

CSC2100B Data Structures Analysis

Irwin King

king@cse.cuhk.edu.hk
<http://www.cse.cuhk.edu.hk/~king>

Department of Computer Science & Engineering
The Chinese University of Hong Kong



Algorithm

- An **algorithm** is a clearly specified set of simple instructions to be followed to solve a problem.
- How to estimate the time required for a program.
- How to reduce the running time of a program from days or years to fractions of a second.
- What is the storage complexity of the program.
- How to deal with trade-offs.



Running Time

- There are two contradictory goals:
 - We would like an algorithm that is **easy** to understand, code, and debug.
 - We would like an algorithm that makes **efficient** use of the computer's resources, especially, one that runs as fast as possible.

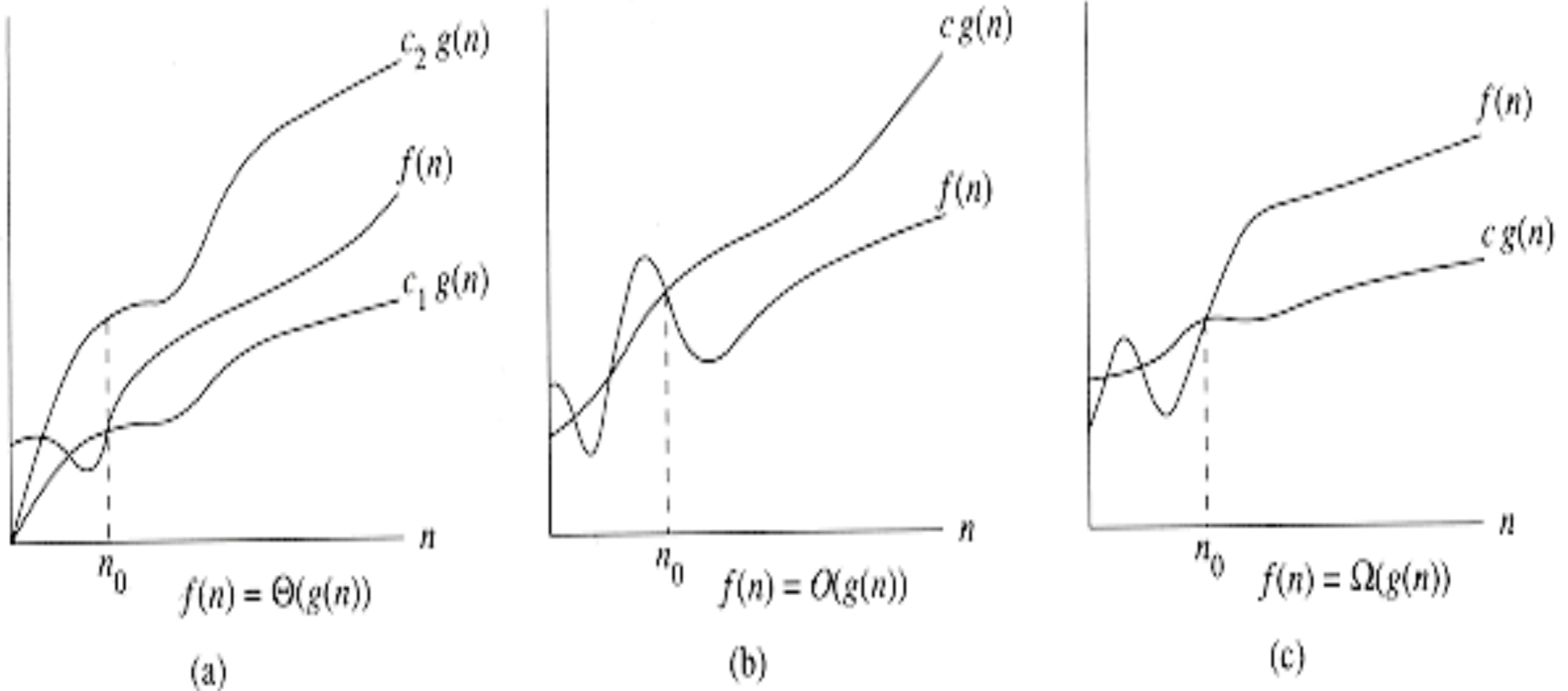


Function Comparison

- Given two functions, $f(N)$ and $g(N)$, what does it mean when we say that
$$f(N) < g(N)?$$
- Should this hold for all N ?
- We need to compare their relative rates of growth.



Example



<http://science.slc.edu/~jmarshall/courses/2002/spring/cs50/BigO/index.html>



Why Use Bounds

- The idea is to establish a **relative order** among functions.
- We are more concerned about the **relative rates of growth** of functions.
- For example, which function is greater, $1,000N$ or N^2 ?
- The turning point is $N = 1,000$ where N^2 will be greater for larger N .



First Definition

- It says that there is some point n_0 past which $c f(N)$ is always at least as large as $T(N)$.
- In our case, $T(N) = 1000N$, $f(N) = N^2$, $n_0 = 1,000$, and $c = 1$.
- We could also use $n_0 = 10$, and $c = 100$.
- So we can say that $1000N = O(N^2)$.
- It is an **upper bound** on $T(N)$.



Other Definitions

- The second definition says that the growth rate of $T(N)$ is greater than or equal to that of $g(N)$.
- The third definition says that the growth rate of $T(N)$ equals the growth rate of $h(N)$.
- The fourth definition says that the growth rate of $T(N)$ is less than the growth rate of $p(N)$.



Big-O Notation

- If $f(n)$ and $g(n)$ are functions defined for positive integers, then to write $f(n)$ is $O(g(n))$.
- $f(n)$ is **big-O** of $g(n)$ means that there exists a constant c such that $|f(x)| \leq c|g(n)|$ for all sufficiently large positive integers n .
- Under these conditions we also say that “ $f(n)$ has **order** at most $g(n)$ ” or “ $f(n)$ grows no more rapidly than $g(n)$ ”.



Examples

- $f(n) = 100n$ then $f(n) = O(n)$.
- $f(n) = 4n + 200$ then $f(n) = O(n)$.
- $f(n) = n^2$ then $f(n) = O(n^2)$.
- $f(n) = 3n^2 - 100$ then $f(n) = O(n^2)$.



Rules

- If $T_1(N) = O(f(N))$ and $T_2(N) = O(g(N))$, then
 - $T_1(N) + T_2(N) = \max(O(f(N)), O(g(N)))$,
 - $T_1(N) * T_2(N) = O(f(N)) * g(N)$,
- If $T(N)$ is a polynomial of degree k , then $T(N) = O(N^k)$.
- $\log^k N = O(N)$ for any constant k .
- This tells us that logarithms grow very slowly.



Watch Out!

- It is bad to include constants or low-order terms inside a Big-Oh notation.
- Do not say $T(N) = O(2N^2)$ or $T(N) = O(N^2 + N)$.
- In both cases, $T(N) = O(N^2)$.



Observations

- If $f(n)$ is a polynomial in n with degree r , then $f(n)$ is $O(n^r)$, but $f(n)$ is not $O(n^s)$ for any power s less than r .
- Any logarithm of n grows more slowly (as n increases) than any positive power of n .
- Hence $\log n$ is $O(n^k)$ for any $k > 0$, but n^k is never $O(\log n)$ for any power $k > 0$.



Common Orders

- $O(1)$ means computing time that is bounded by a **constant** (not dependent on n)
- $O(n)$ means that the time is directly proportional to n , and is called **linear time**.
- $O(n^2)$ means **quadratic** time.
- $O(n^3)$ means **cubic** time.
- $O(2^n)$ means **exponential** time.
- $O(\log n)$ means **logarithmic** time.
- $O(\log^2 n)$ means **log-squared** time.



Algorithm Analyses

- On a list of length n , sequential search has running time $O(n)$.
- On an ordered list of length n , binary search has running time $O(\log n)$.
- The sum of the sum of integer index of a loop from 1 to n is $O(n^2)$, i.e., $1 + 2 + 3 + \dots + n$.
- For $i = 1$ to n
 - For $j = i$ to n



Recurrence Relations

- Recurrence relations are useful in certain counting problems.
- A recurrence relation relates the n -th element of a sequence to its predecessors.
- Recurrence relations arise naturally in the analysis of recursive algorithms.



Sequences and Recurrence Relations

- A (numerical) sequence is an ordered list of number.
 - 2, 4, 6, 8, ... (positive even numbers)
 - 0, 1, 1, 2, 3, 5, 8, ... (the Fibonacci numbers)
 - 0, 1, 3, 6, 10, 15, ... (numbers of key comparisons in selection sort)



Definitions

- A **recurrence relation** for the sequence a_0, a_1, \dots is an equation that relates a_n to certain of its predecessors a_0, a_1, \dots, a_{n-1} .
- **Initial conditions** for the sequence a_0, a_1, \dots are explicitly given values for a finite number of the terms of the sequence.



Example

- A person invests \$1,000 at 12% compounded annually. If A_n represents the amount at the end of n years, find a recurrence relation and initial conditions that define the sequence A_n .
- At the end of $n-1$ years, the amount is A_{n-1} . After one more year, we will have the amount A_{n-1} plus the interest. Thus $A_n = A_{n-1} + (0.12) A_{n-1} = (1.12) A_{n-1}, n \geq 1$.
- To apply this recurrence relation for $n = 1$, we need to know the value of A_0 which is 1,000.



Solving Recurrence Relations

- **Iteration** - we use the recurrence relation to write the n -th term a_n in terms of certain of its predecessors a_{n-1}, \dots, a_0 .
- We then successively use the recurrence relation to replace each of a_{n-1}, \dots by certain of their predecessors.
- We continue until an explicit formula is obtained.



Some Definitions of Linear Second-order recurrences with constant coefficients

- **kth-order**
 - Elements $x(n)$ and $x(n-k)$ are k positions apart in the unknown sequence.
- **Linear**
 - It is a linear combination of the unknown terms of the sequence.
- **Constant coefficients**
 - The assumption that a , b , and c are some fixed numbers.
- **Homogeneous**
 - If $f(x) = 0$ for every n .



Solving Recurrence Relations

- **Linear homogeneous** recurrence relations with constant coefficients - a linear homogeneous recurrence relation of order k with constant coefficients is a recurrence relation of the form

$$a_0 = c_0, a_1 = c_1, \dots, a_{k-1} = c_{k-1},$$

- Notice that a linear homogeneous recurrence relation of order K with constant coefficients, together with the k initial conditions

$$a_n = c_1 a_{n-1} + c_2 a_{n-2} + \dots + c_k a_{n-k}, c_i \geq 0$$

- uniquely defines a sequence a_0, a_1, \dots



Example

- Nonlinear
 - $a_n = 3 a_{n-1} a_{n-2}$.
- Inhomogeneous
 - $a_n - a_{n-1} = 2_n$.
- Homogeneous recurrence relation with nonconstant coefficients
 - $a_n = 3 n a_{n-1}$.



Iteration Example

- We can solve the recurrence relation $a_n = a_{n-1} + 3$ subject to the initial condition $a_1 = 2$, by iteration.
 - $a_{n-1} = a_{n-2} + 3.$
 - $a_n = a_{n-1} + 3 = a_{n-2} + 3 + 3 = a_{n-2} + 2 \times 3.$
 - $a_{n-2} = a_{n-3} + 3.$
 - $a_n = a_{n-2} + 2 \times 3 = a_{n-3} + 3 + 2 \times 3 = a_{n-3} + 3 \times 3.$
 - $a_n = a_{n-k} + k \times 3 = 2 + 3(n - 1).$



Iteration Example

- In general, to solve $a_n = a_{n-1} + k$, $a_1 = c$, one obtains $a_n = c + k(n-1)$.
- We can solve the recurrence relation
 - $a_n = k a_{n-1}$, $a_0 = c$.
 - $a_n = k a_{n-1} = k(k a_{n-2}) = \dots = k^n a_0 = c k^n$.



Linear Homogeneous Recurrence Example

$$a_n = 5 a_{n-1} - 6 a_{n-2}, a_0 = 7, a_1 = 16$$

- Since the solution was of the form $a_n = t^n$, thus for our first attempt at finding a solution of the second-order recurrence relation, we will search for a solution of the form $a_n = t^n$.
 - $t_n = 5 t^{n-1} - 6 t^{n-2}$
 - $t^2 - 5t + 6 = 0$



Example

- Solving the above we obtain, $t = 2, t = 3$.
- At this point, we have two solutions S and T given by
 - $S_n = 2^n, T_n = 3^n$.
- We can verify that S and T are solutions of the above, then $bS + dT$, where b and d are any numbers whatever, is also a solution of the above.



Example

- In our case, if we define the sequence U by the equation
 - $U_n = b S_n + d T_n$
 - $= b 2^n + d 3^n$
- To satisfy the initial conditions, we must have
 - $7 = U_0 = b 2^0 + d 3^0 = b + d.$
 - $16 = U_1 = b 2^1 + d 3^1 = 2b + 3d.$



Example

- Solving these equations for b and d , we obtain
 - $b = 5, d = 2$.
- Therefore, the sequence U defined by
 - $U_n = 5 \times 2^n + 2 \times 3^n$
satisfies the recurrence relation and the initial conditions.



Fibonacci Sequence

- The Fibonacci sequence is defined by the recurrence relation
 - $f_n = f_{n-1} + f_{n-2}, n \geq 3$ and initial conditions
 - $f_1 = 1, f_2 = 2.$
- We begin by using the quadratic formula to solve
 - $t^2 - t - 1 = 0.$
- The solutions are

$$t = \frac{1 \pm \sqrt{5}}{2}.$$



Example

- Thus the solution is of the form

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

- To satisfy the initial conditions, we must have

$$b \left(\frac{1 + \sqrt{5}}{2} \right) + d \left(\frac{1 - \sqrt{5}}{2} \right) = 1,$$

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



Tower of Hanoi

- Find an explicit formula for a_n , the minimum number of moves in which the n -disk Tower of Hanoi puzzle can be solved.
- $a_n = 2 a_{n-1} + 1, a_1 = 1.$
- Applying the iterative method, we obtain

$$\begin{aligned} a_n &= 2a_{n-1} + 1 \\ &= 2(2a_{n-2} + 1) + 1 \\ &= 2^2 a_{n-2} + 2 + 1 \\ &= 2^2 (2a_{n-3} + 1) + 2 + 1 \\ &= 2^3 a_{n-3} + 2^2 + 2 + 1 \\ &\text{M} \\ &= 2^{n-1} a_1 + 2^{n-2} + 2^{n-3} + \dots + 2 + 1 \\ &= 2^{n-1} + 2^{n-2} + 2^{n-3} + \dots + 2 + 1 \\ &= 2^n - 1 \end{aligned}$$



Common Recurrence Types

- Decrease-by-one
 - $T(n) = T(n-1) + f(n)$
- Decrease-by-a-constant-factor
 - $T(n) = T(n/b) + f(n)$
- Divide-and-conquer
 - $T(n) = aT(n/b) + f(n)$

