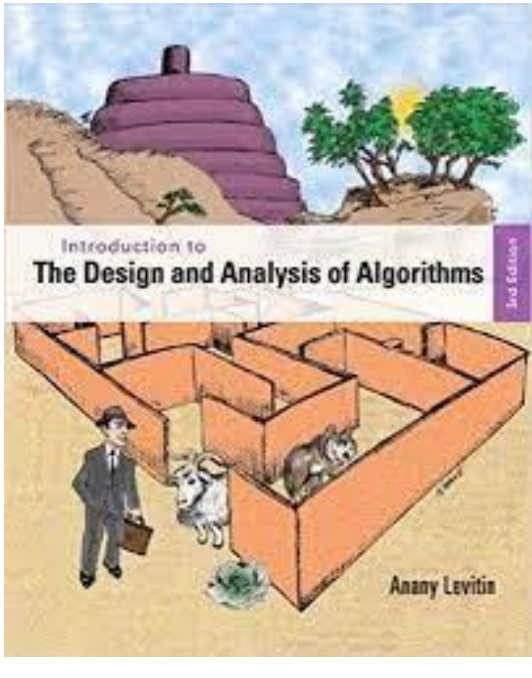
2-Fundamentals of the Analysis of Algorithm Efficiency



Analysis of algorithms

- Issues:
  – **Correctness**
  – **Optimality**
  – ***Time efficiency***, also called ***time complexity***, indicates how fast an algorithm in question runs.
  – ***Space efficiency***, also called ***space complexity***, refers to the amount of memory units required by the algorithm in addition to the space needed for its input and output

Analysis of algorithms

- Approaches:
  - theoretical analysis
  - empirical analysis

Theoretical analysis of time efficiency

Time efficiency is analyzed by determining the number of repetitions of the *basic operation* as a function of *input size*

- *Basic operation*: the operation that contributes most towards the running time of the algorithm

input size

$$T(n) \approx c_{op}C(n)$$

running time

execution time
for basic operation

Number of times
basic operation is
executed

Input size and basic operation examples

Problem	Input size measure	Basic operation
Searching for key in a list of n items	Number of list's items, i.e. n	Key comparison
Multiplication of two matrices	Matrix dimensions or total number of elements	Multiplication of two numbers
Checking primality of a given integer n	n'size = number of digits (in binary representation)	Division
Typical graph problem	#vertices and/or edges	Visiting a vertex or traversing an edge

Empirical analysis of time efficiency

- Select a specific (typical) sample of inputs

- Use physical unit of time (e.g., milliseconds)

  or

  Count actual number of basic operation's executions

- Analyze the empirical data

Best-case, average-case, worst-case

For some algorithms efficiency depends on form of input:

- Worst case: $C_{worst}(n)$ – maximum over inputs of size n
- Best case: $C_{best}(n)$ – minimum over inputs of size n
- Average case: $C_{avg}(n)$ – "average" over inputs of size n
  - Number of times the basic operation will be executed on typical input
  - NOT the average of worst and best case
  - Expected number of basic operations considered as a random variable under some assumption about the probability distribution of all possible inputs

Example: Sequential search

ALGORITHM *SequentialSearch*$(A[0..n-1], K)$

//Searches for a given value in a given array by sequential search
//Input: An array $A[0..n-1]$ and a search key K
//Output: The index of the first element of A that matches K
// or -1 if there are no matching elements

$i \leftarrow 0$
while $i < n$ **and** $A[i] \neq K$ **do**
  $i \leftarrow i + 1$
if $i < n$ **return** i
else return -1

- Input size:
- Basic operation:

- Worst case
- Best case
- Average case

Types of formulas for basic operation's count

- Exact formula
- e.g., $C(n) = n(n-1)/2$

- Formula indicating order of growth with specific multiplicative constant
- e.g., $C(n) \approx 0.5\, n^2$

- Formula indicating order of growth with unknown multiplicative constant
- e.g., $C(n) \approx cn^2$

Order of growth

- Most important: Order of growth within a constant multiple as $n \to \infty$

- Example:
  - How much faster will algorithm run on computer that is twice as fast?
  - How much longer does it take to solve problem of double input size?

Values of some important functions as $n \to \infty$

TABLE 2.1 Values (some approximate) of several functions important for analysis of algorithms

n	$\log_2 n$	n	$n \log_2 n$	n^2	n^3	2^n	$n!$
10	3.3	10^1	$3.3 \cdot 10^1$	10^2	10^3	10^3	$3.6 \cdot 10^6$
10^2	6.6	10^2	$6.6 \cdot 10^2$	10^4	10^6	$1.3 \cdot 10^{30}$	$9.3 \cdot 10^{157}$
10^3	10	10^3	$1.0 \cdot 10^4$	10^6	10^9		
10^4	13	10^4	$1.3 \cdot 10^5$	10^8	10^{12}		
10^5	17	10^5	$1.7 \cdot 10^6$	10^{10}	10^{15}		
10^6	20	10^6	$2.0 \cdot 10^7$	10^{12}	10^{18}		

Asymptotic order of growth

A way of comparing functions that ignores constant factors and small input sizes

- $O(g(n))$: class of functions $f(n)$ that grow <u>no faster</u> than $g(n)$

- $\Theta(g(n))$: class of functions $f(n)$ that grow <u>at same rate</u> as $g(n)$

- $\Omega(g(n))$:class of functions $f(n)$ that grow <u>at least as fast</u> as $g(n)$

Big-O notation

Let f and g be functions from the set of integers or the set of real numbers to the set of real numbers. We say that $f(x)$ is $O(g(x))$ if there are constants C and k such that

$$|f(x)| \le C|g(x)|$$

whenever $x > k$. [This is read as "$f(x)$ is big-oh of $g(x)$."]

Example:

$10n \rightarrow O(n^2)$
$5n + 20 \rightarrow O(n)$

Theorems

THEOREM Suppose that $f_1(x)$ is $O(g_1(x))$ and that $f_2(x)$ is $O(g_2(x))$. Then $(f_1 + f_2)(x)$ is $O(\max(|g_1(x)|, |g_2(x)|))$.

COROLLARY Suppose that $f_1(x)$ and $f_2(x)$ are both $O(g(x))$. Then $(f_1 + f_2)(x)$ is $O(g(x))$.

THEOREM Suppose that $f_1(x)$ is $O(g_1(x))$ and $f_2(x)$ is $O(g_2(x))$. Then $(f_1 f_2)(x)$ is $O(g_1(x)g_2(x))$.

Big-O notation

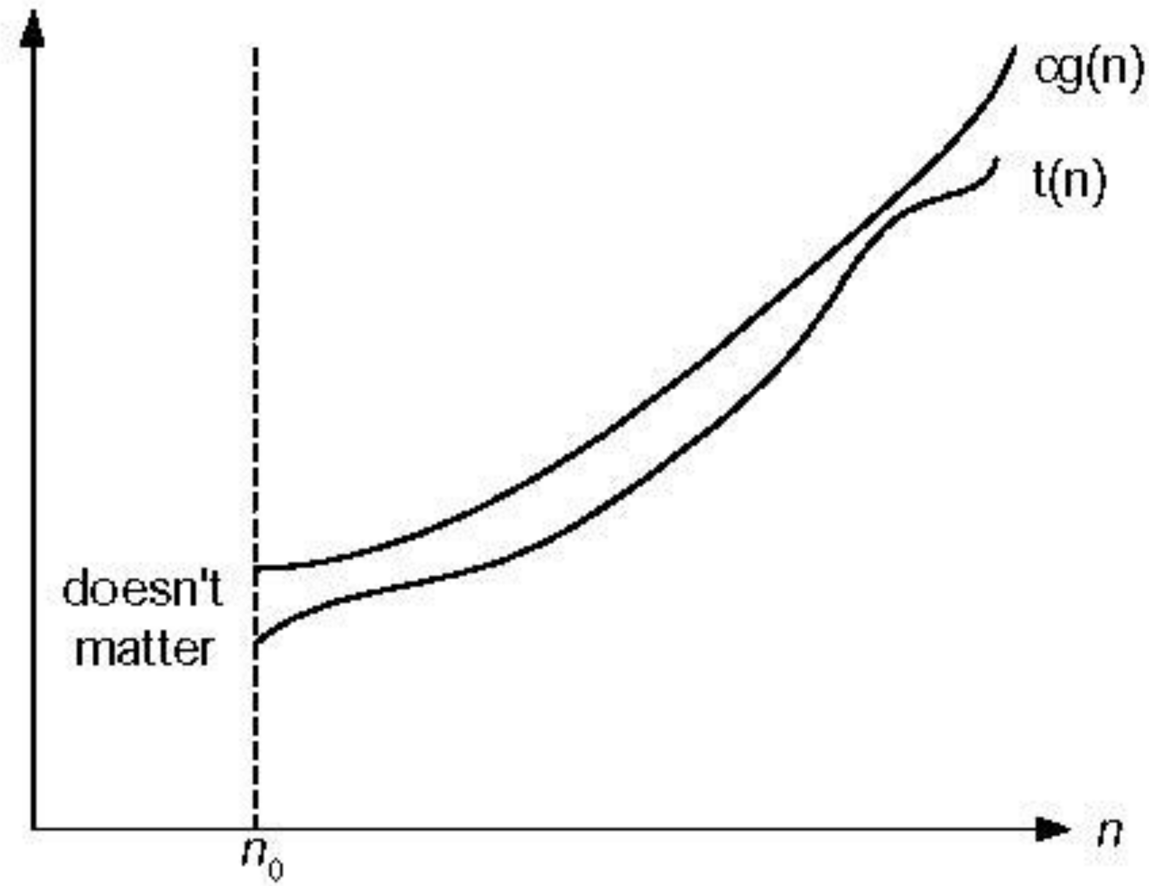


Figure 2.1 Big-oh notation: $t(n) \in O(g(n))$

Big-Omega

- Big-O notation does not provide a lower bound for the size of f(x) for large x
- Let f and g be functions from the set of integers or the set of real numbers to the set of real numbers. We say f(x) is $\Omega(g(x))$ if there are positive constants C and k s.t.

  $|f(x)| \geq C|g(x)|$ when $x>k$
- Read as f(x) is big-Omega of g(x)

Big-Omega

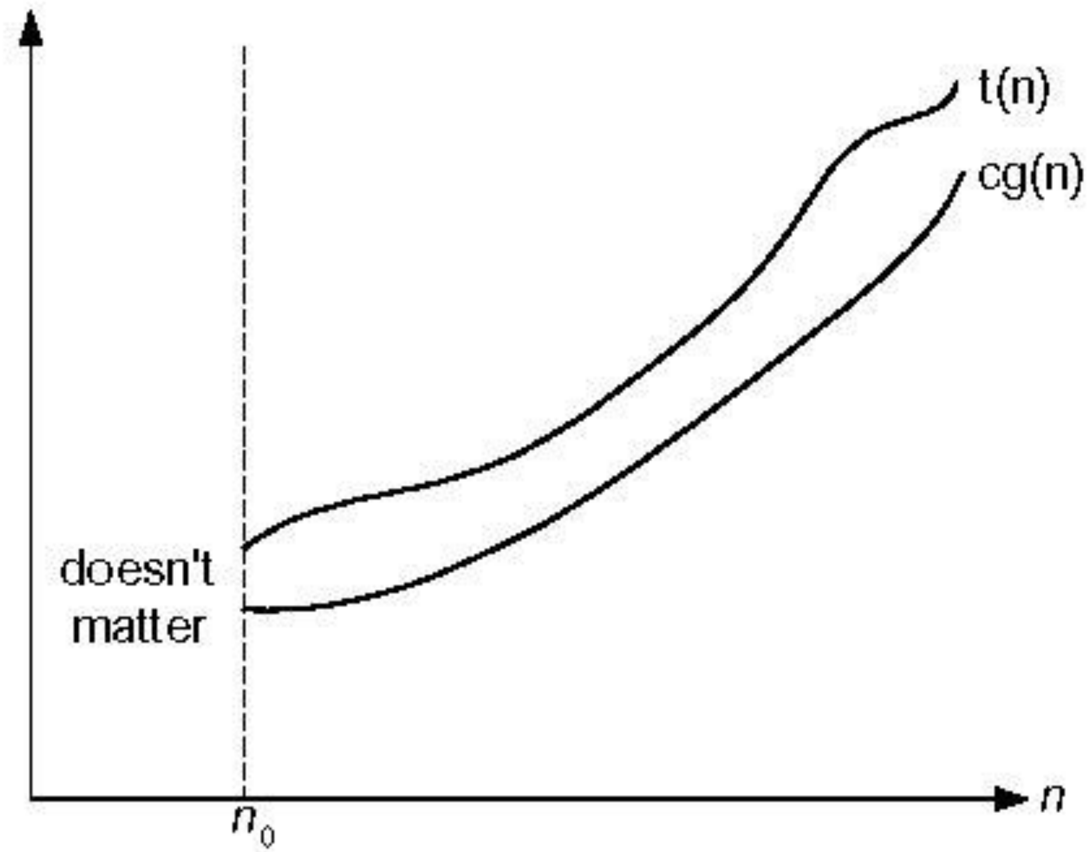


Fig. 2.2 Big-omega notation: $t(n) \in \Omega(g(n))$

Big-Theta notation

- Want a reference function g(x) s.t. f(x) is O(g(x)) and f(x) is Ω(g(x))
- Let f and g be functions from the set of integers or the set of real numbers to the set of real numbers. We say that f(x) is θ(g(x)) if f(x) is O(g(x)) and f(x) is Ω(g(x))
- When f(x) is θ(g(x)) , we say f is big-Theta of g(x), and we also say f(x) is of order g(x)

Big-Theta notation

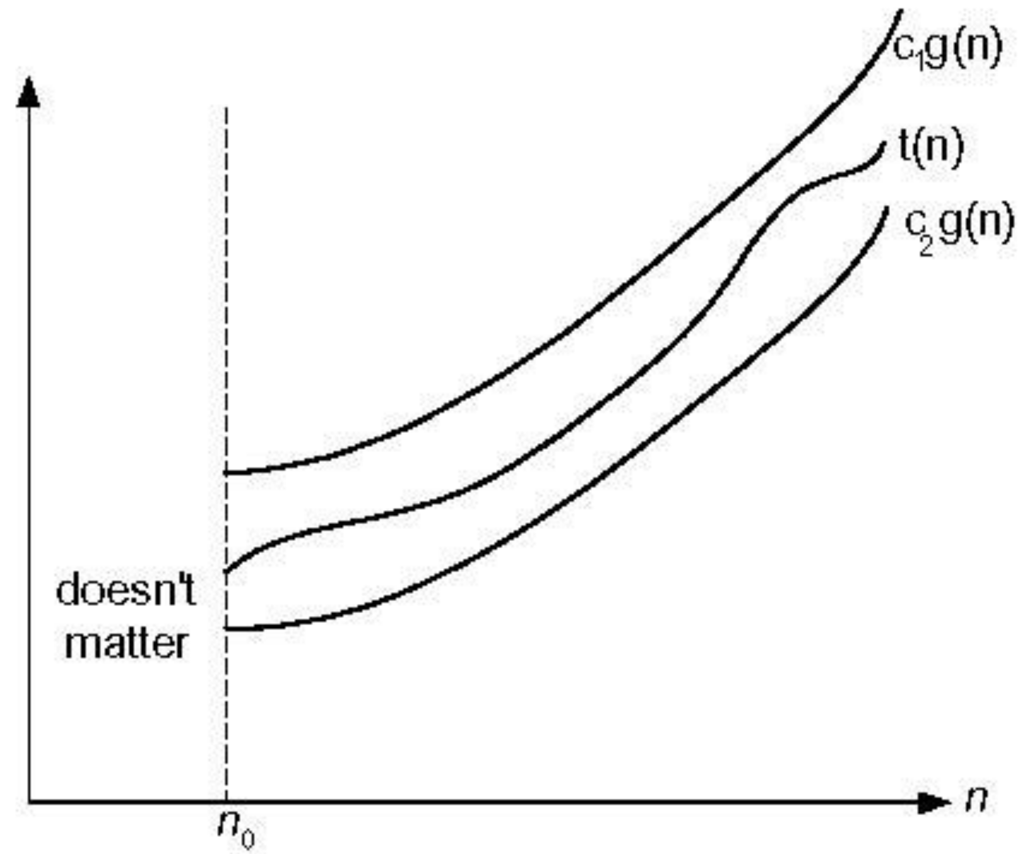


Figure 2.3 Big-theta notation: $t(n) \in \Theta(g(n))$

Establishing order of growth using limits

$$\lim_{n\to\infty} \frac{t(n)}{g(n)} = \begin{cases} 0 & \text{implies that } t(n) \text{ has a smaller order of growth than } g(n), \\ c & \text{implies that } t(n) \text{ has the same order of growth as } g(n), \\ \infty & \text{implies that } t(n) \text{ has a larger order of growth than } g(n). \end{cases}$$

Note that the first two cases mean that $t(n) \in O(g(n))$, the last two mean that $t(n) \in \Omega(g(n))$, and the second case means that $t(n) \in \Theta(g(n))$.

L'Hôpital's rule and Stirling's formula

L'Hôpital's rule: If $lim_{n\to\infty}\, t(n) = lim_{n\to\infty}\, g(n) = \infty$ and the derivatives t', g' exist, then

$$\lim_{n\to\infty} \frac{t(n)}{g(n)} = \lim_{n\to\infty} \frac{t'(n)}{g'(n)}$$

Stirling's formula

$$n! \approx \sqrt{2\pi n}\left(\frac{n}{e}\right)^n \text{ for large values of } n.$$

Example#1

- Compare the orders of growth of $logn$ and n

Example#2

- Compare the orders of growth of $\frac{1}{2}n(n-1)$ and n^2

Example#3

- Compare the orders of growth of $log_2 n$ and $\sqrt{n}$.

Example#4

Compare the orders of growth of $n!$ and 2^n

Orders of growth of some important functions

- All logarithmic functions $\log_a n$ belong to the same class $\Theta(\log n)$ no matter what the logarithm's base $a > 1$ is
- All polynomials of the same degree k belong to the same class: $a_k n^k + a_{k-1} n^{k-1} + \ldots + a_0 \in \Theta(n^k)$
- Exponential functions a^n have different orders of growth for different a's
- order $\log n$ < order n^α $(\alpha>0)$ < order a^n < order $n!$ < order n^n

Basic asymptotic efficiency classes

1	**constant**
log *n*	**logarithmic**
n	**linear**
n* log *n	***n*-log-*n* or linearithmic**
n^2	**quadratic**
n^3	**cubic**
2^n	**exponential**
$n!$	**factorial**

MATHEMATICAL ANALYSIS OF NONRECURSIVE ALGORITHMS

General Plan for Analyzing the Time Efficiency of Nonrecursive Algorithms

- Decide on parameter *n* indicating ***input size***
- Identify algorithm's ***basic operation***
- Determine ***worst***, ***average***, and ***best*** cases for input of size *n*
- Set up a sum for the number of times the basic operation is executed
- Simplify the sum using standard formulas and rules

Useful summation formulas and rules

$\Sigma_{l \le i \le u} 1 = 1+1+ \cdots +1 = u - l + 1$

In particular, $\Sigma_{1 \le i \le u} 1 = n - 1 + 1 = n \in \Theta(n)$

$\Sigma_{1 \le i \le n}\, i = 1+2+ \cdots +n = n(n+1)/2 \approx n^2/2 \in \Theta(n^2)$

$\Sigma_{1 \le i \le n}\, i^2 = 1^2+2^2+ \cdots +n^2 = n(n+1)(2n+1)/6 \approx n^3/3 \in \Theta(n^3)$

$\Sigma_{0 \le i \le n}\, a^i = 1 + a + \cdots + a^n = (a^{n+1} - 1)/(a - 1)$ for any $a \neq 1$

In particular, $\Sigma_{0 \le i \le n}\, 2^i = 2^0 + 2^1 + \cdots + 2^n = 2^{n+1} - 1 \in \Theta(2^n)$

$\Sigma(a_i \pm b_i) = \Sigma a_i \pm \Sigma b_i \qquad \Sigma c a_i = c \Sigma a_i$

$\Sigma_{l \le i \le u} a_i = \Sigma_{l \le i \le m} a_i + \Sigma_{m+1 \le i \le u} a_i$

Example 1: Maximum element

ALGORITHM $MaxElement(A[0..n-1])$

//Determines the value of the largest element in a given array
//Input: An array $A[0..n-1]$ of real numbers
//Output: The value of the largest element in A
$maxval \leftarrow A[0]$
for $i \leftarrow 1$ **to** $n-1$ **do**
    if $A[i] > maxval$
        $maxval \leftarrow A[i]$
return $maxval$

Example 2: Element uniqueness problem

ALGORITHM $UniqueElements(A[0..n-1])$

//Determines whether all the elements in a given array are distinct
//Input: An array $A[0..n-1]$
//Output: Returns "true" if all the elements in A are distinct
//   and "false" otherwise

for $i \leftarrow 0$ **to** $n-2$ **do**
    for $j \leftarrow i+1$ **to** $n-1$ **do**
        if $A[i] = A[j]$ **return false**
return true

Example 3: Matrix multiplication

ALGORITHM $MatrixMultiplication(A[0..n-1, 0..n-1], B[0..n-1, 0..n-1])$

//Multiplies two square matrices of order n by the definition-based algorithm
//Input: Two $n \times n$ matrices A and B
//Output: Matrix $C = AB$

for $i \leftarrow 0$ **to** $n-1$ **do**
    for $j \leftarrow 0$ **to** $n-1$ **do**
        $C[i, j] \leftarrow 0.0$
        for $k \leftarrow 0$ **to** $n-1$ **do**
            $C[i, j] \leftarrow C[i, j] + A[i, k] * B[k, j]$
return C

Example 4: Gaussian elimination

```
Algorithm GaussianElimination(A[0..n-1,0..n])
//Implements Gaussian elimination of an n-by-(n+1) matrix A
for i ← 0 to n - 2 do
    for j ← i + 1 to n - 1 do
        for k ← i to n do
            A[j,k] ← A[j,k] - A[i,k] * A[j,i] / A[i,i]
```

Find the efficiency class and a constant factor improvement.

Example 5: Counting binary digits

ALGORITHM *Binary*(n)

//Input: A positive decimal integer n
//Output: The number of binary digits in n's binary representation
$count \leftarrow 1$
while $n > 1$ **do**
  $count \leftarrow count + 1$
  $n \leftarrow \lfloor n/2 \rfloor$
return $count$

It cannot be investigated the way the previous examples are.

MATHEMATICAL ANALYSIS OF RECURSIVE ALGORITHMS

Plan for Analysis of Recursive Algorithms

- Decide on a parameter indicating an input's size.
- Identify the algorithm's basic operation.
- Check whether the number of times the basic op. is executed may vary on different inputs of the same size. (If it may, the worst, average, and best cases must be investigated separately.)
- Set up a recurrence relation with an appropriate initial condition expressing the number of times the basic op. is executed.
- Solve the recurrence (or, at the very least, establish its solution's order of growth) by backward substitutions or another method

Example 1: Recursive evaluation of n!

Definition: $n\,! = 1 \cdot 2 \cdot \ldots \cdot (n\text{-}1) \cdot n$ for $n \geq 1$ and $0! = 1$

Recursive definition of n!:

$$F(n) = F(n-1)\cdot n \ \ for\, n \geq 1 \ \ and$$
$$F(0) = 1$$

ALGORITHM $F(n)$

//Computes $n!$ recursively
//Input: A nonnegative integer n
//Output: The value of $n!$
if $n = 0$ **return** 1
else return $F(n-1) * n$

Size:
Basic operation:
Recurrence relation:

Solving the recurrence for M(n)

$M(n) = M(n\text{-}1) + 1$, $M(0) = 0$

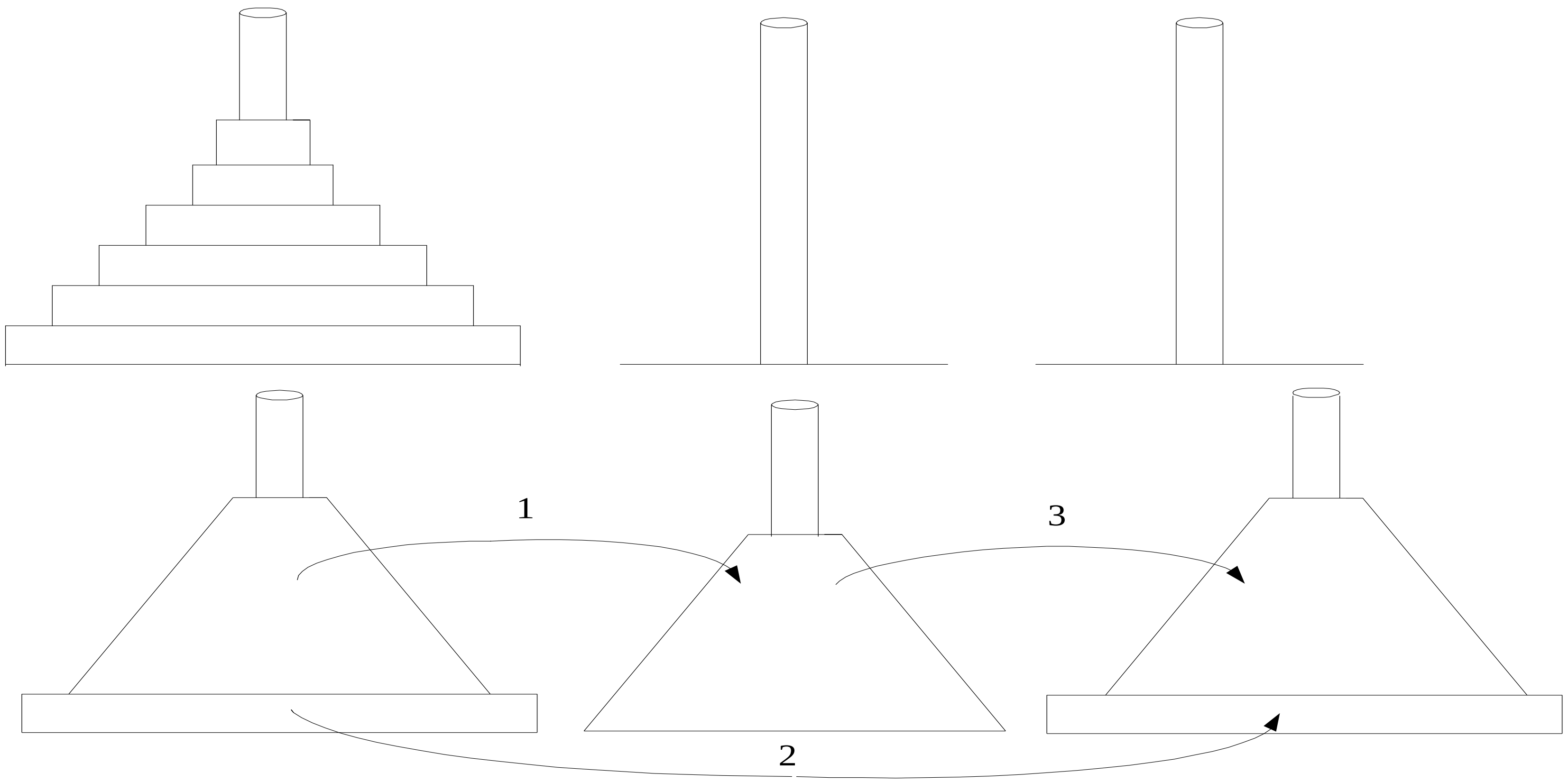
Example 2: The Tower of Hanoi Puzzle

- **Towers of Hanoi**
- Story: According to the legend, the life on the world will end when Buddhist monks in a Far-Eastern temple move 64 disks stacked on a peg in a decreasing order in size to another peg. They are allowed to move one disk at a time and a larger disk can never be placed over a smaller one

https://upload.wikimedia.org/wikipedia/commons/6/60/Tower_of_Hanoi_4.gif

Doç.Dr. Borahan Tümer (Marmara Üniversitesi Bilgisayar Müh. Bölümü) tarafından verilen CSE225 ders slaytları (http://mimoza.marmara.edu.tr/~berna.altinel/courses/cse225/)

Example 2: The Tower of Hanoi Puzzle

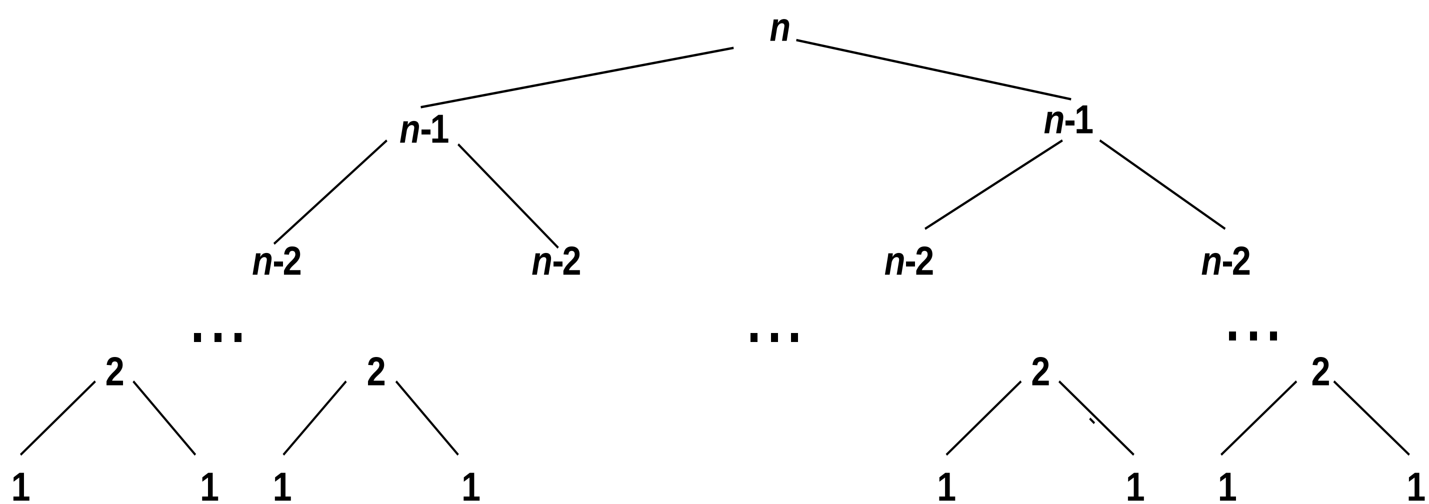


Recurrence for number of moves:

Solving recurrence for number of moves

- $M(n) = 2M(n\text{-}1) + 1$, $M(1) = 1$

Tree of calls for the Tower of Hanoi Puzzle



Example 3: Counting #bits

ALGORITHM $BinRec(n)$

//Input: A positive decimal integer n

//Output: The number of binary digits in n's binary representation

if $n = 1$ **return** 1

else return $BinRec(\lfloor n/2 \rfloor) + 1$

Fibonacci numbers

The Fibonacci numbers:

0, 1, 1, 2, 3, 5, 8, 13, 21, …

The Fibonacci recurrence:

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

$F(0) = 0$

$F(1) = 1$

General 2nd order linear homogeneous recurrence with constant coefficients:

$$aX(n) + bX(n-1) + cX(n-2) = 0$$

Solving $aX(n) + bX(n\text{-}1) + cX(n\text{-}2) = 0$

- Set up the characteristic equation (quadratic)

$$ar^2 + br + c = 0$$

- Solve to obtain roots r_1 and r_2

- General solution to the recurrence

  if r_1 and r_2 are two distinct real roots: $X(n) = \alpha r_1^{\,n} + \beta r_2^{\,n}$

  if $r_1 = r_2 = r$ are two equal real roots: $X(n) = \alpha r^n + \beta n r^{\,n}$

- Particular solution can be found by using initial conditions

Application to the Fibonacci numbers

$F(n) = F(n\text{-}1) + F(n\text{-}2)$ or $F(n) - F(n\text{-}1) - F(n\text{-}2) = 0$

Characteristic equation:

Roots of the characteristic equation:

General solution to the recurrence:

Particular solution for F(0) =0, F(1)=1:

Computing Fibonacci numbers

1. Definition-based recursive algorithm
2. Nonrecursive definition-based algorithm
3. Explicit formula algorithm
4. Logarithmic algorithm based on formula:

$$\begin{bmatrix} F(n-1) & F(n) \\ F(n) & F(n+1) \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 1 & 1 \end{bmatrix}^n \quad \text{for } n \geq 1$$