# FOUNDATIONS of COMPUTING

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# PREFACE

One who is serious all day will never have a good time, while one who is frivolous all day will never establish a houshold.
*Ptahhotpe, 24th century BC*

Science is a discipline in which even a fool of this generation should be able to go beyond the point reached by a genius of the last.
*Scientific folklore, 20th century AC*

It may sound surprising that in computing, in a field that develops so fast that future often turns to past before ever being presence, there is not too much more stable and more worth to learn than its foundations.

It may sound less surprising that in the field with such a revolutionary methodological impact on all sciences and technologies, and practically on all our intellectual endeavours, the importance of foundations of computing goes far beyond computing and it should be of interest to all those trying and needed to understand laws and essence of the information processing world and also to all those who want and need to have a firm ground for their life-long reeducation process—what everybody in computing has to expect.

This book presents the automata-algorithm-complexity part of foundations of computing in a new way, from several points of view, in order to meet new requirements for learning and teaching.

First of all, the book takes a broader and more coherent view of theory and its foundations than it used to be the case. It presents not only basics of automata, grammars, formal languages, universal computers, computability, computational complexity, but also of parallelism, randomization, communications, cryptography, interactive protocols, communication complexity and even of theoretical computer/communication architecture.

Secondly, the book presents foundations of computing as very rich on deep, important and exciting results that help, in an irreplacable way, to see the problems, laws, and potentials in computing and to cope with its complexity. Thirdly, the book tries to find a new balance between formal rigorousity needed to present basic concepts and results and informal motivations, illustrations and interpretations, needed to grasp their merit. Fourthly, the book tries to offer the reader or the student a systematic, complex and also up-to-date presentation of the main basic concepts, models, methods and results as well as those main new trends and results, a detailed presentation of which would require special lectures. In order to achieve that the basic concepts, models, methods and results are presented and illustrated in detail but other deep/new results, with too hard or not too illuminating proofs, are just stated, explained, interpreted and commented.

Topics covered by the book are very broad. Each chapter could be extended into a several volumes monograph/handbook. This textbook tries to concentrate only on subjects that are central for the field; on concepts, methods and models that are simple enough to present and on results that are either deep or important or useful or surprising or interesting or have several of these properties.

The aim of the book is to present foundations only to the extent that everyone should know who wants to be an expert in computing, or in areas with a deeper need for computing and its methodologies. For that reason the book tries to present only what everybody finishing university studies in computing or in related area should know from theory. Furthermore, the book is oriented to those for whom theory is only, or mainly, a tool. For those more interested in particular areas of theory the book could be a good starting point for their way through unlimited and exciting theory adventures. A detailed bibliography and historical/bibliographical notes should help those wishing to go more deeply into a subject or to find proofs and a more detailed treatment of particular subjects.

The main aim of the book is to serve as a textbook. However, because of its broad view of the field and an up-to-date presentation of the concepts, methods and results of foundations, the book can serve also as a reference book. Detailed historical and bibliographical comments at the end of each chapter, an extensive bibliography and a very detailed index are aimed to help the book to serve all its purposes.

The book is a significantly extended version of the lecture notes for a one-semester, four hours a week, course that was held at the University of Hamburg.

The book should be reasonably easy to follow and grasp for an interestyed and/or ambitious reader. It keeps formal presentation concise, it presents basic concepts, models, methods and results in a straightforward way and it devotes a large attention to examples, exercises, motivations, interpretations and explanation of connections between various approaches as well as to the impact of theory results in and also outside of computing. The book tries to demonstrate that the basic concepts, models, methods and results—products of many geniuses of the past—are, if properly seen and presented, actually very simple, with deep implications and important applications. The book tries to demonstrate that foundations of computing is an intellectually very rich, and practically very applied body of knowledge. It tries also to illustrate the ways theoretical concepts are often modified in order to get ones directly applicable. More difficult sections are marked by asterisks.

A large number of examples (235) and figures/tables (232) aim to help to understand presented concepts, models, methods, and results. The same is the rôle of a large number of exercises (1124). Quite a few of them (597) are included directly into the text to be an inherent part of it. They are mostly (very) easy or of a reasonable difficulty and should help the reader to get an immediate feedback and, at the same time, to extend knowledge and skill. Those more difficult are marked by one or two asterisks—to encourage ambitious readers with enough desire, time and energy and not to discourage the others. The rest of the exercises (512) is placed at the end of chapters. Some of them are of the same character as those in the text, only slightly different or additional ones. Other extend the subject delt with in the main text. Those that are more difficult are marked by one or two asterisks.

INTERNET suplement. The book will have an internet extension/supplement regularly upadated. It will contain three items. (i) Chapter 12: FRONTIERS, describing very recent and promising developments in computing models and modes (quantum, molecular,...); (ii) Additional examples and exercises; (iii) Corrections.

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# Contents

# Chapter 1

# FUNDAMENTALS

## INTRODUCTION

Foundations of computing is making an extensive and increasing use of a variety of very basic concepts, some very new some very old, methods and results to analyze computational problems and systems and to formulate, explore and harvest laws and limitations of information processing. This chapter therefore systematically introduces a variety of concepts, techniques and results needed for quantitative analysis in computing and for making use of randomization to increase efficiency, to extend feasibility, to innovate the concept of evidence and to secure communications. All concepts introduced are therefore of importance far beyond foundations of computing. They are needed for dealing with efficiency in and also outside of computing.

## LEARNING OBJECTIVES

The aim of the chapter is to learn:

1. methods to solve recurrences arising in the analysis of computing systems;
2. a powerful concept of generating functions with a variety of applications;
3. main asymptotic notations and techniques to use and to manipulate them;
4. basic concepts of number theory, especially those related to primes and congruences;
5. methods to solve various congruences;
6. intriguing problems of computing discrete square roots and discrete logarithms that play an important rôle in randomized computations and secure communications;
7. basics of discrete probability;
8. modern approaches to randomness and pseudo-random generators.

> The firm, the enduring, the simple
> and the modest are near to virtue.
>
> *Confucius (531-439 BC)*

Efficiency and inherent complexity play a key rôle in computing and are of growing importance also outside of computing. They provide both practically important quantitative evaluations and benchmarks as well as theoretically deep insights into the nature of computing and communication. Their importance grows with maturing of the discipline and also with the increase of performance of computing and communication systems. Therefore the main concepts, tools, methods and results of complexity analysis belong to the very basic body of knowledge and techniques in computing. They are also natural subjects to begin with in a textbook on foundations of computing, because of their importance throughout the book. Moreover, their simplicity and elegance provides a natural basis to start in order to present, demonstrate and exercise the richness and power of the concepts and methods of foundations of computing.

The following three important approaches concerning complexity issues in designs and performance analysis of computing systems are considered in this chapter: recursion, (asymptotic) estimations, and randomization.

Complex systems that we are able to design, describe or understand are often recursive by nature or designs. Their complexity analysis leads therefore naturally to recurrences. That is, why we start this chapter with methods to solve recurrences.

In the analysis of complex computational systems we are generally unable to determine exactly resources needed. For example, the exact number of computer operations to solve a problem. Fortunately, we mostly actually do not need to do that. Simple, but good enough, asymptotic estimations, that provide robust and a particular computer independent results, are in most of the cases not only quite satisfactory, but often much more useful. Methods how to handle, in a simple but precise way, asymptotic characterizations of functions are therefore of key importance for analysis of computing systems and are also treated in detail in this chapter.

The discovery that randomness is an important resource to manage complexity is one of the most important outcomes of foundations of computing in the last years. The understanding has developed already for a longer time that the analysis of algorithms with respect to a random distribution of input data may provide more realistic results. A new, and actually currently the main use of randomness, is in randomized algorithms, communication protocols, designs, proofs, etc. Coin-tossinging techniques allow to manage in many cases the complexity surprisingly well. Elements of the probability theory and of randomness are therefore also included into this introductory chapter and will be needed throughout the book. Interesting enough, these very modern approaches to use randomness to provide security are often based on old and basic concepts, methods, and results of the number theory, which will be also introduced in this chapter.

## 1.1 Examples -November 8, 2005

Quantitative analysis of computational resources—time, storage, processors, program, communication, randomness, interactions, knowledge, or of the size of computing systems: circuits, networks, automata, grammars, computers, algorithms or protocols—is of great importance. It may provide irreplaceable information how good a particular system is, and also deep insights into the nature of the underlying computational and communication problems.

Large and/or complex computing systems are often designed or described recursively. Their quantitative analysis leads naturally to recurrences. A **recurrence** is a system of equations or inequalities that describes a function in terms of its values for smaller inputs.

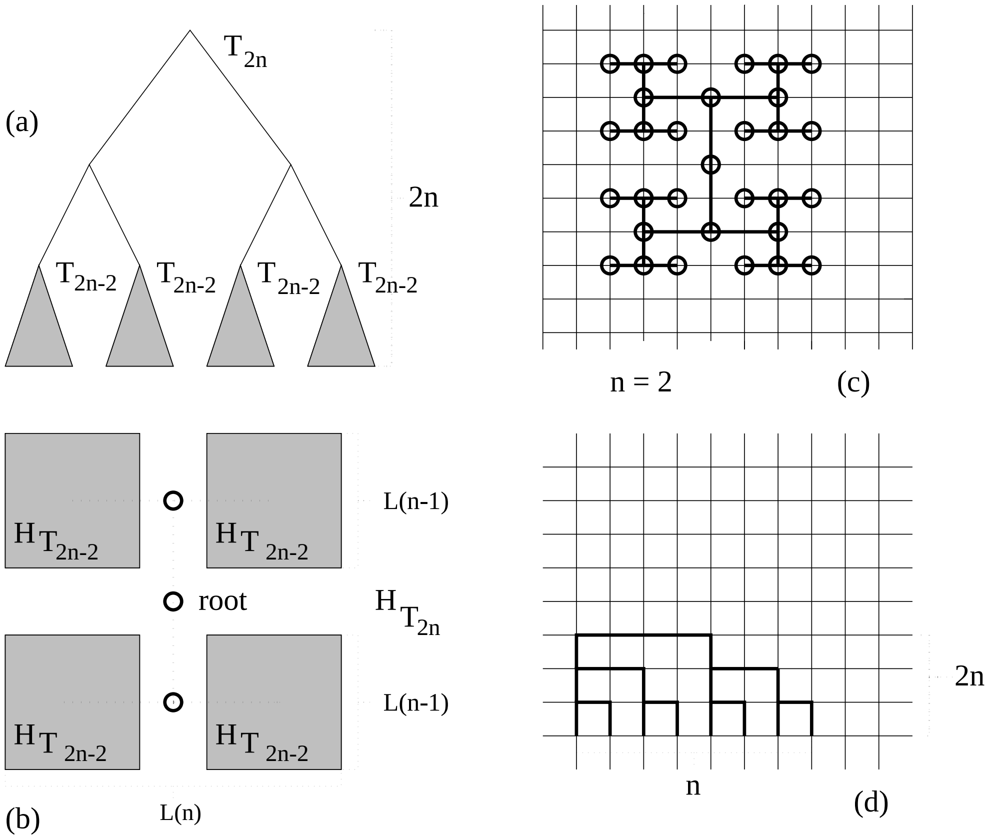


Figure 1.1: $H$-layout of complete binary trees 70%

**Example 1.1.1 ($H$-layout of binary trees)** *A layout of a graph $G$ into the two-dimensional grid is a mapping of different nodes of $G$ into different nodes of the grid and edges $(u, v)$ of $G$ into non-overlapping paths, along the grid lines, between the images of nodes $u$ and $v$ in the grid.*

*The so-called $H$-layout $H_{T_{2n}}$ of a complete binary tree $T_{2n}$ of depth $2n$, $n \geq 0$ (see Figure 1.1a for $T_{2n}$ and its subtrees $T_{2n-2}$), is described recursively in Figure 1.1c.*

A more detailed treatment of such layouts is in Section 10.6. For the moment it is for us of importance only the fact that for the length $L(n)$ of the side of the layout $E_n$ we get the recurrence

$$L(n) = \begin{cases} 2, & \text{if } n = 1; \\ 2L(n-1) + 2, & \text{if } n > 1. \end{cases}$$

As we shall see later, $L(n) = 2^{n+1} - 2$. A complete binary tree of depth $2n$ has $2^{2n+1} - 1$ nodes. The total area $A(m)$ of the $H$-layout of a complete binary tree with $m$ nodes is therefore proportional to the number of nodes of the tree.[1] Observe that in the "natural layout of the binary tree", shown in Figure 1.1d, the area of the smallest rectangle that contains the layout is proportional to $m \log m$. To express this concisely we will use notation $A(m) = \Theta(m)$ in the first case and $A(m) = \Theta(m \lg m)$ in the second case. The notation $f(n) = \Theta(g(n))$—that means that "$f(n)$ grows proportionally to $g(n)$"[2]—is discussed in detail and formally in Section 1.5.

Algorithmic problems have often a recursive solution even if their usual formulation does not indicate that.

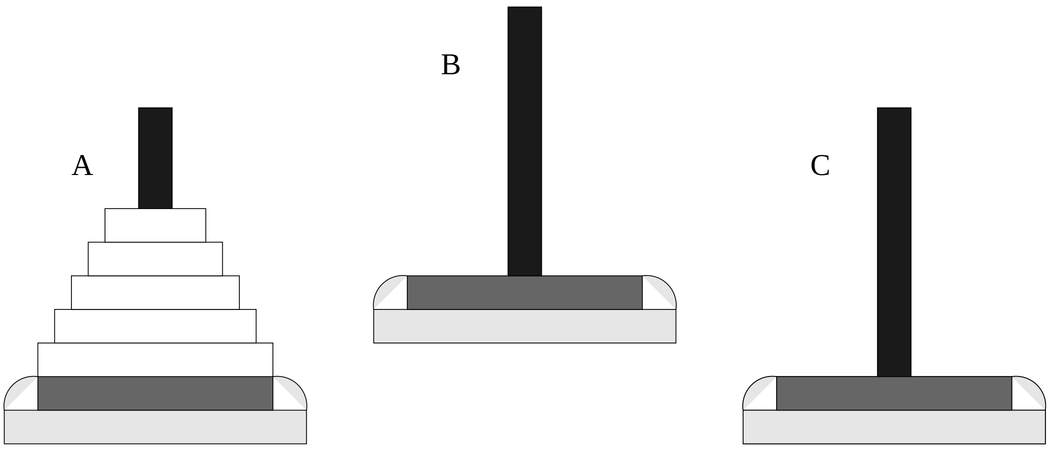


Figure 1.2: Towers of Hanoi-70%

**Example 1.1.2 (Towers of Hanoi Problem)** *Suppose we are given three rods $A, B, C$, and $n$ rings piled in the descending order of magnitude on $A$ while the other rods are empty—see Figure 1.2 for $n = 5$. The task is to move rings from $A$ to $B$, using perhaps $C$ in this process, in such a way that in one step only one ring is moved, and at no instant a ring is placed atop of a smaller one.*

There is a simple recursive algorithm to solve the problem:

**Algorithm 1.1.3 (Towers of Hanoi—a recursive algorithm)**

[1]The task to design layouts of various graphs into the two-dimensional grid, with as small area as possible, is of importance for VLSI designs. For more on layouts see Section 10.6.

[2]Or, more exactly, that there are constants $c_1, c_2 > 0$ such that $c_1|g(n)| \leq f(n) \leq c_2|g(n)|$ for all but finitely many $n$.

1. Move $n-1$ top rings from $A$ to $C$;
2. Move the largest ring from $A$ to $B$;
3. Move all $n-1$ rings from $C$ to $B$.

The correctness of this algorithm is obvious. It is also clear that the number $T(n)$ of ring moves satisfies the equations:

$$T(n) = \begin{cases} 1, & \text{if} \quad n = 1; \\ 2T(n-1) + 1, & \text{if} \quad n > 1. \end{cases} \tag{1.1}$$

In spite of the simplicity of the above algorithm, it is natural to ask whether there exist a faster algorithm—one that performs less ring moves. It is actually a simple task to show that such an algorithm does not exist. Indeed, denote by $T_{min}(n)$ the minimal number of moves needed to solve the task. Clearly, $T_{min}(n) \geq 2T_{min}(n-1) + 1$, because in order to remove all rings from the rod $A$ to $B$ we have first to move the top $n-1$ of them to $C$, then the largest one to $B$, and finally the remaining ones to $B$. This implies that our solution is the best possible.

Algorithm 1.1.3 is very simple. However, it is not so easy to be performed "by hand", because of the need to keep a track of many levels of recursion. The second, "iterative" algorithm presented bellow is from this point of view much simpler; even a child can follow it. (Try to apply both algorithms for $n = 4$).

**Algorithm 1.1.4 (Towers of Hanoi—an iterative algorithm)**

Do the following alternating steps, starting with step 1, until all rings are properly transferred:

1. Move the smallest top ring in the clockwise order ($A \to B \to C \to A$) if the number of rings is odd; and in anti-clockwise order if the number of rings is even.
2. Make the only possible move that does not involve the smallest top ring.

In spite of the simplicity of Algorithm 1.1.4, it is far from obvious that this algorithm is correct. It is also far from obvious how to determine the number of its ring moves—until one shows, what can be done by induction, that both algorithms perform exactly the same sequence of ring moves.

Consider now the following modification of the Towers of Hanoi problem: The goal is the same, but it is never allowed to move rings from $A$ on $B$ or from $B$ on $A$. It is easy to show that also in this case there is a similar simple recursive algorithm to solve the problem and for its number $T'(n)$ of ring moves we have $T'(1) = 2$ and

$$T'(n) = 3T'(n-1) + 2, \quad \text{for} \quad n > 1. \tag{1.2}$$

There is a modern legend saying that after creating the world, Brahma also designed three rods made of diamond and 64 golden rings on one of them near a monastery in Tibet and ordered monks to transfer rings, following the rules described above. According to the legend, the world would come to the end when monks finish their task.[3]

**Exercise 1.1.5** *Use both algorithms for the Towers of Hanoi Problem to solve the cases: (a) $n = 3$; (b) $n = 5$; (c)* $n = 6$.*

**Exercise 1.1.6** **(Parallel version of the Towers of Hanoi problem) Assume that in each step more than one ring can be moved with the following restriction: in each step from each rod at most one ring is removed and to each rod at most one ring is added. Determine the recurrence for the minimal number $T_p(n)$ of parallel moves needed to solve the parallel version of the Towers of Hanoi problem. (Hint: Determine $T_p(1)$, $T_p(2)$ and $T_p(3)$ and express $T_p(n)$ using $T_p(n-2)$.)*

Two previous examples are not singular. Complexity analysis leads to recurrences whenever algorithms or systems are designed using one of the most powerful design method—**divide-and-conquer**.

**Example 1.1.7** *We can often easily and efficiently solve an algorithmic problem $P$ of the size $n = c^i$, where $c, i$ are integers, using the following recursive method, where $b_1, b_2$ and $d$ are constants—see Figure 1.3:*

1. *Decompose $P$, in time $b_1 n$, to $a$ subproblems of the same type and size $\frac{n}{c}$.*
2. *Solve all subproblems recursively—using the same method.*
3. *Compose, in time $b_2 n$, the solution of $P$ from solutions of all its $a$ subproblems.*

*For the time complexity $T(n)$ of the resulting algorithm we have the recurrence:*

$$T(n) = \begin{cases} d, & \text{if } n = 1; \\ aT(\frac{n}{c}) + b_1 n + b_2 n, & \text{if } n > 1. \end{cases} \tag{1.3}$$

As an illustration, we present the well known recursive algorithm for sorting a sequence of $n = 2^k$ numbers:

**Algorithm 1.1.8 (MERGESORT)**

1. Divide the sequence in the middle into two subsequences.
2. Sort recursively both subsequences.
3. Merge both—already sorted—subsequences.

If arrays are used to represent sequences, steps (1) and (3) can be performed in the time proportional to $n$.

[3] Such a prophecy is not unreasonable. Since $T(n) = 2^n - 1$, as it will be seen soon, it would take more than 500 000 years to finish the task if monks move one ring per second.

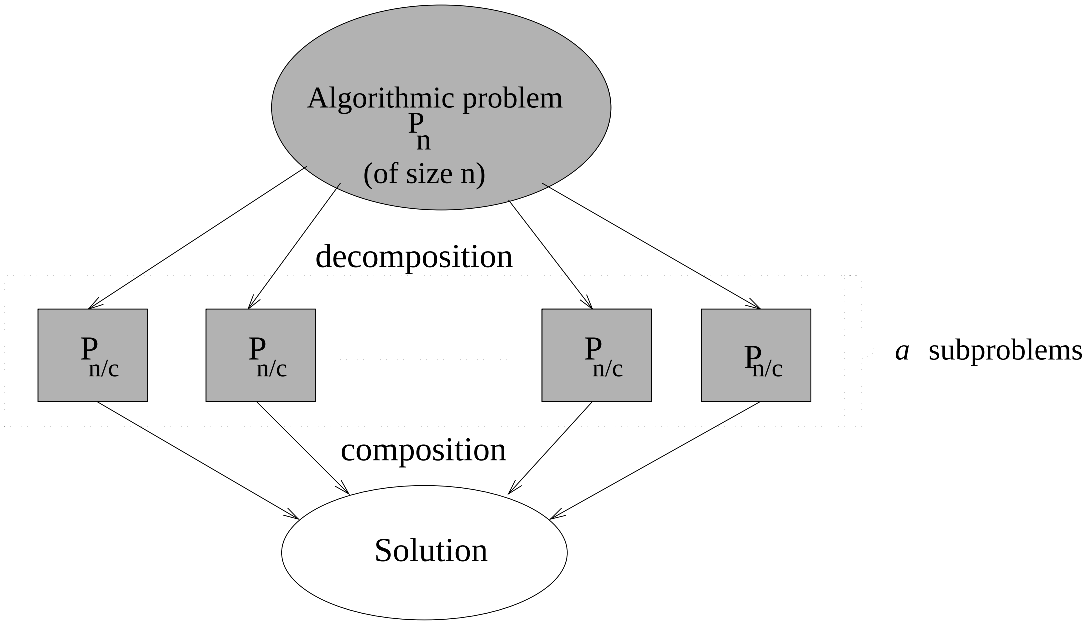


Figure 1.3: Divide-and-conquer method-70%

**Remark 1.1.9** Note that we have derived the recurrence (1.3) without knowing the nature of the problem $P$ and the computational model to be used. The only information we have utilized is that both decomposition and composition can be performed in the time proportional to the size of problem.

**Exercise 1.1.10** *Suppose that $n$ circles are drawn in the plane in such a way that no three circles meet in a point and each pair of circles intersects in exactly two points. Determine the recurrence for the number of distinct regions of the plane created by such $n$ circles?*

An analysis of computational complexity of algorithms depends often quite significantly on the underlying model of computation and the exact analysis is often impossible; either because of the complexity of the algorithm or of the computational model (device) that is used. Fortunately, the exact analysis is most of the time not only unnecessary; it is often superfluous. Simple, the so-called asymptotic estimations provide not only more insights but they can also be to a large degree independent of a particular computing model/device.

**Example 1.1.11 (Matrix multiplication)** *Multiplication of two matrices $A = \{a_{ij}\}_{i,j=1}^n$, $B = \{b_{ij}\}_{i,j=1}^n$, of degree $n$, with the resulting matrix $C = AB = \{c_{ij}\}_{i,j=1}^n$, using the well known relation*

$$c_{ij} = \sum_{k=1}^{n} a_{ik} b_{kj}, \tag{1.4}$$

*requires $T(n) = 2n^3 - n^2$ arithmetical operations to perform.*

It is again simpler to say, and mostly sufficiently informative, that $T(n) = \Theta(n^3)$ than to write exactly $T(n) = 2n^3 - n^2$. If a program to compute $c_{ij}$ using the formula (4.3.3) is written in a natural way in a high-level programming language and implemented on a usual sequential computer, then the exact analysis of the number of computer instructions to perform, or of the time $T(n)$ needed, is practically impossible, because it depends also on the available compiler, operating system, computer, and so on. Nevertheless, the basic claim $T(n) = \Theta(n^3)$ remains valid, in any case—provided we assume that each arithmetical operation takes a unit of time.

**Remark 1.1.12** If, on the other hand, parallel computations are allowed, quite different results concerning the number of steps needed to multiply two matrices are obtained. Using $n^3$ processors all multiplications in (4.3.3) can be performed in one parallel step. Since any sum of $n$ numbers $x_1 + \ldots + x_n$ can be computed with $\frac{n}{2}$ processors using the so-called **recursive doubling technique**[4] in $\lceil \log_2 n \rceil$ steps; in order to compute all $c_{ij}$ in (4.3.3) by the above method we need $\Theta(n^3)$ processors and $\Theta(\log n)$ parallel steps.

**Example 1.1.13 (Exponentiation)** *Let $b_{k-1} \ldots b_0$ be the binary representation of an integer $n$ with $b_0$ as the least significant bit and $b_{k-1} = 1$. Exponentiation $e = a^n$ can be done in $k = \lceil \log_2(n+1) \rceil$ steps using the following so-called* **repeated squaring method** *based on the equalities:*

$$e = a^{\sum_{i=0}^{k-1} b_i 2^i} = \prod_{i=0}^{k-1} a^{b_i 2^i} = \prod_{i=0}^{k-1} (a^{2^i})^{b_i}.$$

**Algorithm 1.1.14 (Exponentiation)**

**begin** $e \leftarrow 1; p \leftarrow a$;
    **for** $i \leftarrow 0$ **to** $k-1$
        **do if** $b_i = 1$ **then** $e \leftarrow e \cdot p$;
            $p \leftarrow p \cdot p$
        **od**
**end**

**Exercise 1.1.15** *Determine exactly the number of multiplications Algorithm 1.1.14 performs.*

**Remark 1.1.16** The term recurrence is sometimes used to denote only the equation in which the inductive definition is made. This terminology is used often explicitely in cases when the specific value of initial conditions is not important.

[4]For example, to get $x_1 + \ldots + x_8$, we compute in the first step $z_1 = x_1 + x_2$, $z_2 = x_3 + x_4$, $z_3 = x_5 + x_6$, $z_4 = x_7 + x_8$, in the second step $z_5 = z_1 + z_2$, $z_6 = z_3 + z_4$, and in the last step $z_7 = z_5 + z_6$.

## 1.2 Solution of Recurrences—Basic Methods

Several basic methods to solve recurrences are presented in this chapter. It is not always easy to decide which one to try first. However, in any case it is a good practice to start with computing some of the values of the unknown function; for several small arguments. This often helps:

1. to guess the solution;
2. to verify a to-be-solution.

**Example 1.2.1** *For small values of* $n$ *the unknown functions* $T(n)$ *and* $T'(n)$ *from the recurrences (1.1) and (1.2) have the following values:*

| $n$ | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| $T(n)$ | 1 | 3 | 7 | 15 | 31 | 63 | 127 | 255 | 511 | 1023 |
| $T'(n)$ | 2 | 8 | 26 | 80 | 242 | 728 | 2186 | 6560 | 19682 | 59049 |

and from this table we can easily guess that $T(n) = 2^n - 1$ and $T'(n) = 3^n - 1$. Such guesses have then to be verified, for example by induction, as we shall do later for $T(n)$ and $T'(n)$.

**Example 1.2.2** *The recurrence*

$$Q_n = \begin{cases} \alpha, & \textit{if} \quad n = 0; \\ \beta, & \textit{if} \quad n = 1; \\ \frac{\alpha\beta + \beta^2 - \beta Q_{n-1}}{Q_{n-2}}, & \textit{if} \quad n > 1; \end{cases}$$

*where* $\alpha, \beta > 0$, *looks quite complicated. However, it is easy to determine that* $Q_2 = \beta, Q_3 = \alpha, Q_4 = \beta$. *Hence*

$$Q_n = \begin{cases} \alpha, & \textit{if } n = 3k \textit{ for some } k; \\ \beta, & \textit{otherwise.} \end{cases}$$

### 1.2.1 Substitution Method

Once we have guessed the solution of a recurrence, induction is often a good method to verify the correctness of the guess.

**Example 1.2.3 (Tower of Hanoi problem)** *We show by induction that our guess* $T(n) = 2^n - 1$ *is correct. Since* $T(1) = 2^1 - 1 = 1$, *the initial case* $n = 1$ *is verified. From the inductive assumption* $T(n) = 2^n - 1$ *and the recurrence (1.1), we get, for* $n > 1$,

$$T(n+1) = 2T(n) + 1 = 2(2^n - 1) + 1 = 2^{n+1} - 1.$$

*This completes the induction step.*

Similarly, we can show that $T'(n) = 3^n - 1$ is the correct solution of the modified Tower of Hanoi problem, and $L(n) = 2^{n+1} - 2$ is the length of the side of the $H$-layoutin Example 1.1.1. The inductive step in the last case is: $L(n+1) = 2L(n) + 2 = 2(2^{n+1} - 2) + 2 = 2^{n+2} - 2$.

### 1.2.2 Iteration Method

Using an **iteration (unrolling)** of a recurrence, we can often reduce the recurrence to a summation that may be easier to compute or estimate.

**Example 1.2.4** *For the recurrence (1.2), of the modified Towers of Hanoi problem, we get by an unrolling*

$$\begin{aligned} T'(n) &= 3T'(n-1)+2 = 3(3T'(n-2)+2)+2 = 9T'(n-2)+6+2 \\ &= 9(3T'(n-3)+2)+6+2 = 3^3T'(n-3)+2\times 3^2+2\times 3+2 \\ &\vdots \\ &= \sum_{i=0}^{n-1} 3^i \times 2 = 2\sum_{i=0}^{n-1} 3^i = 2\frac{3^n-1}{3-1} = 3^n-1. \end{aligned}$$

**Example 1.2.5** *For the recurrence $T(1) = g(1)$ and $T(n) = T(n-1) + g(n)$, for $n > 1$, the unrolling yields:*

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

**Example 1.2.6** *By an unrolling of the recurrence*

$$T(n) = \begin{cases} b, & \text{if } n = 1; \\ aT(\frac{n}{c}) + bn, & \text{if } n = c^i > 1; \end{cases}$$

*obtained at the analysis of divide-and-conquer algorithms, we get*

$$\begin{aligned} T(n) &= aT\left(\frac{n}{c}\right) + bn = a\left(aT\left(\frac{n}{c^2}\right)+b\frac{n}{c}\right)+bn = a^2T\left(\frac{n}{c^2}\right)+bn\frac{a}{c}+bn \\ &= a^2\left(aT\left(\frac{n}{c^3}\right)+b\frac{n}{c^2}\right)+bn\frac{a}{c}+bn = a^3T\left(\frac{n}{c^3}\right)+bn\frac{a^2}{c^2}+bn\frac{a}{c}+bn \\ &\vdots \\ &= bn\sum_{j=0}^{\log_c n}\left(\frac{a}{c}\right)^j. \end{aligned}$$

*Therefore:*

- *Case 1, $a < c$:* $T(n) = \Theta(n)$, *because the sum* $\sum_{i=0}^{\infty}\left(\frac{a}{c}\right)^i$ *converges.*
- *Case 2, $a = c$:* $T(n) = \Theta(nlogn)$ .
- *Case 3, $a > c$:* $T(n) = \Theta(n^{\log_c a})$.

*Indeed, in Case 3 we get*

$$\begin{aligned} T(n) &= bn\sum_{i=0}^{\log_c n}\left(\frac{a}{c}\right)^i = bn\frac{\left(\frac{a}{c}\right)^{\log_c n+1}-1}{\frac{a}{c}-1} \\ &\approx bn\left(\frac{a}{c}\right)^{\log_c n} \\ &= bn\frac{a^{\log_c n}}{n} = ba^{\log_c n} = bn^{\log_c a}, \end{aligned}$$

*using the identity* $a^{\log_c n} = n^{\log_c a}$.

Observe that the time complexity of a *divide-and-conquer* algorithm depends only on the ratio $\frac{a}{c}$ and neither on the problem being solved, nor on the computing model (device) being used; provided that the decomposition and composition require only linear time.

**Exercise 1.2.7** *Solve recurrences obtained by solving Exercises 1.1.6 and 1.1.10.*

**Exercise 1.2.8** *Solve the following recurrence using the iteration method:* $T(n) = 3T(\frac{n}{4}) + n$, *for* $n = 4^k > 1$.

**Exercise 1.2.9** *Determine* $g_n, n$ *a power of 2, defined by the recurrence*

$$g_1 = 3 \text{ and } g_n = (2^{\frac{n}{2}} + 1)g_{\frac{n}{2}} \text{ for } n \geq 2.$$

**Exercise 1.2.10** *Express* $T(n)$ *in terms of the function* $g$ *for the recurrence:* $T(1) = a$, $T(n) = 2^pT(n/2) + n^pg(n)$, *where* $p$ *is an integer,* $n = 2^k$, $k > 0$ *and* $a$ *is a constant.*

### 1.2.3 Reduction on Algebraic Equations

A large class of recurrences, the so-called **homogeneous linear recurrences**, can be solved by a reduction to algebraic equations. Before we present the general method, let us demonstrate its basic idea on an example.

**Example 1.2.11 (Fibonacci numbers)** *Leonardo Fibonacci*[5] *introduced in 1202 a se-*

[5]Leonardo of Pisa (1170-1250), known also as Fibonacci, perhaps the most influential mathematician of the medieval Christian world. Educated in Africa, by a Muslim teacher, he was famous for his possesion of the mathematical knowledge of his own and the preceeding genarations. In his celebrated and influential classics *Liber Abachi* (that appeared in print only in 19th century) he introduced to the Latin world Arabic positional system and Hindu methods of calculations with fractions, square roots, cube roots,. . . The following problem from *Liber Abachi* led to the Fibonacci numbers: *How many pair of rabbits will be produced in a year, beginning with a single pair, if in every month each pair bears a new pair which becomes productive from the second month on.*

*quence of numbers defined by the recurrence*

$$F_0 = 0, \quad F_1 = 1, \qquad \textit{(the initial conditions);} \tag{1.5}$$

$$F_n = F_{n-1} + F_{n-2}, \quad \textit{if} \quad n > 1 \qquad \textit{(the inductive equation).} \tag{1.6}$$

*Fibonacci numbers form one of the most interesting sequences of natural numbers:*

$$0, 1, 1, 2, 3, 5, 8, 13, 21, 34, 55, 89, 144, 233, 377, 610, \ldots$$

**Exercise 1.2.12** *Explore the beauty of Fibonacci numbers: (a) find all $n$ such that $F_n = n$ and all $n$ such that $F_n = n^2$; (b) determine $\sum_{i=0}^{k} F_i$; (c) show that $F_{n+1}F_{n-1} - F_n^2 = (-1)^n$ for all $n$; (d) show $F_{2n+1} = F_n^2 + F_{n+1}^2$ for all $n$; (e) compute $F_{16}, \ldots, F_{49}$ ($F_{50} = 12586269025$).*

It is natural to ask whether, given an integer $n$, we can determine $F_n$ without computing $F_i$ for all $i < n$. More exactly, can we find an explicit formula for $F_n$?

Let us first try to find a solution of the inductive equation (1.6) in the form $F_n = r^n$, where $r$ is, so far, an unknown constant. Suppose $r^n$ is a solution of (1.6), then

$$r^n = r^{n-1} + r^{n-2},$$

has to hold for all $n > 1$, and therefore either $r = 0$, which is an uninteresting case, or $r^2 = r + 1$. The last equation has two roots:

$$r_1 = \frac{1+\sqrt{5}}{2}, \qquad r_2 = \frac{1-\sqrt{5}}{2}.$$

Unfortunately, none of the functions $r_1^n, r_2^n$ satisfies initial conditions in (1.5). We are therefore not ready yet. Fortunately, each linear combination $\lambda r_1^n + \mu r_2^n$ also satisfies the inductive equation (1.6). Therefore, if $\lambda, \mu$ are chosen in such a way that also the initial conditions (1.5) are met; that is if

$$\lambda r_1^0 + \mu r_2^0 = F_0 = 0, \qquad \lambda r_1^1 + \mu r_2^1 = F_1 = 1, \tag{1.7}$$

then $F_n = \lambda r_1^n + \mu r_2^n$ is the solution of recurrences (1.5) and (1.6). From (1.7) we get:

$$\lambda = -\mu = \frac{1}{\sqrt{5}}$$

and thus

$$F_n = \frac{1}{\sqrt{5}} \left( \left( \frac{1+\sqrt{5}}{2} \right)^n - \left( \frac{1-\sqrt{5}}{2} \right)^n \right).$$

Since $\lim_{n\to\infty} \left(\frac{1-\sqrt{5}}{2}\right)^n = 0$, we get also a simpler, approximate, expression for $F_n$ in the form

$$F_n \approx \frac{1}{\sqrt{5}} \left( \frac{1+\sqrt{5}}{2} \right)^n, \qquad \text{for } n \to \infty.$$

□

The method used in the previous example will be now generalized. Let us consider a **homogeneous linear recurrence**; that is, the recurrence where the value of the unknown function is expressed as a linear combination of a fixed number of its values for smaller arguments:

$$u_n = a_1 u_{n-1} + a_2 u_{n-2} + \cdots + a_k u_{n-k}, \qquad \text{if } n \geq k, \qquad \text{(the inductive equation)} \tag{1.8}$$

$$u_i = b_i, \qquad \text{if } 0 \leq i < k, \qquad \text{(the initial conditions)} \tag{1.9}$$

where $a_1, \ldots, a_k$ and $b_0, \ldots, b_{k-1}$ are constants and let

$$P(r) = r^k - \sum_{j=1}^{k} a_j r^{k-j} \tag{1.10}$$

be the so-called **characteristic polynomial** of the inductive equation (1.8) and $P(r) = 0$ its **characteristic equation**. The roots of the polynomial (1.10) are called **characteristic roots** of the inductive equation (1.8). The following theorem says that we can always find a solution of a homogeneous linear recurrence when the roots of its characteristic polynomial are known.

**Theorem 1.2.13** *(1) If the characteristic equation $P(r) = 0$ has $k$ different roots $r_1, \ldots r_k$, then the recurrence (1.8) with the initial conditions (1.9) has the solution*

$$u_n = \sum_{j=1}^{k} \lambda_j r_j^n, \tag{1.11}$$

*where $\lambda_j$ are solutions of the system of linear equations*

$$b_i = \sum_{j=1}^{k} \lambda_j r_j^i, \quad 0 \leq i < k. \tag{1.12}$$

*(2) If the characteristic equation $P(r) = 0$ has $p$ different roots, $r_1, \ldots, r_p$, $p < k$, and the root $r_j$, $1 \leq j \leq p$, has the multiplicity $m_j \geq 1$, then also $r_j^n, nr_j^n, n^2 r_j^n, \ldots, n^{m_j-1} r_j^n$, are solutions of the inductive equation (1.8), and there is the solution of (1.8), satisfying the initial conditions (1.9), in the form $u_n = \sum_{j=1}^{p} P_j(n) r_j^n$, where each $P_j(n)$ is a polynomial of the degree $m_j - 1$, the coefficient of which can be obtained as the unique solution of the system of linear equations $b_i = \sum_{j=1}^{p} P_j(i) r_j^i$, $1 \leq i \leq k$.*

**Proof.** (1) Since the inductive equation (1.8) is satisfied with $u_n = r_j^n$ for $1 \leq j \leq k$, it is satisfied also with an arbitrary linear combination $\sum_{j=1}^{k} a_j r_j^n$. In order to prove the first part of the theorem, it is therefore sufficient to show that the system of linear equations (1.12) has a unique solution. This is the case when the determinant of the matrix of the system does not equal zero. However, this is the well known result from linear algebra, because the corresponding (Vandermond) matrix and determinant have the form:

$$det \begin{vmatrix} 1 & 1 & \ldots & 1 \\ r_1 & r_2 & \ldots & r_k \\ \vdots & \vdots & & \vdots \\ r_1^{k-1} & r_2^{k-1} & \ldots & r_k^{k-1} \end{vmatrix} = \prod_{j>i} (r_i - r_j) \neq 0.$$

(2) A detailed proof of the second part of the theorem is quite technical and we present here only its basic idea.

We have first to show that if an $r_j$ is a root of the equation $P(r) = 0$ of a multiplicity $m_j > 1$, then all functions $u_n = r_j^n$, $u_n = nr_j^n$, $u_n = n^2r_j^n, \ldots, u_n = n^{m_j-1}r_j^n$ satisfy the inductive equation (1.8). In order to prove that, we can make use of the well-known fact from calculus, namely that if $r_j$ is a root of multiplicity $m_j > 1$ of the equation $P(r) = 0$, then $r_j$ is also the root of the equations $P^{(j)}(r) = 0$, $1 \le j < m_j$, where $P^{(j)}(r)$ is the $j$-th derivative of $P(r)$.

Let us consider the polynomial

$$Q(r) = r \cdot (r^{n-k}P(r))' = r \cdot [(n-k)r^{n-k-1}P(r) + r^{n-k}P'(r)].$$

Since $P(r_j) = P'(r_j) = 0$, we have $Q(r_j) = 0$. However,

$$\begin{aligned} Q(r) &= r[r^n - a_1r^{n-1} - \cdots - a_kr^{n-k}]' \\ &= nr^n - a_1(n-1)r^{n-1} - \cdots - a_{k-1}(n-k+1)r^{n-k+1} - a_k(n-k)r^{n-k} \end{aligned}$$

and, since $Q(r_j) = 0$, we have that $u_n = nr_j^n$ is the solution of the inductive equation (1.8).

In a similar way we can show by induction that all $u_n = n^sr_j^n$, $1 < s < m_j$, are solutions of (1.8), by considering the following sequence of polynomials: $Q_1(r) = Q(r)$, $Q_2(r) = rQ_1'(r), \ldots, Q_s(r) = rQ_{s-1}'(r)$.

It remains then to show that the matrix of the system of linear equations $b_i = \sum_{j=1}^{p} P_j(i)r_j^i$, $1 \le i \le k$, is nonsingular. This is an (nontrivial) exercise from linear algebra. □

**Example 1.2.14** *The recurrence*

$$\begin{aligned} u_n &= 3u_{n-1} - 2u_{n-2}, \quad n > 2; \\ u_0 &= 0, \quad u_1 = 1, \end{aligned}$$

*has the characteristic equation* $r^2 = 3r - 2$ *with two roots:* $r_1 = 2, r_2 = 1$. *Hence* $u_n = \lambda_1 2^n + \lambda_2$, *where* $\lambda_1 = 1$ *and* $\lambda_2 = -1$ *are solutions of the system of equations:* $0 = \lambda_1 2^0 + \lambda_2 1^0$ *and* $1 = \lambda_1 2^1 + \lambda_2 1^1$.

**Example 1.2.15** *The recurrence*

$$\begin{aligned} u_n &= 5u_{n-1} - 8u_{n-2} + 4u_{n-3}, \quad n \ge 3; \\ u_0 &= 0, \quad u_1 = -1, \quad u_2 = 2, \end{aligned}$$

*has the characteristic equation* $r^3 = 5r^2 - 8r + 4$, *which has one simple root,* $r_1 = 1$, *and one root of multiplicity 2,* $r_2 = 2$. *The recurrence has therefore the solution* $u_n = a + (b + cn)2^n$, *where* $a, b, c$ *satisfy equations:*

$$0 = a + (b + c \cdot 0)2^0, \quad -1 = a + (b + c \cdot 1)2^1, \quad 2 = a + (b + c \cdot 2)2^2.$$

**Example 1.2.16** *(a) The recurrence* $u_0 = 3, u_1 = 5$ *and* $u_n = u_{n-1} - u_{n-2}$*, for* $n > 2$*, has two roots:* $x_1 = \frac{1+i\sqrt{3}}{2}$ *and* $x_2 = \frac{1-i\sqrt{3}}{2}$ *and the solution* $u_n = (\frac{3}{2} - \frac{7}{6}i\sqrt{3})x_1^n + (\frac{3}{2} + \frac{7}{6}i\sqrt{3})x_2^n$*. (Verify that all* $u_n$ *are integers!)*

*(b) For the recurrence* $u_0 = 0, u_1 = 1$ *and* $u_n = 2u_{n-1} - 2u_{n-2}$*, for* $n \geq 2$*, the characteristic equation has two roots:* $x_1 = (1+i)$ *and* $x_2 = (1-i)$*, and we get*

$$u_n = \frac{1}{2}i((1-i)^n - (1+i)^n) = 2^{\frac{n}{2}}\sin(\frac{n\pi}{4}),$$

*using a well-known identity from calculus.*

**Exercise 1.2.17** *Solve the recurrences: (a)* $u_0 = 6$*,* $u_1 = 8$*,* $u_n = 4u_{n-1} - 4u_{n-2}$*,* $n \geq 2$*; (b)* $u_0 = 1$*,* $u_1 = 0$*,* $u_n = 5u_{n-1} - 6u_{n-2}$*,* $n \geq 2$*; (c)* $u_0 = 4$*,* $u_1 = 10$*,* $u_n = 6u_{n-1} - 8u_{n-2}$*,* $n \geq 2$*.*

**Exercise 1.2.18** *Solve the recurrences: (a)* $u_0 = 0$*,* $u_1 = 1$*,* $u_2 = 1$*,* $u_n = 2u_{n-2} + u_{n-3}$*,* $n \geq 3$*; (b)* $u_0 = 7$*,* $u_1 = -4$*,* $u_2 = 8$*,* $u_n = 2u_{n-1} + 5u_{n-2} - 6u_{n-3}$*,* $n \geq 3$*; (c)* $u_0 = 1$*,* $u_1 = 2$*,* $u_2 = 3$*,* $u_n = 6u_{n-1} - 11u_{n-2} + 6u_{n-3}$*,* $n \geq 3$*.*

**Exercise 1.2.19** * *Using some substitutions of variables, transform the following recurrences to the cases dealt with in this section and in this way solve the recurrences: (a)* $u_1 = 1$*,* $u_n = u_{n-1} - u_n u_{n-1}$*,* $n \geq 2$*; (b)* $u_1 = 0$*,* $u_n = n(u_{n/2})^2$*, n is a power of 2; (c)* $u_0 = 1$*,* $u_1 = 2$*,* $u_n = \sqrt{u_{n-1}u_{n-2}}$*,* $n \geq 2$*.*

Finally, we present an interesting open problem due to Lothar Collatz (1930)—a class of recurrences that look like linear but their solution is not known.

For any positive integer $i$ we define the so-called $(3x+1)$-recurrence by (a Collatz' process) $u_0^{(i)} = i$ and for $n > 0$

$$u_{n+1}^{(i)} = \begin{cases} \frac{u_n^{(i)}}{2}, & \text{if } u_n^{(i)} \text{ is even;} \\ 3u_n^{(i)} + 1, & \text{if } u_n^{(i)} \text{ is odd.} \end{cases}$$

It was verified that for any $i < 2^{40}$ there exists an integer $n_i$ such that $u_{n_i}^{(i)} = 1$ (and therefore $u_{n_i+1}^{(i)} = 4, u_{n_i+2}^{(i)} = 2, u_{n_i+3}^{(i)} = 1, \ldots$ ). However, it is an open problem, since the early 1950's, the so-called the Collatz' problem, whether this is true for all $i$.

**Exercise 1.2.20** *Denote by* $\sigma(n)$ *the smallest i such that* $u_n^{(i)} < n$*. Determine: (a)* $\sigma(26)$*,* $\sigma(27)$*,* $\sigma(28)$*; (b)** $\sigma(2^{50}-1)$*,* $\sigma(2^{50}+1)$*,* $\sigma(2^{500}-1)$*,* $\sigma(2^{500}+1)$*.*

## 1.3 Special Functions

There are several simple functions that are often used in the design and analysis of computing systems. In this section we deal with some of them: ceiling and floor functions for reals-to-integers conversions, logarithms, and binomial functions.

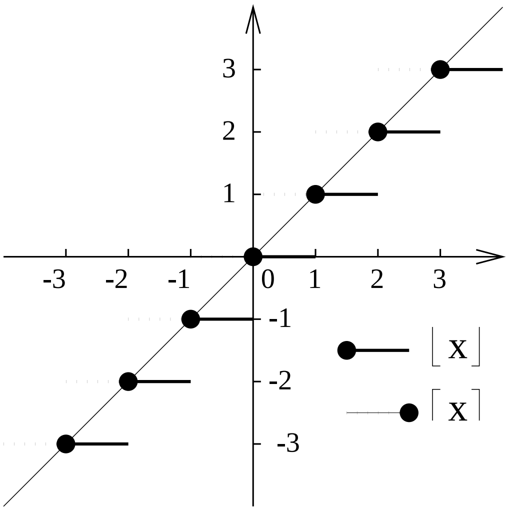


Figure 1.4: Ceiling and floor-65%

In spite of their apparent simplicity these functions have various interesting properties and, as discussed later, also a surprising computational power in case of ceiling and floor functions.

### 1.3.1 Ceiling and Floor

Integers play an important rôle in computing and communication and the same is true also for two basic reals-to-integers conversion functions.

| | | | |
|---|---|---|---|
| Floor: | $\lfloor x \rfloor$ – the largest integer | $\leq x$ |
| Ceiling: | $\lceil x \rceil$ – the smallest integer | $\geq x$ |

For Example:

$$\begin{array}{lclcl} \lfloor 3.14 \rfloor = & 3 & = \lfloor 3.75 \rfloor, & \qquad \lfloor -3.14 \rfloor = & -4 & = \lfloor -3.75 \rfloor; \\ \lceil 3.14 \rceil = & 4 & = \lceil 3.75 \rceil, & \qquad \lceil -3.14 \rceil = & -3 & = \lceil -3.75 \rceil. \end{array}$$

The following basic properties of the floor and ceiling functions are easy to verify:

$$\lfloor x+n \rfloor = \lfloor x \rfloor + n \text{ and } \lceil x+n \rceil = \lceil x \rceil + n, \quad \text{if } n \text{ is an integer;}$$

$$\lfloor x \rfloor = x \Leftrightarrow x \text{ is an integer } \Leftrightarrow \lceil x \rceil = x;$$
$$x - 1 < \lfloor x \rfloor \le x \le \lceil x \rceil < x + 1, \quad \text{for any } x;$$
$$\lfloor -x \rfloor = -\lceil x \rceil \text{ and } \lceil -x \rceil = -\lfloor x \rfloor, \quad \text{for any } x;$$
$$\lfloor x \rfloor \le \left\lceil \frac{x}{2} \right\rceil + \left\lfloor \frac{x}{2} \right\rfloor \le \lceil x \rceil;$$
$$\left\lceil \frac{x}{2} \right\rceil = \left\lfloor \frac{x+1}{2} \right\rfloor, \text{ for any } x;$$
$$\lceil x \rceil - \lfloor x \rfloor = \begin{cases} 0, & \text{if } x \text{ is an integer;} \\ 1, & \text{otherwise.} \end{cases}$$

In spite of the simplicity of ceiling and floor functions, expressions that involve more occurrences of these functions are usually not easy to handle. It is therefore natural to ask when we can remove some of these functions from formulas without effecting their values. The case $\lfloor \lceil x \rceil \rfloor$ is trivial. It is less obvious that we can do that also in such expressions as $\lfloor \sqrt{\lfloor x \rfloor} \rfloor$ and $\lceil \log \lceil x \rceil \rceil$. This follows from the following general result.

**Lemma 1.3.1** *Let $f(x)$ be a continuous and strictly monotonically increasing function such that if $f(x)$ is an integer, then so is $x$. Then*

$$\lfloor f(\lfloor x \rfloor) \rfloor = \lfloor f(x) \rfloor \quad \textit{and} \quad \lceil f(\lceil x \rceil) \rceil = \lceil f(x) \rceil.$$

**Proof.** We show the result for the floor function. The proof for the ceiling is similar. If $\lfloor x \rfloor = x$, then there is nothing to prove. Therefore, let $\lfloor x \rfloor < x$. Then $f(\lfloor x \rfloor) < f(x)$, since $f$ is increasing. Thus $\lfloor f(\lfloor x \rfloor) \rfloor \le \lfloor f(x) \rfloor$. If $\lfloor f(\lfloor x \rfloor) \rfloor < \lfloor f(x) \rfloor$, there must exist a number $y$ such that $\lfloor x \rfloor < y \le x$, $f(y) = \lfloor f(x) \rfloor$, because $f$ is continuous. This means that $f(y)$ is an integer and, because of the special property of $f$, so must be $y$. This is a contradiction—there is no integer between $\lfloor x \rfloor$ and $x$. Thus $\lfloor f(\lfloor x \rfloor) \rfloor = \lfloor f(x) \rfloor$. □

**Exercise 1.3.2** *Draw the graphs of functions: (a) $f(x) = \lfloor 2x \rfloor$; (b) $f(x) = \lfloor x/2 \rfloor$; (c) $f(x) = \lfloor x^2 \rfloor$.*

**Exercise 1.3.3** *Show: (a) $\lfloor 2x \rfloor = \lfloor x \rfloor + \lfloor x + \frac{1}{2} \rfloor$, for any real $x$;*
*(b) $\lceil n/k \rceil = \lfloor (n-1)/k \rfloor + 1$, for any integers $n, k \in \mathbf{N}^+$;*
*(c) $\lfloor \sqrt{2n(n+1)} \rfloor = \lfloor \sqrt{2}(n + \frac{1}{2}) \rfloor$.*

The ceiling and the floor functions often occur in recurrences obtained from an analysis of divide-and-conquer algorithms. For example, for the number of comparisons of the MERGESORT we get:

$$T(1) = 0; \tag{1.13}$$
$$T(n) = n - 1 + T(\lfloor n/2 \rfloor) + T(\lceil n/2 \rceil) \tag{1.14}$$

because the most balanced partition of a sequence of $n$ elements is to $\lfloor \frac{n}{2} \rfloor$ and $\lceil \frac{n}{2} \rceil$ elements. With this type of recurrences we deal in Section 1.6.2.

The following two identities indicate that sums of floors and also ceilings, that look complicated, have simple solutions. For integers $m, n$ and $k$ we have:

$$\sum_{k=0}^{m-1} \left\lfloor \frac{n+k}{m} \right\rfloor = n;$$

$$\sum_{k=0}^{n-1} \lfloor \sqrt{k} \rfloor = na - \frac{1}{3}a^3 - \frac{1}{2}a^2 - \frac{1}{6}a, \text{ where } a = \lfloor \sqrt{n} \rfloor.$$

### 1.3.2 Logarithms

The logarithmic function $\log_a x$, $a > 1$, is continuous, and monotonously increasing for $x \geq 1$. If $a$ is an integer, then $\log_a x$ acquires integer values only at integer points. By Lemma 1.3.1 we therefore get $\lceil \log_a \lceil x \rceil \rceil = \lceil \log_a x \rceil$ and $\lfloor \log_a \lfloor x \rfloor \rfloor = \lfloor \log_a x \rfloor$ for $x \geq 1$. Logarithmic functions with the bases $2, e,$ and 10 are so often used that a special notation has been developed for them:

$$\begin{array}{rcll} \lg n & = & \log_2 n & \{\textit{binary logarithm}\}; \\ \ln n & = & \log_e n & \{\textit{natural logarithm}\}; \\ \log n & = & \log_{10} n & \{\textit{decimal logarithm}\}. \end{array}$$

Since $\log_a b = \frac{\log_c b}{\log_c a}$ we have the following relations between the main logarithms:

$$\lg x \approx 1.4426952 \ln x \approx 3.3219286 \log x.$$

There are various interpretations of binary logarithms worth to notice: $\lceil \lg(n+1) \rceil$ is the number of bits in the binary representation of the integer $n$. $\lceil \lg n \rceil$ is the minimal depth of the binary tree with $n$ leaves and also the minimal number of parallel steps to compute $x_1 \circ x_2 \circ \cdots \circ x_n$, where $\circ$ is an associative binary operation.

Since $\ln x = \ln 2 + \ln \frac{x}{2}$, of a special importance are properties of the function $\ln(x+1)$, for $|x| < 1$. Two of them, derived in calculus:

$$\ln(x+1) = x - \frac{x^2}{2} + \frac{x^3}{3} - \frac{x^4}{4} + \frac{x^5}{5} - \cdots, \quad \text{for } |x| < 1;$$
$$\frac{x}{1+x} \leq \ln(1+x) \leq x.$$

In the analysis of computations we often encounter powers and compositions of logarithmic functions. The following notation has been developed for them:

$$\begin{array}{rcl} \lg^k n & = & (\lg n)^k, \quad k \text{ is an integer}; \\ \lg \lg n & = & \lg(\lg n); \\ \lg \lg \lg n & = & \lg(\lg(\lg n)); \\ \lg^{(k)} n & = & \underbrace{\lg \lg \ldots \lg}_{k \text{ times}} n, \quad \text{if } \lg^{(k-1)} n > 0\ . \end{array}$$

Another related function, that also occurs often in the complexity analysis, is the so-called **iterated logarithm**:

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

This function grows so slowly that its value is at most 5 for all "feasible" arguments. Indeed,

$$\lg^* 2 = 1, \qquad \lg^* 4 = 2, \qquad \lg^* 16 = 3;$$
$$\lg^* 65536 = 4, \qquad \lg^* (2^{65536}) = 5.$$

(Observe that $2^{65536}$ is much greater than most of the current estimates for the number of atoms in the universe.) However, also the functions $\lg \lg n$ and $\lg \lg \lg n$ grow very slowly. Indeed,

$$\lg \lg 2^{65536} = 16, \quad \lg \lg \lg 2^{65536} = 4.$$

This shows that doubly logarithmic and iterated logarithmic functions, which occur often in the analysis of algorithms, actually contribute to the overall complexity, as an additive or a multiplicative factor, only by a small amount.

The inverse to the natural logarithm function is $e^x$—$exp(x)$ is another notation sometimes more convinient.

### 1.3.3 Binomial Functions—Coefficients

The binomial function, or the binomial coefficient—what is a more common terminology—$\binom{r}{k}$ is defined for an arbitrary real $r$ and an integer $k$ as follows:

$$\binom{r}{k} = \begin{cases} \frac{r(r-1)\cdots(r-k+1)}{k(k-1)\cdots 1}, & k > 0; \\ 1, & k = 0; \\ 0, & k < 0. \end{cases} \tag{1.15}$$

Observe that if $r > k > 0$ are integers, then $\binom{r}{k}$ is the number of possibilities to choose $k$ elements from $r$ elements.

There are various reasons why binomial coefficients occur often in discrete computations. One of them is the identity:

$$\boxed{\textbf{Binomial theorem: } (x+y)^n = \sum_{0 \leq k \leq n} \binom{n}{k} x^k y^{n-k}.}$$

Another reason, of immediate importance for us, is that binomial coefficients occur often as coefficients of generating functions—a useful tool, as we shall see in the next section, to solve recurrences.

Some important identities for binomial coefficients are listed below. They can be easily proved using the basic definition. The acquaintance with them may help to find simple solutions for quite complicated expressions and sums.

$$\begin{array}{llll}
\binom{n}{k} = \frac{n!}{k!(n-k)!}, & n \geq k \geq 0 & \binom{n}{k} = \binom{n}{n-k}, & n \geq 0, \\
\binom{r}{k} = \frac{r}{k}\binom{r-1}{k-1}, & k \neq 0 & \binom{r}{k} = \frac{r}{r-k}\binom{r-1}{k}, & r \neq k, \\
\binom{r}{k} = \binom{r-1}{k} + \binom{r-1}{k-1}, & (*) & \binom{r}{m}\binom{m}{k} = \binom{r}{k}\binom{r-k}{m-k} & (*)
\end{array}$$

**Exercise 1.3.4** *Prove the identities listed above using the basic definition of* $\binom{n}{k}$.

**Example 1.3.5** *If $n \geq r \geq 0$ are integers, then we can use the first identity in $(*)$ to compute the following sum:*

$$\sum_{0 \leq k \leq n} \binom{r+k}{k} = \binom{r}{0} + \binom{r+1}{1} + \binom{r+2}{2} + \cdots + \binom{r+n}{n} = \binom{r+n+1}{n} \tag{1.16}$$

*Indeed, it holds*

$$\begin{array}{llllllll}
\binom{r}{0} = & \binom{r+1}{0} & & & & & & \\
 & + & \binom{r+1}{1} \underbrace{=}_{by(*)} & \binom{r+2}{1} & & & & \\
 & & & + & \binom{r+2}{2} \underbrace{=}_{by(*)} & \binom{r+3}{2} & & \\
 & & & & & + & \binom{r+3}{3} \underbrace{=}_{by(*)} & \binom{r+4}{3} \\
 & & & & & & & + \quad \cdots \underbrace{=}_{by(*)} \binom{r+n+1}{n}
\end{array}$$

*and using this idea we can easily proove (1.16) by induction.*

**Example 1.3.6** *Let $n \geq m \geq 0$ be integers. Compute*

$$\sum_{k=0}^{m} \frac{\binom{m}{k}}{\binom{n}{k}}.$$

*Using the second identity in $(*)$ we get:*

$$\sum_{k=0}^{m} \frac{\binom{m}{k}}{\binom{n}{k}} = \sum_{k=0}^{m} \frac{\binom{n-k}{m-k}}{\binom{n}{m}} = \frac{1}{\binom{n}{m}} \sum_{k=0}^{m} \binom{n-k}{m-k}.$$

*To solve the problem, we now need to compute the last sum. If we replace in that sum $k$ by $m-k$, and then use the result of the previous example, we get*

$$\sum_{k=0}^{m}\binom{n-k}{m-k} = \sum_{k=0}^{m}\binom{n-(m-k)}{m-(m-k)} \tag{1.17}$$

$$= \sum_{k=0}^{m}\binom{n-m+k}{k} = \binom{n+1}{m}. \tag{1.18}$$

*The overall result is therefore* $\frac{n+1}{n-m+1}$.

**Exercise 1.3.7** * *Show the following identities for all natural numbers* $a, b$ *and* $n > 1$*:*
*(a)* $\binom{a+b}{n} = \sum_{k=0}^{\min(n,a)} \binom{a}{k}\binom{b}{n-k}$; *(b)* $\binom{2n}{n} = \sum_{k=0}^{n} \binom{n}{k}^2$;
*(c)* $\binom{3n}{n} = \sum_{k=0}^{n}\sum_{i=0}^{n-k} \binom{n}{k}\binom{n}{i}\binom{n}{i+k}$.

**Exercise 1.3.8** * *Show:* $\sum_{k=0}^{n}\binom{n}{k}\binom{n-k}{m-k} = 2^m\binom{n}{m}$.

## 1.4 Solution of Recurrences—Generating Function Method

The concept of **generating functions** is fundamental and represents an important methodology with numerous applications. In this chapter we describe and illustrate two of them. The first one is to solve recurrences.

The essence of the power of generating functions, as a methodology, is that they allow to reduce complex manipulations with infinite objects (sequences) onto easy operations with finite objects; for example, with rational functions. This often allows to solve quite complicated problems in a surprisingly simple way.

### 1.4.1 Generating Functions

With any infinite sequence $\langle a_0, a_1, a_2, \ldots\rangle$ of numbers we associate the following **generating function—formal power series:**

$$A(z) = a_0 + a_1 z + a_2 z^2 + \cdots = \sum_{k\geq 0} a_k z^k = \sum a_k z^k, \tag{1.19}$$

where the use of the symbol '$z$' for a variable indicates that we may deal with complex numbers; (even in cases we are interested only in natural numbers). The word **formal** emphasizes that the role of powers $z^n$ in (1.19) is mostly that of **position holders** for elements $a_n$. (The question of convergences will not be of importance for us and will be discussed later.) Concerning coefficients it is sometimes convenient to assume that $a_k = 0$ for $k < 0$ and to use the notation $\sum a_k z^k$, see (1.19), with $k$ running through all integers. Observe also that some $a_k$ in (1.19) may be equal to zero. Therefore also finite sequences can be represented by generating functions. For coefficient of $z^n$ in a generating function $A(z)$ we use the notation:

$$[z^n]A(z) = a_n \tag{1.20}$$

The main reason why generating functions are so important is that they—as functions of complex variables—may have simple, closed-form expressions that represent the whole (infinite or finite), sequence, as the following example illustrates.

**Example 1.4.1** (1) $(1+z)^r$ *is the* generating function *for the sequence* $\langle \binom{r}{0}, \binom{r}{1}, \binom{r}{2}, \binom{r}{3}, \ldots \rangle$. *Indeed, by the binomial theorem and the fact that* $\binom{r}{k} = 0$ *for* $k > r$, *we get*

$$(1+z)^r = \sum_{k \geq 0} \binom{r}{k} z^k.$$

(2) $\frac{1}{1-z}$ *is the generating function for the power series* $\sum_{n \geq 0} z^n$, *because*

$$(1-z)(\sum_{n \geq 0} z^n) = 1. \tag{1.21}$$

Such basic operations as addition, subtraction, multiplication, inverse of a function (if $a_0 \neq 0$), special division by $z^n$, derivation, and integration can be performed on generating functions "component-wise" . Table 1.1, in which

$$F(z) = \sum_n f_n z^n \qquad \text{and} \qquad G(z) = \sum_n g_n z^n,$$

summarizes some basic operations on generating functions and on the corresponding formal power series. These identities can be derived in a straightforward way. Some examples:

**Linear combination:**

$$\alpha F(z) + \beta G(z) = \alpha \sum_n f_n z^n + \beta \sum_n g_n z^n = \sum_n (\alpha f_n + \beta g_n) z^n.$$

**Multiplication** with $z^m$ ($m \geq 0$):

$$z^m G(z) = \sum_n g_n z^{n+m} = \sum_n g_{n-m} z^n.$$

**Derivation**

$$G'(z) = g_1 + 2g_2 z + 3g_3 z^2 + \cdots = \sum_n (n+1) g_{n+1} z^n$$

and therefore $G'(z)$ is the generating function for the sequence $\langle (n+1)g_{n+1} \rangle = \langle g_1, 2g_2, \ldots \rangle$ and $zG'(z)$ for the sequence $\langle n g_n \rangle = \langle 0, g_1, 2g_2, \ldots \rangle$ .

$$
\begin{aligned}
\alpha F(z) + \beta G(z) &= \textstyle\sum_n (\alpha f_n + \beta g_n)\, z^n \\
F(z)G(z) &= \textstyle\sum_n (\sum_{k=0}^{n} f_k g_{n-k})\, z^n \\
\tfrac{1}{1-z} G(z) &= \textstyle\sum_n (\sum_{k=0}^{n} g_k)\, z^n \quad \{\text{summation rule}\} \\
F^{-1}(z) &= \textstyle\sum_{n\geq 0} b_n z^n \quad \text{where } b_0 = f_0^{-1} \\
& \quad\ b_n = -f_0^{-1} \textstyle\sum_{k=1}^{n} f_k b_{n-k} \\
z^m G(z) &= \textstyle\sum_n g_{n-m} z^n \qquad m \geq 0 \\
\tfrac{G(z) - g_0 - g_1 z - \cdots - g_{m-1} z^{m-1}}{z^m} &= \textstyle\sum_{n\geq 0} g_{n+m} z^n \\
G'(z) &= \textstyle\sum_n (n+1) g_{n+1} z^n \\
zG'(z) &= \textstyle\sum_n n g_n z^n \\
\textstyle\int_0^z G(t)dt &= \textstyle\sum_{n\geq 1} \frac{1}{n} g_{n-1} z^n
\end{aligned}
$$

Table 1.1: Operations on generating functions and the corresponding sequences

For **multiplication** we get:

$$
\begin{aligned}
F(z)G(z) &= (f_0 + f_1 z + f_2 z^2 + \cdots)(g_0 + g_1 z + g_2 z^2 + \cdots) \\
&= f_0 g_0 + (f_0 g_1 + f_1 g_0) z + (f_0 g_2 + f_1 g_1 + f_2 g_0) z^2 + \cdots
\end{aligned}
$$

and therefore

$$[z^n]F(z)G(z) = (f_0 g_n + f_1 g_{n-1} + \cdots + f_n g_0) = \sum_{k=0}^{n} f_k g_{n-k}.$$

The product $F(z)G(z)$ where $[z^n]A(n)B(n) = \sum_{k=0}^{n} f_k g_{n-k}$ is called the **discrete convolution** of $F(z)$ and $G(z)$.

**Summation rule** from Table 1.1is a special case of multiplication with $F(z) = \frac{1}{1-z}$.

**Remark 1.4.2** In case of generating functions we often do not care about convergence of the corresponding power series. It is therefore natural to ask whether our manipulations with infinite sums, as for example in (1.21), are correct. There are two reasons not to worry. First of all, one can show formally that all operations mentioned above are correct. The second reason is quite different. It is often not very important to care whether all operation we perform on generating functions are indeed correct. Why? Once we get, using these operations, some results, we can use other methods, for example an induction, to show their correctness.

Let us illustrate this approach on an example:

**Example 1.4.3** *The functions* $(1+z)^r$ *and* $(1+z)^s$ *are generating function for sequences* $\langle \binom{r}{0}, \binom{r}{1}, \binom{r}{2}, \ldots \rangle$ *and* $\langle \binom{s}{0}, \binom{s}{1}, \binom{s}{2}, \ldots \rangle$. *Because* $(1+z)^r(1+z)^s = (1+z)^{r+s}$ *we have*

$$[z^n](1+z)^r(1+z)^s = \sum_{k=0}^{n} \binom{r}{k}\binom{s}{n-k} = \binom{r+s}{n} = [z^n](1+z)^{r+s}.$$

In a similar way we can show, using the identity $(1-z)^r(1+z)^r = \left(1-z^2\right)^r$, that

$$\sum_{k=0}^{n} \binom{r}{k}\binom{r}{n-k}(-1)^k = (-1)^{\frac{n}{2}}\binom{r}{\frac{n}{2}}, \quad \text{if } n \text{ is even.}$$

In this way we have easily obtained two far from obvious identities for sums of binomial coefficients. Their correctness can now be verified by induction.

Generating functions for some important sequences are listed in the Table 1.2. Some of the results in the table follow in a straightforward way from the rules in the Table 1.1. The generating function for the sequence $\langle 1,2,3,\ldots\rangle$ can be obtained using the summation rule with $G(z) = \frac{1}{1-z}$. Since the sequence $\langle 1,2,3,\ldots\rangle$ has also the form $\langle 1, 2, \binom{3}{2}, \binom{4}{3}, \binom{5}{4}, \ldots \rangle$ we get, using the summation rule and the identity from Example 1.3.5, that $\frac{1}{(1-z)^3}$ is the generating function for the sequence $\langle 1, 3, \binom{4}{2}, \binom{5}{3}, \binom{6}{4}, \ldots \rangle$. By induction we can then show, using again the summation rule and the identity from Example 1.3.5, that, for an arbitrary integer $c$, $\frac{1}{(1-z)^c}$ is the generating function for the sequence $\langle 1, c, \binom{c+1}{2}, \binom{c+2}{3}, \ldots \rangle$. Generating functions for the last three sequences in Table 1.1 are well known from calculus.

**Exercise 1.4.4** *Find a closed form of the generating function for the sequences:*

$$(a)\ a_n = 3^n + 5^n + n, n \geq 1; \ (b)\ \langle 0, 2, 0, \frac{2}{3}, 0, \frac{2}{5}, 0, \frac{2}{7}, \ldots \rangle.$$

**Exercise 1.4.5** * *Find a generating function* $F(z)$ *such that* $[z^n]F(z) = \sum_{i=0} \binom{n}{i}\binom{n}{n-2i}$, *for* $n \geq 1$.

**

**Exercise 1.4.6** *Use generating functions to show that* $\sum_{i=0}^{n} \binom{n}{i}^2 = \binom{2n}{n}$.

| sequence | generating function | closed form |
|---|---|---|
| $\langle 1, 1, 1, \ldots \rangle$ | $\sum_{n\geq 0} z^n$ | $\frac{1}{1-z}$ |
| $\langle 1, -1, 1, -1, \ldots \rangle$ | $\sum_{n\geq 0} (-1)^n z^n$ | $\frac{1}{1+z}$ |
| $\langle \underbrace{1, 0, 0, \ldots,}_{m} \underbrace{1, 0, 0, \ldots,}_{m} 1 \ldots \rangle$ | $\sum_{n\geq 0} [m \setminus n] z^n$ | $\frac{1}{1-z^m}$ |
| $\langle 1, 2, 3, 4, \ldots \rangle$ | $\sum_{n\geq 0} (n+1) z^n$ | $\frac{1}{(1-z)^2}$ |
| $\langle 1, c, \binom{c}{2}, \binom{c}{3}, \ldots \rangle$ | $\sum_{n\geq 0} \binom{c}{n} z^n$ | $(1+z)^c$ |
| $\langle 1, c, \binom{c+1}{2}, \binom{c+2}{3}, \ldots \rangle$ | $\sum_{n\geq 0} \binom{c+n-1}{n} z^n$ | $\frac{1}{(1-z)^c}$ |
| $\langle 0, 1, \frac{1}{2}, \frac{1}{3}, \frac{1}{4}, \ldots \rangle$ | $\sum_{n\geq 1} \frac{1}{n} z^n$ | $\ln \frac{1}{1-z}$ |
| $\langle 0, 1, -\frac{1}{2}, \frac{1}{3}, -\frac{1}{4}, \ldots \rangle$ | $\sum_{n\geq 1} \frac{(-1)^{n+1}}{n} z^n$ | $\ln(1+z)$ |
| $\langle 1, 1, \frac{1}{2!}, \frac{1}{3!}, \ldots \rangle$ | $\sum_{n\geq 0} \frac{1}{n!} z^n$ | $e^z$ |

Table 1.2: Generating functions for some sequences and their closed forms

### 1.4.2 Solution of Recurrences

The following general method can be often useful to find a closed form for elements of a sequence $\langle g_n \rangle$ the elements of which are defined through a recurrence:

**Step 1** Form a single equation in which $g_n$ is expressed through other elements of the sequence. It is important that this equation holds for any $n$; also for those $n$ for which $g_n$ is defined through the initial values, and also for $n < 0$ (assuming $g_n = 0$).

**Step 2** Multiply both sides of the resulting equation by $z^n$ and sum over all $n$. This gives on the left-hand side $G(z) = \sum g_n z^n$—the generating function for $\langle g_n \rangle$. Arrange the right-hand side in such a way that an expression in terms of $G(z)$ is obtained.

**Step 3** Solve the equation to get a closed form for $G(z)$.

**Step 4** Expand $G(z)$ into a power series. The coefficient at $z^n$ is a closed form for $g_n$.

#### Examples

In the following three examples we show how to perform the first three steps of the above method. Later we present a method how to perform Step 4—usually the most difficult one. This method will then be applied to finish the examples.

In the examples, and also in the rest of the book , we use the following mapping of the truth values of predicates $P(n)$ onto integers:

$$[P(n)] = \begin{cases} 1, & \text{if } P(n) \text{ is true;} \\ 0, & \text{if } P(n) \text{ is false.} \end{cases}$$

**Example 1.4.7** *Let us apply the above method on the recurrences (1.5) and (1.6) for Fibonacci numbers with the initial conditions* $f_0 = 0, f_1 = 1$ *and the inductive equation*

$$f_n = f_{n-1} + f_{n-2}, \quad n > 1.$$

**Step 1**: The single equation capturing both the inductive step and the initial conditions has the form

$$f_n = f_{n-1} + f_{n-2} + [n = 1].$$

(Observe, and this is important, that the equation is valid also for $n \leq 1$, because $f_n = 0$ for $n < 0$.)
**Step 2**: A multiplication by $z^n$ and a summation produce:

$$\begin{aligned} F(z) = \sum_n f_n z^n &= \sum_n (f_{n-1} + f_{n-2} + [n = 1])\, z^n \\ &= \sum_n f_{n-1} z^n + \sum_n f_{n-2} z^n + \sum_n [n = 1] z^n \\ &= zF(z) + z^2 F(z) + z. \end{aligned}$$

**Step 3** From the previous equation we get

$$F(z) = \frac{z}{1 - z - z^2}.$$

**Example 1.4.8** *Solve the recurrence:*

$$g_n = \begin{cases} 1, & \textit{if } n = 0; \\ 2, & \textit{if } n = 1; \\ 2g_{n-1} + 3g_{n-2} + (-1)^n, & \textit{if } n > 1. \end{cases}$$

**Step 1**: A single equation for $g_n$ has the form:

$$g_n = 2g_{n-1} + 3g_{n-2} + (-1)^n [n \geq 0] + [n = 1].$$

**Step 2**: Multiplication by $z^n$ and summation give:

$$\begin{aligned} G(z) = \sum_n g_n z^n &= \sum_n (2g_{n-1} + 3g_{n-2} + (-1)^n [n \geq 0] + [n = 1])\, z^n \\ &= \sum_n 2g_{n-1} z^n + 3 \sum_n g_{n-2} z^n + \sum_{n \geq 0} (-1)^n z^n + \sum_{n=1}^{1} z^n \\ &= 2zG(z) + 3z^2 G(z) + \frac{1}{1+z} + z. \end{aligned}$$

**Step 3** By solving the last equation for $G(z)$ we get

$$G(z) = \frac{z^2 + z + 1}{(1+z)^2(1-3z)}.$$

As it is illustrated by the following example, the generating function method can be used also to solve recurrences with two unknown functions. It also shows that such recurrences can arise in a natural way even in the case when the task is to determine only one unknown function.

**Example 1.4.9 ( Domino-Problem)** *Determine the number $u_n$ of ways one can cover a $3 \times n$ rectangle with the identical dominoes of size $1 \times 2$.*

Clearly $u_n = 0$ for $n = 1, 3$ and $u_2 = 3$. To deal with the general case let us introduce a

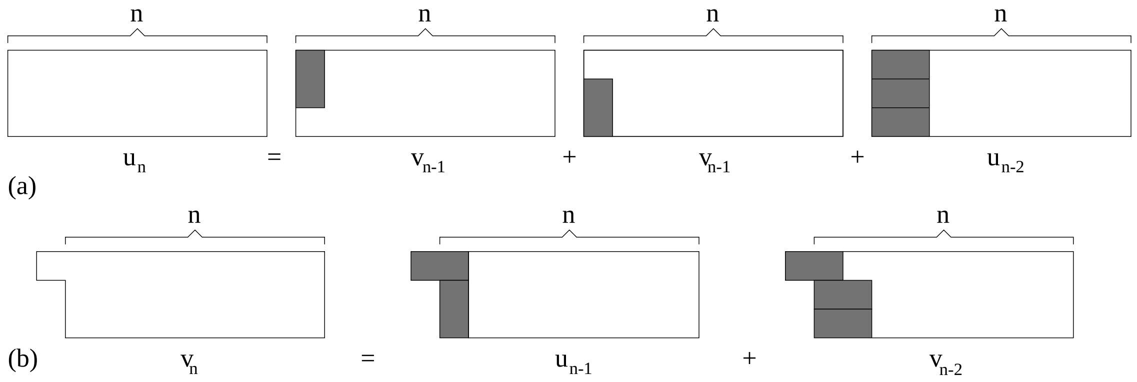


Figure 1.5: Recurrences for tiling by dominoes-60%

new variable $v_n$ to denote the number of ways we can cover a $3 \times n$ with-a-corner-rectangle (see Figure 1.5b) with such dominoes. For the case $n = 0$ we have exactly one possibility to cover a $3 \times n$ rectangle—to use no domino. We get therefore the recurrencies:

$$\begin{array}{lll} u_0 = 1, \quad u_1 = 0; & v_0 = 0, \quad v_1 = 1; & \\ u_n = 2v_{n-1} + u_{n-2}; & v_n = u_{n-1} + v_{n-2}, & n \geq 2. \end{array}$$

Let us now perform Steps 1 to 3 of the above method:

**Step 1**: $u_n = 2v_{n-1} + u_{n-2} + [n = 0], \qquad v_n = u_{n-1} + v_{n-2}.$

**Step 2**: $U(z) = 2zV(z) + z^2U(z) + 1, \qquad V(z) = zU(z) + z^2V(z).$

**Step 3**: The solution of this system of two equations in two unknown functions has the form:

$$U(z) = \frac{1 - z^2}{1 - 4z^2 + z^4}, \qquad V(z) = \frac{z}{1 - 4z^2 + z^4}.$$

### A general method to perform step 4

In the last three examples, the task in Step 4 was to determine the coefficients $[z^n]R(z)$ of a rational function $R(z) = P(z)/Q(z)$. This can be done using the following general method.

If the degree of the polynomial $P(z)$ is greater than or equal to the degree of $Q(z)$, then by dividing $P(z)$ with $Q(z)$ we can express $R(z)$ in the form $T(z) + S(z)$, where $T(z)$ is a polynomial and $S(z) = P_1(z)/Q(z)$ is a rational function with the degree of $P_1(z)$ smaller than that of $Q(z)$. Since $[z^n]R(z) = [z^n]T(z) + [z^n]S(z)$, the task has been reduced to that of finding $[z^n]S(z)$.

From the sixth row of the Table 1.2 we find that

$$\frac{a}{(1-\rho z)^{m+1}} = \sum_{n\geq 0} \binom{m+n}{n} a\rho^n z^n$$

and therefore we are easily done with finding the coefficient $[z^n]S(z)$ in case that $S(z)$ has the form

$$\sum_{i=1}^{m} \frac{a_i}{(1-\rho_i z)^{m_i - 1}} \tag{1.22}$$

for some constants $a_i, \rho_i$ and $m_i, 1 \leq i \leq m$. This implies that in order to dvelope a methodology to solve Step 4 of the above method, it issufficient to show that $S(z)$ can always be transformed either to the above form or to a similar one.

In order to transform $Q(z) = q_0 + q_1 z + \cdots q_m z^m$ into the form $Q(z) = q_0(1-\rho_1 z)(1-\rho_2 z)\dots(1-\rho_m z)$ we need to determine the roots $\frac{1}{\rho_1}, \dots, \frac{1}{\rho_m}$ of $Q(z)$. Once these roots are found, one can use one of the following theorems to perform Step 4:

**Theorem 1.4.10** *If* $S(z) = \frac{P_1(z)}{Q(z)}$, *where* $Q(z) = q_0(1-\rho_1 z)\dots(1-\rho_m z)$, *the numbers* $\rho_1, \dots, \rho_m$ *are distinct, and the degree of* $P_1(z)$ *is smaller than that of* $Q(z)$, *then*

$$[z^n]S(z) = a_1 {\rho_1}^n + \cdots + a_l {\rho_m}^n,$$

*where*

$$a_k = \frac{-\rho_k P_1(\frac{1}{\rho_k})}{Q'(\frac{1}{\rho_k})}.$$

**Proof.** It is a well known fact from calculus that in case all $\rho_i$ are different there exists a decomposition

$$S(z) = \frac{a_1}{(1-\rho_1 z)} + \cdots + \frac{a_l}{(1-\rho_l z)}$$

where $a_1, \dots, a_l$ are constants and thus

$$[z^n]S(z) = a_1 \rho_1^n + \cdots + a_l \rho_l^n.$$

Therefore, for $i = 1, \dots, l$,

$$a_i = \lim_{z \to 1/\rho_i} (1-\rho_i z)R(z)$$

and using l'Hospital's rule we obtain:

$$a_i = \frac{-\rho_i P_1(\frac{1}{\rho_i})}{Q'(\frac{1}{\rho_i})},$$

where $Q'$ is the derivative of the polynomial $Q$. ▯

The second theorem deals with the case of multiple roots of the denominator. For the proof that is more technical see bibliographical references.

**Theorem 1.4.11** *Let $R(z) = \frac{P(z)}{Q(z)}$, where $Q(z) = q_0(1-\rho_1 z)^{d_1} \ldots (1-\rho_l z)^{d_l}$, $\rho_i$ are distinct, and the degree of $P(z)$ is smaller than that of $Q(z)$; then*

$$[z^n]R(z) = f_1(n)\rho_1^n + \cdots f_l(n)\rho_l^n, \quad n \geq 0,$$

*where each $f_i(n)$ is a polynomial of the degree $d_i - 1$, the main coefficient of which is*

$$a_i = \frac{(-\rho_i)^{d_i} P(\frac{1}{\rho_i}) d_i}{Q^{(d_i)}(\frac{1}{\rho_i})},$$

*where $Q^{(d_i)}$ is the i-th derivative of $Q$.*

To apply Theorems 1.4.10 and 1.4.11 to a rational function $\frac{P(z)}{Q(z)}$ with $Q(z) = q_0 + q_1 z + \cdots + q_m z^m$ we have to express $Q(z)$ in the form $Q(z) = q_0(1-\rho_1 z)^{d_1} \ldots (1-\rho_m z)^{d_m}$. The numbers $\frac{1}{\rho_i}$ are clearly roots of $Q(z)$. Applying the transformation $y = \frac{1}{z}$ and then replacing $y$ by $z$ we get that $\rho_i$ are roots of the "reflected" polynomial

$$Q^R(z) = q_m + q_{m-1}z + \cdots + q_0 z^m$$

and this polynomial is sometimes more easy to handle.

**Examples—continuation**

Let us now apply Theorems 1.4.10 and 1.4.11 to finish Examples 1.4.7, 1.4.8, and 1.4.9. In Example 1.4.7 it remains to determine

$$[z^n]\frac{z}{1-z-z^2}.$$

The reflected polynomial $z^2 - z - 1$ has two roots

$$\phi_1 = \phi = \frac{1+\sqrt{5}}{2}, \ \phi_2 = \bar{\phi} = \frac{1-\sqrt{5}}{2}.$$

Theorem 1.4.10 therefore yields

$$F_n = [z^n]\frac{z}{1-z-z^2} = a_1\phi^n + a_2\bar{\phi}^n,$$

where $a_1 = \frac{1}{\sqrt{5}}, a_2 = -\frac{1}{\sqrt{5}}$.

To finish Example 1.4.8 we have to determine

$$g_n = [z^n]\frac{1+z+z^2}{(1-3z)(1+z)^2}.$$

The denominator already has the required form. Since one root has multiplicity 2, we need to use Theorem 1.4.11. Calculations yield

$$g_n = (\frac{1}{4}n + c)(-1)^n + \frac{13}{16}3^n.$$

The constant $c = \frac{3}{16}$ can be determined using the equation $1 = g_0 = c + \frac{13}{16}$. Finally, in Example 1.4.9, the task remained to determine:

$$[z^n]U(z) = [z^n]\frac{1-z^2}{1-4z^2+z^4} \quad \text{and} \quad [z^n]V(z) = [z^n]\frac{z}{1-4z^2+z^4}. \tag{1.23}$$

In order to apply our method directly, we would need to find roots of a polynomial of degree 4. This, but also the whole task, can be simplified by realizing that all powers in (1.23) are even. Indeed, if we define

$$W(z) = \frac{1}{1-4z+z^2}$$

then

$$U(z) = (1-z^2)W(z^2) \text{ and } V(z) = zW(z^2).$$

Therefore

$$\begin{array}{rclcl} U_{2n+1} & = & [z^{2n+1}]U(z) & = & 0, \qquad U_{2n} = W_n - W_{n-1}; \\ V_{2n} & = & [z^{2n}]V(z) & = & 0, \qquad V_{2n+1} = W_n; \end{array}$$

where

$$W_n = [z^n]\frac{1}{1-4z-z^2}$$

what is more easy to determine.

**Exercise 1.4.12** *Use the generating function method to solve recurrences from Exercises 1.2.17 and 1.2.18.*

**Exercise 1.4.13** *Use the generating function method to solve recurrences:*

*(a)* $u_0 = 0,\ u_1 = 1,\ u_n = u - n - 1 + u_{n-2} + (-1)^n,\ n \geq 2;$

*(b)* $g_n = 0$, *if* $n < 0$, $g_0 = 1$ *and* $g_n = g_{n-1} + 2g_{n-2} + \ldots + ng_0$ *for* $n > 0$.

**Exercise 1.4.14** *Use the generating function method to solve the system of recurrences:* $a_0 = 1,\ b_0 = 0;\ a_n = 5a_{n-1} + 12b_{n-1},\ b_n = 2a_{n-1} + 5b_{n-1},\ n \geq 1.$

**Remark 1.4.15** In all previous methods for solving recurrences it has been assumed that all components—constants and functions—are fully determined. This is, however, not always the case in practice. Mostly only some estimations of them are available. In Section 1.6.2 we show how to deal also with such cases. Before doing that we switch to a detailed treatment of asymptotic estimations.

## 1.5 Asymptotics

Asymptotic estimations allow to produce often surprisingly simple, deep, powerful, useful and technology independent analysis of the performance or of the size of computing systems. Their existence has been an important factor contributing much to the fast development of a deep and practically relevant theory of computing.

In the asymptotical analysis of a function $T(n)$ (from integers to reals) or $A(x)$ (from reals to reals), the task is to determine an "**estimation in limit**" of $T(n)$ for $n \rightarrow \infty$ or of $A(x)$, for $x \rightarrow a$, where $a$ is a real. The aim is to determine an estimation as good as possible, or at least good lower and upper bounds for it.

The key underlying problem is how to compare 'in a limit' the growth of two functions. The main approaches to this problem and relations between them will now be discussed. Especially important rôle play here the $\mathcal{O}$-, $\Omega-$ and $\Theta-$ notation s and we shall discuss in detail ways how to handle them.

Because of special importance and peculiarities of asymptotic estimations a discussion of their merits seems to be appropriate.

There is a quite widespread illusion that in science and technology the exact solutions, analyses, and so on, are what is really needed and to be aimed for. Estimations are seen often as substitutes, when exactness is not available or achievable. However, this does not apply to the analysis of computing systems. Simple and good estimations are what is really needed. There are several reasons for that.

**Feasibility.** Exact analyses are often impossible, even for apparently simple systems. There are often too many factors of enormous complexity involved. For example, for a really detailed time analysis of even a simple program one would mostly need to study complicated compilers, operating systems, computers, and in case of multiuser systems also the patterns of their interactions.

**Usefulness.** An exact analysis could easily be many pages long and therefore incomprehensible. Moreover, as the results of asymptotic analysis indicate, most of that would be of negligible importance. In addition, what we really need, are such results of an analysis of computing systems that are independent of a particular computer and, in general, of the underlying hardware and software technology. What we need are estimations that are some kinds of **invariants** of computing technologies. Various constant factors, that reflect these technologies are therefore not of prime interest. Finally, what is mostly needed, is not the performance of particular systems for particular data, but mainly the knowledge about the growth of the performance of systems as a function of the growth of the size of their input data. Again, factors with a negligeable growth and constant factors are not of prime importance for asymptotic analysis—even though they may be of large importance for applications.

**Example 1.5.1** *How much time is needed to multiply two n-digit integers (by a person or by a computer) when a classical school algorithm is used?*

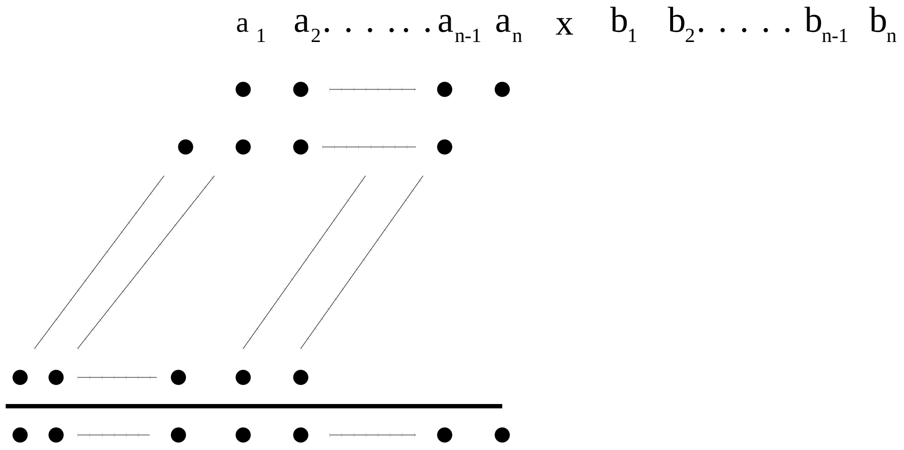


Figure 1.6: Integer multiplication-60%.

The exact analysis may be quite complicated. It depends also on many factors: which of many variants of the algorithm is used (see one in Figure 1.6); who is to execute it; or on a way it is programmed, and on the computer on which it is run. However, all these cases have, however, one thing in common. $k^2$-times more time is needed to multiply $k$-times larger integers. We can therefore say, simply and in a full generality, that the time to multiply two integers by a school algorithm is $\Theta(n^2)$. Observe also that this result holds no matter which kind of positional number system is used to represent integers: binary, ternary, decimal, and so on.

It is also important to realize that simple and well understood estimations are of large importance even in cases the exact solutions are available. Some examples:

**Example 1.5.2** *At the analysis of algorithms one encounters often the so-called* **harmonic numbers:**

$$H_n \; = \; 1 + \frac{1}{2} + \frac{1}{3} + \cdots + \frac{1}{n} \; = \; \sum_{i=1}^{n} \frac{1}{i}. \tag{1.24}$$

Using definition (1.24) we can exactly determine $H_n$ for any given integer $n$. This is, however, not always enough. Mostly we need to know how big $H_n$ is in general, as a function of $n$, and not for a particular $n$. Unfortunately, no closed form for $H_n$ is known. Therefore, good approximations for $H_n$ are much needed. For example:

$$\ln n < H_n < \ln n + 1, \qquad \text{for } n > 1.$$

This is often enough, although sometimes a better approximation is required. For example,

$$H_n = \ln n + 0.5772156649 + \frac{1}{2n} - \frac{1}{12n^2} + \Theta(n^{-4}).$$

**Example 1.5.3** *The factorial $n! = 1 \cdot 2 \cdot \ \ldots \ \cdot n$ is another function of importance for the analysis of algorithmsThe fact that we can determine $n!$ exactly is not always good enough for complexity analysis. The following approximation, due to James Stirling (1692-1770),*

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

*may be much more useful. For example, this approximation yields:*

$$\lg n! = \Theta(n \log n).$$

### 1.5.1 An Asymptotic Hierarchy

An important formalization of the intuitive idea that one function grows essentially faster than another function is captured by the relation $\prec$ defined by

$$f(n) \prec g(n) \Leftrightarrow \lim_{n\to\infty} \frac{f(n)}{g(n)} = 0.$$

Basic properties of this relation can be summarized as follows:

$$\begin{aligned}
f(n) \prec g(n), g(n) \prec h(n) \quad &\Rightarrow \quad f(n) \prec h(n), && \text{(transitivity)}; && (1.25)\\
f(n) \prec g(n) \quad &\Leftrightarrow \quad \frac{1}{g(n)} \prec \frac{1}{f(n)}, && \text{(for } f, g \text{ never equal zero)}; && (1.26)\\
1 \prec f(n) \prec g(n) \quad &\Rightarrow \quad c^{|f(n)|} \prec c^{|g(n)|}, && \text{(if } c > 1 \text{ is a constant)}; && (1.27)\\
n^\alpha \prec n^\beta \quad &\Leftrightarrow \quad \alpha < \beta, && \text{if } (\alpha, \beta \text{ are positive reals}). && (1.28)
\end{aligned}$$

These properties, as well as the following hierarchy (with $0 < \varepsilon < 1 < c$), can be derived from the basic definition of the relation $\prec$ using elementary methods of calculus.

$$1 \prec \lg^\star n \prec \lg\lg n \prec \lg n \prec n^\varepsilon \prec n^c \prec n^{\lg n} \prec c^n \prec n^n \prec c^{c^n}. \tag{1.29}$$

These results remain valid when lg is replaced by ln or log.

**Example 1.5.4** *Where does in this hierarchy the function $2^{\sqrt[m]{\lg n}}$, $m > 1$, lie?*

*Clearly, $\lg\lg n \prec \sqrt[m]{\lg n} \prec \varepsilon \lg n$, for any $\varepsilon > 0$, and therefore, by (1.27), $2^{\lg\lg n} \prec 2^{\sqrt[m]{\lg n}} \prec 2^{\varepsilon \lg n}$. Since $2^{\lg\lg n} = \lg n$ and $2^{\varepsilon\lg n} = n^\varepsilon$, we get*

$$\lg n \prec 2^{\sqrt[m]{\log n}} \prec n^\varepsilon.$$

**Exercise 1.5.5** *Which of the following functions grow faster:*
*(a)* $n^{(\ln n)}$ *or* $(\ln n)^n$*; (b)* $(\ln n)!$ *or* $n^{\ln n \ln \ln n}$ *?*

In a similar way, we can formalize the intuitive idea that two functions $f(n)$ and $g(n)$ have the same rate of growth as follows:

$$f(n) \sim g(n) \Leftrightarrow \lim_{n\to\infty} \frac{f(n)}{g(n)} = 1. \tag{1.30}$$

It would be nice could we say that for any two functions $f(n)$ and $g(n)$ one of the relations $f(n) \prec g(n)$, $f(n) \sim g(n)$, or $g(n) \prec f(n)$ holds. This is, however, not the case. For example, for the pairs $f(n) = n$, $g(n) = 2n$ and $f(n) = 1$, $g(n) = \sin n$ none of these relations holds. The relation $\sim$ is simply too strong.

There is another formalization of the intuitive idea that two functions have the same rate of growth:

$$f(n) \asymp g(n) \quad \Leftrightarrow \quad |f(n)| \leq c|g(n)| \quad \text{and} \quad |g(n)| \leq c|f(n)| \tag{1.31}$$
$$\text{for a constant } c \text{ and every large enough } n,$$

that has a nice and important property that for any two the so-called **logarithmico-exponential functions** $f(n)$ and $g(n)$ exactly one of the relations $f(n) \prec g(n)$,$f(n) \asymp g(n)$ or $g(n) \prec f(n)$ holds.

The family of logarithmico-exponential functions contains practically all functions one encounters in the asymptotic analysis. It has been defined by G. H. Hardy (1910), as the smallest family $\mathcal{L}$ of functions satisfying the following properties.

1. Functions $f(n) = n$ and $f(n) = c$ (a constant) are in $\mathcal{L}$.
2. If $f(n), g(n)$ are in $\mathcal{L}$, then so are functions: $f(n)+g(n)$, $f(n)-g(n)$, $f(n)\cdot g(n)$, $e^{f(n)}$, $g(n)/f(n)$ and $\log f(n)$—if $f(n) > 0$ for almost all $n$.

Asymptotic relations such as $\prec$ and the ones defined later, that capture 'in limit' our intuition about the growths of functions require to stretch our imagination and to **THINK BIG**. For example, if $f(n) \prec g(n)$, then this does mean that eventually, for all $n \geq n_0$ for some $n_0$, $f(n) < g(n)$. However, such an $n_0$ can be very large! For example,

$$\log n \prec n^{0.0001}$$

but the smallest $n_0$ such that $\log n < n^{0.0001}$ for all $n \geq n_0$ is between $10^{10^3}$ and $10^{10^4}$.

In general, the asymptotic analysis results are more relevant larger arguments we have. This also implies that practical importance of the asymptotic analysis results grows with the growth of the performance of computers and of the size of problems that need to be solved.

### 1.5.2 $\mathcal{O}$-, $\Theta$-, and $\Omega$-notation

The main concepts of the asymptotic analysis: 'to grow as fast as', 'to grow not faster than' and 'to grow at least as fast as' seem to be captured in the best way by the following $\mathcal{O}-, \Theta-$, and $\Omega$-notation; with a function $g(n)$ as an argument.

$$\boxed{\begin{aligned}
\Theta(g(n)) &= \{f(n) \mid \exists c_1, c_2 : c_1|g(n)| \leq |f(n)| \leq c_2|g(n)|\}. \\
\mathcal{O}(g(n)) &= \{f(n) \mid \exists c : |f(n)| \leq c|g(n)|\}. \\
\Omega(g(n)) &= \{f(n) \mid \exists c > 0 : c|g(n)| \leq |f(n)|\}.
\end{aligned}}$$

$\mathcal{O}$-notation was introduced in 1892 by a German mathematician G. H. Bachmann (1837-1890). It got more widely known through the work of another German mathematician Edmund Landau (1877-1938) and it has been known as Landau notation. However, it was actually D. E. Knuth who introduced $\Omega$- and $\Theta$-notation and much popularized all these notations.

$\Theta(g(n))$, $\mathcal{O}(g(n))$, $\Omega(g(n))$ are sets of functions. However,

$$\begin{array}{rlllllllll}
\text{instead of} & f(n) & \in & \Theta(g(n)), & f(n) & \in & \mathcal{O}(g(n)), & f(n) & \in & \Omega(g(n)), \\
\text{we usually write:} & f(n) & = & \Theta(g(n)), & f(n) & = & \mathcal{O}(g(n)), & f(n) & = & \Omega(g(n)).
\end{array}$$

There are two reasons for using this notation with the "equal" sign. The first one is a tradition. The $\mathcal{O}$-notation with the equals sign has been well established in mathematics, especially in number theory. Moreover, we often read "=" as "is". For example, we read $H_n = \Theta(\lg n)$ as "$H_n$ is a big theta of $\lg n$". The second reason is that in asymptotic calculations, as illustrated later, we often need to use this notation in the middle of expressions. Our intuition is then better satisfied if we interpret the equals sign as an equality rather than as an inclusion, as discussed later.

Relations between functions $f(n)$ and $g(n)$ such that $f(n) = \Theta(g(n))$, or $f(n) = \Omega(g(n))$, or $f(n) = \mathcal{O}(g(n))$ are illustrated in Figure 1.7:

Transitivity is one of the basic properties for $\mathcal{O}$-, $\Theta$- and $\Omega$-notation. For example,

$$f(n) = \mathcal{O}(g(n)) \text{ and } g(n) = \mathcal{O}(h(n)) \Rightarrow f(n) = \mathcal{O}(h(n)).$$

The $\mathcal{O}$-, $\Theta$-, and $\Omega$-notation is used also with various restrictions on variables. For example, the notation

$$f(n) = \Theta(g(n)), \qquad \text{for } n \to \infty \tag{1.32}$$

means that there are $c_1, c_2 > 0$, and $n_0$ such that $c_1|g(n)| \leq |f(n)| \leq c_2|g(n)| \quad \text{for } n \geq n_0$.

Note, that notation $\Theta(f(n)$, and also $\mathcal{O}$- and $\Omega$-notations are very often used as in ( 1.32), without writing $n \to \infty$ explicitly.

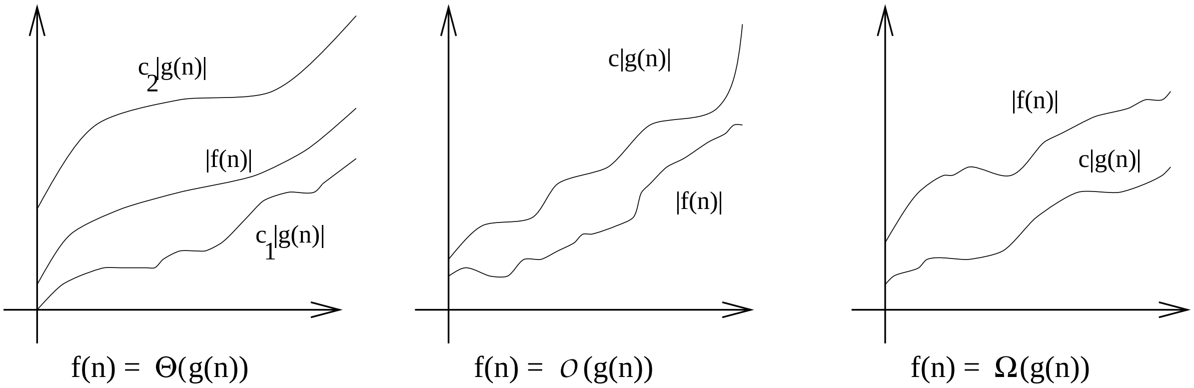


Figure 1.7: Asymptotic relations between functions-75%

**Example 1.5.6** *In order to show* $(n+1)^2 = \Theta(n^2)$ *we look for* $c_1, c_2 > 0$ *such that*

$$c_1 n^2 \leq |n^2 + 2n + 1| \leq c_2 n^2, \quad \textit{for } n > 0,$$

*or, after dividing by* $n^2$, $c_1 \leq 1 + \frac{2}{n} + \frac{1}{n^2} \leq c_2$. *This inequality is satisfied, for example, with* $c_1 = 1$ *and* $c_2 = 4$.

**Example 1.5.7** *To show* $\frac{n^2-1}{n+1} = \Theta(n)$, *for* $n \to \infty$, *we need constants* $c_1, c_2 > 0$ *such that*

$$c_1 n \leq \left| \frac{n^2 - 1}{n + 1} \right| \leq c_2 n, \quad \textit{for} \quad n \geq n_0.$$

*For* $n > 1$, *this is equivalent to finding* $c_1, c_2$ *such that* $c_1 n \leq |n - 1| \leq c_2 n$, *or, equivalently,*

$$c_1 \leq |1 - \frac{1}{n}| \leq c_2.$$

*This inequality is satisfied, for* $n > 1$, *with* $c_1 = \frac{1}{2}$ *and* $c_2 = 1$.

**Example 1.5.8** *Since*

$$\sum_{i=1}^{n} i^k \leq \sum_{i=1}^{n} n^k$$

*we get*

$$\sum_{i=1}^{n} i^k = \mathcal{O}(n^{k+1}).$$

**Example 1.5.9** *To prove* $4n^3 \neq \mathcal{O}(n^2)$, *for* $n \to \infty$, *let us assume that there are* $c_1$ *and* $n_0$ *such that* $4n^3 \leq c_1 n^2$, *for* $n \geq n_0$. *This would imply* $n \leq c_1/4$, *for all* $n \geq n_0$*—a contradiction.*

The $\Theta$-, $\mathcal{O}$-, and $\Omega$-notation is also used for functions with variables over reals and for convergence to a real. For example, the notation

$$f(x) = \mathcal{O}(g(x)), \qquad \text{for } x \to 0,$$

means that there are constants $c, \varepsilon > 0$ such that

$$|f(x)| \leq c|g(x)|, \qquad \text{for } 0 < |x| \leq \varepsilon.$$

**Example 1.5.10** $x^2 = \mathcal{O}(x)$, *for* $x \to 0$.

**Exercise 1.5.11** *Show that (a)* $\lfloor x \rfloor \lceil x \rceil = \Theta(x^2)$; *(b)* $(x^2+1)/(x+1) = \Theta(x)$.

**Exercise 1.5.12** *Give an* $\mathcal{O}$*-estimation, as good as possible, for the following functions:*
*(a)* $(n! + 3^n)(n^2 + \log(n^3+1))$; *(b)* $(2^n + n^2)(n^3 + 5^n)$; *(c)* $n^{2^n} + n^{n^2}$.

The $\mathcal{O}$-notation has its peculiarities which we shall now discuss in more detail. The expressions of the type $f(n) = \mathcal{O}(g(n))$, for example

$$\frac{1}{2}n^3 - 2n^2 + 3n - 4 = \mathcal{O}(n^3),$$

should be seen as a **one-way-equality**,and should never been written with the sides reversed. For example, we should not write $\mathcal{O}(n^3) = \frac{1}{2}n^3 - 2n^2 + 3n - 4$ ! This could lead to incorrect conclusions. For example, from $n = \mathcal{O}(n^3)$ and $\mathcal{O}(n^3) = n^2$ one could be inclined to conclude that $n = \mathcal{O}(n^3) = n^2$. This does not mean that the $\mathcal{O}$-notation can not be used on the left side of an equation. It has only to be dealt with properly and interpreted consistently as a set of functions. One can also write $\mathcal{O}(g_1(n)) + \mathcal{O}(g_2(n))$ or $\mathcal{O}(g_1(n)) \cdot \mathcal{O}(g_2(n))$, and so on, with the usual interpretation of operations on sets. For example,

$$\mathcal{O}(g_1(n)) + \mathcal{O}(g_2(n)) = \{h(n) \mid h(n) = h_1(n) + h_2(n), h_1(n) = \mathcal{O}(g_1(n)), h_2(n) = \mathcal{O}(g_2(n))\}.$$

We can therefore write

$$2n + \mathcal{O}(n^2) + \mathcal{O}(n^3) = \mathcal{O}(n^3)$$

what actually means that $2n + \mathcal{O}(n^2) + \mathcal{O}(n^3) \subseteq \mathcal{O}(n^3)$.

If the $\mathcal{O}$-notation is used in an environment it actually represents a set of functions over all variables that are 'free' in that environment. Let us illustrate this on the use of $\mathcal{O}$-notation within a sum—what happens often in the analysis of algorithms. We show the identity

$$\sum_{k=0}^{n} \Big(2k^2 + \mathcal{O}(k)\Big) = \frac{1}{3}n^3 + \mathcal{O}(n^2).$$

The expression $2k^2 + \mathcal{O}(k)$ represents, in this context, a set of functions of the form $2k^2 + f(k,n)$, for which there is a constant $c$ such that $f(n,k) \leq ck$, for $0 \leq k \leq n$. Therefore

$$\begin{aligned} \sum_{k=0}^{n} 2k^2 + f(k,n) \leq 2\sum_{k=0}^{n} k^2 + c\sum_{k=0}^{n} k &= 2(\frac{n^3}{3} + \frac{n^2}{2} + \frac{n}{6}) + c\frac{n^2}{2} + c\frac{n}{2} && (1.33) \\ &= \frac{2}{3}n^3 + (1 + \frac{c}{2})n^2 + (\frac{1}{3} + \frac{c}{2})n && (1.34) \\ &\leq \frac{2}{3}n^3 + c_1 n^2, \text{ for } c_1 = c + 2. && (1.35) \end{aligned}$$

During a complexity analysis it often happens that estimations depend on more than one parameter. For example, the complexity of a graph algorithm may depend on the number of nodes and also on the number of edges. To deal with such cases, the $\mathcal{O}$-,$\Theta$- and $\Omega$-notation is generalized in a natural way. For example,

$$\mathcal{O}(f(m,n)) = \{g(m,n) \,|\, \exists c, n_0 : \ |f(m,n)| \leq c|g(m,n)|, \text{ for all } n \geq n_0, m \geq n_0\}.$$

Notation $\mathcal{O}$ is sometimes used also to relate functions $f, g : \Gamma \to \mathbf{N}$, where $\Gamma$ is an arbitrary infinite set. $f(x) = \mathcal{O}(g(x))$ then means that there exists a constant $c$ such that $f(x) \leq cg(x)$ for almost all $x \in \Gamma$.

**Exercise 1.5.13** *Show: (a) $n^a = \mathcal{O}(n^b)$ if $0 \leq a \leq b$; (b) $a^n = \mathcal{O}(b^n)$ if $1 \leq a \leq b$; (c) $n^a = \mathcal{O}(b^n)$, for any $a > 0, b > 1$.*

**Exercise 1.5.14** *Show: (a) $n!$ is not $\mathcal{O}(2^n)$; (b) $n^n$ is not $\mathcal{O}(n!)$.*

**Exercise 1.5.15** *Show that $f(n) = \mathcal{O}(n^k)$ for some $k$ if and only if $f(n) \leq kn^k$ for some $k > 0$.*

**Remark 1.5.16** *One of the main use of $\Theta-$, $\Omega$- and $\mathcal{O}$-notation is in the computational analysis of algorithms. For example, in case of the running time $T(n)$ of an algorithm the notation $T(n) = \Theta(f(n))$ means that $f(n)$ is an asymptotically tight bound; notation $T(n) = \Omega(f(n)$ means that $f(n)$ is an asymptotical lower bound and, finally, notation $T(n) = \mathcal{O}(f(n))$ demonstrate that $f(n)$ is an asymptotical upper bound.*

### 1.5.3 Relations between Asymptotic Notations

The following relations between the $\mathcal{O}$-, $\Theta$- and $\Omega$-notations follow directly from the basic definition:

$$\begin{aligned} f(n) = \mathcal{O}(g(n)) &\Leftrightarrow g(n) = \Omega(f(n)), \\ f(n) = \Theta(g(n)) &\Leftrightarrow f(n) = \mathcal{O}(g(n)) \text{ and } f(n) = \Omega(g(n)). \end{aligned}$$

In addition,

$$f(n) = \Theta(g(n)) \Leftrightarrow f(n) \asymp g(n).$$

The following 'little oh' notation

$$f(n) = o(g(n)) \Leftrightarrow |f(n)| \leq \varepsilon |g(n)| \text{ for all } \varepsilon > 0,\ n > n_0(\varepsilon)$$

and its 'inverse' notation

$$f(n) = \omega(g(n)) \Leftrightarrow g(n) = o(f(n))$$

are also sometimes used. Between the 'little oh' and $\asymp$ notation, there is the relation:

$$f(n) \asymp g(n) \Leftrightarrow f(n) = g(n) + o(g(n)).$$

**Exercise 1.5.17** *Show (a)* $x^3 = o(x^4)$*; (b)* $x \lg x = o(x^2)$*; (c)* $x = o(x^{1+\varepsilon})$ *if* $\varepsilon > 0$*; (d)* $x^2 = o(2^x)$.

Given two functions $f(n)$ and $g(n)$, it may not be obvious which of the asymptotic relations hold between them. The following theorem contains a useful sufficient condition to determine that.

**Theorem 1.5.18** *If* $f(n), g(n) > 0$*, for all* $n > 0$*, then*

(1) $\lim_{n\to\infty} \frac{f(n)}{g(n)} = a \neq 0 \quad \Rightarrow \quad f(n) = \Theta(g(n))$;

(2) $\lim_{n\to\infty} \frac{f(n)}{g(n)} = 0 \quad \Rightarrow \quad f(n) = \mathcal{O}(g(n)),\ f(n) = o(g(n))$ *but not* $f(n) = \Theta(g(n))$;

(3) $\lim_{n\to\infty} \frac{f(n)}{g(n)} = \infty \quad \Rightarrow \quad g(n) = \mathcal{O}(f(n))$ *and not* $g(n) = \Theta f(n)$.

**Proof.** Let $\lim_{n\to\infty} \frac{f(n)}{g(n)} = a \neq 0$. Then there are $\varepsilon \geq 0$ and an integer $n_0$ such that, for all $n > n_0$,

$$\left| \frac{f(n)}{g(n)} - a \right| \leq \varepsilon.$$

This implies $(a - \varepsilon) g(n) \leq f(n) \leq (a + \varepsilon) g(n)$. Therefore $f(n) = \Theta(g(n))$. Proofs of (2) and (3) are left as exercises.

**Example 1.5.19** *For* $a, b > 1$, $\lim_{n\to\infty} \frac{(\log n)^a}{n^b} = 0$ *and therefore* $(\log n)^a = \mathcal{O}(n^b)$.

**Exercise 1.5.20** *Fill an entry in the following table by a cross whenever the pair of functions in that row is in the relation $A = \psi(B)$, where $\psi$ is the symbol shown by the column head. In the table we use integer constants $k, c \geq 1$ and $\varepsilon > 0$.*

| $A$ | $B$ | $\mathcal{O}$ | $o$ | $\Omega$ | $\omega$ | $\Theta$ |
|---|---|---|---|---|---|---|
| $\ln^k n$ | $n^\varepsilon$ | | | | | |
| $n^k$ | $c^n$ | | | | | |
| $n \lg n$ | $n^{cosn}$ | | | | | |
| $2^n$ | $3^{\frac{3}{2}}$ | | | | | |
| $n^{\log m}$ | $m^{\log n}$ | | | | | |
| $\lg n!$ | $\lg n^n$ | | | | | |

### 1.5.4 Manipulations with the $\mathcal{O}$-notation

There are several simple rules how to manipulate $\mathcal{O}$-expressions that follow easily from the basic definition:

$$\begin{aligned}
n^m &= \mathcal{O}(n^{m'}), \quad \text{if } m \leq m'; && (1.36)\\
f(n) &= \mathcal{O}(f(n)); && (1.37)\\
c\mathcal{O}(f(n)) &= \mathcal{O}(cf(n)) \quad = \quad \mathcal{O}(f(n)); && (1.38)\\
\mathcal{O}(\mathcal{O}(f(n))) &= \mathcal{O}(f(n)); && (1.39)\\
\mathcal{O}(f(n)) + \mathcal{O}(g(n)) &= \mathcal{O}(\max\{|f(n)|, |g(n)|\}); && (1.40)\\
\mathcal{O}(f(n))\mathcal{O}(g(n)) &= \mathcal{O}(f(n)g(n)); && (1.41)\\
\mathcal{O}(f(n)g(n)) &= f(n)\mathcal{O}(g(n)). && (1.42)
\end{aligned}$$

For example, from $(1.36), (1.38)$ and $(1.40)$ we get for a fixed $m$:

$$\sum_{i=0}^{m} a_i n^{m-i} = \sum_{i=0}^{m} \mathcal{O}(n^m) = \mathcal{O}(mn^m) = \mathcal{O}(n^m).$$

The rule $(1.40)$ is often used in the analysis of algorithms to get the overall $\mathcal{O}$-estimation of time complexity of an algorithm from the estimations of complexity of its parts.

Manipulations with power series aimed to get better and better estimations play also an important rôle in the complexity analysis: For example, if the power series

$$S(z) = \sum_{n \geq 0} a_n z^n$$

converges absolutely for a complex number $z_0$, then $S(z) = \mathcal{O}(1)$ for all $|z| \leq |z_0|$ because

$$|S(z)| \leq \sum_{n \geq 0} |a_n||z|^n \leq \sum_{n \geq 0} |a_n||z_0|^n = c < \infty,$$

for a constant $c$. This implies that we can truncate the power series after each term and to estimate the remainder with $\mathcal{O}$ as follows:

$$\begin{aligned} S(z) &= a_0 + \mathcal{O}(z); \\ S(z) &= a_0 + a_1 z + \mathcal{O}(z^2); \\ &\vdots \\ S(z) &= \textstyle\sum_{i=0}^{k} a_i z^i + \mathcal{O}(z^{k+1}). \end{aligned}$$

The following power series are of a special interest in the asymptotic analysis:

$$e^z = 1 + z + \frac{z^2}{2!} + \frac{z^3}{3!} + \frac{z^4}{4!} + \mathcal{O}(z^5); \tag{1.43}$$

$$\ln(1+z) = z - \frac{z^2}{2} + \frac{z^3}{3} - \frac{z^4}{4} + \mathcal{O}(z^5). \tag{1.44}$$

With the truncation method one can use these power series to show the correctness of the following rules:

$$\ln(1 + \mathcal{O}(f(n))) = \mathcal{O}(f(n)), \quad \text{if } f(n) \prec 1; \tag{1.45}$$

$$e^{\mathcal{O}(f(n))} = 1 + \mathcal{O}(f(n)), \quad \text{if } f(n) = \mathcal{O}(1); \tag{1.46}$$

$$(1 + \mathcal{O}(f(n)))^{\mathcal{O}(g(n))} = 1 + \mathcal{O}(f(n)g(n)), \quad \text{if } f(n) \prec 1, f(n)g(n) = \mathcal{O}(1). \tag{1.47}$$

**Proof** of (1.45): Since $f(n) \prec 1$, whenever $g(n) \in \mathcal{O}(f(n))$ there are constants $C, c$ such that $|g(n)| \leq c|f(n)| \leq C < 1$, for $n \geq n_0$. Hence

$$\ln(1 + g(n)) = g(n)\left(1 - \frac{1}{2}g(n) + \frac{1}{3}g^2(n) - \cdots\right) \tag{1.48}$$

$$\leq g(n)\left(1 + \frac{1}{2}C + \frac{1}{3}C^2 + \cdots\right) \leq (\frac{1}{1-C})g(n) = \mathcal{O}(f(n)) \tag{1.49}$$

and therefore $\ln(1 + \mathcal{O}(f(n))) = \mathcal{O}(f(n))$. In a similar way we can show (1.46). It also holds

$$\begin{aligned} (1 + \mathcal{O}(f(n)))^{\mathcal{O}(g(n))} &= e^{\mathcal{O}(g(n))\ln(1+\mathcal{O}(f(n)))} &&= e^{\mathcal{O}(g(n))\mathcal{O}(f(n))} \\ &= e^{\mathcal{O}(f(n)g(n))} &&= 1 + \mathcal{O}(f(n)g(n)). \end{aligned}$$

**Exercise 1.5.21** *Determine $\mathcal{O}(f(n))$ for: (a) $f(n) = (1+n^2)^{\frac{1}{n^3}}$; (b) $f(n) = e^{\frac{1}{\sqrt{n}}}$.*

### 1.5.5 Asymptotic Notation—Summary

In Table 1.3 we present simpler definitions for the $\mathcal{O}$-,$\Theta$-, and $\Omega$-notation which are often used and are mostly sufficient. We also summarize definitions for the $o$- and $\omega$-notation. The notation $\overset{\infty}{\underset{n}{\forall}}$ used there means "for almost all $n$"; $f(n)$ and $g(n)$ are non-negative functions from integers to integers.

$$
\begin{array}{rcl}
f(n) = \mathcal{O}(g(n)) & \Leftrightarrow & \exists c \in \mathbf{N} \overset{\infty}{\underset{n}{\forall}} f(n) \leq cg(n) \\
f(n) = \Omega(g(n)) & \Leftrightarrow & g(n) = \mathcal{O}(f(n)) \\
 & \Leftrightarrow & \exists c \in \mathbf{N} \overset{\infty}{\underset{n}{\forall}} f(n) \geq \frac{1}{c}g(n) \\
f(n) = o(g(n)) & \Leftrightarrow & \forall c \in \mathbf{N} \overset{\infty}{\underset{n}{\forall}} f(n) \leq \frac{1}{c}g(n) \\
f(n) = \omega(g(n)) & \Leftrightarrow & g(n) = o(f(n)) \\
 & \Leftrightarrow & \forall c \in \mathbf{N} \overset{\infty}{\underset{n}{\forall}} f(n) \geq cg(n) \\
f(n) = \Theta(g(n)) & \Leftrightarrow & f(n) = \mathcal{O}(g(n)) \text{ and } f(n) = \Omega(g(n))
\end{array}
$$

Table 1.3: Summary of asymptotic notations

In the following we say that an algorithm is a **polynomial time algorithm** if it runs in time $\mathcal{O}(n^k)$ for some constant $k$ on a typical sequential computer. Such an algorithm will be also called **feasible** or even efficient. An algorithmic problem is called feasible or tractable if it can be solved by an algorithm running in polynomial time. Otherwise it is called **unfeasible** or **intractable**. This will be discussed more in Section 1.10 and especially in Chapters 4 and 5.

## 1.6 Asymptotics and Recurrences

Two basic problems concerning the use of asymptotics in solving recurrences and methods how to solve them will now be considered. First, we show a method how to use asymptotics to find asymptotical solutions of recurrences. Second, we show how to solve recurrences some terms of which are known only asymptotically. This is actually the most frequent case we find in practice when attempting to analyze the efficiency of complex recursive systems.

### 1.6.1 Bootstrapping

This is a quite general method how to find better and better approximations for terms of sequences defined by recurrences. The basic idea is simple. One first guesses an approximation (after computing some of the first values), then substitutes this approximation in the recurrence to obtain a better approximation. This process terminates when it does not seem to provide an improvement any more.

**Example 1.6.1** *Find, for $n \to \infty$, an approximation of the coefficients $g_n$ of the generating function*

$$G(z) = exp(\sum_{k=1}^{\infty} \frac{z^k}{k^2}) = \sum_{n=0}^{\infty} g_n z^n. \tag{1.50}$$

Differentiation of $G(z)$, according to $z$, yields

$$G'(z) = \sum_{n=0}^{\infty} n g_n z^{n-1} = \left( \sum_{k=1}^{\infty} \frac{z^{k-1}}{k} \right) G(z)$$

and if we compare the coefficients by $z^{n-1}$ on both sides of the equation we get

$$n g_n = \sum_{k=0}^{n-1} \frac{g_k}{n-k}. \tag{1.51}$$

It is easy to see, from (1.50), that $g_0 = 1$ and from (1.51), that $g_1 = 1$. Moreover, by induction we can prove that $0 < g_n \leq 1$, for all $n$. We can therefore start with the approximation $g_n = \mathcal{O}(1)$. From (1.51) we get

$$n g_n = \sum_{k=0}^{n-1} \frac{\mathcal{O}(1)}{n-k} = \left( \sum_{k=0}^{n-1} \frac{1}{n-k} \right) \mathcal{O}(1) = H_n \mathcal{O}(1) = \mathcal{O}(\log n)$$

and we have the second approximation

$$g_n = \mathcal{O}\left( \frac{\log n}{n} \right), \qquad \text{for } n > 1.$$

After the next step of bootstrapping

$$\begin{aligned}
n g_n &= \tfrac{1}{n} + \sum_{0<k<n} \tfrac{\mathcal{O}((\log k)/k)}{n-k} &&= \tfrac{1}{n} + \sum_{0<k<n} \tfrac{\mathcal{O}(\log n)}{k(n-k)} \\
&= \tfrac{1}{n} + \sum_{0<k<n} \left( \tfrac{1}{k} + \tfrac{1}{n-k} \right) \tfrac{\mathcal{O}(\log n)}{n} &&= \tfrac{1}{n} + \tfrac{2}{n} H_{n-1} \mathcal{O}(\log n) \\
&= \tfrac{1}{n} \mathcal{O}(\log n) \mathcal{O}(\log n) &&= \tfrac{1}{n} \mathcal{O}(\log n)^2,
\end{aligned}$$

and we get the third approximation

$$g_n = \mathcal{O}\left( \frac{\log n}{n} \right)^2.$$

One could continue with bootstrapping but the next step does not lead to an improvement.

**Exercise 1.6.2** *Use the bootstrapping to solve the recurrence*
$u_0 = 1,\ u_n = n + u_{n-1},\ n \geq 1.$

### 1.6.2 Analysis of Divide-and-conquer Algorithms

We present now a general method how to solve recurrences arising from analysis of algorithms and systems that are designed using the divide-and-conquer method. They are recurrences

$$T(n) = aT(\frac{n}{c}) + f(n) \tag{1.52}$$

where for $f(n)$ only an asymptotic estimation is known. The following theorem shows how to determine $T(n)$ for most of the cases.

**Theorem 1.6.3** *Let $T(n) = aT(\frac{n}{c}) + f(n)$ for all sufficiently large $n$ and constants $a \geq 1$, $c > 1$. Let $\frac{n}{c}$ mean here either $\lfloor \frac{n}{c} \rfloor$ or $\lceil \frac{n}{c} \rceil$. Then*

1. *If $f(n) = \mathcal{O}(n^{(\log_c a)-\varepsilon}), \varepsilon > 0,$ then $T(n) = \Theta(n^{\log_c a})$;*
2. *If $f(n) = \Theta(n^{\log_c a}),$ then $T(n) = \Theta(n^{\log_c a} \log n)$;*
3. *If $f(n) = \Omega(n^{(\log_c a)+\varepsilon}), \varepsilon > 0,$ $af(\frac{n}{c}) \leq bf(n)$ for almost all $n$ and some $b > 1$, then $T(n) = \Theta(f(n))$.*

The proof of this "master theorem" for the asymptotic analysis is very technical and it can be found in Cormen, Leiserson and Rivest (1990), pages 62-72. We present here only some remarks concerning the theorem and its applications.

1. It is important to see that one does not have to know $f(n)$ exactly in order to be able to determine $T(n)$ asymptotically exactly. For more complex systems an exact determination of $f(n)$ is practically impossible anyway.

2. From the asymptotical point of view $T(n)$ equals the maximum of $\Theta(f(n))$ and $\Theta(n^{\log_c a})$, unless both terms are equal. In such a case $T(n) = \Theta(n^{\log_c a} \log n)$.

3. In order to apply Case 1 it is necessary that $f(n)$ is not only asymptotically smaller than $n^{\log_c a}$; it must be smaller by a polynomial factor—this is captured by the "$-\varepsilon$" in the exponent. Similarly, in Case 3, $f(n)$ has to be larger by a polynomial factor, again captured by "$+\varepsilon$" in the exponent.

4. Observe that the theorem does not deal with all possible cases for $f(n)$.

**Example 1.6.4** *Consider the recurrence $T(n) = T(\frac{2n}{3}) + 1$. We have $a = 1, c = \frac{3}{2}, n^{\log_c a} = n^0 = 1$. Therefore Case 2 applies and yields $T(n) = \Theta(\log n)$.*

**Example 1.6.5** *Consider the recurrence $T(n) = 3T(\frac{n}{4}) + n \log n$. We have $a = 3, c = 4$, $n^{\log_c a} = \mathcal{O}(n^{0.793})$, and therefore $f(n) = \Omega(n^{\log_4 3+\varepsilon})$, for $\varepsilon = 0.2$. Moreover, $af(\frac{n}{c}) = 3\frac{n}{4}\log(\frac{n}{4}) \leq \frac{3}{4} n \log n$. Therefore, Case 3 of theorem applies and $T(n) = \Theta(n \log n)$.*

**Example 1.6.6 (Integer multiplication)** *Consider the following divide-and-conquer algorithm for an integer multiplication.*

*Let $x$ and $y$ be two $n$-bit integers, where $n$ is even. Then $x = x_1 2^{\frac{n}{2}} + x_2$, $y = y_1 2^{\frac{n}{2}} + y_2$ where $x_1, x_2, y_1, y_2$ are $\frac{n}{2}$-bit integers. Then*

$$xy = x_1 y_1 2^n + (x_1 y_2 + x_2 y_1) 2^{\frac{n}{2}} + x_2 y_2.$$

*This seems to mean that in order to compute $x \cdot y$ one needs to perform four multiplications of $\frac{n}{2}$-bit integers, two additions and two shifts. There is, however, another method for computing $x_1y_1$, $x_1y_2 + x_2y_1$ and $x_2y_2$. We first compute $x_1y_1$, $x_2y_2$, what needs three multiplications, and then*

$$z_1 = (x_1 + x_2)(y_1 + y_2) = x_1y_1 + x_1y_2 + x_2y_1 + x_2y_2$$

*what requires the third multiplication. Finally, we compute $z_1 - x_1y_1 - x_2y_2 = x_1y_2 + x_2y_1$ what requires only two subtractions.*

This means that the problem of multiplication of two $n$-bit integers can be reduced to the problem of three multiplications of $\frac{n}{2}$-bit integers and some additions, subtractions and shifts—what requires an amount of time proportional to $n$. The method can be easily adjusted for the case when $n$ is odd. Since in this algorithm $a = 3$, $c = 2$ we have the Case 1 of Theorem 1.6.3. The algorithm requires therefore time $\Theta(n^{\log_2 3}) = \Theta(n^{1.73})$.

**Example 1.6.7 (MERGESORT)** *Concerning the analysis of the number of comparisons of MERGESORT, Theorem 1.6.3 yields, on the basis of the recurrence (1.14), $T(n) = \Theta(n \lg n)$.*

**Exercise 1.6.8** *Find asymptotic solutions for the following recurrences:*
*(a) $T(n) = 7T(\frac{n}{3}) + n^2$; (b) $T(n) = 7T(\frac{n}{2}) + n^2$; (c) $T(n) = 2T(\frac{n}{4}) + \sqrt{n}$.*

## 1.7 Primes and Congruences

Primes and congruences induced by modulo operation on integers have been playing an important rôle for more than two thousands years in perhaps the oldest mature science—number theory. Nowadays they are the key concepts and tools in many theoretically advanced and also practically important areas of computing, especially in randomized computations, secure communications, and in the analysis of algorithms.

We start with the introduction and analysis of perhaps the oldest algorithm that still plays an important rôle in modern computing and its foundations.

### 1.7.1 Euclid's Algorithm

If $n, m$ are integers, then the **quotient of** $n$ **divided by** $m$ is $\lfloor n/m \rfloor$. For the **remainder** the notation '$n \bmod m$' is used—$m$ is called **modulus**. This motivation lies in the background of the following definition in which $n$ and $m$ are arbitrary integers:

$$n \bmod m = \begin{cases} n - m\lfloor n/m \rfloor, & \text{for } m \neq 0; \\ 0, & \text{otherwise.} \end{cases}$$

For example:

$$7 \bmod 5 = 2, \qquad 7 \bmod -5 = -3;$$
$$-7 \bmod 5 = 3, \qquad -7 \bmod -5 = -2.$$

The basic concepts of divisibility are closely related. We say that an integer $m$ *divides an integer* $n$ (notation $m \setminus n$) if $n/m$ is an integer, i.e.:

$$m \setminus n \Leftrightarrow (n \bmod m = 0). \tag{1.53}$$

A similar relation is '*$n$ is a multiple of $m$*'. Related concepts are those of the **greatest common divisor** of integers $m$ and $n$—$\gcd(m,n)$—and of the **least common multiple** of $m$ and $n$—$\mathrm{lcm}(m,n)$, that are defined for $m+n>0$, $m\geq 0$, $n\geq 0$:

$$\begin{aligned} \gcd(m,n) &= \max\{k \mid k \setminus m \text{ and } k \setminus n\}; & (1.54)\\ lcm(m,n) &= \min\{k \mid k>0, m \setminus k \text{ and } n \setminus k\}. & (1.55)\end{aligned}$$

To compute $\gcd(m,n)$, $0\leq m<n$, we can use the following, more than 2300 years old, algorithm—a recurrence:

**Algorithm 1.7.1 (Euclid's algorithm)** *For $0 \leq m < n$,*

$$\begin{aligned} \gcd(0,n) &= n;\\ \gcd(m,n) &= \gcd(n \bmod m, m), \quad \textit{for} \ \ m>0. \end{aligned}$$

For example, $\gcd(27,36)=\gcd(9,27)=\gcd(0,9)=9$; $gcd(214,352)=gcd(138,214)=gcd(76,138)=gcd(62,76)=gcd(14,62)=gcd(6,14)=gcd(2,6)=gcd(0,3)=3$.

Euclid's algorithm can also be used to compute, given $m\leq n$, integers $n'$ and $m'$ such that

$$m'm + n'n = \gcd(m,n)$$

and this is one of its most important applications. Indeed, if $m=0$, then $m'=0$ and $n'=1$ will do. Otherwise, take $r=n \bmod m$, and compute recursively $r'', m''$ such that $r''r+m''m=\gcd(r,m)$. Since $r=n-\lfloor n/m\rfloor m$ and $\gcd(r,m)=\gcd(m,n)$, we get:

$$r''(n-\lfloor n/m\rfloor m)+m''m=\gcd(m,n)=(m''-r''\lfloor n/m\rfloor)m+r''n.$$

**Example 1.7.2** *For $m=57, n=237$ we have $gcd(57,237)=gcd(9,57)=gcd(3,9)=3$. Thus*

$$\begin{aligned} 237 &= 4\cdot 57+9,\\ 57 &= 6\cdot 9+3, \end{aligned}$$

*and therefore*

$$3 = 57-6\cdot 9 = 57-6\cdot(237-4\cdot 57) = 25\cdot 57-6\cdot 237.$$

If $\gcd(m,n)=1$, we say that the numbers $n$ and $m$ are **relatively prime**—notation $n \perp m$. The above result therefore implies that if $m,n$ are relatively prime, then we can find, using the Euclid's algorithm, an integer denoted by $m^{-1} \bmod n$, and called the **multiplicative inverse** of $m$ modulo $n$, such that $m(m^{-1} \bmod n)\equiv 1 \pmod n$.

**Exercise 1.7.3** *Compute $a, b$ such that $ax+by = gcd(x,y)$ for the following pairs $x, y$: (a)* $(34, 51)$*; (b)* $(315, 53)$*; (c)* $(17, 71)$.

**Exercise 1.7.4** *Compute: (a)* $17^{-1} \bmod 13$*; (b)* $7^{-1} \bmod 19$*; (c)* $37^{-1} \bmod 97$.

### Analysis of the Euclid's Algorithm

Let us now turn to the complexity analysis of the Euclid's algorithm.

In spite of the fact that we have presented a variety of methods for complexity analysis they are far from covering all cases. Complexity analysis of many algorithms requires a specific approach. The Euclid's algorithm is one of them.

The basic recurrence has the form, for $0 < m \leq n$,

$$gcd(m,n) = gcd(n \bmod m, m).$$

This means that after the first recursive step, the new arguments are $(n_1, m)$, with $n_1 = n \bmod m$, and after the second step, the arguments are $(n_1, m_1)$, with $m_1 = m \bmod n_1$. Since $a \bmod b < \frac{a}{2}$, for any $0 < b < a$ (see Exercise 49), we have $m_1 \leq \frac{m}{2}, n_1 \leq \frac{n}{2}$. This means that after two recursion steps of the Euclid's algorithm, both arguments have at most half of the original value. Hence $T(n) = \mathcal{O}(\lg n)$ for the number of steps of the Euclid's algorithm in case $n$ is the largest argument.

This analysis was made more precise by E. Lucas (1884) and Lamé (1884), in perhaps the first deeper analysis of algorithms.

It is easy to see that if $F_n$ is the $n$-th Fibonacci number, then after the first recursive step with arguments $(F_n, F_{n-1})$ we get arguments $(F_{n-1}, F_{n-2})$. This implies that for arguments $(F_n, F_{n-1})$ the Euclid's algorithm performs $n-2$ recursive steps.

There were established even deeper relations between Euclid's algorithm and Fibonacci numbers. They are summarized in the following theorem. The first part of the theorem is easy to prove by induction using the fact that if $m \geq F_{k+1}, n \bmod m \geq F_k$, then $n \geq m + (n \bmod m) \geq F_{k+1} + F_k = F_{k+2}$. The second part of theorem follows from the first part.

**Theorem 1.7.5** *(1) If $n > m \geq 0$, and the application of Euclid's algorithm to arguments $n, m$ results in $k$ recursive steps, then $n \geq F_{k+2}, m \geq F_{k+1}$.*

*(2) If $n > m \geq 0, m < F_{k+1}$, then the application of Euclid's algorithm to the arguments $n, m$ requires less than $k$ recursive steps.*

**Remark 1.7.6** It is natural to ask whether the Euclid's algorithm is the fastest way to compute the greatest common divisor. This problem was open till 1989 and it is discussed in more detail in Section 4.2.4.

### 1.7.2 Primes

A positive integer $p > 1$ is called **prime** if it has just two divisors: 1 and $p$; otherwise it is called **composite**. The first 25 primes are the following ones:

$$2, 3, 5, 7, 11, 13, 17, 19, 23, 29, 31, 37, 41, 43, 47, 53, 59, 61, 67, 71, 73, 79, 83, 89, 97.$$

Primes play a central rôle among integers and also in computing. This will be demonstrated especially in the chapter on cryptography. The following easy to show theorem is the first reason for that.

**Theorem 1.7.7 (Fundamental theorem of arithmetic)** *Each integer $n$ has a unique prime decomposition in the form $n = \prod_{i=1}^{k} p_i^{e_i}$, where $p_i < p_{i+1}, i = 1, \dots, k-1$, are primes and $e_i$ are integers.*

There exist infinitely many primes. This can be deduced easily from the observation that if we take primes $p_1, \dots, p_k$, none of them divides $p_1 \cdot p_2 \cdot \dots \cdot p_k + 1$. There are even infinitely many primes of special forms. For example

**Theorem 1.7.8** *There exist infinitely many primes of the form $4k + 3$.*

**Proof.** Suppose there exist only finitely many primes $p_1, p_2, \dots, p_s$ of the form $4k + 3$, i.e., $p_i \bmod 4 = 3$, $1 \le i \le s$, and take $N = 4 \cdot p_1 \cdot p_2 \cdot \dots \cdot p_s - 1$. Clearly, $N \bmod 4 = 3$. Since $N > p_i, 1 \le i \le s$, $N$ can not be a prime of the form $4k + 3$ and cannot be divided by a prime of such a form. Moreover, since $N$ is odd, $N$ is also not divisible by a number of the type $4k + 2$ or $4k$. Hence $N$ has to be a product of primes of the type $4k + 1$. However, this is also impossible. Indeed, $(4k+1)(4l+1) = 4(kl+k+l)+1$, for any integers $k, l$, and therefore any product of primes of the form $4k + 1$ is again a number of such a form—but $N$ is of the form $4k + 3$. This way we have ruled out all possibilities for $N$, and therefore our assumption, namely that the number of primes of the form $4k + 3$ is finite, has to be wrong. $\square$

Discovery of as large primes as possible is an old problem. All primes up to $10^7$ were computed already in 1909. The largest discovered prime at the time this book went to print is due to D. Slowinski and Gage in 1994, using computer Cray: $2^{859433} - 1$ and has 258 716 digits.[6]

[6]Finding as large primes as possible is an old and big challenge for both scientists and technology. The first recorded method is the "sieve method" of Eratosthenes of Cyrene (284-202 BC). Fibonacci (around 1200) improved the method by observing that sieving can be stopped when the square root of the number to be tested is reached. This was the fastest general method up to 1974, when R. S. Lehman showed that primality testing of an integer $n$ can be done in $\mathcal{O}(n^{\frac{1}{3}})$ time.

The previous "world records" were $2^{756839} - 1$ (1992) and $2^{216091} - 1$ (1985)—all due to D. Slowinski. The largest prime from the pre-computer era was $2^{127} - 1$ (1876). This record lasted 76 years. Next world records were from 1952: $2^{521} - 1$, $2^{607} - 1$, $2^{1279} - 1$, $2^{2203} - 1$, $2^{2281} - 1$. All known very large primes have the form $2^p - 1$, where $p$ is a prime; they are called Mersenne primes. It is certainly a challenge to find new very large Mersenne primes; especially because all numbers smaller as $2^{350000}$ and also in the range $2^{430000} - 2^{520000}$ have already been checked for primality, and it is not known whether there are infinitely many Mersenne primes.

Another important question is how many primes are among the first $n$positive integers; for this number the notation $\pi(n)$ is used. The basic estimation $\pi(n) = \Theta(\frac{n}{\ln n})$ was guessed already by Gauss[7] at the age of 15. Better estimations are

$$\frac{n}{\ln n} < \pi(n) \leq \frac{5}{4}\frac{n}{\ln n}, \qquad \text{for } n \geq 114$$

and

$$\pi(n) = \frac{n}{\ln n} + \frac{n}{(\ln n)^2} + \frac{2!n}{(\ln n)^3} + \frac{3!n}{(\ln n)^4} + \frac{4!n}{(\ln n)^5} + \Theta\left(\frac{n}{(\ln n)^6}\right). \tag{1.56}$$

Additional information about distribution of primes is given in the following theorem in which $\phi$ is the so-called **Euler's phi function**; $\phi(n)$ is the number of positive integers smaller than $n$ that are relatively prime to $n$—for example $\phi(p) = p - 1$ and $\phi(pq) = (p-1)(q-1)$ if $p, q$ are primes.

**Theorem 1.7.9** *(Prime Number Theorem)*[8] *If $gcd(b, c) = 1$, then for the number $\pi_{b,c}(n)$ of primes of the form $bk + c$ we have:*

$$\pi_{b,c}(n) \sim \frac{1}{\phi(b)}\frac{n}{\ln n}.$$

The following table shows how good is the estimation $\pi(n) = n/\ln n$.

| n | $10^4$ | $10^7$ | $10^{10}$ |
|---|---|---|---|
| $\pi(n)$ | $1,229$ | $664,579$ | $455,052,511$ |
| $n/\ln n$ | $1,089$ | $621,118$ | $434,782,650$ |
| $\pi(n)/(n/\ln n)$ | 1.128 | 1.070 | 1.046 |

The largest computed value of $\pi(x)$ is $\pi(10^{18}) = 24,739,954,287,740,860$ by Deliglise and Rivat in 1994.

We deal with the problem how to determine whether a given integer is prime in Section 5.5.2 and with the problem of finding large primes in Section 8.3.4. The importance of primes in cryptography is due to the fact that we can find efficiently large primes, but we are not able to factorize efficiently large products of primes. Moreover, some important computations can be done in polynomial time if an argument is prime but seem to be unfeasible if this argument is an arbitrary integer.

[7]Karl Frederic Gauss (1752-1833)—a German mathematician, physicist, and astronomer considered as the greatest mathematician of his time, made fundamental contributions in algebra, number theory, complex variable, differential geometry, approximation theory, calculation of orbits of planets and comets, electro- and geomagnetism. Gauss developed foundations for absolute metric system and with W. Weber, invented electrical telegraph.

[8]The term "Prime Number Theorem" is used also for the Gauss estimation for $\pi(n)$ or for the estimation (1.56).

**Exercise 1.7.10** *Show that if $n$ is composite, then so is $2^n - 1$.*

**Exercise 1.7.11** ** *Show that there exist infinitely many primes of the type $6k+5$.*

### 1.7.3 Congruence Arithmetic

The modulo operation and the corresponding congruence relation

$$a \equiv b \pmod{m} \Leftrightarrow a \bmod m = b \bmod m \tag{1.57}$$

defined for arbitrary integers $a, b$ and $m > 0$, play an important rôle in producing (pseudo-)randomness and in randomized computations and communications. We read '$a \equiv b \pmod{m}$' as '$a$ **is congruent to** $b$ **modulo** $m$'. From (1.57) we also get that $a \equiv b \pmod{m}$ if and only if $a - b$ is a multiple of $m$. This congruence defines an equivalence relation on $\mathbf{Z}$ and its equivalence classes are called **residue classes modulo $n$**. $\mathbf{Z}_n$ is used to denote the set of all such residue classes and $\mathbf{Z}_n^*$ its subset consisting of those classes elements of which are relatively prime to $n$.

The following properties of congruence can be verified using the definition (1.57):

$$\begin{aligned}
a \equiv b \text{ and } c \equiv d \pmod{m} &\Rightarrow a + c \equiv b + d \pmod{m}; && (1.58)\\
a \equiv b \text{ and } c \equiv d \pmod{m} &\Rightarrow a - c \equiv b - d \pmod{m}; && (1.59)\\
a \equiv b \text{ and } c \equiv d \pmod{m} &\Rightarrow ac \equiv bd \pmod{m}; && (1.60)\\
ad \equiv bd \pmod{m} &\Leftrightarrow a \equiv b \pmod{m} \text{ for } d \perp m; && (1.61)\\
ad \equiv bd \pmod{md} &\Leftrightarrow a \equiv b \pmod{m} \text{ for } d \neq 0; && (1.62)\\
a \equiv b \pmod{mn} &\Leftrightarrow a \equiv b \pmod{m} \text{ and } a \equiv b \pmod{n} \text{ if } m \perp n. && (1.63)
\end{aligned}$$

The property (1.63) can be used to simplify the computation of congruences as follows: If $\prod_{i=1}^{k} p_i^{e_i}$ is the prime decomposition of $m$, then

$$a \equiv b \pmod{m} \Leftrightarrow a \equiv b \pmod{p_i^{e_i}}, \text{ for } 1 \leq i \leq k. \tag{1.64}$$

Congruences modulo powers of primes are therefore building blocks for all congruences modulo integers.

**Exercise 1.7.12** *Show that* $((a \bmod n)(b \bmod n) \bmod n) = ab \bmod n$, *for any integers $a$, $b$, $r$.*

**Exercise 1.7.13** *Show:* $2^{xy^2} \bmod (2^{xy} - x) = x^y$.

One of the main use of the modulo operation in randomization is related to the fact that solving "nonlinear" congruence equations is in general computationally intractable task.

On the other hand the linear congruence equations

$$cx \equiv d \pmod{m}$$

are easy to deal with. Indeed, we have

**Theorem 1.7.14** *A linear congruence $cx \equiv d \pmod{m}$ has a solution if and only if $d$ is a multiple of $gcd(c, m)$. In this case, the equation has exactly $k = gcd(c, m)$ distinct integer solutions*

$$x_0\frac{d}{k}, x_0\frac{d}{k} + \frac{m}{k}, \ldots, x_0\frac{d}{k} + (k-1)\frac{m}{k},$$

*in the interval $(0, m)$, where $x_0$ is the unique integer solution of the equation $cx + ym = gcd(c, m)$—that can be found using the Euclid's algorithm.*

The proof is easy once we realize that the problem to solve the equation $cx \equiv d \pmod{m}$ is equivalent to the one to find integer solutions of the equation $cx + ym = d$.

Another useful fact is that if $cx \equiv d \pmod{m}$, then also $c(x + m) \equiv d \pmod{m}$.

**Example 1.7.15** *For the congruence $27x \equiv 1 \pmod{47}$ we have $gcd(27, 47) = 1$ and $7 \cdot 27 - 4 \cdot 47 = 1$. Hence $x = 7$ is the unique solution.*

**Example 1.7.16** *For the congruence $51x \equiv 9 \pmod{69}$ we have $gcd(51, 69) = 3$ and $-4 \cdot 51 + 3 \cdot 69 = 3$. Hence $x = -12, 11, 34$ or, expressed using only positive integers,*

$$x = 11, 34, 57.$$

**Exercise 1.7.17** *Solve the linear congruence equations: (a) $4x \equiv 5 \bmod 9$; (b) $2x \equiv 17 \bmod 19$.*

There is also an old method to solve special systems of linear congruences. The following result, easy to verify, has been attributed to Sun Tsŭ from China—around 350 AD.

**Theorem 1.7.18 (Chinese Remainder Theorem)** *Let $m_1, ..., m_t$ be integers, $m_i \perp m_j$ for $i \neq j$, and $a_1, \ldots, a_t$ be integers with $0 < a_i < m_i$. Then the system of congruences*

$$x \equiv a_i \pmod{m_i}, \quad \textit{for } i = 1, ..., t,$$

*possesses the solution (what is straightforward to verify),*

$$x = \sum_{i=1}^{t} a_i M_i N_i, \tag{1.65}$$

*where $M = \prod_{i=1}^{t} m_i, M_i = M/m_i$ and $N_i = M_i^{-1} \bmod m_i, 1 \leq i \leq t$. Moreover, the solution (1.65) is unique up to the congruence modulo $M$, i.e., $z \equiv x \pmod{M}$ for any other solution $z$.*

The Chinese Remainder Theorem has numerous applications. One of them is the following modular representation of integers:

Let $m_1, ..., m_n$ be pairwise relatively prime and $M$ their product. It follows from Theorem 1.7.18 that each integer $0 \leq x < M$ is uniquely represented by the $n$-tuple

$$(x \bmod m_1, \ldots, x \bmod m_n).$$

For example, if $m_1 = 2, m_2 = 3, m_3 = 5$, then $(1,0,2)$ represents 27. Such a modular representation of integers may look artificial. However, it has its advantages because it allows parallel, component-wise, performance of basic arithmetic operations.

**Exercise 1.7.19** *(a) Find modular representations of integers* $7, 13, 20, 6$ *and* $91$ *with respect to the 4-tuple of integers* $(2, 5, 11, 19)$*;*

*(b) Show that if* $(x_1, \ldots, x_n)$ *is a modular representation of the integer* $x$ *and* $(y_1, \ldots, y_n)$ *of the number* $y$*, both with respect to pairwise primes* $(m_1, \ldots, m_n)$*, and* $\circ$ *is one of the operations: addition, subtraction or multiplication, then*

$$((x_1 \circ y_1) \bmod m_1, \ldots, (x_n \circ y_n) \bmod m_n)$$

*represents the number* $x \circ y$*—provided this number is smaller than* $m$*.*

In cryptographical applications one often needs to compute **modular exponentiation** $a^b \bmod n$, where $a, b$ and $n$ can be very large; $n$ may have between 512 and 1024 bits and $a$ has also about that number of bits. Moreover, $b$ can have easily several hundred of bits. In such a case $a^b$ would have more than $10^{30}$ bits. To compute such numbers seems to be difficult. Fortunately, congruences have various properties that allow to simplify computation of modular exponentiations essentially. For example,

$$a^2 \equiv (a \bmod n)^2 \pmod n$$

for any $a$ and $b$. This allows, together with the exponentiation Algorithm 1.1.14, to compute $a^b \bmod n$ in such a way that one has never to work with numbers that have more than twice more bits than numbers $a, b, n$. For example

$$a^8 \bmod n \equiv (((a \bmod n)^2 \bmod n)^2 \bmod n)^2 \bmod n.$$

Efficient modular exponentiation is also in the heart of the efficient primality testing as shown in Section 5.5.2. To simplify modular exponentiation one can also use the following theorem and its subsequent generalization. Both of these results play an important rôle also in cryptography:

**Theorem 1.7.20 (Fermat's[9] Little Theorem—1640)** *If* $p$ *is a prime,* $n \in \mathbf{N}^+$*,* $a \in \mathbf{N}$*, then*

$$a^p \equiv a \pmod p \tag{1.66}$$

*and if $a$ is not divisible by $p$, then*

$$a^{p-1} \equiv 1 \pmod{p}. \tag{1.67}$$

**Proof.** It is true for $a = 1$. Assuming that it is true for $a$, then by induction $(a+1)^p \equiv a^p + 1 \equiv a + 1 \pmod{p}$, because $\binom{p}{k} \equiv 0 \pmod{p}$ for $0 < k < p$. So Theorem 1.7.20 holds for all $a \in \mathbf{N}$. □

A more general version of this theorem, that needs quite a different proof, the so-called **Euler's Totient Theorem**, has the form

$$n^{\phi(m)} \equiv 1 \pmod{m} \text{ if } n \perp m. \tag{1.68}$$

**Example 1.7.21** *In order to compute* $3^{1000} \bmod 19$ *we can use the fact that by Fermat's Little Theorem,* $3^{18} \equiv 1 \bmod 19$. *Since* $1000 = 18 \cdot 55 + 10$, *we get*

$$3^{1000} = 3^{18 \cdot 55 + 10} = (3^{18})^{55}(3^5)^2 \equiv (3^5 \bmod 19)^2 \equiv (15)^2 \equiv 225 \equiv 16 \pmod{19}.$$

**Exercise 1.7.22** *Compute: (a)* $2^{340} \bmod 11$*; (b)* $3^{100} \bmod 79$*; (c)* $5^{10000} \bmod 13$.

**Exercise 1.7.23** *Show that* $\sum_{i=1}^{p-1} i^{p-1} \equiv -1 \pmod{p}$.

## 1.8 Discrete Square Roots and Logarithms*

In these section we deal with two interesting and computationally intriguing problems of large importance especially for modern cryptography.

### 1.8.1 Discrete Square Roots

The problem of solving quadratic congruence equations

$$x^2 \equiv a \pmod{m}$$

or, in other words, computing "discrete" square roots modulo $m$, is intriguing and of importance for various applications.

For an integer $m$ denote

$$\begin{aligned}
\mathbf{Z}_m &= \{0, 1, \ldots, m-1\} \\
\mathbf{Z}_m^* &= \{a \mid a \in \mathbf{Z}_m, gcd(a, m) = 1\}
\end{aligned}$$

and let their elements to denote the corresponding residue classes. Observe that $\mathbf{Z}_n^*$ has $\phi(n)$ elements.

**Example 1.8.1** $\mathbf{Z}^*_{10} = \{1,3,7,9\}, \mathbf{Z}^*_{11} = \{1,2,3,4,5,6,7,8,9,10\}$.

An integer $x \in \mathbf{Z}^*_m$ is called a **quadratic residue modulo** $m$ if $x \equiv y^2 \pmod m$ for some $y \in \mathbf{Z}^*_m$; otherwise $x$ is called a **quadratic nonresidue modulo** $m$. Notation:

$$\begin{array}{rcl} QR_m & — & \text{the set of all quadratic residues modulo } m, \\ QNR_m & — & \text{the set of all quadratic nonresidues modulo } m. \end{array}$$

**Exercise 1.8.2** *Show that if $p$ is prime, then each quadratic residue modulo $p$ has exactly two distinct square roots.*

**Exercise 1.8.3** **Explain why exactly half of the numbers $1,\dots,p-1$ are quadratic residues modulo $p$.*

**Exercise 1.8.4** ** Find all square roots of 64 modulo 105.*

To deal with quadratic residues it is useful to use the following notation defined for any integer $m$ and $x \in \mathbf{Z}^*_m$:

$$(x|m) = \begin{cases} 1, & \text{if } x \in QR_m \quad \text{and } m \text{ is a prime;} \\ -1, & \text{if } x \in QNR_m \quad \text{and } m \text{ is a prime;} \\ \prod_{i=1}^n (x|p_i), & \text{if } m = \prod_{i=1}^n p_i, x \perp m \text{ and } p_i \text{ are primes.} \end{cases}$$

$(x|m)$ is called **Legendre symbol** if $m$ is prime and **Legendre-Jacobi**[10] **symbol** if $m$ is composite. It is easy to determine whether an $x \in \mathbf{Z}^*_m$ is a quadratic residue modulo $m$ if $m$ is a prime—one needs only to compute $(x|m)$. This can be done in $\mathcal{O}(\lg m)$ time using the following identities:

**Theorem 1.8.5** *Let $x, y \in \mathbf{Z}^*_m$.*

1. [11] $x^{(p-1)/2} \equiv (x|p) \pmod p$ *for any prime $p > 2$ and $x \in Z^*_p$.*
2. *If $x \equiv y \pmod m$, then $(x|m) = (y|m)$.*
3. $(x|m) \cdot (y|m) = (x \cdot y|m)$.
4. $(-1|m) = (-1)^{(m-1)/2}$, *if $m$ is odd.*
5. $(2|m) = (-1)^{(m^2-1)/8}$, *if $m$ is odd.*
6. [12] *If $m \perp n$ and $m, n$ are odd, then $(n|m)(m|n) = (-1)^{(m-1)(n-1)/4}$.*

[10] Adrien Marie Legendre (1752-1833)—a French mathematician; Carl Gustav Jacobi (1804-1851)—a German mathematician.

[11] This claim is also called the Euler's criterion.

[12] This assertion, due to F. L. Gauss, is known as the Law of Quadratic Reciprocity. It plays an important rôle in number theory and, by Gesternhaber (1963), at least 152 different proofs of this "law" are known.

**Example 1.8.6**

$$\begin{aligned}(28|97) &= (2|97)\cdot(2|97)\cdot(7|97) = (7|97)\\ &= (97|7)\cdot(-1)^{(97-1)(7-1)/4} = (6|7)\\ &= (2|7)\cdot(3|7) = (-1)^6(3|7) = (7|3)\cdot(-1)^3\\ &= -(1|3) = -1.\end{aligned}$$

**Exercise 1.8.7** *Compute: (a)* $(32|57)$*; (b)* $(132|37)$*; (c)* $(47,53)$*; (d)* $(3|p)$*, where* $p$ *is prime.*

It is straightforward to see from the Euleur's criterion in Theorem 1.8.5 that if $p$ is a prime of the form $4k+3$ and $x \in QR_p$, then $\pm x^{(p+1)/4} \bmod p$ are two square roots of $x$ modulo $p$. For such a $p$ and $x$, one can therefore efficiently compute square roots. On the other hand no efficient deterministic algorithm for computing square roots is known when $p$ is a prime of the form $4k+1$. However, we show now that even in such a case there is an efficient randomized algorithm to do that.

Informally, an algorithm is called random if its behaviour is determined not only by the input but also by the values produced by a random number generator. For example, if in a computation step a number is randomly choosen (or produced by a random number generator). Informally again, an algorithm is called polynomial time algorithm if it can be realised on a typical sequential computer in such a way that time of computation grows polynomially, with respect to the size of the input data.

The concepts of "a randomized algorithm" and a "polynomial time" algorithm belong to the most basic ones investigated in foundation of computing and one of the main outcomes is, as we shall see later, that these two concepts are very robust and practically independent for from the choice of a computer model or a source of randomness. This also justifies that we can start to use them now on the base of the above informal description. A formal description provided later will be necessary once we try to show properties of these concepts or even non-existence of such algorithms for some problems.

**Theorem 1.8.8 (Adleman-Manders-Miller's Theorem)** *There exists a randomized polynomial time algorithm to compute the square root of a modulo p, where* $a \in QR_p$*, and* $p$ *is a prime.*

**Proof.** Let us consider a decomposition $p-1 = 2^e P$, where $P$ is odd. Choose randomly[13] $b \in QNR_p$ and let us define the sequence $a_1, a_2, \ldots$ of elements from $QR_p$ and of integers $e \geq k_1 > k_2 > \ldots > k_i > \ldots$ inductively as follows:

- $a_1 = a$;
- $k_i =$ the smallest $k \geq 0$ such that $a_i^{2^k P} \equiv 1 \pmod p$, for $i \geq 1$;

[13] This means one chooses randomly $b \in \mathbf{Z}_p$ and verifies whether $b \in QR_p$. If not, one chooses another $b$ until a $b \in QNR_p$ is found. Due to Exercise 1.8.3, this can be done with high probability efficiently.

- $a_i = a_{i-1}b^{2^{e-k_{i-1}}} \bmod p$, for $i > 1$.

We show now that $k_i < k_{i-1}$ for all $i > 1$. In doing so we make use of the minimality of $k_i$ and of the fact that $b^{2^{e-1}P} = b^{(p-1)/2} \equiv (b|p) \equiv -1 \pmod p$, by (6) of Theorem 1.8.5. Since

$$a_i^{2^{k_{i-1}-1}P} \equiv (a_{i-1}b^{2^{e-k_{i-1}}})^{2^{k_{i-1}-1}P} \equiv a_{i-1}^{2^{k_{i-1}-1}P}b^{2^{e-1}P} \equiv (-1)(-1) \equiv 1 \pmod p,$$

$k_i$ has to be smaller than $k_{i-1}$. Therefore there has to exist an $n < e$ such that $k_n = 0$. For such an $n$ we have $a_n^{p+1} \equiv a_n \bmod p$, what implies that $a_n^{(p+1)/2}$ is a square root of $a_n$.

Let us now define, by the reverse induction, the sequence $r_n, r_{n-1}, \ldots, r_1$ as follows:

- $r_n = a^{(P+1)/2} \bmod p$,
- $r_i = r_{i+1}(b^{2^{e-k_i-1}})^{-1} \bmod p$, for $i < n$.

It is easy to verify that $a_i = r_i^2 \bmod p$ and therefore $a = r_1^2 \bmod p$.

Clearly, $n < \lg p$ and therefore the algorithm requires polynomial time in length of $p$ and $a$—plus time to choose randomly a $b$ such that $(b|p) = -1$. □

There is a conceptually much simpler algorithm to compute square roots. However, it requires to work with congruences on polynomials and to apply Euclid's algorithm also to find the greatest common divisor of two polynomials—what can be done in quite a natural way. In other words a little bit more sophisticated mathematics has to be used.

Suppose that $a$ is a quadratic residue in $\mathbf{Z}_p^*$ and we want to find its square roots. Observe first that the problem of finding an $x$ such that $x^2 \equiv a \pmod p$ is equivalent to the problem, for an arbitrary $c \in \mathbf{Z}_p^*$, to find an $x$ such that $(x-c)^2 \equiv a \pmod p$—in order to solve the original problem only a shift of roots is required. Suppose now that $(x-c)^2 - a \equiv (x-r)(x-s) \pmod p$. In such a case $rs \equiv c^2 - a \pmod p$ and, by (2) in Theorem 1.8.5, $((c^2-a)|p) = (r|p)(s|p)$. So if $((c^2-a)|p) = -1$, then one of $r$ and $s$ is a quadratic residue. On the other hand, it follows from (Euler's criterion) of Theorem 1.8.5, that all quadratic residues in $\mathbf{Z}_p^*$ are roots of the polynomial $x^{(p-1)/2} - 1$. This implies that the greatest common divisor of the polynomials $(x-c)^2 - a$ and $x^{(p-1)/2} - 1$ is the first degree polynomial whose root is that root of $(x-c)^2 - a$ which is the quadratic residue. This leads to our second randomized algorithm.

**Algorithm 1.8.9**

- *Choose randomly* $c \in \mathbf{Z}_p^*$.
- *If* $((c^2-a)|p) = -1$, *then compute* $gcd(x^{(p-1)/2} - 1, (x-c)^2 - a) = \alpha x - \beta$.
- *Output* $\pm(c + \alpha^{-1}\beta)$ *as the square root of* $a$ *modulo* $p$.

The efficiency of the algorithm is based on the following fundamental result from the number theory: if $a$ is a quadratic residue from $\mathbf{Z}_p^*$ and $c$ is chosen randomly from $\mathbf{Z}_p^*$, then with the probability larger than $\frac{1}{2}$ we have $((c^2-a)|p) = -1$.

Another important fact is that there is an effective way to compute square roots modulo $n$ even in the case $n$ is composite—if prime factors of $n$ are known.

**Theorem 1.8.10** *If $p, q > 2$ are primes, then $x \in QR_{pq} \Leftrightarrow x \in QR_p \wedge x \in QR_q$. Moreover, there is a polynomial time algorithm which, given as inputs $x, u, v, p, q$ such that $x \equiv u^2 \bmod p$, $x \equiv v^2 \bmod q$, computes $w$ such that $x \equiv w^2 \bmod pq$.*

**Proof.** The first claim follows directly from (3) of Theorem 1.8.5. To prove the rest of the theorem, let us assume that $x, u, y, v, p$ and $q$ satisfy the hypothesis. Using Euclid's algorithm we can compute $a, b$ such that $ap + bq = 1$. If we now denote $c = bq = 1 - ap$ and $d = ap = 1 - bq$, then

$$c \equiv 0 \bmod q, \quad d \equiv 0 \bmod p, \quad c \equiv 1 \bmod p, \quad d \equiv 1 \bmod q. \tag{1.69}$$

This will now be used to show that for $w = cu + dv$ we have $x = w^2 \bmod pq$. In order to do that it is enough, due to the first part of the theorem, to prove that $x = w^2 \bmod p$ and $x = w^2 \bmod q$. We do that only for $p$; the other case can be treated similarly. By (1.69)

$$w^2 = (cu + dv)^2 = c^2u^2 + 2cduv + d^2v^2 \equiv u^2 \equiv x \pmod p.$$

□

On the other hand, no effective algorithm is known, given an integer $n$ and an $a \in QR_n$, to compute a square root of $a$ modulo $n$. As shown in Theorem 1.8.15, this problem is as difficult as the problem of factorization of integers—the problem on intractability of which many modern cryptographical techniques are based—see Chapters 8 and 9.

Before presenting the next theorem let us look deeper into the problem of finding square roots modulo a composite integer $n$.

**Lemma 1.8.11** *Any quadratic residue $a \in QR_n$, $n = pq$, $p$ and $q$ are odd primes, has four square roots modulo $n$.*

**Proof.** Let $a \in QR_n$ and $a \equiv a_1^2 \pmod n$. By Chinese Remainder Theorem there are integers $u, v$ such that

$$u \equiv a_1 \bmod p, \qquad u \equiv -a_1 \bmod q;$$

$$v \equiv a_1 \bmod q, \qquad v \equiv -a_1 \bmod p.$$

Since $p, q$ are odd, $u, v, a_1$ and $-a_1$ have to be distinct. Moreover, $u^2 \equiv v^2 \equiv_1^2 \bmod pq$ and therefore $u, v, a_1, -a_1$ are four distinct square roots of $a$. □

**Exercise 1.8.12** * *Find all four solutions of congruences: (a) $x^2 \equiv 25 \pmod{33}$;*
*(b) $x^2 \equiv 11 \pmod p$.*

**Exercise 1.8.13** *Determine in general the number of square roots modulo $n$ for an $a \in QR_n$.*

Of a special interest is the case when $n = pq$ and $p \equiv q \equiv 3 \pmod 4$—such integers are called **Blum integers**. In such a case by Theorem 1.8.5:

$$(-x|n) = (-x|p)(-x|q) = (x|p)(-1)^{(p-1)/2}(x|q)(-1)^{(q-1)/2} = (x|p)(x|q) = (x|n).$$

Moreover, it holds

**Theorem 1.8.14** *(1) If $x^2 \equiv y^2 \bmod n$ and $x, y, -x, -y$ are distinct modulo $n$, then $(x|n) = -(y|n)$.*

*(2) If $n = pq$ is a Blum integer, then the mapping*

$$x \to x^2 \bmod n$$

*is a permutation on $QR_n$. In other words, each quadratic residue has a unique square root that is also a quadratic residue and it is called its* **principal square root.**

**Proof.** (1) Since $pq$ divides $(x^2 - y^2) = (x+y)(x-y)$ and $x, y, -x, -y$ are distinct modulo $n$, neither $x+y$ nor $x-y$ can be divided by both $p$ and $q$. Without loss of generality assume that $p$ divides $(x-y)$ and $q$ divides $(x+y)$; the other case can be dealt with similarly. Then $x \equiv y \bmod p, x \equiv -y \bmod q$ and therefore $(x|p) = (y|p), (x|q) = -(y|q)$. Thus $(x|n) = -(y|n)$.

(2) Let $a$ be any quadratic residue modulo $n$. By Lemma 1.8.11, $a$ has exactly 4 roots; say $x, -x, y, -y$. By (1) $(x|n) = -(y|n)$. Let $x$ be such a square root that $(x|p) = 1$. Then either $(x|p) = (x|q) = 1$ or $(-x|p) = (-x|q) = 1$. Hence either $x$ or $-x$ is a quadratic residue modulo $n$. ☐

For Blum integers two key algorithmic problems of modern cryptography are computationally equivalent, with respect to the existence of polynomial time randomized algorithm.

**Theorem 1.8.15 (Rabin's Theorem)** *The following statements are equivalent:*

*(1) There is a polynomial time randomized algorithm to factor Blum integers.*

*(2) There is a polynomial time randomized algorithm to compute the principal square root for $x \in QR_n$, if $n$ is a Blum integer.*

**Proof.** (1) Assume that a polynomial time randomizd algorithm $\mathcal{A}$ to compute square roots modulo Blum integers is given. A Blum integer $n$ can be factored as follows: :

1. Chose a random $y$ such that $(y|n) = -1$.
2. Compute $x \equiv y^2 \bmod n$.
3. Find, using $\mathcal{A}$, an $z \in QR_n$ such that $x \equiv z^2 \bmod n$.

We show now that $gcd(y+z, n)$ is a prime factor of $n$. Clearly, $pq$ divides $(y-z)(y+z)$. Since $(-z|n) = (-1|n)(z|n) = (-1)^{\frac{p-1}{2}}(-1)^{\frac{q-1}{2}}(z|n) = 1$, we have $y \not\equiv -z \bmod n$ and therefore $gcd(y+z, n)$ has to be one of the prime factors of $n$.

(2) Assume now that we can efficiently factor $n$ to get $p, q$ such that $n = pq$. We show now how to compute principal square roots modulo $n$. Let $x \in QR_n$

- Using the Adleman-Menders-Miller's algorithm compute $u \in QR_p$ and $v \in QR_q$ such that $x \equiv u^2 \bmod p, x \equiv v^2 \bmod q$.

- Using the Euclid's algorithm compute $a, b$ such that $ap + bq = 1$.

- Compute $c = bq, d = ap$.

We show now that $w = cu + dv$ is in $QR_n$ and it is a square root of $a$. Indeed, since $c \equiv 1 \bmod p$ and $d \equiv 1 \bmod q$, we have $w^2 \equiv u^2 \equiv x \bmod p, w^2 \equiv v^2 \equiv x \bmod q$, and by (1.63), $w^2 \equiv x \bmod n$. To show that $w \in QR_n$ we proceed as follows:

Since $c \equiv 0 \bmod q, d \equiv 0 \bmod p$, we get $(w|p) = (u|p) = 1, (w|q) = (v,q) = 1$ and therefore $(w|pq) = (w|p)(w|q) = 1$. □

### 1.8.2 Discrete Logarithm Problem

It is the problem to determine, given integers $a, n, x$, an integer $m$ such that $a^m \equiv x \bmod n$—if such an $m$ exists.

It may happen that there are two such $m$—for example, $m = 10$ and $m = 4$ for the equation $5^x \equiv 16 \bmod 21$; or none, for example, for the equation $5^x \equiv 3 \bmod 21$. An important case is when $g$ is a **generator** or a **principal root** of $\mathbf{Z}_n^*$, that is if

$$\mathbf{Z}_n^* = \{g^i \bmod n \mid 0 \leq i \leq \phi(n)\}.$$

In such a case to any $x \in \mathbf{Z}_n^*$ there is a unique $m < \phi(n)$ such that $x \equiv g^m \bmod n$. Such an $m$ is called the **discrete logarithm** or **index** of $x$ with respect to $n$ and $g$; in short $index_{n,g}(x)$.

If $\mathbf{Z}_n^*$ has a principal root, then it is called cyclic. It has been known already to F. L. Gauss that $\mathbf{Z}_n^*$ is cyclic if and only if $n$ is one of the numbers $2, 4, p^i, 2p^i$, where $p > 2$ is a prime and $i$ is a positive integer.

**Example 1.8.16** *The table of indices, or discrete logarithms for $\mathbf{Z}_{13}^*$ and the generator 2:*

| $x$ | *1* | *2* | *3* | *4* | *5* | *6* | *7* | *8* | *9* | *10* | *11* | *12* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *2* | *0* | *1* | *4* | *2* | *9* | *5* | *11* | *3* | *8* | *10* | *7* | *6* |

There is no efficient deterministic algorithm known to compute, given $a$, $n$ and $x$, the discrete logarithm $m$ such that $a^m \equiv x \bmod n$. This fact plays an important rôle in cryptography and its applications and also for (perfect) random number generators—see next section. An exception is the case that $p$ is a prime and factors of $p - 1$ are small—of the order $\mathcal{O}(\log p)$.[14]

[14] In the general case of a prime $p$ the fastest algorithm, due to Adleman (1980), runs in time $\Theta(2^{\sqrt{\lg p \lg \lg p}})$. However, there is a polynomial time randomized algorithm for (potential) quantum computer to compute the discrete logarithm due to Shor (1994).

**Exercise 1.8.17** *Find all principal roots in* $\mathbf{Z}_{11}^*$ *and compute all discrete logarithms of elements in* $\mathbf{Z}_{11}^*$, *with respect to these principal roots.*

**Exercise 1.8.18** * *Let $g$ be a principal root modulo the prime $p > 2$. Show that for all $a, b \in \mathbf{Z}_p^*$: (a)* $index_{p,g}(ab) \equiv index_{p,g}(a) + index_{p,g}(b) \pmod{p-1}$; *(b)* $index_{p,g}(a^n) \equiv n \cdot index_{p,g}(a) \pmod{p-1}$.

## 1.9 Probability and Randomness

In the design of algorithms, communication protocols or even networks, an increasingly important rôle is played by randomized methods, where random bits, or, less formally, coin-tossing, are used to make decisions. The same is true for randomized methods in the analysis of computing systems—both deterministic and randomized. Basic concepts and methods of discrete probability and randomness are therefore introduced in this section.

### 1.9.1 Discrete Probability

A **probability** (or **sample) space** is a set $\Omega$ (of all possible things that can happen), together with a **probability distribution** $Pr$—a mapping that maps each element of $\Omega$ onto a nonnegative real such that

$$\sum_{\omega \in \Omega} Pr(\omega) = 1.$$

A subset $E \subseteq \Omega$ is called an **event**; its probability is defined as $Pr(E) = \sum_{\omega \in E} Pr(\omega)$. Elements of $\Omega$ are called **elementary events**. If all elementary events have the same probability we talk about a **uniform probability distribution**.

For example, let $\Omega_0$ be the set of all possible outcomes of throwing simultaneously three dice. $|\Omega_0| = 216$ and if all dice are perfect, then each elementary event has the probability $\frac{1}{216}$.

From the definition of a probability distribution the following identities, in which $A, B$ are events, follow easily:

$$Pr(\bar{A}) = 1 - Pr(A) \qquad Pr(A \cup B) = Pr(A) + Pr(B) - Pr(A \cap B).$$

**Exercise 1.9.1** *Let $E_1, \ldots, E_n$ be events. Show: (a)* **Bonferroni's inequality***:*
$Pr(E_1 \cap E_2 \cap \ldots \cap E_n) \geq Pr(E_1) + Pr(E_2) + \cdots + Pr(E_n) - (n-1)$;
*(b)* **Bode's inequality***:* $Pr(E_1 \cup E_2 \cup \ldots \cup E_n) \leq Pr(E_1) + \cdots + Pr(E_n)$.

The **conditional probability** of an event $A$, given that another event $B$ occurs, is defined by

$$Pr(A|B) = \frac{Pr(A \cap B)}{Pr(B)}. \tag{1.70}$$

This formalizes an intuitive idea of having a priory partial knowledge of the outcome of an experiment.

Comparing $Pr(A|B)$ and $Pr(B|A)$, expressed by (1.70), we get:

**Theorem 1.9.2 (Bayes Theorem)**

$$Pr(A)Pr(B|A) = Pr(B)Pr(A|B).$$

Two events $A, B$ are called **independent** if $Pr(A \cap B) = Pr(A) \cdot Pr(B)$.

**Exercise 1.9.3** *What is the conditional probability that a randomly generated bit string of length four contains at least two consecutive* 0*'s assuming that probabilities of* 0 *and* 1 *are equal and the first bit is* 1*?*

A **random variable** $X$is any function from a sample space $\Omega$ to reals. The function $F_X(x) = Pr(X = x)$ is called the **probability density function** of $X$.

For example, if $X(\omega)$ $(\omega \in \Omega_0)$, is the sum of numbers on dices, then its probability density function has the form:

| X | 3 | 4 | 5 | 6 | 7 | 8 | 9 | ... |
|---|---|---|---|---|---|---|---|---|
| $f_X(x)$ | $\frac{1}{216}$ | $\frac{3}{216}$ | $\frac{6}{216}$ | $\frac{10}{216}$ | $\frac{12}{216}$ | $\frac{21}{216}$ | $\frac{25}{216}$ | ... |

Two random variables $X$ and $Y$ over the same sample space $\Omega$ are called **independent** if for any $x, y \in \Omega$:

$$Pr(X = x \text{ and } Y = y) = Pr(X = x)Pr(Y = y).$$

**Exercise 1.9.4** ***[Schwartz' Lemma] Let $p$ be a polynomial with $n$ variables that has degree at most $k$ in each of its variables. Show that if $p$ is not identically* 0 *and the values $\alpha_i$, $i = 1, 2, \ldots, n$, are chosen in the interval $[0, N-1]$ independently of each other according to the uniform distribution, then $Pr(p(\alpha_1, \ldots, \alpha_n) = 0) \leq \frac{kn}{N}$. (Use induction and the decomposition $p = p_1x_1 + p_2x_1^2 + \ldots + p_tx_1^t$, where $p_1, \ldots, p_t$ are polynomials of variables $x_2, \ldots, x_n$.)*

An intuitive concept of an average value of a random variable $X$ on a probability space $\Omega$ is defined formally as the **mean** or **expected value**

$$EX = \sum_{\omega \in \Omega} X(\omega)Pr(\omega) \tag{1.71}$$

provided this potentially infinite sum exists.

If $X, Y$ are random variables, then so are $X+Y$, $cX$, $X \cdot Y$, where $c$ is a constant. Directly from (1.71) we easily get:

$$\begin{aligned} E(X+Y) &= EX + EY & (1.72) \\ E(cX) &= cE(X) & (1.73) \\ E(X \cdot Y) &= EX \cdot EY, \qquad \text{if } X, Y \text{ are independent.} & (1.74) \end{aligned}$$

**Exercise 1.9.5** *A ship with crew of 77 sailors sleeping in 77 cabins, each for 77 sailors, arrives at a port and sailors go out to have fun. Later at night they return and being in the state of inebriation they choose randomly a cabin to sleep in. What is the epected number of sailors sleeping in their own cabins? (Hint: Consider random variables $X_i$ the value of which is 1 if i-th sailor sleeps in his own cabin and 0 otherwise. Compute $E[\sum_{i=1}^{77} X_i]$.)*

Other important attributes of a random variable $X$ are its **variance** $VX$ and **standard deviation** $\sigma X = \sqrt{VX}$, where

$$VX = E((X - EX)^2).$$

Since

$$\begin{aligned} E((X^2 - EX)^2) &= E(X^2 - 2X(EX) + (EX)^2) & (1.75) \\ &= E(X^2) - 2E(X)E(X) = (EX)^2 & (1.76) \end{aligned}$$

we get another formula for $VX$:

$$VX = E(X^2) - (EX)^2. \qquad (1.77)$$

The variance captures how much are values of a variable spread around the expected value. The deviation just scales down the variance that may take very large values otherwise.

**Example 1.9.6** *Let $X, Y$ be two random variables on the sample space $\Omega = \{1, 2, \ldots, 10\}$, where all elementary events have the same probability, and $X(i) = i$, $Y(i) = i - 1$. For $i \leq 5$, $Y(i) = i + 1$, for $i > 5$. It is easy to check that $EX = EY = 5.5, E(X^2) = \frac{1}{10}\sum_{i=1}^{10} i^2 = 38.5, E(Y^2) = 44.5$ and therefore $VX = 8.25, VY = 14.25$.*

The probability density function of a random variable $X$ whose values are natural numbers can be represented by the following **probability generating function**

$$G_X(z) = \sum_{k \geq 0} Pr(X = k) z^k.$$

Since $\sum_{k\geq 0} Pr(X=k)=1$, we get $G_X(1)=1$. Probability generating functions allow often to compute quite easily the mean and the variance. Indeed,

$$\begin{aligned} EX &= \sum_{k\geq 0} kPr(X=k) = \sum_{k\geq 0} Pr(X=k)(k1^{k-1}) & (1.78)\\ &= G'_X(1) & (1.79)\end{aligned}$$

and since

$$\begin{aligned} E(X^2) &= \sum_{k\geq 0} k^2 Pr(X=k) = \sum_{k\geq 0} Pr(X=k)(k(k-1)1^{k-2}+k1^{k-1}) & (1.80)\\ &= G''_X(1)+G'_X(1), & (1.81)\end{aligned}$$

we get from (1.77):

$$VX = G''_X(1)+G'_X(1)-G'_X(1)^2.$$

Two important distributions are connected with experiments called **Bernoulli trials**; the experiments with two possible outcomes: **success** with the probability $p$ and **failure** with the probability $q=1-p$. Coin-tossing is an example of a Bernoulli trial experiment.

Let the random variable $X$ be the number of trials needed to obtain a success. Then $X$ has values in the range $\mathbf{N}$ and it clearly holds $Pr(X=k)=q^{k-1}p$. The probability distribution $X$ on $\mathbf{N}$ with $Pr_X(k)=q^{k-1}p$ is called the **geometric distribution**.

**Exercise 1.9.7** *Show that for the geometric distribution*

$$EX=\frac{1}{p}, \qquad VX=\frac{q}{p^2}. \tag{1.82}$$

Let the random variable $Y$ express the number of successes in $n$ trials. Then $Y$ has values in the range $\{0,1,2,\dots n\}$ and we have

$$Pr(Y=k)=\binom{n}{k}p^k q^{n-k}.$$

The probability distribution $Y$ on the set $\{1,2,\dots,n\}$ with $Pr(Y=k)=\binom{n}{k}p^kq^{n-k}$ is called **the binomial distribution**.

**Exercise 1.9.8** *Show that for the binomial distribution*

$$EY=np \qquad VY=npq. \tag{1.83}$$

Geometric and binomial distributions are illustrated for $p=0.35$ and $n=14$ in Figure 1.8.

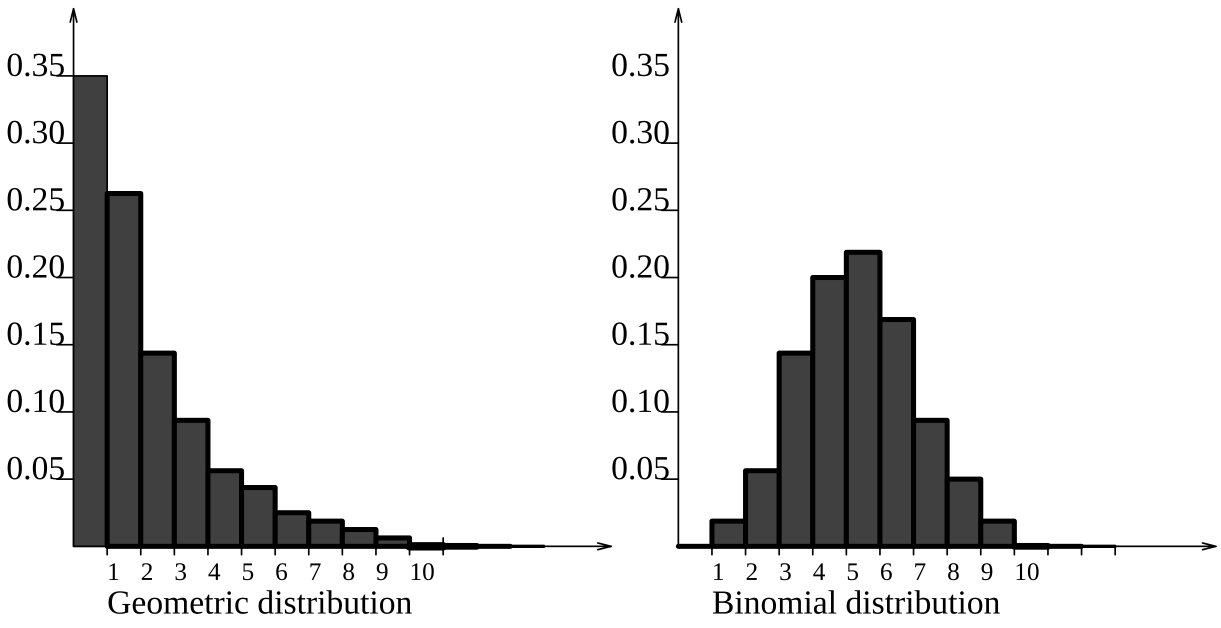


Figure 1.8: Geometric and binomial distributions.

**Exercise 1.9.9** **[Balls and Bins] Consider the process of tossing randomly balls into $b$ bins in such a way that at each toss the probability that a tossed ball falls in any given bin is $\frac{1}{b}$. Answer the following questions about this process.*

1. *How many balls fall on the average into a given bin at $n$ tosses?*
2. *How many balls must one toss, on the average, until a given bin contains a ball?*
3. *How many balls must one toss, on the average, until every bin contains a ball?*

The following example illustrates a probabilistic average-case analysis of algorithms. By that we mean the following. For an algorithm $\mathcal{A}$ let $T_{\mathcal{A}}(x)$ denote the computation time of $\mathcal{A}$ for an input $x$ and let $Pr_n$ be, for all integer $n$, a probability distribution on the set of all inputs of $\mathcal{A}$ of length $n$. By the average-case complexity of $\mathcal{A}$—$ET_{\mathcal{A}}(w)$ we then mean the function

$$ET_{\mathcal{A}}(n) = \sum_{|x|=n} Pr_n(x)T_{\mathcal{A}}(x).$$

**Example 1.9.10** *Determine the average-time complexity of the Algorithm 1.9.11 for the following problem: given an array $X[1], X[2], \ldots, X[n]$ of distinct elements, determine the maximal $j$ such that $X[j] = max\{X[i] \,|\, 1 \leq i \leq n\}$*

**Algorithm 1.9.11 (Finding the last maximum)**

**begin** $j \leftarrow n; m \leftarrow X[n]$;
  **for** $k \leftarrow n-1$ **downto** 1 **do if** $X[k] > m$
    **then** $j \leftarrow k; m \leftarrow X[k]$
**end**

The time complexity of this algorithm for a conventional sequential computer is $T(n) = k_1 n + k_2 A + k_3$, where $k_1, k_2, k_3$ are constants and $A$ equals the number of times the algorithm executes the statements $j \leftarrow k$; $m \leftarrow X[k]$. The term $k_1 n + k_2$ captures here for $n-1$ decrement and comparison operations. The value of $A$ clearly does not depend on particular values in the array $X$, only on the permutation represented by the sequence $X[1], \ldots, X[n]$.

If we assume that all permutations of data in $X$ have the same probability, then the average-time complexity of the above algorithm depends on the average value $A_n$ of $A$.

Let $p_{nk}$, for $0 \leq k < n$, be the probability that $A = k$. Then

$$p_{nk} = \frac{\text{number of permutations of } n \text{ elements such that } A = k}{n!}$$

and the following fact clearly holds:

$$A_n = \sum_{k=0}^{n-1} k p_{nk}.$$

Our task now is to determine $p_{nk}$. Without loss of generality we can assume that data in the array form a permutation $x_1, \ldots, x_n$ of $\{1, 2, \ldots, n\}$ and we need to determine the value of $A$ for such a permutation. If $x_1 = n$, then the value of $A$ is 1 higher than that for $x_2, \ldots, x_n$—in this case $X[1] \geq m$ in the algorithm. If $x_1 \neq n$, then the value of $A$ is the same as for $x_2, \ldots, x_n$—in this case $X[1] < m$. Since the probability that $x_1 = n$ is $\frac{1}{n}$, and the probability that $x_1 \neq n$ is $\frac{n-1}{n}$, we get the following recurrence for $p_{nk}$

$$p_{nk} = \frac{1}{n} p_{(n-1)(k-1)} + \frac{n-1}{n} p_{(n-1)k} \tag{1.84}$$

with the initial conditions

$$p_{10} = 1, \ p_{1k} = 0, \quad \text{for} \quad k > 0; \ p_{nk} = 0 \text{ for } k < 0.$$

In order to determine $A_n$ let us consider the generating function

$$G_n(z) = \sum_{k=0}^{n} p_{nk} z^k.$$

Clearly $G_n(1) = 1$ and from (1.84) we get

$$G_n(z) = \frac{z}{n} G_{n-1}(z) + \frac{n-1}{n} G_{n-1}(z) = \frac{z+n-1}{n} G_{n-1}(z). \tag{1.85}$$

We know, see (1.79), that $A_n = G'_n(1)$. For $G'_n(z)$ we get from (1.85):

$$G'_n(z) = \frac{1}{n} G_{n-1}(z) + \frac{z+n-1}{n} G'_{n-1}(z)$$

and therefore

$$G'_n(1) = \frac{1}{n} + G'_{n-1}(1).$$

Thus

$$A_n = \sum_{i=2}^{n} \frac{1}{i} = H_n - 1$$

where $H_n$ is the $n$-th Harmonic number. $\Box$

### 1.9.2 Bounds on Tails of Binomial Distributions*

It is especially the binomial distribution—expressing the probability of $k$ successes during $n$ Bernoulli trails (coin tossings)—that plays an important rôle by randomization in computing. For the analysis of randomized computing of importance is often to know how large are **tails of binomial distributions**—regions of the distribution far from the mean.

Several bounds are known for tails. For the case of one random variable $X$ with the probability of success $p$ and of failure $q = 1 - p$, the following basic bounds for $Pr(X \geq k)$ and for $Pr(X \leq l)$ can be derived by making careful estimations on binomial coefficients. The first two bounds are general, the last two are for tails far from the mean.

For any $0 \leq k, l \leq n$

$$Pr(X \geq k) \leq \binom{n}{k} p^k, \qquad Pr(X \leq l) \leq \binom{n}{l} q^{n-l} \tag{1.86}$$

and for $n > k > np > l > 0$:

$$Pr(X > k) < \binom{n}{k} \frac{n-k}{k-np} p^{k+1} q^{n-k} \qquad Pr(X < l) < \binom{n}{l} \frac{kq}{np-k} p^k q^{n-k+1}. \tag{1.87}$$

Also the following bound is often used:

**Lemma 1.9.12 (Markov's Inequality)** $Pr(X \geq kEX) \leq \frac{1}{k}$ *for any random variable* $X$ *acquiring non-negative integer values and* $k > 0$.

**Proof.** The Lemma follows from the following inequality

$$E(X) = \sum_{i \in \mathbf{N}} iPr(X = i) = \sum_{i < kE(X)} iPr(X = i) + \sum_{i \geq kE(X)} iPr(X = i) \geq kE(X)Pr(X \geq kE(X)).$$

$\Box$

In order to motivate the next bound, that will play an important rôle later, especially in Chapter 9, let us assume that we have a biased coin-tossing of one side has the probability $\frac{1}{2} + \varepsilon$ and of other side $\frac{1}{2} - \varepsilon$—but we do not know which one. How to find out this? The basic idea is simple. Toss the coin many times and pick up the side that comes most of the time as the one with probability $\frac{1}{2} + \varepsilon$. However, how many times one has to toss the coin in order to make a correct guess with a high probability?

**Lemma 1.9.13 (Chernoff's Bound)** *Suppose $X_1, \ldots, X_n$ are independent random variables that acquire values 1 and 0 with probabilities $p$ and $1-p$, respectively, and consider their sum $X = \sum_{i=1}^{n} X_i$. Then for all $0 \leq \theta \leq 1$,*

$$Pr(X \geq (1+\theta)pn) \leq e^{-\frac{\theta^2}{3}pn}.$$

**Proof.** Since $Pr(X \geq (1+\varepsilon)pn) = Pr(e^{tX} \geq e^{t(1+\varepsilon)pn})$, for any $t \geq o$ and $\varepsilon > 0$, Markov's Inequality yields

$$Pr(X \geq (1+\varepsilon)pn) = e^{-t(1+\varepsilon)pn} e^{t(1+\varepsilon)pn} Pr(e^{tX} \geq e^{t(1+\varepsilon)pn}) \leq e^{-t(1+\varepsilon)pn} E(e^{tX}).$$

Since $X = \sum_{i=1}^{n} X_i$ and $X_i$ are independent, we get, making a use of the inequality $(1+a)^n \leq e^{an}$, that holds for any $a \in \mathbf{R}, n \in \mathbf{N}$,

$$E(e^{tX}) = (E(e^{tX_1}))^n = ((pe^t + (1-p))^n = (1+p(e^t-1))^n \leq e^{pn(e^t-1)},$$

Putting $t = \ln(1+\varepsilon)$ yields

$$Pr(X \geq (1+\varepsilon)pn) \leq (1+\varepsilon)^{-(1+\varepsilon)pn} e^{\varepsilon pn}$$

and therefore

$$Pr(X \geq (1+\varepsilon)pn) \leq \left(\frac{e^{\varepsilon}}{(1+\varepsilon)^{1+\varepsilon}}\right)^{pn}.$$

Since $\varepsilon - (1+\varepsilon)\ln(1+\varepsilon) = -\frac{1}{2}\varepsilon^2 + \frac{1}{3}\varepsilon^3 - \ldots \leq -\frac{1}{3}\varepsilon^2$, for $0 \leq \varepsilon \leq 1$, we get the inequality **??**.
□

**Exercise 1.9.14** *Show: (a) $Pr(X \geq (1+\varepsilon)pn) \leq \left(\frac{e}{1+\varepsilon}\right)^{(1+\varepsilon)pn}$;*
*(b) $Pr(X \geq r) \leq 2^{-r}$, for $r \geq 6pn$.*

**Exercise 1.9.15** *Show: $Pr(X \leq (1-\varepsilon)pn) \leq e^{-\frac{\varepsilon^2}{2}pn} \leq \left(\frac{e^{\varepsilon}}{(1+\varepsilon)^{1+\varepsilon}}\right)^{pn}$, if $0 \leq \varepsilon \leq 1$.*

In other words, Chernoff's bound says that a big difference from the expected value is unlikely.

### 1.9.3 Randomness and Pseudo-random Generators

A **random number generator** can be seen as a stochastic process RANDOM$(a, b)$ which, each time it is activated, produces an integer between $a$ and $b$, inclusive. With each such an integer being equally likely, and with each new integer produced by the process RANDOM$(a, b)$ as being independent from integers returned on previous calls of RANDOM$(a, b)$. For example, RANDOM$(0,1)$ produces 0 or 1 both with probability $\frac{1}{2}$. One can imagine RANDOM$(a,b)$ as rolling a perfect $(b-a+1)$-sided dice to obtain its output.

The basic problem is how to realize such a random number generator. There are quantum-mechanical processes that produce true randomness. Of course, they are not cheap. It is therefore natural to try to use deterministic algorithms that could produce long sequences of pseudo-random bits, if they get as input a few of really random bits. That would be sufficiently good for many applications.

Intuitively, a sequence of bits

$$0101010101010101010101010101010101010$$

is less random than the sequence

$$1001011000101111011000100111110100011101010101111$$

but how to formalize this intuition? A classical way to deal with this problem is through **statistical tests** (e.g. the so-called the $\chi^2$-test, Kolmogorov-Smirnov's test) or empirical tests on frequency, uniformity, permutations, subsequences and so on.

An infinite sequence of bits $b = (b_1, b_2, \ldots)$ is said to be random with respect to a set $\mathcal{S}$ of (statistical and other) tests of randomness if $b$ passes all tests from $\mathcal{S}$. There are many tests available.

Some examples of tests: A random infinite sequence of bits has to be **normal**— for each integer $k$ it has to hold that the frequency of occurrences of each particular subword of length $k$ in the prefix of length $n$ has to go to the limit $2^{-k}$ for $n \to \infty$. The number of 1's minus the number of 0's in the prefix of length $n$ has to be positive for infinitely many $n$ and also negative for infinitely many $n$.

The view of randomness through **polynomial time indistinguishability** s discussed below seems to be better suited for computing. Still another approach to randomness is discussed in Section 6.5.

Deterministic algorithms that take as an input a short random sequence and produce longer "almost random" sequence of bits are called pseudo-random generators. They play, surprisingly, as we shall see, the fundamental rôle in theory and practice of computing.

More formally: A **pseudo-random generator** is a deterministic polynomial time algorithm which expands short random sequences (called **seeds**) into longer bit sequences (each with certain probability) such that the resulting probability distribution is **in polynomial time indistinguishable** from the uniform probability distribution.

More specifically, the pseudo-random generator, say $G$, expands an $n$-bit sequence into a longer, say $n^k$-bit sequence, for some $k \in \mathcal{N}$, such that for every polynomial time algorithm with 0-1-output—called **test**—$T$, for any $\varepsilon > 0$, and for sufficiently large $n$

$$|Pr(T(G(X_n)) = 1) - Pr(T(X_{n^k}) = 1)| \leq n^{-\varepsilon}$$

where $X_m$ is a random variable obtaining as values strings of length $m$, with uniform probability distribution. (One says also that a generator of pseudo-random numbers can **fool** any polynomial time algorithm $T$ trying to check whether its outcomes are really random numbers. Observe also, that what we can do with nonpolynomial time algorithms is not of interest to us because they can not finish their work in a reasonable time.)

A classical proposal for a pseudo-random generator is the **linear congruential generator** from D. H. Lehmer (1948). One chooses four $n$-bit numbers $m, a, b, X_0$ and generate an $n^3$ bit sequence $X_1 X_2 \ldots X_{n^2}$ of $n$-bit numbers by the iterative process

$$X_{i+1} = (aX_i + b) \bmod m.$$

The choice of parameters $m$, $a$, $b$ and $X_0$ is crucial. Although the resulting sequence $X_0, X_1, X_2, \ldots$ is eventually periodic, it is desirable that the period is as large as possible. For example, for $a = b = 7$, $m = 10$ and $X_0 = 7$ we get $7, 6, 9, 0, 7, \ldots$.[15]

**Exercise 1.9.16** *Show that for the linear congruential generator:*
*(a)* $x_n \equiv a^n x_0 + (a^{n-1} + a^{n-2} + \cdots + a + 1) \pmod m$*;*
*(b) if* $gcd(a, m) = 1$*, then* $(a-1) \setminus b \Rightarrow x_n = x_{\phi(m)+n}$.

It was shown that Lehmer's pseudo-random generator does not satisfy strong requirements stated above. For example, there is a polynomial time algorithm (with respect to $\lg m$), such that given a sufficiently long sequence $X_0, X_1, \ldots X_t$ produced by a linear congruential generator, the algorithm determines $a, b$ and $m$ used to produce this sequence. However, there are no proofs yet but there is already strong evidence that pseudo-random generators satisfying strong requirements formulated above do exist.

The existing candidates are based on the fact that there are **intractable algorithmic problems** for which no polynomial time algorithms exist. For example, the existence of pseudo-random generators satisfying such strong requirements has been proven under the assumption that factorization of integers is intractable. One such candidate is called **Blum-Micali pseudo-random generator** or **index generator**, and it is based on the intractability of the discrete logarithm problem. It is defined as follows:

Let $p$ be a prime such that $p-1$ has only small factors (smaller than $\lg p$), and let $g$ be a principal root of $Z_p^*$. Blum-Micali pseudo-random generator is based on the iteration

$$X_{i+1} = g^{X_i} \bmod p$$

and producing the sequence of bits

$$b_1, b_2, b_3, \ldots$$

where

$$b_i = \begin{cases} 1, & X_i \leq \frac{p-1}{2}; \\ 0, & \text{otherwise,} \end{cases}$$

satisfies the condition on polynomial time indistinguishability provided computing discrete logarithm is intractable.

[15] It has turned out that for 32-bit arithmetic an appropriate choice of parameters for linear congruential generator is $m = 2^{31} - 1$, $b = 0$ $a = 7^5 = 16807$.

Another example of a simple pseudo-random generator that satisfies the requirement of polynomial time indistinguishibility under the assumption that factoring of integers is intractable is the so-called BBS pseudo-random generator. It is based on the iteration

$$x_{i+1} = x_i^2 \bmod n,$$

where $x_0 \in QR_n$ is randomly chosen and $n$ is a Blum integer, and produces the pseudo-random sequence $b_0, b_1, b_2, \ldots$, where $b_i = x_i \bmod 2$. In more detail we discuss the design of pseudo-random generators in Chapter 8.

The fact that computer time is much cheaper for producing pseudo-randomness than quantum mechanical processes to produce true randomness is not the only reason for using pseudo-random generators. We often need to repeat randomized computational processes for various reasons, including error checking. In such a case, if our source of randomness is a real one, then the only way to use random bits again is to store them. Moreover, in many applications we actually do not need truly random bits. For example, in cryptography pseudo-random bits are fully sufficient.

Randomness has become a computational resource. The question of how much and how good randomness we really need for specific tasks, is one of the key problems of computing. Also the task to economize the amount of randomness needed for particular applications is of importance. The concept of randomness presented above for sequences can be transferred to other objects. For example, an integer is said to be random if its binary representation is a random string (sequence). To generate a random integer of $n$ bits therefore means to generate an $n$-bit binary sequence.

A more general random generator can be used. For example, a process can be used that for any two real numbers $a < b$, as parameters, returns a real number $x$ randomly, uniformly and independently chosen in the interval $a \leq x \leq b$. Similarly, RANDOM($X$), for a set $X$, is expected to return an element chosen randomly, uniformly and independently, among the elements of $X$. Such random number generators can often be constructed using a $RANDOM(0,1)$ generator as the basic source of randomness.

A theory of pseudo-randomness is being developed that is aimed at understanding the minimum amount of randomness that a randomized method of computation really needs.

### 1.9.4 Probabilistic Recurrences*

If efficiency of recursive randomized algorithms or designs is analyzed, a special type of recurrences, the so-called probabilistic recurrences, with random variables arise.

For example, consider a randomized algorithm $\mathcal{A}$ that generates, on an input $x$, in time $a(x)$ a subproblem of size $S(x)$, where $S(x)$ is a random variable with values in $[0, x]$, whose probability distribution depends on $\mathcal{A}$—and then solves the subproblem recursively. The time complexity of the algorithm is then described by the **(probabilistic) recurrence**:

$$T(x) = a(x) + T(S(x)). \tag{1.88}$$

$T(x)$ is therefore a random variable whose distribution depends on the distribution of $S(x)$.

The performance of such a randomized algorithm can be charaed by various statements on the distribution of the random variable $T$. For example, by information on the tail of the distribution of $T$. We discuss two such bounds: They have quite general character and are easy to apply.

Consider again the recurrence (1.88), where $E(S(x)) \leq m(x)$ for a fixed function $m$ such that $0 \leq m(x) \leq x$ and where $a$ is a nondecreasing function. The recurrence

$$u(x) = a(x) + u(m(x)) \tag{1.89}$$

is regarded as the deterministic counterpart of the probabilistic recurrence (1.88).

Using the iteration method to solve recurrences, we get that whenever the recurrence 1.89 has a solution, then this solution has the form $u(x) = \sum_{i \geq 0} a(m^{(i)}(x))$, where $m^{(0)}(x) = x$ and $m^{(i+1)}(x) = m(m^{(i)}(x))$ for $i \geq 0$.

We are now in the position to formulate two bounds on tails of $T$.

**Theorem 1.9.17 (Karp's bound)** *If $m(x)$ and $a(x)$ are continuous functions such that $m(x)/x$ is nondecreasing and $a(x)$ is increasing on $\{x \,|\, a(x) > 0\}$, then for every $x \in \mathbf{R}^+$ and $w \in \mathbf{N}^+$*

$$Pr[T(x) \geq u(x) + wa(x)] \leq \left(\frac{m(x)}{x}\right)^w,$$

*where $u$ is the solution of the deterministic recurrence (1.89) and $T$ of the probabilistic recurrence (1.88).*

The second bound, is weaker but easier to apply.

**Theorem 1.9.18** *If $m, a, u$ and $T$ are as in Theorem 1.9.17, then for any sufficiently large $k \in \mathbf{N}$*

$$Pr[T(x) \geq ku(x)] \leq \left(\frac{m(x)}{x}\right)^{\frac{k}{2}-1}.$$

Proofs of both theorems are beyond the scope of this book even though the proof of the second one is based on Markov's inequality and a variation of Chernoff's bound—see references.

**Example 1.9.19 (Maximal clique of the graph)** *A clique of a graph $G$ is its subgraph which is a complete graph—each two of its nodes are connected by an edge. There is no polynomial time algorithm known to find a maximal clique in a graph. However, there is a very simple randomized algorithm to do it—and this is, surprisingly, the fastest known randomized algorithm for this problem.*

**Algorithm 1.9.20** *Start with the given graph $G$ and an empty clique $\mathcal{C}$ and repeat the following step until the set of nodes of the considered graph is empty.*

- *Choose randomly a node from the current graph, add it to the clique $\mathcal{C}$, remove from the considered graph the chosen node and also all nodes that are not adjacent to it.*

In order to analyze the algorithm we need to consider its application to a random graph $G_{n,p}$ with $n$ nodes in which each edge is presented with the probability $p$. At a step of algorithm, when the set of vertices has size $m$, the expected number of vertices that do not get deleted is $p(n-1)$. Denote by $C(n)$ the size of the clique when the algorithm is applied to $G_{n,p}$ for any fixed $p$. Then

$$C(n) = 1 + C(S(n)),$$

where $E(S(n)) = p(n-1) \leq pn$. The corresponding deterministic recurrence is therefore $u(n) = 1 + u(pn)$. Using methods of Section 1.2 we get $u(n) = \lg n/\lg(1/p)$. An application of Theorem **??** gives, for sufficiently large $k$, the bound

$$Pr[C(n) > \frac{k \lg n}{\lg(1/p)}] < p^{\frac{k}{2}-1}$$

and an application of Theorem 1.9.17 yields

$$Pr[C(n) > \frac{\lg n}{\lg(1/p)} + w] < p^{w}.$$

**Exercise 1.9.21** * *If $C'(n)$ denotes the number of adjancency checks of the above randomized algorithm, then for $C'(n)$ we have the recurrence $C'(n) = n - 1 + C'(S(n))$. Get bounds for the tails of $C'(n)$.*

## 1.10 Asymptotic Complexity Analysis

A variety of concepts, methods and results of fundamental importance for complexity analysis were formally introduced and demonstrated in previous sections. Now we discuss informally global problems, paradigms, tools, methods, but also pitfalls of complexity investigations and interpretations. In doing so we have three main aims in mind:

1. To complement the presentation of technical tools introduced so far with a global view of complexity analysis, its aims, problems, methods and merits.

2. To introduce informally concepts vital for complexity considerations that will be formally defined and investigated later in this book, but will be used already starting with the next chapter.

3. To provide a motivation for the contents of the book and a summary of its main aims and topics.

### 1.10.1 Tasks of Complexity Analysis.

The main goal of complexity analysis is to determine how good are, asymptotically, the best possible solutions of important problems in computing and communication. For example, problems to design algorithms, automata, computers, networks or circuits to perform certain tasks—with respect to various computational or communication models and computational resources. In other words, to determine the inherent complexity of computational or communication problems. For example, the minimum number of arithmetical operations needed to multiply two matrices of degree $n$.

To establish the inherent complexity of computational problems is of large practical and theoretical importance. If it is known how good is the best possible solution, then a **benchmark** is established with which any specific solution can be compared. Moreover, it turned out that the study of inherent complexity of computational, communication, and design problems brings deep insights into the nature of computing.

There are two basic approaches how to determine the inherent complexity. First, a direct one, where the inherent complexity of a specific problem is explicitly determined. For example, $\Theta(n \lg n)$ is the inherent complexity of sorting of $n$ numbers with respect to the number of comparisons. Second, an indirect one, in which relations between complexities of various problems are established. For example, it is shown that the complexity of one problem is not larger than of another one, or that two problems have asymptotically the same complexity. Another possibility is to show that a problem is feasible if and only if another one is such. For example, matrix multiplication has been shown to be of the same complexity, with respect to the number of arithmetical operations, as matrix inversion; integer factorization was shown, Section 1.7, feasible if and only if computing square roots of modulo an arbitrary integer is such. Methods of this chapter are of importance for both of these approaches. In order to develop the indirect approach, a deeper knowledge of the structure of complexity classes and reduction methods is needed—with this we will deal in Chapter 5.

There are two basic types of computational problems—those with complete information about input and those with incomplete or contaminated information. Problems of the first type, for example computational problems on graphs, are typical for computing with discrete objects and they are of main interest in this book. Their solutions and asymptotic complexity analyses require to use methods of discrete mathematics as discussed in this chapter. Problems of the second type, for example computing an integral of a function given by its values in certain points only, are typical for computing with continuous objects and their solutions. Asymptotical complexity analysis requires to use in such cases also deep methods of calculus. With these problems we deal not in this book. They are also of large importance for computing but would require to extend the scope of the book essentially.

There are also two basic types of computational and communication paradigms—determinism and randomization. Randomized algorithms are those that make random choices during their execution. Different methods are used for complexity analysis of deterministic and randomized systems. Deterministic algorithms are further divided onto those providing exact and those providing approximate solutions. Complexity analysis of approximation algorithms requires also special approaches and tools.

Randomization seems to be very powerful. For many problems we have fast randomized algorithms, but no fast deterministic one. Computation of square roots modulo a prime is such an example. On the other hand, we still miss proofs that polynomial time randomized computing is essentially more powerful than deterministic —this is dealt with in Chapter 5.

There are several basic types of randomized algorithms and communication protocols:

- **Las Vegas**—results are always correct, but it may happen, with small probability, that no result is produced.

- **Monte Carlo**—results of certain type are always correct; others may be wrong, but probability of that is small—we talk also about **one-sided Monte Carlo** algorithms. (For example a Monte Carlo algorithm may test primality in such a way that if it says that a given integer is composite, then this is 100% true; however, if it says that it is a prime this may be, with a small probability, wrong.) (

- **BPP (Bounded Error Probability)**—no output is 100% correct, but in any case the probability of error is small and bounded—we talk also about **two-sided Monte Carlo** algorithms.

Power and methods of randomization are discussed intensively in this book. Probabilistic finite automata are considered in Chapter 3, randomized computations on universal computers in Chapter 4, randomized complexity classes in Chapter 5, limitations of randomness in Chapter 6. An intensive use of randomness is in cryptography (Chapter 8), interactive protocols (Chapter 9) and in communications (Chapter 11). Randomization plays an important rôle also in futuristic approaches to computing. For example, quantum computing is in principle randomized.

It is natural to ask what makes randomization so powerful. The explanation is simple. It is sometimes preferable to choose, during a computation, a course of actions at random than to spent time to find out which alternative is better or to try all of them. Such situations arise when the time needed to determine the optimal choice is too large, compared to the time saved on average by making the optimal choice.

### 1.10.2 Methods of Complexity Analysis

The complexity analysis of computational, communication and design problems and systems depends on several factors:

**Inputs** — the way inputs are presented and their size measured;

**Computer and communication models** — models of sequential computers (Turing machines, RAM—a model of a conventional sequential computer,...), models of parallel computers (PRAM—a parallel version of RAM,...), automata, circuits, networks, ....

**Computing and communication modes** —deterministic, nondeterministic, randomized, ...

**Complexity analysis modes** — worst-case, average-case, expected-case,...

**Computation resources** — time, storage, program, processors, communication, randomness, ...

All these problems are considered in this book. Various representations of integers, graphs and other objects are considered in Chapter 2; several types of automata in Chapters 3 and 7; models of universal computers in Chapter 4; networks in Chapter 10, circuits in Chapters 2, 4, 5 and 11; interactive protocols in Chapter 9, communication models in Chapter 11.

Computational analysis is performed with respect to the size of input data as the main parameter. Since there are usually many inputs of the same size, two basic approaches are used to deal with this problem: to determine the so-called worst-case complexity or to determine the average-case complexity for inputs of a given size.

The worst-case complexity analysis is in general simpler. It is of main importance for critical real-time applications and it has been very successful in providing insights into the nature of computing. The worst-case complexity analysis results may be, however, quite irrelevant for some applications—or at least questionable. For example, for cryptography. This is due to the fact that the worst case may be achieved only for pathologically "bad" input data that do not normally, or often, occur—it may happen that these "bad" data are actually "nice" ones. For example, QUICKSORT performs at worst for already sorted inputs.

The average-case complexity analysis seems to be producing results that are more realistic for many applications. The difficulty here lies in the fact that one has to know the probability distribution of the input data—and this is rarely easily available. The usual assumption, namely that all data of a given size have the same probability, is often easy to deal with, but rarely realistic. Moreover, it can be shown that for an important probability distribution, the so-called apriori probability distribution - see Section 6.5.3 - the average-case complexity actually equals the worst case complexity. Finally, for some important algorithmic problems no good average-case analysis is known and for some others there is no big difference between the worst-case and the average-case results. For example, for HEAPSORT the worst-case and the average-case complexity are the same—$\Theta(n \lg n)$.

The aim is to get asymptotic analysis results in terms of $\Theta$-notation. This is in general not easily achievable. The task is then to find the smallest possible upper bound and the largest possible lower bound. To get a better upper bound a better system, for example a faster algorithm, is needed. To improve a lower bound a better proof technique is needed.

In case of randomized algorithms we also speak of **expected-time** performance. It is the mean time of solving a problem for the same input. This is essentially different from the concept of the average-case complexity that refers to deterministic algorithms and the average peformance when all inputs are considered—each with certain probability. It is therefore meaningful to speak about the average-case expected time and the worst-case expected time.

Asymptotic complexity analysis results are robust. In order to get them one usually ignores details of the algorithm and concentrates on their loop and data structures. This robustness is the strength and but also the weakness of the asymptotic analysis. In any case, however, this robustness, coupled with the fact that asymptotically better systems are mostly also better in practice, makes the asymptotic complexity analysis so interesting and important.

### 1.10.3 Efficiency and Feasibility

Table 1.4 shows time needed by algorithms of different complexities to solve problems with a different sizes of inputs.[16] The table demonstrates that algorithms whose time complexity

[16] Some numbers, according to Dyson (1979), that help to get a more real feeling how large are some numbers from Table 1.4: time to the next ice age—$2^{28}$ sec.; the age of the universe—$2^{48}$sec.; total life time of the universe (if the universe is closed)—$2^{61}$ sec.; time until all matter is liquid at zero temperature—$2^{240}$;

grows exponentially cannot be used to solve larger problems; no matter how fast computers are available.

| size of inputs / function | $2^3$ | $2^5$ | $2^7$ | $2^9$ | $2^{11}$ |
|---|---|---|---|---|---|
| $\lg^* n$ | 2 | 2 | 2 | 3 | 3 |
| $\lg n$ | 3 | 5 | 7 | 9 | 11 |
| $8n$ | $2^6$ | $2^8$ | $2^{10}$ | $2^{12}$ | $2^{14}$ |
| $n \lg n$ | $3 \cdot 2^3$ | $5 \cdot 2^5$ | $7 \cdot 2^7$ | $9 \cdot 2^9$ | $11.2^{11}$ |
| $n^2$ | $2^6$ | $2^{10}$ | $2^{14}$ | $2^{18}$ | $2^{22}$ |
| $2^n$ | $2^8$ | $2^{32}$ | $2^{128}$ | $2^{512}$ | $2^{2048}$ |
| $n!$ | $2^{15}$ | $2^{118}$ | 717 | $2^{3876}$ | $2^{19581}$ |
| $n^n$ | $2^{24}$ | $2^{160}$ | $2^{896}$ | $2^{4608}$ | $2^{22528}$ |

Table 1.4: Growth of some functions—results for $n!$ are shown as $2^x$, where $2^x < n! \leq 2^{x+1}$.

Unfortunately, for too many practically important problems we know only algorithms with exponential time complexity. Three of them — **travelling salesman problem, graph isomorphism problem**, and **integer factorization**, will be discussed from several points of view uter foreseeable that could find the shortest route for a traveler who wants to visit 10000 cities or to decompose a 1000 bit long composite integer. For many of these problems there is still a very large gap, actually exponential, between the best known upper bound (exponential) and lower bound (sometimes even linear).

There are several ways how to deal with the fact that for some practically very important computational problems no polynomial time sequantial algorithm—with respect to the worst-case complexity—is known.

1. To design (heuristic) algorithms that have exponential worst-case complexity but their average-case complexity is polynomial; or algorithms that have been experimentally verified to be fast on data occurring in real applications.
2. In case of optimization algorithms to develop, if possible, fast and good approximation algorithm. This is an intriguing problem discussed in Chapter 5.
3. To develop fast randomized algorithms, provided they exist. Computational hardness can often be trade-off for randomness and randomness becomes precious computational resource.

The development of an understanding when to consider an algorithmic problem or an algorithm as tractable (feasible) is one of central tasks of foundations of computing discuss intensively in Chapters 4, 5, 9. There is a quite good consensus that a problem should be called tractable if it can be solved in polynomial time. However, views differ which computational modes to consider: deterministic, randomized, interactive,... All that may provide very substantial difference, as shown in Chapter 9.

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number of atoms in universe (black matter excluded)—$2^{265}$; volume of the universe $2^{280}$ cm$^3$; time until all matter collapses to black holes—$10^{10^{76}}$.

It is now undoubtedly that consideration of sequential deterministic polynomial time computations as the ones representing feasible computations has been very successful with respect to the development of efficient computing systems and that it has also brought deep insights into the nature of computing. On the other hand, this standpoint is not without serious problems. Why to consider algorithms time complexity of which is proportional to a very high degree polynomial as feasible? For example, one can certainly hardly consider as practical an algorithm time complexity of which is $n^{10000}$. Fortunately, it has turned out that if there is a polynomial time algorithm for a reasonable problem that has a simple, understandable formulation, then the degree of such a polynomial is reasonable small.

A polynomial time algorithm is in general considered as an acceptable solution of a problem. However, as really fast we consider only algorithms of complexity $O(n)$ or $O(n \lg n)$, in case of sequential computing, and of complexity $O(\lg n)$ or $O(\lg^2 n)$ for parallel computing.

Algorithms to solve a problem may differ dramatically in their efficiency. This is clear for the case that there is an exponential time and also a polynomial time algorithm for the same problem. It seems to be less obvious that even apparently very small time complexity differences, for example $\Theta(n^2)$ and $\Theta(n \lg n)$, between algorithms, can produce practically quite dramatic difference.

Assume, for example, that an $\Theta(n^2)$ algorithm $A_1$ has been cleverly programmed for a supercomputer, with $10^8$ operations per second, to run in time $T(n) = 2n^2$, and that another algorithm, $A_2$, for the same problem, with the asymptotic complexity $\Theta(n \lg n)$, is badly programmed for a PC, with $10^6$ operations per second, to run in time $50n \log n$. For $n = 10^6$, $A_1$ needs 2000 seconds and $A_2$ needs 100 seconds!

We see that even small asymptotic differences in time performance of algorithms may have a larger practical impact than the difference between performance of a personal computer and supercomputer. Observe also that in the above example, even supercomputers with $\Theta(n^2)$ algorithm could not beat a PC with a $\Theta(n \lg n)$ algorithm. Algorithms, networks,... should therefore be seen as an important technology and progress in this technology can be matched with that in hardware. Asymptotic complexity analysis with its benchmarks and performance evaluation is an important factor contributing to the fast development of this technology.

### 1.10.4 Complexity Classes and Complete Problems

One of the important tasks of foundation of computing is to develop understanding of the power and structure of main computational and communication complexity classes. What kind of problems can be solved using a particular computing model and a specific amount of computational resources? Which relations hold between various complexity classes and what kind of structure do these classes have?

Table 1.5 summarizes main resource bounds used in complexity analysis and the following list contains main complexity classes.

**NC** Class of problems solvable by circuits of polynomial size and polylogarithmic depth; or, alternatively, the class of problems solvable by PRAM in polynomial time with polylog number of processors.

| | |
|---|---|
| constant | $\mathcal{O}(1)$ |
| almost constant | $\mathcal{O}(\lg^* n)$ |
| polylog | $\mathcal{O}(\lg^{\mathcal{O}(1)})$ |
| subpolynomial | $n^{o(1)}$ |
| polynomial | $n^{\mathcal{O}(1)}$ |
| superpolynomial | $n^{polylog}$ |
| subexponential | $2^{n^{o(1)}}$ |
| exponential | $2^{n^{\mathcal{O}(1)}}$ |

Table 1.5: Main resource bounds.

**P** Class of problems solvable in polynomial time by a sequential machine (RAM, Turing machine,...).[17]

**NP** Class of problems that have solutions verifiable in polynomial time on sequential computers.

**PSPACE** Class of problems solvable in polynomial space by a sequential computer or in polynomial time by a parallel computer or by an interactive protocol.

One of the main outcomes of foundations of computing is that all above listed complexity classes are very robust and to a large degree independent on details of a specific computer model. Robustness of these concepts also justifies their use in this book even before they are formally introduced.

Another robust and key concept is that of **complete problems**—for a complexity class and a type of reductions. Informally, complete problems of a complexity class are the hardest problems of that class. All other problems in that class can be reduced to them using an "easy" reduction. The so-called **NP**-complete problems are of a special importance. They are those problems in **NP** that any other problem in **NP** can be reduced to them in polynomial time. Several thousands of (important) algorithmic problems have already been identified to be **NP**-complete. For none of these problems a polynomial time deterministic algorithm is known, and also a proof that no such algorithm exists is missing. Their importance lies especially in the fact that finding a polynomial time deterministic algorithm for one of them would provide polynomial time deterministic algorithms for all of them.

### 1.10.5 Pitfalls

Asymptotic complexity analysis has many pitfalls and it is important to be aware of them. Let us discuss some of them.

[17]The distinguished rôle of polynomial time algorithms is underscored by the fact that some natural syntactical conditions can be imposed on algorithms that are equivalent to the requirement that they run in polynomial time. For example, an algorithm runs in a polynomial time if and only if it can be programmed in Pascal without constructs **goto**, **repeat** and **while** and with upper bounds in the size of input for **for** cycles.

1. As already stated, the real meaning of complexity analysis results presented in terms of $\mathcal{O}$-, $o$-, $\Omega$-, $\omega$-, $\Theta$-notation may depend much on the way inputs are presented, their size counted, a computing model used, complexity measures considered,... . These dependences are not always clearly stated in papers and books.

For example, it is usually stated that the time complexity of MERGESORT is $O(n \lg n)$. This is true in the sense that there is a constant $c$ such that for any n elements drawn from a totally ordered set, at most $cn \lg n$ comparisons are needed to produce a sorted sequence. This means that nothing else is counted except the number of comparisons; each comparison is considered to take one time unit. Other time consuming operations, as transportation of elements, are ignored as well as the size of elements.

2. Constant factors, that are for good reasons ignored by the asymptotic complexity analysis, may be sometimes prohibitively large. Because of that it may turn out that an algorithm with larger asymptotic complexity is more efficient for practical purposes.

3. A care is also needed by the interpretation of complexity results in cases when the complexity depends, apart from the size of input, also on particular input data. For example, for complexity $T(n)$ of INSERTSORT we get $T(n) = \Omega(n)$ and $T(n) = O(n^2)$. Neither the lower bound nor the upper bound can be improved, because there are inputs requiring quadratic time and inputs for which linear time is enough. However, if the worst-case complexity is considered, then $T_w(n) = \Theta(n^2)$.

4. There is often a confusion between $\mathcal{O}$-notation and $\Theta$-notation; $\mathcal{O}$-notation is often used where actually $\Theta$-notation is more appropriate because the indicated upper bound is asymptotically also a lower bound.

**Moral**. The analysis of even simple computing systems can be a challenge. Complexity analysis is an art, science and an engineering task. A good rule of thumb by complexity analysis is therefore, as in life, to use common sense, exercise good taste, and to listen to your conscience.

## 1.11 Exercises

1. Denote by $u_n$ the number of binary strings of length $n$ that do not contain two consecutive 0's. We have $u_1 = 3, u_2 = 8, u_3 = 22$. Construct a recurrence and determine $u_n$, for any $n$.

2. Find a recurrence relation, including the initial conditions, for the number of ways to climb $n$ stairs if the person climbing the stairs can take one stair or two stairs at a time.

3. Find a recurrence relation, including the initial conditions, for the number of binary strings of length $n$ containing a pair of consecutive 0's.

4. Find a recurrence for the number of bit strings of length $n$ containing neither three consecutive 0's nor three consecutive 1's.

5. Express $T(n)$ from the recurrence:

$$T(1) = a, \qquad T(n) = kT(n/2) + g(n)$$

as a function of $g$—for example, by a reduction to the problem in Exercise 1.2.10 in the text.

6. Find a recurrence for the number of distinct binary trees with $n$ nodes.

7. Solve the recurrence: $u_1 = 1, u_n = au_{n/b} + d(n)$, where $d(n)$ is a multiplicative function and $b$ is a constant, i.e., $d(xy) = d(x)d(y)$ for any $x, y$—as a consequence: $d(b^i) = (d(b))^i$ for any $i \in \mathbf{N}$.

8. Solve the recurrences with $u_1 = 1$ and for every $n > 1$: (a) $u_n = 4u_{n/2} + n$; (b) $u_n = 4u_{n/2} + n^2$; (c) $u_n = 4u_{n/2} + n^3$.

9. Solve the recurrence: $u_0 = a, u_n = 3\sum_{k=0}^{n-1} u_k + 1$ for $n \geq 1$. (There is a very easy solution.)

10. Show the identities: (a) $F_{n+1} = \sum_{k=0}^{n} \binom{n-k}{k}$; (b) $F_{2n} = \sum_{k=0}^{n} F_k$.

11. Show the following properties of Fibonacci numbers:

    (a) $F_{n+m} = F_m F_{n+1} + F_{m+1} F_n$; (b) $F_{n+1} = \sum_{k=0}^{n} \binom{n-k}{k}$;

    (c) $F_{2n} = \sum_{k=1}^{n} F_{2k-1}$; (d) $\sum_{k=0}^{n} F_k^2 = F_n F_{n+1}$.

12. The **Lucas numbers** satisfy the recurrence: $L_0 = 2, L_1 = 1, L_n = L_{n-1} + L_{n-2}$. (a) Determine $L_n$; (b) show that $L_{n+1} = F_n + F_{n+1}$; (c) show that $\sum_{i=0}^{n} L_i^2 = L_n L_{n+1} + 2$.

13. Solve the recurrence: $u_1 = a, u_{2n} = 2u_n + 3, u_{2n+1} = 2u_n + 8$ for $n > 1$.

14. * Show that for the recurrence

$$u_n = a_1 u_{n-1} + \cdots + a_k u_{n-k} + b^n p(n), \tag{1.90}$$

    where $b, a_1, \ldots, a_k$ are constants and $p(n)$ is a polynomial of degree $d$, the corresponding characteristic equation has the form:

$$(x^k - a_1 x^{k-1} - \cdots - a_{k-1} x - a_k)(x - b)^{d+1} = 0$$

    and once this equation is solved we can find the solution of the recurrence (1.90) in a similar way as in the homogeneous case (when $p(n) = 0$).

15. Solve the recurrence:

    (a) $u_1 = 1, u_n = u_{n-1} + 4^n$ for $n > 1$; (b) $u_1 = 1, u_n = 3u_{n-1} + n$, for $n > 1$.

16. Show that $\lceil \frac{n}{m} \rceil = \left\lfloor \frac{n+m-1}{m} \right\rfloor$ for each $m \in \mathbf{N}^+$ and $n \in \mathbf{N}$.

17. Show, for any integer $n$ and reals $a, b > 0$: (a) $\lceil \lceil n/a \rceil / b \rceil = \lceil n/ab \rceil$;

    (b) $\lfloor \lfloor n/a \rfloor / b \rfloor = \lfloor n/ab \rfloor$.

18. Let $f : R \to R$ be a monotonically increasing function such that $0 < f(x) < x$, for $x > 0$. Define $f^{(0)}(x) = x, f^{(i+1)}(x) = f(f^{(i)})(x)$ and for a $c > 0$ $f_c^*(x) = \min\{i \geq 0, f^{(i)}(x) < c\}$. Determine $f_c^*(x)$ for: (a) $f(x) = \frac{x}{2}, c = 1$; (b)$f(x) = \sqrt{x}, c = 1$.

19. ** Show the inequalities: (a) $n! > ((\frac{n}{2})!)^2$, if $n$ is even; (b) $n! \geq (\frac{n+1}{2})!(\frac{n-1}{2})!$, if $n$ is odd; (c) $(\frac{n}{3})^n < n! < (\frac{n}{2})^n$, for all $n \geq 6$.

20. Show the following identities, where $n, k$ are integers and $r$ is a real:
(a) $\binom{-r}{k} = (-1)^k \binom{r+k-1}{k}$; (b) $\sum_{k=0}^{m} (-1)^k \binom{n}{k} = (-1)^m \binom{n-1}{m}$;
(c) $\sum_{k=0}^{n} (-1) k \binom{n}{k} = 0, n \geq 1$.

21. * Show the following identities: (a) $\binom{n}{r-1} = \binom{n+2}{r+1} - 2\binom{n+1}{r+1} + \binom{n}{r+1}$; (b) $\sum_{j=1}^{n} \binom{j}{2} = \binom{n+1}{3}$.

22. * Prove the following identities for binomial coefficients: (a) $\sum_{k=1}^{n} k\binom{n}{k} = n2^{n-1}$;
(b)$\sum_{k=1}^{n} k\binom{n}{k}^2 = n\binom{2n-1}{n-1}$.

23. Show the inequalities: (a) $\binom{k}{l} \leq \left(\frac{k \cdot e}{l}\right)^l$; (b) $\binom{b}{r} \left(\frac{1}{n}\right)^r \leq \left(\frac{e}{r}\right)^r$, where $e$ is the base of natural logarithms.

24. Find the generating function for the sequence $\langle F_{2i} \rangle_{i=0}^{\infty}$.

25. * Show, e.g., by expressing the generating function for Fibonacci numbers properly, that
$$\sum_{k=0}^{n} F_k F_{n-k} = \frac{1}{5}(2nF_{n+1} - (n+1)F_n).$$

26. In how many ways can one tile a $2 \times n$ rectangle with $2 \times 1$ and $2 \times 2$ "dominoes"?

27. Use the concept of generating functions to solve the following problem: determine the number of ways one can pay $n$ dollars with dimes, quarters and half dollars.

28. Show: (a) $\sqrt{4 + \sqrt{3x}} = \Theta(x^{\frac{1}{2}})$; (b) $(1 + \frac{2}{x})^x = \Theta(1)$.

29. Show: (a) $x^2 + 3x \sim x^2$; (b) $\sin \frac{1}{x} \sim \frac{1}{x}$.

30. Find two functions $f(n)$ and $g(n)$ such that neither of the relations $f(n) = \mathcal{O}(g(n))$ nor $g(n) = \mathcal{O}(f(n))$ hold.

31. Find an $\mathcal{O}$-estimation for $\sum_{j=1}^{n} j(j+1)(j+2)$.

32. Show that if $f(n) = a, f(n) = cf(n-1) + p(n)$ for $n > 1$, where $p(n)$ is a polynomial and $c$ is a constant, then $f(n) = \Theta(n)$.

33. Show $\sum_{i=1}^{n} i^k = \Theta(n^{k+1})$.

34. Which of the following statements are true? (a) $(n^2 + 2n + 2)^3 \sim n^6$; (b) $n^3(\lg\lg n)^2 = o(n^3 \lg n)$; (c) $\sin x = \Omega(1)$; (d) $\sqrt{\lg n + 2} = \Omega(\lg\lg n)$.

35. Find a function $f$ such that $f(x) = \mathcal{O}(x^{1+\varepsilon})$ is true for every $\varepsilon > 0$ but $f(x) = \mathcal{O}(x)$ is not true.

36. * Order the following functions according to their asymptotic growths, i.e., find an ordering $f_1(n), ..., f_{35}(n)$ of the following functions such that $f_{i+1}(n) = \Omega(f_i(n))$.

$$\begin{array}{ccccc}
\lg(\lg^* n) & 2^{\lg^* n} & F_n & (\sqrt{2})^{\lg n} & n^2 \\
n! & (\lg n)!(4/3)^n & n^3 & 2^{\lg^8 n} & e^{\lg n^3} \\
\lg^2 n & \lg(n!) & 2^{2^n} & n^{1/\ln n} & \ln\ln n \\
\lg^* n & n \cdot 2^n & n^{\lg\lg n} & \ln n & H_n \\
1 & \pi(n) & 2^{\lg n} & (\ln n)^{\ln n} & e^n \\
8^{\lg n} & (n+1)! & \sqrt{\ln n} & \lg^*(\lg n) & \lg^* \lg^* n \\
2^{\sqrt{3}\lg n} & n & 2^n & n\lg n & 2^{2^{n+2}}
\end{array}$$

37. Suppose that $f(x) = \mathcal{O}(g(x))$. Does it imply that (a) $2^{f(x)} = \mathcal{O}(2^{g(x)})$; (b) $\lg f(x) = \mathcal{O}(\lg g(x))$; (c) $f^k(x) = \mathcal{O}(g^k(x))$, for $k \in \mathbf{N}$?

38. Show that if $f_1(x) = o(g(x)), f_2(x) = o(g(x))$, then $f_1(x) + f_2(x) = o(g(x))$.

39. Show: (a) $\sin x = o(x)$; (b) $\frac{1}{x} = o(1)$; (c) $100\lg x = o(x^{0.3})$.

40. Show that: (a) $\frac{1}{1+x^2} = \mathcal{O}(1)$; (b) $\frac{1}{1+x^2} = o(1)$.

41. Does $f(x) = o(g(x))$ imply $2^{f(x)} = o(2^{g(x)})$?

42. Show that $f(x) = o(g(x)) \Rightarrow f(x) = \mathcal{O}(g(x))$ but not necessarily $f(x) = \mathcal{O}(g(x)) \Rightarrow f(x) = o(g(x))$.

43. Show that if $f_1(x) = \mathcal{O}(g(x)), f_2(x) = o(g(x))$, then $f_1(x) + f_2(x) = \mathcal{O}(g(x))$.

44. Show that $o(g(n)) \cap \omega(g(n))$ is the empty set for any function $g(n)$.

45. What is wrong with the following deduction? Let $T(n) = 2T(\lfloor \frac{n}{2} \rfloor) + n$, $T(1) = 0$. We assume inductively that $T(\lfloor \frac{n}{2} \rfloor) = \mathcal{O}(\lfloor \frac{n}{2} \rfloor)$ and $T(\lfloor \frac{n}{2} \rfloor) \le c\lfloor \frac{n}{2} \rfloor$. Then $T(n) \le 2c\lfloor \frac{n}{2} \rfloor + n \le (c+1)n = \mathcal{O}(n)$?

46. Solve recurrences:

    (a) $T(1) = a, T(n) = 2T(n/2) + n\lg n$;

    (b) $T(1) = a, T(n) = 7T(n/2) + \mathcal{O}(n^2)$.

47. Let $T(n) = 2T(\lfloor \sqrt{n} \rfloor) + \lg n$. Show (i.e., using the substitution $n = 2^m$), that $T(n) = \mathcal{O}(\lg n \lg\lg n)$.

48. Show that $u_n = \mathcal{O}(n!)$ if $u_n$ is defined by recurrence $u_n = 1, u_n = nu_{n-1} + bn^2$. Can you find a better estimation for $u_n$?

49. Show that if $n > m$, then $n \bmod m < \frac{n}{2}$.

50. Show that $d \setminus n \Rightarrow F_d \setminus F_n$

51. Compute the greatest common divisor for pairs of numbers: (a) $(325, 53)$; (b) $(2002, 2339)$; (c) $(3457, 4669)$; (d) $(143, 1326)$; (e) $(585, 3660)$.

52. Express the greatest common divisor of each of the following pairs of integers as a linear combination of these integers: (a) (117, 213); (b) (3454, 4666); (c) (21, 55); (d) (10001, 13422); (e) (10233, 33341).

53. Show, by induction, that the number of steps to compute $\gcd(n, m), n > m$ is smaller than $\log_r n$ where $r = (1 + \sqrt{5})/2$.

54. Find a prime $n$ such that $2^n - 1$ is not prime.

55. Show that the $n$-th prime is smaller than $2^{2^{n+1}}$.

56. Show that an integer $n$ is prime iff there exists an $a$ $(0 < a < n)$ such that $a^{n-1} \equiv 1 \pmod{n}$, and for each prime $q$ dividing $n - 1$ we have $a^{\frac{n-1}{q}} \not\equiv 1(\mathrm{mod} n)$.

57. (Wilson's prime number test.) Show that $(p - 1)! \equiv -1 \bmod p$ iff $p$ is a prime.

58. An integer is called perfect if it equals the sum of its proper divisors. (For example 6 and 28 are perfect integers.) (a) Find the first 10 perfect numbers; (b) Show that if $2^n - 1$ is prime, then $2^{n-1}(2^n - 1)$ is perfect.

59. Compute; (a) $5^{11}3^{14} \bmod 26$; (b) $4^{80} \bmod 65$; (c) $3^{100} \bmod 79$; $3^{1000} \bmod 17$; (d) $5^{11}3^{14} \bmod 26$; (e) $4^{80} \bmod 65$; (f) $2^{34} \bmod 341$.

60. Show that if $a, b \in \mathbf{N}^+$, then: (a) $(2^a - 1) \bmod (2^b - 1) = 2^{a \bmod b} - 1$; (b) $gcd(2^a - 1, 2^b - 1) = 2^{gcd(a,b)} - 1$.

61. Compute: $(\sum_{i=1}^{100} i!) \bmod 12$; (b) $(\sum_{i=1}^{90} i^5) \bmod 4$.

62. Solve congruences (a) $32x \equiv 6 \pmod{70}$; (b) $7x \equiv 3 \pmod{24}$;

    (c) $32x \equiv 1 \pmod{45}$; (d) $14x \equiv 5 \pmod{54}$.

63. Determine inverses: (a) $4^{-1} \bmod 9$; (b) $7^{-1} \bmod 17$; (c) $21^{-1} \bmod 143$.

64. Show that if $a$ is odd, then $a^{2^{n-2}} \equiv 1 \pmod{2^n}$ for each $n \geq 3$.

65. Let $n$ be an integer, $x < 2^n$ a prime, $y < 2^n$ a composite number. Show, i.e., by using the Chinese Remainder Theorem, that there is an integer $p < 2n$ such that $x \not\equiv y \bmod p$.

66. Design the multiplication table for (a) $\mathbf{Z}_9^*$; (b) $\mathbf{Z}_{11}^*$.

67. Let $p > 2$ be a prime and $g$ a principal root of $\mathbf{Z}_p^*$. Then, for any $x \in \mathbf{Z}_p^*, x \in QR_p \Leftrightarrow$ $index_{p,g}(x)$ is even.

68. If $p$ is a prime, $e \in \mathbf{N}$, then the equation $x^2 \equiv 1 \pmod{p^e}$ has only two solutions: $x = 1$ and $x = -1$.

69. Show that if $g$ is a principal root of $Z_n^*$, then the equality $g^x \equiv g^y \pmod{n}$ holds iff $x \equiv y \pmod{\phi(n)}$.

70. Show, for any constant $a, b$ and a random variable $X$: (a) $E(aX + b) = aEX + b$; (b) $V(aX + b) = a^2VX$.

71. (Variance Theorem.) Show, for random variables $X, Y$ and reals $a, b$: (a) $V(aX+bY) = a^2VX + b^2VY + 2abE((X - EX)(Y - EY))$; (b) $V(X + Y) = VX + VY$.

72. Find the probability that a family of four children does not have a girl if the sexes of children are independent and if (a) the probability of a girl is 51%; (b) boys and girls are equally likely.

73. Find the following probabilities when $n$ independent Bernoulli's trials are carried out with probability $p$ of success: (a) the probability of no failure; (b) of at least one failure; (c) of at most one failure; (d) of at most two failures.

74. Determine the probability that exactly seven 0's are generated when 10 bits are generated and the probability that 0 is generated is 0.8, the probability that 1 is generated is 0.2 and bits are generated independently.

75. (Birthday paradox) Birthdays are important days. (a) Determine the probability that in a group of $n$ persons there are at least two with the same birthday (assume that all 366 days are equally likely as birthdays; (b) How many people are needed to make the probability that two people have the same birthday greater than 1/2.

76. There are many variants of the Chernoff's bound. Show correctness of the following one: If $X_1, \ldots, X_n$ are independent random variables and $Pr(X_i = 1) = p$, for all $1 \leq i \leq n$, then $Pr(\sum_{i=1}^{n} X_i \geq pn + a) \leq e^{\frac{-2a^2}{n}}$.

77. Show **Chebyshev's inequality**: If $X$ is a random variable, then $Pr((X - EX) > \alpha) < \frac{VX}{\alpha^2}$, for all $\alpha > 0$.

78. Let $p(x_1, \ldots, p_n)$ be a polynomial with rational coefficients of the degree $d$ and not identically 0. Show that $p(\alpha) \neq 0$ at least for half of all vectors $\alpha \in \{-nd, \ldots, 0, \ldots, nd\}^n$.

79. Show, for the linear congruential generator $x_{i+1} = (ax_i) \bmod m$, that if $m$ is prime and a choice of $a$ yields the maximum period (of $m - 1$), than also $a^k$ yields the maximum period provided $k < m$ and $(m - 1)$ is not divisible by $k$.

80. Suppose that $m, n \in \mathbf{N}^+$. What is the probability that randomly chosen positive integer smaller than $mn$ is not divisible by either $m$ or $n$?

81. Show **Chebyshev's inequality**: If $X$ is a random variable, then $Pr((X - EX) > \alpha) < \frac{VX}{\alpha^2}$, for all $\alpha > 0$.

82. * There are many variants of Chernoff's bound. Show correctness of the following one: If $X_1, \ldots, X_n$ are independent random variables and $Pr(X_i = 1) = p$, for all $1 \leq i \leq n$, then $Pr(\sum_{i=1}^{n} X_i \geq pn + a) \leq e^{\frac{-2a^2}{n}}$.

83. Show, for the iteration $x_{i+1} = (ax_i + b) \bmod m, i \geq 0$: if $a \perp m$ then $x_0$ repeats periodically in $x_1, x_2, \ldots$.

84. Show, for the linear congruential generator and $X'_n = X_{n+1} - X_n$:
(a) $X'_n \equiv a^{n-1}X'_1 \pmod m$; (b) $X'_n = X'_{\phi(m)+n}$.

## QUESTIONS

1. Is $F_n$ larger than $\left(\frac{1+\sqrt{5}}{2}\right)^n$?
2. Is it true that $3^{n+2} = \mathcal{O}(3^n)$ and $3^{2n} = \mathcal{O}(3^n)$?
3. We know that $n! \prec n^n$. Which of the relations $n^n \prec (n!)^2$ and $(n!)^2 \prec n^n$ holds?
4. Are the functions $\lceil \lg n \rceil!$ and $\lceil \lg \lg n \rceil!$ polynomially bounded?
5. Is it true that $\Theta(f(n) + g(n)) = \Theta(\max\{f(n), g(n)\})$?
6. How many primes do we have of a given length $n$?
7. How do you interpret the equation $3n^3 + \Theta(n^2) = \Theta(n^3)$?
8. Which properties have Blum integers?
9. In which cases is it better to use pseudo-random generators than a true random generator?
10. Why are constant factors at the analysis of algorithms not of importance and why they are of importance?

## 1.12 Historical and Bibliographical References

The history of basic concepts, methods and results used in the analysis of algorithms is deeply rooted in the history of mathematics. The most important contribution for their introduction and further development for computing was made by Donald E. Knuth—who received Turing award for 1974. His monumental work and pioneering books [Knuth (1968); Knuth (1969); Knuth (1973); Greene and Knuth (1981); Graham, Knuth and Patashnik (1989)] are also the main sources of detailed historical and bibliographical references. Moreover, the last of these books represents as a textbook a masterpiece of hardly matched quality in computing.

Concrete Mathematics of Graham, Knuth and Patashnik (1989) is not only the main textbook to recommend for a more detailed and deeper treatment of the subject but it has also influenced the choice of material and presentation for a large portion of this chapter. Additional books used and to be recommended are by Kranakis (1986); Harel (1987); Brassard and Brattey (1988); Cormen, Leiserson and Rivest (1990); Aigner (1993); Arnold and Guessarian (1996). An extensive introduction to the analysis of algorithms is due to Sedgewick and Flayolet (1996) and for more advanced tools see a comprehensive book of Hofri (1995).

With layouts of graphs and especially trees we deal in some detail in Section 10.6. The Towers of Hanoi Problem and its legend were introduced by Lucas (1894), according to

Graham, Knuth and Patashnik (1989), where the problem and several of its modifications are analyzed. Its generalization to 4 rods is considered by Gedeon (1992). Methods to solve recurrences are discussed by Bentley, Haken and Saxe (1978), Luecker (1980), Greene and Knuth (1981), Aho, Hopcroft and Ullman (1983), Purdon and Brown (1985), Brassard and Brattey (1988), Graham, Knuth and Patashnik (1989), Cormen, Leiserson and Rivest (1990), Aigner (1993) and Arnold and Guessarian (1996).

The generating function concept has been intensively used since L. Euler, 1741, and L. Laplace, 1812—their application to solving recurrences is elaborated by Graham, Knuth and Patashnik (1989). From there also the domino problem and the bootstraping method come. A detailed proof of Theorem 1.4.11 can be found in Aigner (1993). A survey on $3x+1$ problem is due to Lagarias (1985).

Names and notation for the ceiling and floor functions are due to Iverson (1960); Lemma 1.3.1 is due to Graham, Knuth and Patashnik (1989), where also binomial coefficients are discussed in detail.

The amazing story of primes and records on primes is nicely presented in the book by Ribenboim (1988) and in the expository paper by Zagier (1977). Estimations for $\pi(n)$ can be found in Rosser and Schoenfeld (1962). Prime Number Theorem is due to Dirichlet, Hadamard and de la Vallée Poussin; a proof can be found in Landau (1953).

Quadratic residues, computing of discrete square roots, discrete logarithms and their applications in pseudo-random generators and in cryptography are well presented by Kranakis (1986)—Section 1.7 much profited from it and also the proof of Theorem 1.8.5 can be found there. A polynomial time algorithm for computing square roots modulo prime was first designed by Berlekamp (1970). An elegant Las Vegas algorithm to compute square roots modulo a prime is from Karp (1991) and is credited to Lehmer (1951). A polynomial time algorithm for computing discrete logarithm modulo a prime $p$ such that $p-1$ has only small factors is due to Pohlig and Hellman (1978). Theorem 1.8.15 is, as many basic results in foundations of computing, due to Michael Rabin (1979)—he received the Turing award in 1976. Gauss' characterizations of those $n$ that $Z_N^*$ is cyclic can be found in Kranakis (1986). For a survey of algorithmic number theory see Adleman (1994).

There are many excellent books on probability; for example by Feller (1964) and Billingsley (1986). Execise 1.9.5 follows Motwavi, Raghavan (1995). Classical approaches to pseudo-random generators are treated exhaustively by Knuth (1969) and the complexity based approaches are well presented in Kranakis (1986). For proofs of inequalities (1.86) and (1.87) see, for example, Cormen, Rivest and Leiserson (1990). For Chernoff's bounds see Hagerup and Rüb (1989).The concept of polynomial time indistinguishibility is due to Yao (1982) and Blum and Micali (1982). The BBS pseudo-random generator is due to Blum, Blum and Shub (1986); Blum-Micali pseudo-random generator was introduced by Blum and Micali (1982). The result on predictability of linear congruential generator is due to Plumstead (1982). Methods to solve probabilistic recurrences have been worked out by Richard M. Karp—Turing award for 1985—who has contributed significantly to the development of randomized computing. Theorem 1.9.17 is due to Karp (1991) and Theorem 1.9.18 is due to Chaudhuri and Dubhashi (1995).

D. Harel's Algorithmics (1987) is another masterpiece in providing not too formal but deep insights into computing including complexity analysis and an excellent reference for additional insights about aims, methods, results and merits of complexity analysis discussed in Section 1.10.

# Chapter 2

# FOUNDATIONS

## INTRODUCTION

Foundations of computing are deeply rooted in mathematics and fluency in the basic mathematical culture is a must for the computer science. In addition, computing itself has strong impact on this culture. The chapter serves therefore several aims. First, to summarize in a concise way foundational concepts of mathematics needed in computing and to set up terminology and notational conventions—it therefore serves as a reference source. Secondly, and mainly, it presents, illustrates, and discusses new paradigms computing brought into these foundational areas of mathematics that are of key importance also for computing. In doing so some basic problems are introduced with which this book deals with as well as basic method to solve them. This way the chapter serves as a motivation and introduction to various topics of the book. Thirdly, special concepts and methods to be used later are introduced and illustrated.

## LEARNING OBJECTIVES

The aim of the chapter is to learn:

1. basic concepts, terminology, and notations concerning sets, relations, functions, graphs, languages, and algebras;

2. basic methods of representation of sets, relations, and graphs;

3. new paradigms the computing brought into the foundational areas of mathematics, that are of importance for science in general, and computing science in particular;

4. several methods to visualize words and languages and to represent pictures and images by words and languages.

> If in other sciences we should arrive at certainty without doubt and truth without error, it behooves us to place the foundations of knowledge on mathematics.
>
> *Roger Bacon*[1] *(1214-1294)*

Basic mathematical structures, as sets, relations, functions, graphs, algebras and formal languages, play an important rôle in foundations of any mature science. This alone is a sufficient reason to summarize basic concepts and results of these areas, as well as to fix terminology and notation, in an introductory chapter of a book on foundations of computing. However, the aim of this chapter goes further. Foundations of computing bring also into these foundational areas of modern science new deep paradigms, concepts, methods and problems that are then, in turn, of large importance for the whole computing. The second aim of this chapter is therefore to point out, motivate and illustrate these new viewpoints, concepts, problems and methods. At the same time this provides basic motivations for many subjects the book deals with. Complexity standpoints and asymptotic estimations play an unreplaceable rôle here—they provide guidance and evaluations. This is why this chapter follows, and not precedes, that on fundamentals of complexity analysis and randomness.

## 2.1 Sets-November 8, 2005

The simplest and at the same time perhaps the most complex and richest mathematical objects are sets. Their position and rôle in computing is the same. They are fundamental (discrete) structures on which other (discrete) structures are built. Many key problems of foundation of computing can be seen as problems concerning sets.

### 2.1.1 Basic Concepts

A **set** is a collection of distinguishable objects (elements). The **empty set** $\emptyset$ has no objects. If $A$ is a set, then $x \in A$ ($x \notin A$) denotes that $x$ is (is not) an object of $A$. Notation $A \subseteq B$ expresses that the set $A$ is a **subset** of $B$—each object of $A$ is in $B$. Notation $A \subset B$ (or $A \subsetneq B$) means that $A$ is a **proper subset** of $B$. Sets $A, B$ are **equal**, notation $A = B$, if $A \subseteq B$ and $B \subseteq A$. Two sets are said to be **disjoint** if no object is in both of them. If elements of a set $\mathcal{A}$ are sets we use also term a **family of sets** for $\mathcal{A}$. Notation $x \in_{\mathcal{D}} A$ starts to be used to denote that $x$ is an element of the set $A$ randomly chosen with respect to the probability distribution $\mathcal{D}$. Notation $x \in_{\mathcal{U}} A$ is reserved for choosing an element of $A$ with respect to the uniform distribution.

[1] An English philosopher and natural scientists,considered sometimes as the first theoretician of experimental sciences.

**Exercise 2.1.1** *Find two sets $A, B$ such that $A \in B$ and $A \subseteq B$.*

It is often assumed that all sets we deal with are subsets of a **universal set** $U$. With each $A \subseteq U$ we can then associate a **characteristic function** (or a **membership predicate**) $f_A : U \to \{0, 1\}$, defined by $f_A(x) = [x \in A]$.

**Binary operations on sets:**

$$\begin{array}{rcl}
\textbf{union } A \cup B & = & \{x \mid x \in A \text{ or } x \in B\}; \\
\textbf{intersection } A \cap B & = & \{x \mid x \in A \text{ and } x \in B\}; \\
\textbf{difference } A - B & = & \{x \mid x \in A \text{ and } x \notin B\}; \\
\textbf{symmetric difference} A = B \triangle C & = & A - B \cup B - a; \\
\textbf{Cartesian product } A \times B & = & \{(a, b) \mid a \in A, b \in B\}.
\end{array}$$

The concept of the Cartesian product can be generalized, in a natural way, to more than two sets. Moreover, since the union and intersection are commutative and associative operations, we consider also

$$\begin{array}{rl}
\textbf{generalized union} & \bigcup_{i \in I} A_i = \{x \mid \exists i \in I, x \in A_i\}; \\
\textbf{generalized intersection} & \bigcap_{i \in I} A_i = \{x \mid x \in A_i \forall i \in I\}; \\
\textbf{generalized Cartesian product} & \bigotimes_{i=1}^{n} A_i = \{x \mid x = (x_1, \ldots, x_n), x_i \in A_i\}
\end{array}$$

where $I \neq \emptyset$ is an index set. For a Cartesian product of a set $A$ with itself we use the notation $A^i = \bigotimes_{j=1}^{i} A$.

Two special versions of union and difference operations are of interest in computing: **insertion** $A \cup \{x\}$, and **deletion** $A - \{x\}$, where $A$ is a set and $x$ an object. If the underlying set is clear from the context, a simpler notation INSERT($x$) and DELETE($x$) is often used.

**Unary operations on sets**:

$$\begin{array}{rcl}
\textbf{complement } A^c & = & U - A, \text{ another notation: } \overline{A}; \\
\textbf{power set } 2^A & = & \{B \mid B \subseteq A\}; \\
\textbf{iterations } A^*(A^\omega)[A^{\omega\omega}] & - & \text{a set of all finite (infinite) [bi-infinite] sequences} \\
 & & \text{of elements of } A.
\end{array}$$

**Exercise 2.1.2** *Let $A, B$ be sets. Do the following implications hold?*
*(a) $A \cap B = \emptyset \Rightarrow 2^A \cap 2^B = \emptyset$; (b) $2^A = 2^B \Rightarrow A = B$.*

**Exercise 2.1.3** *Which of the following relations hold?*
*(a) $2^A \cap 2^B = 2^{A \cap B}$; (b) $2^A \cup 2^B = 2^{A \cup B}$.*

**Partition** of a set $A$ is a family, (finite or infinite), of mutually disjoint subsets $B_i, i \in I$, of $A$ such that $A = \bigcup_{i \in I} B_i$. Notation $C = A \dot{\cup} B$ will be used to express that the set $C$ is partitioned into two disjoint subsets $A$ and $B$.

**Important number sets:** $\emptyset$ (the empty set), $\mathbf{N}$ (nonnegative integers), $\mathbf{N}^+$ (positive integers), $\mathbf{Z}$ (all integers), $\mathbf{Q}$ (rational numbers), $\mathbf{R}$ (real numbers), $\mathbf{R}^+$ (positive real numbers), $\mathbf{C}$ (complex numbers), $\mathbf{Z}_n$ (the set of residue classes modulo $n$), and $\mathbf{Z}_n^*$ (those residue classes from $\mathbf{Z}_n$ that contain elements relatively prime to $n$). Moreover, if $n \in \mathbf{N}$, then $[n] = \{0, 1, \ldots, n-1\}$. In particular, $[2] = \{0, 1\}$.

The term **alphabet** will be often used to denote an arbitrary finite nonempty set $A$. In such a case elements of $A$ are called symbols, elements of $A^*$ strings (or words), and elements of $A^\omega$ $\omega$-strings. Subsets of $A^*$ are called languages and subsets of $A^\omega$ are $\omega$-languages. The elements of the set $\mathbf{B} = \{0, 1\}$ will be interpreted, depending on the context, either as integers, or (binary) symbols—bits—or Boolean (truth) values. Elements of the set $\mathbf{B}^*$ are called often **binary strings** and elements of the set $\mathbf{B}^\omega$ are called **infinite binary strings**. The set $\mathbf{B}$ is called also the **binary alphabet**.

**Exercise 2.1.4** *A* **multiset** *is a collection of elements, where an element can occur more than once. Let* $\{m_1.a_1, \ldots, m_k.a_k\}$ *denote the multiset in which the element* $a_i$ *occurs* $m_i$*-times. Define in a natural way operations of union, intersection and difference for multisets, and determine, for* $A = \{2.a, 4.b, 3.c\}, B = \{1.a, 2.b, 3.c\}$, $A \cup B, A \cap B, A - B$.

**Cardinality:** $|A|$ denotes the cardinality of the set $A$. If $A$ is finite, $|A|$ is the number of its elements. For infinite sets cardinality is defined indirectly. Two infinite sets $A, B$ are said to have the same cardinality if there is a bijection between them. Sets that have the same cardinality as $\mathbf{N}$ are called **countable**. The set $\mathbf{R}$ is said to have cardinality of **continuum**.

Power set and iteration operations can much increase cardinality. If $A$ is a finite set, then clearly

$$|2^A| = 2^{|A|}, \qquad |A^*| = |\mathbf{N}|, \qquad |A^\omega| = |\mathbf{R}|. \tag{2.1}$$

In addition, $|2^{\mathbf{N}}| = |\mathbf{R}|$.

**Remark 2.1.5** The description of a set as a collection of objects, based on an intuitive notion of object, is due to G. Cantor (1895). Resulting set theory is called a **naive set theory** and this is what we will use. The discovery by Russel[2] (1902) that this theory leads to **paradoxes**, or **logical inconsistencies**, has first caused nightmare in mathematics. This has been later resolved through the development of an **axiomatic set theory**.

> **Russel's paradox**: Let $S$ be the set that contains a set $X$ if and only if $X$ does not belong to itself—in other words let $S = \{x \mid x \notin x\}$. Is $S \in S$? If yes, then necessarily $S \notin S$. If not, then necessarily $S \in S$. A contradiction in both cases.

[2]Bertrand Arthur William Russel (1872-1970), an English philosopher, logician, mathematician and social reformers. His "Principles of Mathematics" and "Principia Mathematica" (with A. N. Whithead) much influenced modern logic. Wrote more than 68 books. Several times imprisoned for his articles and anti-military activities. Got Nobel price for literature.

The existence of paradoxes looks as a negative phenomenon. However, the paradoxes play, as many other negative results as we shall see later, an important positive rôle in foundation of computing. For example, they were used to show several important results concerning the limitations of computing and formalization. This will be discussed in detail in Chapter 6.

### 2.1.2 Representation of Objects by Words and Sets by Languages

By a representation of objects of a set $A$ by objects of a set $C$—the term **encoding** is often used for that—a mapping $c : C \to A$ is understood that maps uniquely objects of $C$ into objects of $A$. $c(a)$ is then the object represented by the "code" $a$.

It follows from (2.1) that the sets of binary strings and infinite binary strings have enough elements to encode uniquely objects of any set we practically need to deal with in computing. Not only that. For almost all sets we deal with, there is a natural encoding of their elements by binary strings. Moreover, most of the basic problems in computing have a natural formulation in terms of sets (of strings). This is why in foundations of computing it is to a large degree sufficient to deal mainly with sets of (binary) strings—called languages.

**Example 2.1.6 (Binary number representations)** *There are several ways binary strings can be seen as representing integers. Each finite binary word $b = b_1 \dots b_n$ and each infinite binary word $c = c_1c_2\dots$ can be seen as representing an integer, notation $bin(b)$, and a real number in $[0,1]$, notation $bre(c)$, defined by*

$$bin(b) = \sum_{i=1}^{n} b_i 2^{n-i}, \qquad bre(c) = \sum_{i=1}^{\infty} c_i 2^{-i}. \tag{2.2}$$

Observe that the mapping $bre : \mathbf{B}^\omega \to [0,1]$ is one-to-one if we restrict it to the set $\mathbf{B}^\omega - \mathbf{B}^*\{1\}^\omega$. If $x < 2^n$, $x, n \in \mathbf{N}$, then $x$ can be uniquely represented by an $n$-bit string $b = b_1 \dots b_n$, notation $bin_n^{-1}(x)$, such that $bin(bin_n^{-1}(x)) = x$. (Observe that $b_i = \lfloor \frac{x}{2^{n-i}} \rfloor \bmod 2$.) Notation $bin^{-1}(n)$ will be used to denote the binary representation of $n$ with the leftmost bit equal 1 if $n \neq 0$ and $bin^{-1}(0) = 0$, otherwise.

**Exercise 2.1.7 (Dyadic representation of integers.)** *If $w \in \{1,2\}^*$, then define $dya(\varepsilon) = 0$ and for $w = a_{n-1}\dots a_0, a_i \in \{1,2\}$, $dya(w) = \sum_{i=0}^{n-1} a_i 2^i$. (a) Show that each integer has a unique dyadic representation; (b) show dyadic representations for numbers $7, 77, 777, 7777, 777777$; (c) design an algorithm to add two integers given by their dyadic representations.*

**Exercise 2.1.8** *(Fibonacci number representation) (a)* Show that each non-negative integer has a unique "Fibonacci representation" $n = \sum_{i=1}^{k} F_{m_i}$, where $m_i \geq m_{i+1} + 2$, for $1 \leq i < k$, and either $n = 0$ or $m_k \geq 2$; (b) determine the Fibonacci number representations of integers $2^i, 1 \leq i \leq 10$.*

**Example 2.1.9 (Universality of binary representations)** *Let $A = \{a_1, \dots, a_n\}$ be a finite set—the alphabet—and $2^{m-1} \leq n < 2^m$ for some integer $m$. Each element of $A$ can be uniquely encoded by a binary string of length $m$. This can in turn be used to encode each element of $A^*$ and of $A^\omega$ by a finite, or an infinite binary string—each symbol from $A$ is simply replaced by its binary code. This simple encoding of strings from a finite alphabet by binary strings allows often to deal, without loss of generality, only with sets of binary strings.*

**Example 2.1.10 (Binary string representation of matrices)** *Let $M = \{a_{ij}\}$ be an $n \times n$ matrix of nonnegative integers. $M$ can be represented by the following word over the alphabet $\Sigma = \{0, 1, \#\}$:*

$$bin^{-1}(a_{11})\#bin^{-1}(a_{12})\#\dots\#bin^{-1}(a_{1n})\#\#bin^{-1}(a_{21})\#\dots\#bin^{-1}(a_{2n})\#\#\dots\#\#bin^{-1}(a_{n1})\#\dots\#bin^{-1}(a_{nn})$$

*We can then use, for example, the encoding $0 \to 00$, $1 \to 11$ and $\# \to 01$ to get a completely binary encoding of $M$.*

*In special cases much simpler encoding of matrices by binary strings is available. For example, an $n \times n$ symmetric Boolean matrix can be encoded by a binary string of length $n(n+1)/2$ by simply listing, one after another, all rows of the matrix above the main diagonal.*

For each set there are infinitely many ways its objects can be encoded by strings over an alphabet. Which of them is the best depends on the way the set is going to be dealt with.

There are also infinitely many ways strings and sets of strings can be interpreted. It may also happen, as the following example indicates, that very simple sets of strings represent quite complex objects.

**Example 2.1.11** *Each string $(a_1, b_1), \dots, (a_n, b_n)$ over the alphabet $A = \{(0,0), (0,1), (1,0)\}$ can be interpreted as a point of the plane with coordinates $(0.a_1 \dots a_n, 0.b_1 \dots b_n)$. At this interpretation $A^*$ represents the set of points of the fractal structure called the Sierpiński triangle and shown in Figure 2.1a.*

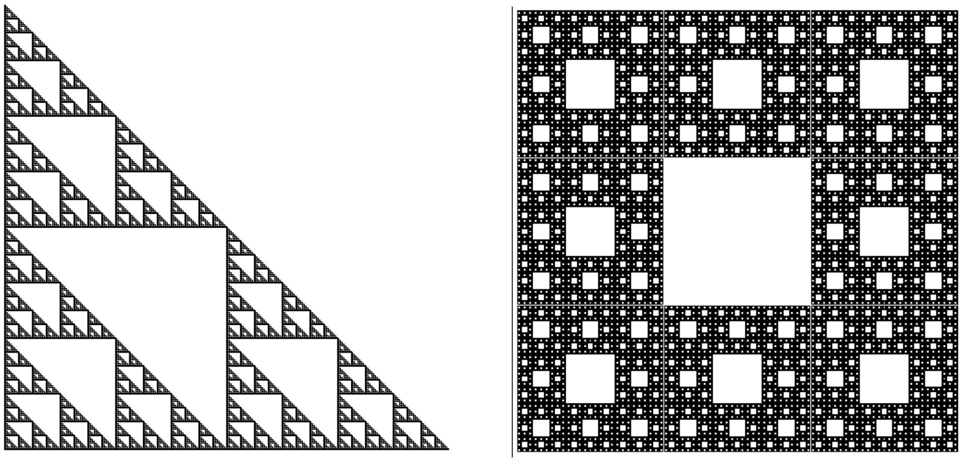
**Exercise 2.1.12** *Find a finite set $A$ and an interpretation of strings over $A$ such that $A^*$ represents the fractal structure called the Cantor carpet and shown in Figure 2.1b.*

**Exercise 2.1.13** *Find a nice and simple set description of the Sierpiński tetrahedron whose construction is shown in Figure 2.2.*

### 2.1.3 Specifications of Sets—Generators, Recognizers and Acceptors

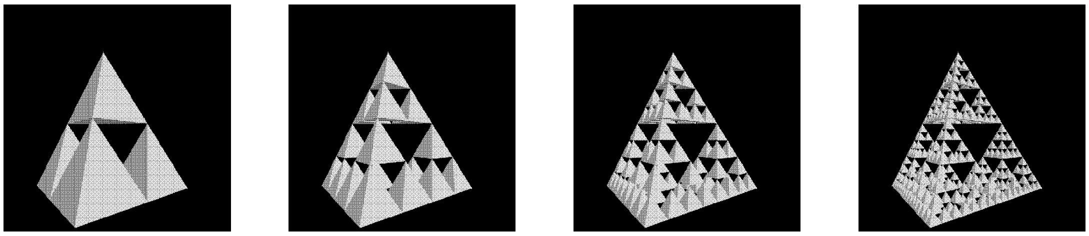
Basic problems concerning set specifications (descriptions) can be summarized as follows.

1. How to specify a set—in a simple and useful way? For example, it is certainly not obvious that the sets of points shown in Figure 2.1 have such simple descriptions.



(a) (b)

Figure 2.1: Sierpiński triangle and Cantor carpet.



(a) (b) (c) (d)

Figure 2.2: A stepwise design of the Sierpińskitetrahedron—

2. How to determine, given a set description, which set it describes? How to determine which objects are in the specified set? For example, which natural numbers are in the set described by formula (2.3) on page 96? In particular, how to find out, given a set specification and an object, whether this object is in the specified set?

3. How to specify important families of sets? For example, those that can be accepted by automata of a certain type.

4. Which properties have sets specified using some particular specification languages? For example, logic formulas of a certain type, programs, automata or grammars of a certain type?

5. Which sets have specifications that allow to find efficiently answers to various basic questions. For example, whether a given element is in the set, or whether the set is empty (infinite)?

All these problems belong to the most fundamental ones in computing and we will deal with them intensively in this book.

There are several basic ways how to specify sets.

1. **Enumeration.** Enumerating elements of a finite set. For example,

$$\begin{aligned} P &= \{19, 31, 61, 89, 107, 127, 521, 607, 1279, 2203, 2281, 3217, 4253, 4423, 9689 \\ &\quad 9941, 11213, 19937, 21701, 23209, 44497, 86243, 216091, 756839, 859433\} \end{aligned}$$

is the set of all primes $p$ such that $2^p - 1$ used to be, starting from 1589, the largest known prime. Enumeration clearly does not work if the set is too big and even if it is not, enumeration can be far from the most effective way of describing a set. For example, *the set of the first* $2^{65536}$ *primes*—that has such a short description—can not be practically enumerated. On the other hand, enumeration is not to forget as the way to describe sets because, as shown later, most of finite sets are so random that there is no shorter way to describe them.

2. **Binary strings representation.** If the universal set $U$ is finite and has $n$ elements $u_1, \ldots, u_n$, then each subset $A \subseteq U$ can be uniquely represented by the binary word $b = b_1 \ldots b_n$, where $b_i = 1 \Leftrightarrow u_i \in A$. Observe that with this representation of subsets of $U$ it is possible to perform, in one parallel step, set union, intersection and subtraction! If $U$ is countable, then any subset of $U$ can be represented by an $\omega$-string.

3. **Logical formulas.** A formal or informal logical formula can be used to describe a set by specifying properties of its objects. For example:

$$F = \{n \mid n \in N, n > 2, \exists \text{ integers } x, y, z > 0, x^n + y^n = z^n\} \tag{2.3}$$

used to be perhaps the most famous description of a set in mathematics.

4. **Generators.** A generator that produces all elements of a set $A$, and no others, can be seen as specifying the set $A$. There are many forms a generator may have. It can be a deterministic automaton—see Figure 2.3a for a generator that generates a set of integers—or a randomized automaton—see Figure 2.3b for an automaton that can be seen as generating, given three points $A$, $B$ and $C$ of the plane forming nodes of an equilateral triangle, Sierpiński triangle with nodes in points $A$, $B$ and $C$—with the exception of few initial points.

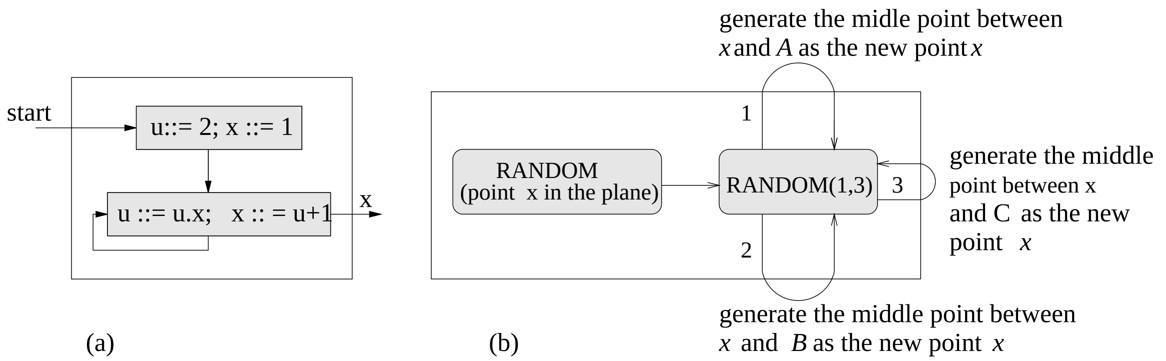



Figure 2.3: Deterministic and randomized generators—gen % 65

A generator can also have the form of a so-called rewriting system. For example, with the (rewriting) rules

$$A \to aAb, \qquad A \to ab \tag{2.4}$$

that are used as follows: The generator starts with the symbol $A$ and in each generation step replaces $A$, in the string generated in the last step—if there is one $A$ there—by the string $aAb$ or by the string $ab$. If the string obtained at the last step does not contain $A$, generation terminates. In this way the rewriting system in (2.4) generates the set of strings $\{a^n b^n \mid n \geq 1\}$.

**Exercise 2.1.14** *Are all integers generated by the generator from Figure 2.3a primes?*

**Exercise 2.1.15** *Design rewriting systems generating: (a) the set of strings* $\{a^n b^n a^m b^m \mid n, m \geq 1\}$*; (b) the set of all palindromes in the English alphabet (or in some other alphabet)—that is those words that are read the same from the left and the right.*

A generator can be specified also by some other processes. For instance, through an recurrence—the recurrence (1.6) in Section 1.2 can be seen as a process (generator) generating Fibonacci numbers.

**Example 2.1.16 (Cantor set)** *The sequence of sets—see Figure 2.4—defined by the recurrence*

$$
\begin{array}{lcl}
C_0 & = & \{x \mid 0 \leq x < 1\} = [0,1), \\
C_i & & i > 0, \textit{ is obtained from } C_{i-1} \textit{ by deleting, in each maximal subinterval } [a,b) \textit{ of } C_{i-1}, \\
 & & \textit{its middle open subinterval } [a + \frac{1}{3}(b-a), a + \frac{2}{3}(b-a)),
\end{array}
$$

*is decreasing and its intersection* $C = \bigcap_{i=0}^{\infty} C_i$ *is called the* **Cantor set**[3]. *(Observe that the*

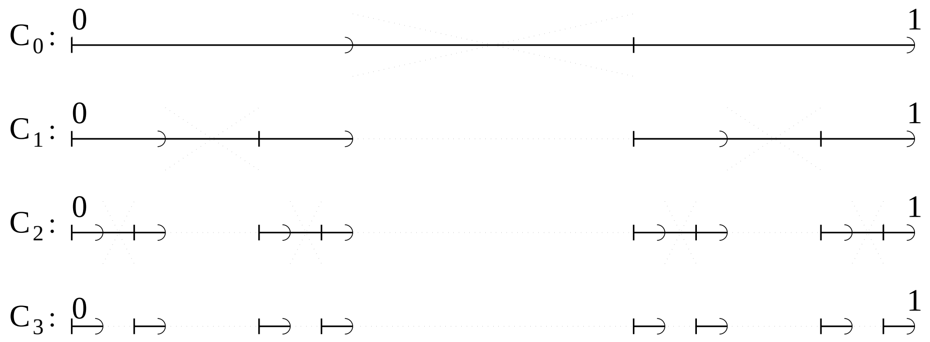



Figure 2.4: Cantor set- 65%

*Cantor set can be seen as a diagonal of the Cantor carpet.)*

[3]Georg Cantor (1845-1918), a German mathematician of the Russian origin, one of the founders of the modern set theory, introduced his set, today named after him, in 1889 as an example of an exceptional (monster) set.