

3.1-3

Explain why the statement, "The running time of algorithm A is at least $O(n^2)$," is meaningless.

3.1-4

Is $2^{n+1} = O(2^n)$? Is $2^{2^n} = O(2^n)$?

3.1-5

Prove Theorem 3.1.

3.1-6

Prove that the running time of an algorithm is $\Theta(g(n))$ if and only if its worst-case running time is $O(g(n))$ and its best-case running time is $\Omega(g(n))$.

3.1-7

Prove that $o(g(n)) \cap \omega(g(n))$ is the empty set.

3.1-8

We can extend our notation to the case of two parameters n and m that can go to infinity independently at different rates. For a given function $g(n, m)$, we denote by $O(g(n, m))$ the set of functions

$$O(g(n, m)) = \{f(n, m) : \text{there exist positive constants } c, n_0, \text{ and } m_0 \\ \text{such that } 0 \leq f(n, m) \leq cg(n, m) \\ \text{for all } n \geq n_0 \text{ or } m \geq m_0\}.$$

Give corresponding definitions for $\Omega(g(n, m))$ and $\Theta(g(n, m))$.

3.2 Standard notations and common functions

This section reviews some standard mathematical functions and notations and explores the relationships among them. It also illustrates the use of the asymptotic notations.

Monotonicity

A function $f(n)$ is *monotonically increasing* if $m \leq n$ implies $f(m) \leq f(n)$. Similarly, it is *monotonically decreasing* if $m \leq n$ implies $f(m) \geq f(n)$. A function $f(n)$ is *strictly increasing* if $m < n$ implies $f(m) < f(n)$ and *strictly decreasing* if $m < n$ implies $f(m) > f(n)$.

Floors and ceilings

For any real number x , we denote the greatest integer less than or equal to x by $\lfloor x \rfloor$ (read "the floor of x ") and the least integer greater than or equal to x by $\lceil x \rceil$ (read "the ceiling of x "). For all real x ,

$$x - 1 < \lfloor x \rfloor \leq x \leq \lceil x \rceil < x + 1. \quad (3.3)$$

For any integer n ,

$$\lceil n/2 \rceil + \lfloor n/2 \rfloor = n,$$

and for any real number $x \geq 0$ and integers $a, b > 0$,

$$\left\lceil \frac{\lfloor x/a \rfloor}{b} \right\rceil = \left\lceil \frac{x}{ab} \right\rceil, \quad (3.4)$$

$$\left\lfloor \frac{\lceil x/a \rceil}{b} \right\rfloor = \left\lfloor \frac{x}{ab} \right\rfloor, \quad (3.5)$$

$$\left\lceil \frac{a}{b} \right\rceil \leq \frac{a + (b - 1)}{b}, \quad (3.6)$$

$$\left\lfloor \frac{a}{b} \right\rfloor \geq \frac{a - (b - 1)}{b}. \quad (3.7)$$

The floor function $f(x) = \lfloor x \rfloor$ is monotonically increasing, as is the ceiling function $f(x) = \lceil x \rceil$.

Modular arithmetic

For any integer a and any positive integer n , the value $a \bmod n$ is the *remainder* (or *residue*) of the quotient a/n :

$$a \bmod n = a - n \lfloor a/n \rfloor. \quad (3.8)$$

It follows that

$$0 \leq a \bmod n < n. \quad (3.9)$$

Given a well-defined notion of the remainder of one integer when divided by another, it is convenient to provide special notation to indicate equality of remainders. If $(a \bmod n) = (b \bmod n)$, we write $a \equiv b \pmod{n}$ and say that a is *equivalent* to b , modulo n . In other words, $a \equiv b \pmod{n}$ if a and b have the same remainder when divided by n . Equivalently, $a \equiv b \pmod{n}$ if and only if n is a divisor of $b - a$. We write $a \not\equiv b \pmod{n}$ if a is not equivalent to b , modulo n .

Polynomials

Given a nonnegative integer d , a *polynomial in n of degree d* is a function $p(n)$ of the form

$$p(n) = \sum_{i=0}^d a_i n^i,$$

where the constants a_0, a_1, \dots, a_d are the *coefficients* of the polynomial and $a_d \neq 0$. A polynomial is asymptotically positive if and only if $a_d > 0$. For an asymptotically positive polynomial $p(n)$ of degree d , we have $p(n) = \Theta(n^d)$. For any real constant $a \geq 0$, the function n^a is monotonically increasing, and for any real constant $a \leq 0$, the function n^a is monotonically decreasing. We say that a function $f(n)$ is *polynomially bounded* if $f(n) = O(n^k)$ for some constant k .

Exponentials

For all real $a > 0$, m , and n , we have the following identities:

$$\begin{aligned} a^0 &= 1, \\ a^1 &= a, \\ a^{-1} &= 1/a, \\ (a^m)^n &= a^{mn}, \\ (a^m)^n &= (a^n)^m, \\ a^m a^n &= a^{m+n}. \end{aligned}$$

For all n and $a \geq 1$, the function a^n is monotonically increasing in n . When convenient, we shall assume $0^0 = 1$.

We can relate the rates of growth of polynomials and exponentials by the following fact. For all real constants a and b such that $a > 1$,

$$\lim_{n \rightarrow \infty} \frac{n^b}{a^n} = 0, \quad (3.10)$$

from which we can conclude that

$$n^b = o(a^n).$$

Thus, any exponential function with a base strictly greater than 1 grows faster than any polynomial function.

Using e to denote $2.71828\dots$, the base of the natural logarithm function, we have for all real x ,

$$e^x = 1 + x + \frac{x^2}{2!} + \frac{x^3}{3!} + \cdots = \sum_{i=0}^{\infty} \frac{x^i}{i!}, \quad (3.11)$$

where “!” denotes the factorial function defined later in this section. For all real x , we have the inequality

$$e^x \geq 1 + x, \quad (3.12)$$

where equality holds only when $x = 0$. When $|x| \leq 1$, we have the approximation

$$1 + x \leq e^x \leq 1 + x + x^2. \quad (3.13)$$

When $x \rightarrow 0$, the approximation of e^x by $1 + x$ is quite good:

$$e^x = 1 + x + \Theta(x^2).$$

(In this equation, the asymptotic notation is used to describe the limiting behavior as $x \rightarrow 0$ rather than as $x \rightarrow \infty$.) We have for all x ,

$$\lim_{n \rightarrow \infty} \left(1 + \frac{x}{n}\right)^n = e^x. \quad (3.14)$$

Logarithms

We shall use the following notations:

$$\begin{aligned} \lg n &= \log_2 n && \text{(binary logarithm) ,} \\ \ln n &= \log_e n && \text{(natural logarithm) ,} \\ \lg^k n &= (\lg n)^k && \text{(exponentiation) ,} \\ \lg \lg n &= \lg(\lg n) && \text{(composition) .} \end{aligned}$$

An important notational convention we shall adopt is that *logarithm functions will apply only to the next term in the formula*, so that $\lg n + k$ will mean $(\lg n) + k$ and not $\lg(n + k)$. If we hold $b > 1$ constant, then for $n > 0$, the function $\log_b n$ is strictly increasing.

For all real $a > 0$, $b > 0$, $c > 0$, and n ,

$$\begin{aligned} a &= b^{\log_b a}, \\ \log_c(ab) &= \log_c a + \log_c b, \\ \log_b a^n &= n \log_b a, \\ \log_b a &= \frac{\log_c a}{\log_c b}, \\ \log_b(1/a) &= -\log_b a, \\ \log_b a &= \frac{1}{\log_a b}, \\ a^{\log_b c} &= c^{\log_b a}, \end{aligned} \quad (3.15)$$

where, in each equation above, logarithm bases are not 1.

By equation (3.15), changing the base of a logarithm from one constant to another changes the value of the logarithm by only a constant factor, and so we shall often use the notation “ $\lg n$ ” when we don’t care about constant factors, such as in O -notation. Computer scientists find 2 to be the most natural base for logarithms because so many algorithms and data structures involve splitting a problem into two parts.

There is a simple series expansion for $\ln(1+x)$ when $|x| < 1$:

$$\ln(1+x) = x - \frac{x^2}{2} + \frac{x^3}{3} - \frac{x^4}{4} + \frac{x^5}{5} - \dots$$

We also have the following inequalities for $x > -1$:

$$\frac{x}{1+x} \leq \ln(1+x) \leq x, \quad (3.17)$$

where equality holds only for $x = 0$.

We say that a function $f(n)$ is *polylogarithmically bounded* if $f(n) = O(\lg^k n)$ for some constant k . We can relate the growth of polynomials and polylogarithms by substituting $\lg n$ for n and 2^a for a in equation (3.10), yielding

$$\lim_{n \rightarrow \infty} \frac{\lg^b n}{(2^a)^{\lg n}} = \lim_{n \rightarrow \infty} \frac{\lg^b n}{n^a} = 0.$$

From this limit, we can conclude that

$$\lg^b n = o(n^a)$$

for any constant $a > 0$. Thus, any positive polynomial function grows faster than any polylogarithmic function.

Factorials

The notation $n!$ (read “ n factorial”) is defined for integers $n \geq 0$ as

$$n! = \begin{cases} 1 & \text{if } n = 0, \\ n \cdot (n-1)! & \text{if } n > 0. \end{cases}$$

Thus, $n! = 1 \cdot 2 \cdot 3 \cdots n$.

A weak upper bound on the factorial function is $n! \leq n^n$, since each of the n terms in the factorial product is at most n . *Stirling’s approximation*,

$$n! = \sqrt{2\pi n} \left(\frac{n}{e}\right)^n \left(1 + \Theta\left(\frac{1}{n}\right)\right), \quad (3.18)$$

where e is the base of the natural logarithm, gives us a tighter upper bound, and a lower bound as well. As Exercise 3.2-3 asks you to prove,

$$\begin{aligned} n! &= o(n^n), \\ n! &= \omega(2^n), \\ \lg(n!) &= \Theta(n \lg n), \end{aligned} \tag{3.19}$$

where Stirling's approximation is helpful in proving equation (3.19). The following equation also holds for all $n \geq 1$:

$$n! = \sqrt{2\pi n} \left(\frac{n}{e}\right)^n e^{\alpha_n} \tag{3.20}$$

where

$$\frac{1}{12n+1} < \alpha_n < \frac{1}{12n}. \tag{3.21}$$

Functional iteration

We use the notation $f^{(i)}(n)$ to denote the function $f(n)$ iteratively applied i times to an initial value of n . Formally, let $f(n)$ be a function over the reals. For non-negative integers i , we recursively define

$$f^{(i)}(n) = \begin{cases} n & \text{if } i = 0, \\ f(f^{(i-1)}(n)) & \text{if } i > 0. \end{cases}$$

For example, if $f(n) = 2n$, then $f^{(i)}(n) = 2^i n$.

The iterated logarithm function

We use the notation $\lg^* n$ (read "log star of n ") to denote the iterated logarithm, defined as follows. Let $\lg^{(i)} n$ be as defined above, with $f(n) = \lg n$. Because the logarithm of a nonpositive number is undefined, $\lg^{(i)} n$ is defined only if $\lg^{(i-1)} n > 0$. Be sure to distinguish $\lg^{(i)} n$ (the logarithm function applied i times in succession, starting with argument n) from $\lg^i n$ (the logarithm of n raised to the i th power). Then we define the iterated logarithm function as

$$\lg^* n = \min \{i \geq 0 : \lg^{(i)} n \leq 1\}.$$

The iterated logarithm is a *very* slowly growing function:

$$\begin{aligned} \lg^* 2 &= 1, \\ \lg^* 4 &= 2, \\ \lg^* 16 &= 3, \\ \lg^* 65536 &= 4, \\ \lg^*(2^{65536}) &= 5. \end{aligned}$$

Since the number of atoms in the observable universe is estimated to be about 10^{80} , which is much less than 2^{65536} , we rarely encounter an input size n such that $\lg^* n > 5$.

Fibonacci numbers

We define the *Fibonacci numbers* by the following recurrence:

$$\begin{aligned} F_0 &= 0, \\ F_1 &= 1, \\ F_i &= F_{i-1} + F_{i-2} \quad \text{for } i \geq 2. \end{aligned} \tag{3.22}$$

Thus, each Fibonacci number is the sum of the two previous ones, yielding the sequence

0, 1, 1, 2, 3, 5, 8, 13, 21, 34, 55, ...

Fibonacci numbers are related to the *golden ratio* ϕ and to its conjugate $\hat{\phi}$, which are the two roots of the equation

$$x^2 = x + 1 \tag{3.23}$$

and are given by the following formulas (see Exercise 3.2-6):

$$\begin{aligned} \phi &= \frac{1 + \sqrt{5}}{2} \\ &= 1.61803\dots, \\ \hat{\phi} &= \frac{1 - \sqrt{5}}{2} \\ &= -.61803\dots \end{aligned} \tag{3.24}$$

Specifically, we have

$$F_i = \frac{\phi^i - \hat{\phi}^i}{\sqrt{5}},$$

which we can prove by induction (Exercise 3.2-7). Since $|\hat{\phi}| < 1$, we have

$$\begin{aligned} \frac{|\hat{\phi}^i|}{\sqrt{5}} &< \frac{1}{\sqrt{5}} \\ &< \frac{1}{2}, \end{aligned}$$

which implies that

$$F_i = \left\lfloor \frac{\phi^i}{\sqrt{5}} + \frac{1}{2} \right\rfloor, \quad (3.25)$$

which is to say that the i th Fibonacci number F_i is equal to $\phi^i / \sqrt{5}$ rounded to the nearest integer. Thus, Fibonacci numbers grow exponentially.

Exercises

3.2-1

Show that if $f(n)$ and $g(n)$ are monotonically increasing functions, then so are the functions $f(n) + g(n)$ and $f(g(n))$, and if $f(n)$ and $g(n)$ are in addition nonnegative, then $f(n) \cdot g(n)$ is monotonically increasing.

3.2-2

Prove equation (3.16).

3.2-3

Prove equation (3.19). Also prove that $n! = \omega(2^n)$ and $n! = o(n^n)$.

3.2-4 ★

Is the function $\lceil \lg n \rceil!$ polynomially bounded? Is the function $\lceil \lg \lg n \rceil!$ polynomially bounded?

3.2-5 ★

Which is asymptotically larger: $\lg(\lg^* n)$ or $\lg^*(\lg n)$?

3.2-6

Show that the golden ratio ϕ and its conjugate $\hat{\phi}$ both satisfy the equation $x^2 = x + 1$.

3.2-7

Prove by induction that the i th Fibonacci number satisfies the equality

$$F_i = \frac{\phi^i - \hat{\phi}^i}{\sqrt{5}},$$

where ϕ is the golden ratio and $\hat{\phi}$ is its conjugate.

3.2-8

Show that $k \ln k = \Theta(n)$ implies $k = \Theta(n / \ln n)$.