) \leq D_1 f(m)$ (ev.) whenever $m = n/b_i$,

$$\begin{aligned} T(n) &= f(n) + \sum_{i=1}^k a_i T\left(\frac{n}{b_i}\right) \\ &\leq f(n) + \sum_{i=1}^k a_i D_1 f(n/b_i) \quad (\text{by induction}) \\ &= f(n) + D_1 c f(n) \quad (\text{by regularity}) \\ &\leq D_1 f(n) \quad (\text{if } D_1 \geq 1/(1-c)) \end{aligned}$$

Q.E.D.

The use of real induction appears to be necessary in this proof: unlike the master recurrence, the multiterm version does not yield to transformations. Again, the generalized regularity condition implies that $f(n) = \Omega(n^{\alpha+\varepsilon})$ for some $\varepsilon > 0$. This is shown by induction:

$$\begin{aligned} f(n) &\geq \frac{1}{c} \sum_{i=1}^k a_i f(n/b_i) \\ &\geq \frac{1}{c} \sum_{i=1}^k a_i D (n/b_i)^{\alpha+\varepsilon} \quad (\text{by induction, for some } D > 0) \\ &= \frac{D}{c} n^{\alpha+\varepsilon} \sum_{i=1}^k \frac{a_i}{b_i^{\alpha+\varepsilon}} \\ &= D n^{\alpha+\varepsilon} \quad (\text{if we choose } c = \sum_{i=1}^k \frac{a_i}{b_i^{\alpha+\varepsilon}}) \end{aligned}$$

Since $\sum_{i=1}^k \frac{a_i}{b_i^{\alpha+\varepsilon}} = 1$, we should be able to choose a $\varepsilon > 0$ to satisfy the last condition. Note that this derivation imposes no condition on D , and so D can be determined based on the initial conditions.

Let us apply the theorem to the recurrence for $T_1(n)$ in the selection problem (91) and $T_2(n)$ in the conjugate tree problem (92). For (91), we see that $\alpha < 1$ and since the regularity condition holds for the function $f(n) = n$, we conclude that $T_1(n) = \Theta(n)$. For (92), we may use a calculator to verify that the watershed value is $\alpha = 0.694\dots$. Since $f(n) = \mathcal{O}(n^{\alpha-\varepsilon})$, we conclude that $T_2(n) = \Theta(n^{0.694\dots})$.

EXERCISES

Exercise 10.17: The following recurrence arises in the analysis of the running time of the “conjugation tree” in computational geometry:

$$T(n) = T(n/2) + T(n/4) + \lg^7 n.$$

⁷The fact $f(n) \geq 0$ (ev.) is a consequence of “ $f \in \mathcal{O}(n^{\alpha-\varepsilon})$ ” and the definition of the big-Oh notation.

Solve for $T(n)$.

◇

Exercise 10.18: To understand the recurrence $T(n) = T(n/2) + T(n/3) + T(n/4) + n$, we will explore numerically the function $h(x) = 2^{-x} + 3^{-x} + 4^{-x}$. We want to determine the α such that $h(\alpha) = 1$. For a simple way to do this, use a user-friendly, powerful software like MATLAB. For instance, consider the following two lines of MATLAB code:

```
>> h = @(x) 2.^(-x) + 3.^(-x) + 4.^(-x);
>> for x=0.9:0.1:1.2, display([x, h(x)]), end
```

The first line defines the function $h(x)$. The second line is a for-loop where x begins with the value 0.9 and each iteration increases the value of x by 0.1 until $x = 1.2$. Each iteration simply prints the pair $(x, h(x))$ of values. This loop produces the values shown in the first of the following four tables:

x	$h(x)$	x	$h(x)$	x	$h(x)$	x	$h(x)$
0.9000	1.1951	1.0700	1.0119	1.0810	1.0011	1.0820	1.0001
1.0000	1.0833	<u>1.0800</u>	1.0021	<u>1.0820</u>	1.0001	<u>1.0821</u>	1.0000
<u>1.1000</u>	0.9828	1.0900	0.9924	1.0830	0.9992	1.0822	0.9999
1.2000	0.8923	1.1000	0.9828	1.0840	0.9982	1.0823	0.9998

By changing the stepsize and limits of the for-loop, we can get more correct digits with run of the for-loop. Each successive table above is obtained this way, each time giving us an extra digit in the decimal expansion of α . Thus, $\alpha \approx 1.0821$. How would you continue this experiment to determine the first 100 digits of α ? ◇

END EXERCISES

§11. Other Recurrences

There is a wide variety of recurrences which we have barely hinted at. For instance, the typical recurrences arising in counting combinatorial structures have an exponential (e.g., $T(n) = 2T(n-1) + f(n)$) or double exponential growth (e.g., $T(n) = T(n-1)^2 + f(n)$). We refer to Knuth for such examples. In this section, we focus on some other types of recurrences.

§11.1. Recurrences with Max

A class of recurrences that arises frequently in computer science involves the max operation. Fredman has investigated the solution of a class of recurrences involving max.

Consider the following variant of QuickSort: each time after we partition the problem into two subproblems, we will solve the subproblem that has the smaller size first (if their sizes are equal, it does not matter which order is used). We want to analyze the depth of the recursion stack. If a problem of size n is split into two subproblems of sizes n_1, n_2 then $n_1 + n_2 = n - 1$. Without loss of generality, let $n_1 \leq n_2$. So $0 \leq n_1 \leq \lfloor (n-1)/2 \rfloor$. If the stack contains problems of sizes $(n_1 \geq n_2 \geq \dots \geq n_k \geq 1)$ where n_k is the problem size at the top of the stack, then we have

$$n_{i-1} \geq n_i + n_{i+1}.$$

Since $n_1 \leq n$, this easily implies $n_{2i+1} \leq n/2^i$ or $k \leq 2 \lg n$. A tighter bound is $k \leq \log_\phi n$ where $\phi = 1.618 \dots$ is the golden ratio. This is not tight either.

The depth of recursion satisfies

$$D(n) = \max_{n_1=0}^{\lfloor (n-1)/2 \rfloor} [\max\{1 + D(n_1), D(n_2)\}]$$

This recurrence involving max is actually easy to solve. Assuming $D(n) \leq D(m)$ for all $n \leq m$, and for any real x , $D(x) = D(\lfloor x \rfloor)$, it is easy to see that $D(n) = 1 + D(n/2)$. Using the fact that $D(1) = 0$, we obtain $D(n) \leq \lg n$. [Note: $D(1) = 0$ means that all problems on the stack has size ≥ 2 .

§11.2. Analysis of ϵ -Nets

The following recurrence arise in the analysis of a class of data structures called ϵ -nets, first studied by Haussler and Welzl. Assuming $0 < \epsilon < 1$ and $m \geq 2$ are fixed,

$$T(n) = 1 + \max_{(n_1, \dots, n_m)} \sum_{i=1}^m T(n_i)$$

where the maximum ranges over all (n_1, \dots, n_m) satisfying $n_i \geq 0$ and $\sum_{i=1}^m n_i \leq \epsilon n$.

There is a trivial solution to this: the constant function

$$T(n) = 1/(1 - \epsilon)$$

for all n . But $T(n) < 0$ in this case and we seek a non-negative solution. Assuming that $T(n)$ is a convex cap⁸, it is easy to see that

$$T(n) = 1 + mT(\epsilon n/m) = \Theta(n^{\log_{m/\epsilon} m}).$$

To show $T(n)$ is a convex cap, we note that it is continuous (exercise) and a monotonic non-decreasing function. Then it suffices (exercise) to prove that

$$T(x) + T(y) \leq 2T((x+y)/2) \quad (95)$$

where we now regard $T(x)$ as a real function defined for all $x \geq 0$. This turns out to be easy to show inductively, assuming the base case where $T(x) = x$ (or $T(x) = 0$) for all $0 \leq x \leq 1$.

§11.3. A Log-square Solution

Consider the recurrence

$$T(n) = 1 + T(n - \frac{n}{\log n}). \quad (96)$$

This does not yield to our standard techniques. To probe deeper, note some simple bounds. It is easy to see that $T(n) \leq n$ since this is the solution to the recurrence $T(n) \leq 1 + T(n-1)$. Likewise $T(n) \geq \lg n$ since this is the solution to $T(n) \geq 1 + T(n/2)$.

⁸We say a real function $f(x)$ is **convex cap** if for all $0 < \alpha < 1$, $f(x) + f(y) \leq 2f(\alpha x + (1-\alpha)y)$. For completeness, we say $f(x)$ is **convex cup** if for all $0 < \alpha < 1$, $f(x) + f(y) \geq 2f(\alpha x + (1-\alpha)y)$.

To get a better upper bound, we note that

$$\begin{aligned}
 T(n) &= 1 + T\left(n\left(1 - \frac{1}{\log n}\right)\right) \\
 &\leq 2 + T\left(n\left(1 - \frac{1}{\log n}\right)^2\right), \quad (\text{why?}) \\
 &\vdots \\
 &\leq k + T\left(n\left(1 - \frac{1}{\log n}\right)^k\right)
 \end{aligned}$$

using monotonicity of $T(n)$. Hence $T(n) = k$ if we assume $T(n) = 0$ for $n \leq 1$ and k is chosen so that

$$\left(1 - \frac{1}{\log n}\right)^k \leq 1/n < \left(1 - \frac{1}{\log n}\right)^{k+1}.$$

Taking natural logs, and assuming for simplicity that $\log = \ln$ in (96), we see that

$$\begin{aligned}
 (k+1) \ln\left(1 - \frac{1}{\ln n}\right) &> -\ln n, \\
 (k+1) \left(-\frac{1}{\ln n}\right) &> -\ln n, \quad (\text{since } \ln(1+x) \leq x \text{ for } |x| < 1), \\
 k+1 &< \ln^2 n.
 \end{aligned}$$

Up to a constant factor, this is also the lower bound: we show that $T(n) \geq C \ln^2 n$ by induction:

$$\begin{aligned}
 T(n) &\geq 1 + C \ln^2\left(n\left(1 - \frac{1}{\log n}\right)\right) \\
 &= 1 + C(\ln n + \ln\left(1 - \frac{1}{\log n}\right))^2 \\
 &\geq 1 + C\left(\ln n - \frac{2}{\ln n}\right)^2, \quad \text{since } \ln(1+x) \geq x - x^2/2 \text{ for } |x| < 1 \\
 &\geq C \ln^2 n.
 \end{aligned}$$

Thus $T(n) = \Theta(\ln^2 n)$.

REMARK: If we were told from the beginning to verify that $T(n) = \Theta(\ln^2 n)$, this would be routine. What we are demonstrating here is the process of discovering that $\Theta(\ln^2 n)$ is the correct answer.

EXERCISES

Exercise 11.1: Try to obtain tight constants for the recurrence (96). What if \log is not the natural logarithm in the original equation? \diamond

Exercise 11.2: Show that $T(x)$ above is continuous by exploiting the fact that the addition and maximum functions are continuous. \diamond

Exercise 11.3: Prove that if $T(x)$ is continuous and satisfies equation (95) then it is a convex cap. \diamond

Exercise 11.4: (Leighton 1996) Show that $T(n) = 2T(\frac{n}{2} - \frac{n}{\lg n})$ has solution $T(n) = \Theta(n \log^{\Theta(1)} n)$. Assume that $T(n) = 1$ for $n \leq 5$, and the recurrence holds for $n > 5$. Thus $T(5 + \varepsilon) = 2$, so this function is discontinuous. \diamond

Exercise 11.5: Analyze the behavior of the function $T(n)$ defined by the recurrence $T(n) = nT(\log n)$. Give upper and lower bounds for $T(n)$ using “closed form expressions” in terms of the functions $\log^{(i)} n$, $i \geq 0$.
Note: This recurrence arises from an early version of the fast integer multiplication algorithm of Schönhage and Strassen. \diamond

Exercise 11.6: Solve the recurrence $T(n) = 1 + \max_{(n_1, n_2, n_3, n_4)} \{T(n_1) + T(n_2) + T(n_3) + T(n_4)\}$ where (n_1, \dots, n_4) ranges over all non-negative numbers such that $\sum_{i=1}^4 n_i = \frac{3n}{2}$ and each $n_i \leq n/2$. \diamond

Exercise 11.7: Solve the following recurrences to Θ -order:

(a) $T(n) = 1 + 2T(n - \frac{n}{\log n})$.

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

(c) $T(n) = 1 + T(\frac{n}{\log n})$.

HINT: these recurrences are considerably harder than most of what we encounter. First guess non-tight upper and lower bounds and verify by induction. Then try to tighten these bounds. \diamond

END EXERCISES

§11.4. Multivariable Recurrences

So far, our recurrences involve only one variable. But multivariable recurrences arise in several ways: one source of such recurrences is multidimensional problems in computational geometry (one of the variable is the dimension).

The pre-processing problem of **point dominance queries** in d -dimensions is as follows: given a set $S \subseteq \mathbb{R}^d$ of n points, construct a data structure $D(S)$ such that for any query point $p \in \mathbb{R}^d$, we can quickly determine if there is any point $x \in S$ that **dominates** p (this means $x \geq p$, componentwise). One solution is to pick some $c \in \mathbb{R}$ such that S splits into two subsets S_1, S_2 of size $n/2$ each, where the first component of each $x \in S_1$ is $\leq c$, and the first component of each $x' \in S_2$ is $\geq c$. To answer the query for p , begin by comparing the first component p_1 of p to c : if $p_1 > c$ then it is sufficient to recursively check if some $x \in S_2$ dominates p . If $p_1 \leq c$, we must do two searches: (i) check if some $x \in S_1$ dominates p and (ii) check if some $x \in S_2$ dominates p . The search in (i) is, however, done in $d - 1$ dimensions since we may ignore the first components. Thus the time for answering queries satisfies the recurrence

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

It is not hard to see that $T(n, 1) = \mathcal{O}(1)$. Then we may verify the solution $T(n, d) = \Theta(\log^{d-1} n)$.

¶32. Output-sensitive algorithms. Multivariable recurrences arise in the analysis of “output-sensitive” algorithms. Such algorithms has, besides the traditional **input parameter** n , an (implicit) **output parameter** h , which measures the size of the output for the given input instance. The computational complexity of such algorithms depends on both n and h . An example is the problem of computing the convex hull of a set of n

points in the plane. The output size is just the number of points in the actual convex hull. There are well-known $\mathcal{O}(n \log n)$ algorithms for this problem. Kirkpatrick and Seidel has given an algorithm whose time complexity satisfies the following recurrence:

$$T(n, h) = \mathcal{O}(n) + \max_{h_1+h_2=h-1} \left\{ T\left(\frac{n}{2}, h_1\right) + T\left(\frac{n}{2}, h_2\right) \right\}.$$

Here, h_i are positive integers. We may assume $T(n, h) = \mathcal{O}(n)$ for $h \leq 3$. To see that $T(n, h) = \mathcal{O}(n \log h)$, we could of course just substitute and verify. But it is more instructive to argue as follows: consider a “recursion tree” corresponding to a possible expansion of the recurrence relation for $T(n, h)$. There are exactly h nodes in this binary tree, where each internal node at depth i (the root is depth 0) carries a “cost” of $n/2^i$. The “cost” of the tree just the sum of these costs at the internal nodes. So $T(n, h)$ is the maximum cost over all possible recursion trees. The *claim* $T(n, h) = \mathcal{O}(n \log h)$ follows if we prove that the maximum cost occurs when the tree has depth at most $\log_2 h$ (since the total cost of all nodes at any depth i is invariably n). For the sake of contradiction, suppose we have a maximum cost tree with depth $d > \log_2 h$. Then there is a node at depth $d - 1$ whose children are leaves at depth d . We can transfer these two children to become the children of some other node at depth $\leq d - 2$. This would increase the cost for the tree, contradiction.

EXERCISES

Exercise 11.8: Show that if $S(n, d)$ is the space requirement for the above data structure, then $S(n, d) = 1 + 2S(n/2, d) + S(n/2, d - 1)$. Solve this recurrence. What is $S(n, 1)$? \diamond

Exercise 11.9: Consider the following recurrence

$$T(n, h) = \mathcal{O}(n) + \max_{h_1+h_2=h-1; c_1+c_2=1} \{T(c_1 n, h_1) + T(c_2 n, h_2)\}.$$

- (a) Solve for $T(n, h)$ with only the assumption $h_i \geq 1, c_i > 0$ in the above.
- (b) Solve for $T(n, h)$ with the *additional* assumption that $c_i \leq \alpha$ where $0 < \alpha < 1$ is fixed. Generalize the above argument about the shape of the maximum cost recursion tree. \diamond

Exercise 11.10: (Sharir-Welzl) The following recurrence arises in analyzing the diameter of n -dimensional polytopes with m facets:

$$f(n, m) = f(n - 1, m - 1) + \frac{2}{m} \sum_{i=1}^m f(n - 1, i).$$

Solve the recurrence. \diamond

END EXERCISES

§12. Orders of Growth

The reader should first review the basic properties of the exponential and logarithm functions in the appendix.

Learning to judge the growth rates of complexity functions is a fundamental skill in algorithmics. This section is a practical one, designed to help students develop this skill.

Most complexity functions in practice are the so-called **logarithmico-exponential functions** (for short, L -functions): such functions $f(x)$ are real and defined for all $x \geq x_0$ for some x_0 depending of f . An L -function is either the identity function x or a constant $c \in \mathbb{R}$, or else obtained as a finite composition with the functions

$$A(x), \quad \ln(x), \quad e^x$$

where $A(x)$ denotes a real branch of an algebraical function. For instance, $A(x) = \sqrt{x}$ is the function that picks the real square-root of x . The reader may have noticed that all the common complexity functions are totally ordered in the sense that for any f, g , either $f \preceq g$ or $g \preceq f$. A theorem⁹ of Hardy [7] confirms this: *if f and g are L -functions then $f \leq g$ (ev.) or $g \leq f$ (ev.).* In particular, each L -function f is eventually non-negative, $0 \leq f$ (ev.), or non-positive, $f \leq 0$ (ev.).

The following are the common categories of functions you will encounter:

CATEGORY	SYMBOL	EXAMPLES
vanishing term	$o(1)$	$\frac{1}{n}, \quad 2^{-n}$
constants	$\Theta(1)$	$1, \quad 2 - \frac{1}{n}$
polylogs	$\log^k n$ (for any $k > 0$)	$H_n, \quad \log^2 n$
polynomials	n^k (for any $k > 0$)	$n^3, \quad \sqrt{n}$
non-polynomials	$n^{\Omega(1)}$	$n!, \quad 2^n, \quad n^{\log \log n}$

Note that $n!$ and H_n are not L -functions, but they can be closely approximated by L -functions. The last category forms a grab-bag of anything growing faster than a polynomial. These 5 categories form a hierarchy of increasingly larger Θ -order.

¶33. Rules for comparing functions. We are interested in comparing functions up to their Θ -order. The trick of comparing two functions by taking their logarithms is this: *if $\log f \preceq \log g$ then clearly $f \preceq g$.* But students often think the converse is also true.

We list some simple rules. Most comparisons of interest to us can be reduced to repeated applications of these rules:

Sum: In a direct comparison involving a sum $f(n) + g(n)$, ignore the smaller term in this sum.

E.g., given $n^2 + n \log n + 5$, you should ignore the “ $n \log n + 5$ ” term. However, beware that if the sum appears in an exponent, the neglected part may turn out be decisive when the dominant terms are identical.

Product: If $0 \preceq f \preceq f'$ and $0 \preceq g \preceq g'$ then $fg \preceq f'g'$. (If, in addition, $f \prec f'$ then we have $fg \prec f'g'$.)

E.g., this rule implies $n^b \prec n^c$ when $b < c$ (since $1 \prec n^{c-b}$, by the logarithm rule next).

Logarithm: $1 \prec \log^{(k+1)} n \prec (\log^{(k)} n)^c$ for any integer $k \geq 0$ and real $c > 0$. Here $\log^{(k)} n$ refers to the k -fold application of the logarithm function and $\log^{(0)} n = n$.

Exponentiation: If $1 \leq f \leq g$ (ev.) then $d^f \preceq d^g$ for any constant $d > 1$. If $1 \leq f \leq cg$ (ev.) for some $c < 1$ then $d^f \prec d^g$.

⁹In the literature on L -functions, the notation “ $f \preceq g$ ” actually means $f \leq g$ (ev.). There is a deep theory involving such functions, with connection to Nevanlinna theory.

¶34. Example. Suppose we want to compare $n^{\lg n}$ versus $(\log n)^n$. By the rule of exponentiation, $n^{\lg n} \prec (\log n)^n$ follows if we take logs and show that $\log^2 n \leq 0.5n \log \log n$ (ev.). In fact, we show the stronger $\log^2 n \prec n \log \log n$. Taking logs again, and by the rule of sum, it is sufficient to show $2 \log \log n \prec \log n$. Taking logs again, and by the rule of sum again, it suffices to show $\log^{(3)} n \prec \log^{(2)} n$. But the latter follows from the rule of logarithms.

EXERCISES

Exercise 12.1: (i) Simplify the following expressions: (a) $n^{1/\lg n}$, (b) $2^{2^{\lg \lg n - 1}}$, (c) $\sum_{i=0}^{k-1} 2^i$, (d) $2^{(\lg n)^2}$, (e) $4^{\lg n}$, (f) $(\sqrt{2})^{\lg n}$.
(ii) Re-do the above, replacing each occurrence of “2” (explicit or otherwise) in the previous expressions by some constant $c > 2$. \diamond

Exercise 12.2: Order these in increasing big-Oh order:

$$n \lg n, \quad n^{-1}, \quad \lg n, \quad n^{\lg n}, \quad 10n + n^{3/2}, \quad \pi^n, \quad 2^n, \quad 2^{\lg n}.$$

 \diamond

Exercise 12.3: Order the following 5 functions in order of increasing Θ -order: (a) $\log^2 n$, (b) $n / \log^4 n$, (c) \sqrt{n} , (d) $n2^{-n}$, (e) $\log \log n$. \diamond

Exercise 12.4: Order the following functions (be sure to parse these nested exponentiations correctly): (a) $n^{(\lg n)^{\lg n}}$, (b) $(\lg n)^{n^{\lg n}}$, (c) $(\lg n)^{(\lg n)^n}$, (d) $(n / \lg n)^{n^{1/(\lg n)}}$, (e) $n^{n^{(\lg n)/n}}$. \diamond

Exercise 12.5: Order the following set of 36 functions in non-increasing order of growth. Between consecutive pairs of functions, insert the appropriate ordering relationship: \preceq , \asymp , \leq (ev.), $=$.

	a	b	c	d	e	f
1.	$\lg \lg n$	$(\lg n)^{\lg n}$	2^n	$2^{\lg n}$	$2^{\lg^* n}$	$2^{2^{n+1}}$
2.	$(1/3)^n$	$n2^n$	$n^{\lg \lg n}$	e^n	$n^{1/\lg n}$	$\lceil \lg n \rceil!$
3.	$2^{\sqrt{2^{\lg n}}}$	$(3/2)^n$	2	$\lg(n!)$	n	$\sqrt{\lg n}$
4.	$2^{(\lg n)^2}$	2^{2^n}	n^2	$n \lg n$	$(n+1)!$	$4^{\lg n}$
5.	$\lg(\lg^* n)$	$\lg^2 n$	$(1 + \frac{1}{n})^n$	$n^{\lg n}$	$n!$	$2^{(\lg n)/n}$
6.	$(\sqrt{2})^{\lg n}$	$\lg^* n$	$(n / \lg n)^2$	\sqrt{n}	$\lg^*(\lg n)$	$1/n$

NOTE: to organize of this large list of functions, we ask that you first order each row. Then the rows are merged in pairs. Finally, perform a 3-way merge of the 3 lists. Show the intermediate lists of your computation (it allows us to visually verify your work). \diamond

Exercise 12.6: Order the following functions:

$$n, \quad \lceil \lg n \rceil!, \quad \lceil \lg \lg n \rceil!, \quad n^{\lceil \lg \lg n \rceil!}, \quad 2^{\lg^* n}, \quad \lg^*(2^n), \quad \lg^*(\lg n), \quad \lg(\lg^* n).$$

 \diamond

Exercise 12.7: (Purdom-Brown)

- (a) Show that $\sum_{i=1}^n i! = n![1 + \mathcal{O}(1/n)]$. NOTE: The summation rule gives only a Θ -order so this is more precise.
(b) $\sum_{i=1}^n 2^i \ln i = 2^{n+1}[\ln n - (1/n) + \mathcal{O}(n^{-2})]$. HINT: use $\ln i = \ln n - (i/n) + \mathcal{O}(i^2/n^2)$ for $i = 1, \dots, n$. \diamond

Exercise 12.8: (Knuth) What is the asymptotic behavior of $n^{1/n}$? of $n(n^{1/n} - 1)$?

HINT: take logs. Alternatively, expand $\prod_{i=1}^n e^{1/(in)}$.

◇

Exercise 12.9: Estimate the growth behavior of the solution to this recurrence: $T(n) = T(n/2)^2 + 1$.

◇

END EXERCISES

¶35. **Bibliographic Notes** Our example of maximum overhang of a brick stack, illustrating Harmonic numbers, is from the book “How Round is Your Circle? Where Engineering and Mathematics Meet”, by John Bryant and Chris Sangwin (Princeton University Press, 2008).

§A. APPENDIX: Exponential and Logarithm Functions

Next to the polynomials, the two most important functions in algorithmics are the **exponential function** and its inverse, the **logarithm function**. Many of our asymptotic results depend on their basic properties. For the student who wants to understand these properties, the following will guide them through some exercises. We define the **natural exponential function** to be

$$\exp(x) = \sum_{i=0}^{\infty} \frac{x^i}{i!}$$

for all real x . This definition is also good for complex x , but we do not need this here. The **base of the natural logarithm** is defined to be the number

$$e := \exp(1) = \sum_{i=0}^{\infty} \frac{1}{i!} = 2.71828\dots$$

The next exercise derives some asymptotic properties of the exponential function.

Exercise A.1: Show that

- (a) $\exp(x)$ is continuous,
- (b) $\frac{d \exp(x)}{dx} = \exp(x)$ and hence $\exp(x)$ has all derivatives,
- (c) $\exp(x)$ is positive, strictly increasing,
- (d) $\exp(x) \rightarrow 0$ as $x \rightarrow -\infty$, $\exp(x) \rightarrow \infty$ as $x \rightarrow \infty$,
- (e) $\exp(x + y) = \exp(x) \exp(y)$,

◇

We often need explicit bounds on exponential functions (not just asymptotic behavior). Derive the following bounds:

Exercise A.2:

- (a) $\exp(x) \geq 1 + x$ for all $x \geq 0$ with equality iff $x = 0$.
- (b) $\exp(x) > \frac{x^{n+1}}{(n+1)!}$ for $x > 0$. Hence $\exp(x)$ grow faster than any polynomial in x .
- (c) For all real $n \geq 0$,

$$\left(1 + \frac{x}{n}\right)^n \leq e^x \leq \left(1 + \frac{x}{n}\right)^{n+(x/2)}.$$

It follows that an alternative definition of e^x is

$$e^x = \lim_{n \rightarrow \infty} \left(1 + \frac{x}{n}\right)^n.$$

(d) $\exp(x) \left(1 - \frac{x^2}{n}\right) \leq \left(1 + \frac{x}{n}\right)^n$ for all $x, n \in \mathbb{R}$, $n \geq 1$ and $|x| \leq n$. See [13]. \diamond

The **natural logarithm** function $\ln(x)$ is the inverse of $\exp(x)$: $\ln(x)$ is defined¹⁰ to be the real number y such that $\exp(y) = x$. Note that this is a partial function because it is defined for all and only positive x .

Exercise A.3: Show that

- (a) $\frac{d \ln(x)}{dx} = \frac{1}{x}$,
- (b) $\ln(xy) = \ln(x) + \ln(y)$,
- (c) $\ln(x)$ increases monotonically from $-\infty$ to $+\infty$ as x increases from 0 to $+\infty$. \diamond

These two functions now allow us to define exponentiation to any base: for any positive b and any real α , we define

$$\exp_b(\alpha) := \exp(\alpha \ln(b)). \quad (97)$$

Usually, we write $\exp_b(\alpha)$ as b^α . Note that if $b = e$ then we obtain e^α , a familiar notation for $\exp(\alpha)$.

We see from (97) that b must be positive since $\ln(b)$ is otherwise undefined. Moreover, the case $b = 1$ is highly degenerate since b^α is identically equal to 1. It is easy to check that $(1/b)^\alpha = b^{-\alpha}$, and hence it is not necessary to explicitly consider the case $b < 1$ (since we can replace such a b by $1/b$ which would be > 1).

Once we have the definition of $\exp_b(x) = b^x$, the logarithm function $\log_b(x)$ to an arbitrary base $b > 0$ is defined to be the inverse of the function $\exp_b(x) = b^x$. Thus the logarithm to base b is defined as long as $b \neq 1$.

Exercise A.4: We show some familiar properties: the base b is omitted if it does not affect the stated property.

- (a)

$$\begin{aligned} \log 1 &= 0, & \log_b b &= 1, & \log_b x &= (\log_c x)/(\log_c b), \\ y &= x^{\log_x y}, & \log(x^y) &= y \log x, & \log(ab) &= (\log a) + (\log b). \end{aligned}$$
- (b) $\log(1/x) = -\log x$, $\log_b x = 1/(\log_x b)$, $a^{\log b} = b^{\log a}$.
- (c) $\frac{dx}{dx}(x^\alpha) = \alpha x^{\alpha-1}$.
- (d) For $b > 1$, the function $\log_b(x)$ increases monotonically from $-\infty$ to $+\infty$ as x increases from 0 to ∞ . At the same time, for $0 < b < 1$, $\log_b(x)$ decreases monotonically from $+\infty$ to $-\infty$. \diamond

Notations for Logarithms. Logarithms to base 2 is important in computer science and we will write “lg” for \log_2 . Of course, \ln denotes **natural logarithm** which has base $e = 2.71828 \dots$ and is extremely important in mathematics and calculus. Many authors use $\text{Log} := \log_{10}$ for logarithm to base 10. Our default assumption is that the base of logarithms is some $b > 1$, so that $\log_b x$ is a monotonically increasing function. When the actual value of b is immaterial (except that $b > 1$), we simply write ‘log’ without specifying the base (for the *anonymous logarithm*). We also write $\log^{(k)} n$ for the k -fold application of the logarithm function to n . Thus $\log^{(2)} n = \log \log n$, and by definition, $\log^{(0)} n = n$. This is to be distinguished from “ $\log^k n$ ” which equals $(\log n)^k$. On the black board, we might sometimes write $\ell \log n$, $\ell \ell \log n$ for $\log \log n$, $\log \log \log n$, etc.

¹⁰This real value y is called the principal value of the logarithm. That is because if we view $\exp(\cdot)$ as a complex function, then $\ln(x)$ is a multivalued function that takes all values of the form $y + 2n\pi$, $n \in \mathbb{Z}$.

¶36. **Bounds on logarithms.** For approximations involving logarithms, it is useful to recall a fundamental series for logarithms:

$$\ln(1+x) = x - \frac{x^2}{2} + \frac{x^3}{3} - \cdots = -\sum_{i=1}^{\infty} \frac{(-x)^i}{i}$$

valid for $|x| < 1$. We easily see that $x - x^2/2 < \ln(1+x) < x$. To see that $\ln(1+x) < x$ we must show that $R = \sum_{i=2}^{\infty} (-x)^i/i > 0$. This follows because if we pair up the terms in R we obtain

$$R = (x^2/2 - x^3/3) + (x^4/4 - x^5/5) + \cdots,$$

which is clearly a sum of positive terms. A similar argument shows $\ln(1+x) > x - x^2/2$.

How do we evaluate $\ln(y)$ for a general $y > 2$? Assume that we have (a good approximation) to $\ln(2)$. Then we can write $y = 2^n(1+x)$ and thus evaluate $\ln(y)$ as $n \ln(2) + \ln(1+x)$. Alternatively, we can write $y = n(1+x)$ where $n \in \mathbb{N}$ and write $\ln(y) = \ln(n) + \ln(1+x)$. To evaluate $\ln(n)$ we use the fact $\ln(n) = H_n - \gamma - (2n)^{-1} - \mathcal{O}(n^{-2})$ (see §5).

¶37. **Log-star function.** We define the **log-star function**: $\log^* x$ is the maximum non-negative integer n such that $\lg^{(n)}(x)$ is defined. Thus $\log^*(x) = 0, 1, 2$ iff $x \leq 0, 0 < x \leq 1, 1 < x \leq 2$ (respectively). So log-star is integer-valued. Although we have used base 2 in its definition, it could be defined generally for any $b > 1$.

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