

COMP215: Design & Analysis of Algorithms



# Today

- The Gist
- Big-O Notation
- Examples



- Asymptotic notation provides the basic vocabulary for discussing the design and analysis of algorithms.
- Asymptotic notation is coarse enough to suppress all the details you want to ignore, details that depend on
  - The choice of architecture,
  - The choice of programming language,
  - The choice of compiler.
- It is useful to make comparisons between different highlevel algorithmic approaches to solving a problem, especially on larger input







 Consider first the problem of searching an array for a given integer t. The code just checks each array entry in turn. If it ever finds the integer t it returns true, and if it falls off the end of the array without finding t it returns false.

Searching One Array

**Input:** array A of n integers, and an integer t. **Output:** Whether or not A contains t.

for i := 1 to n do if A[i] = t then return TRUE return FALSE

 What is the asymptotic running time of the code for searching one array, as a function of the array length n?



- Suppose we're now given two integer arrays A and B, both of length n, and we want to know whether a target integer t is in either one. Let's again consider the straightforward algorithm, where we just search through A, and if we fail to find t in A, we then search through B. If we don't find t in B either, we return false.
- What is the asymptotic running time of the code for searching Two arrays, as a function of the arrays length n?

#### Searching Two Arrays

**Input:** arrays A and B of n integers each, and an integer t.

**Output:** Whether or not A or B contains t.

for $i := 1$ to $n$ do	
if $A[i] = t$ then	
return TRUE	
for $i := 1$ to $n$ do	
if $B[i] = t$ then	
return TRUE	
return FALSE	



- Suppose we want to check whether or not two given arrays of length n have a number in common. The simplest solution is to check all possibilities. That is, for each index i into the array A and each index j into the array B, we check if A[i] is the same number as B[j]. If it is, we return true. If we exhaust all the possibilities without ever finding equal elements, we can safely return false.
- What is the asymptotic running time of the code for checking for a common element, as a function of the arrays length n?

Checking for a Common Element

**Input:** arrays A and B of n integers each. **Output:** Whether or not there is an integer t contained in both A and B.

for i := 1 to n do for j := 1 to n do if A[i] = B[j] then return TRUE return FALSE



• Suppose we're looking for duplicate entries in a single array A, rather than in two different arrays.

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Checking for Duplicates

Input: array A of n integers.

Output: Whether or not A contains an integer more

than once.

for i := 1 to n do

for j := i + 1 to n do

if A[i] = A[j] then
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return TRUE

return FALSE

• What is the asymptotic running time of the code for checking for duplicates in one array, as a function of the array length n?



# **Big-O Notation**

• The formal definition of big-O notation:

Big-O Notation (English Version) T(n) = O(f(n)) if and only if T(n) is eventually bounded above by a constant multiple of f(n)



 $\begin{array}{l} \mbox{Big-O Notation (Mathematical Version)} \\ T(n) = O(f(n)) \mbox{ if and only if there exist positive constants c and } n_0 \mbox{ such } \\ \mbox{ that } T(n) \ <= c \cdot f(n) \qquad (2.1) \\ \mbox{ for all } n >= n_0. \end{array}$ 



# **Big-O Notation**

- If you want to prove that T(n) = O(f(n)), then your task is to choose the constants c and n<sub>0</sub> so that
   (2.1) holds whenever n>= n<sub>0.</sub>
- OR:
- If T(n) = O(f(n)), then there are constants c and
   n<sub>0</sub> such that (2.1) holds for all n >= n<sub>0</sub>



- Degree-k Polynomials are O(n<sup>k</sup>)
- Degree-k Polynomials Are Not O(n<sup>k-1</sup>)



#### 1. Degree-k Polynomials are O(n<sup>k</sup>)

If T(n) is a polynomial with some degree k, then T(n) = O(n<sup>k</sup>).
 How?

$$T(n) = a_k n^k + \cdots a_1 n + a_0,$$

where  $k \ge 0$  is a nonnegative integer and the  $a_i$ 's are real numbers (positive or negative). Then  $T(n) = O(n^k)$ .

 Proposition 2.1 says that with a polynomial, in big-O notation, all you need to worry about is the highest degree that appears in the polynomial. Thus, big-O notation really is suppressing constant factors and lower-order terms. Prove?



- Find c and n<sub>0.</sub>
  - 1. Try  $n_0 = 1$  and c equal to the sum of absolute values of the coefficients:  $c = |a_k| + \cdots + |a_1| + |a_0|$ .
  - We now need to show that these choices of constants satisfy the definition, meaning that T(n) <= c\*n<sup>k</sup> for all n >=n<sub>0</sub> = 1.
  - To verify this inequality, fix an arbitrary positive integer n n0 = 1. We need a sequence of upper bounds on T(n) (for coefficients and power of n), culminating in an upper bound of c · nk. First let's apply the definition of T(n):

$$T(n) = a_k n^k + \cdots a_1 n + a_0,$$



- 4. For coefficients, if we take the absolute value of each coefficient ai on the right-hand side, the expression only becomes larger  $T(n) \leq |a_k|n^k + \dots + |a_1|n + |a_0|.$
- For power of n, n<sup>k</sup> is only bigger than n<sup>i</sup> for every i in {0, 1, 2,...,k}
- 6. Since  $|a_i|$  is nonnegative,  $|a_i|n^k$  is only bigger than  $|a_i|n^i$ . This means that

$$T(n) \le |a_k| n^k + \dots + |a_1| n^k + |a_0| n^k = \underbrace{(|a_k| + \dots + |a_1| + |a_0|)}_{=c} \cdot n^k.$$



- Degree-k Polynomials Are Not O(n<sup>k-1</sup>)
- Proposition 2.2 Let k 1 be a positive integer and define T(n)
   = n<sup>k</sup>. Then T(n) is not O(n<sup>k-1</sup>).
- Proof by contradiction:
  - Assume that  $n^k$  is in fact O( $n^{k-1}$ ), for all  $n > n_0$
  - That is, there are positive constants c and  $n_0$  such that  $n^k \leq c \cdot n^{k-1}$
  - Cancel n<sup>k-1</sup> from both sides of this inequality to derive n <= C, for all n> n<sub>0</sub>



False statement

# **Big-O Notation**

- Practice:
  - Arrange the following functions in order of increasing growth rate, with g(n) following f(n) in your list if and only if f(n) = O(g(n)).

a) 
$$2^{\log_2 n}$$
  
b)  $2^{2^{\log_2 n}}$   
c)  $n^{5/2}$   
d)  $2^{n^2}$   
e)  $n^2 \log_2 n$ 



# **Big-Omega and Big-Theta Notation**

- Big-O is analogous to "less than or equal to (≤),"
- Big-omega is analogous to "greater than or equal(≥)
- Big-theta is "equal to (=),"





#### **Big-Omega**

#### Big-Omega Notation (Mathematical Version)

 $T(n) = \Omega(f(n))$  if and only if there exist positive constants c and  $n_0$  such that

$$T(n) \ge c \cdot f(n)$$

for all  $n \ge n_0$ .





#### **Big-Theta**

#### **Big-Theta Notation (Mathematical Version)**

 $T(n) = \Theta(f(n))$  if and only if there exist positive constants  $c_1, c_2$ , and  $n_0$  such that

 $c_1 \cdot f(n) \le T(n) \le c_2 \cdot f(n)$ 

for all  $n \ge n_0$ .









#### Quiz 2.5

Let  $T(n) = \frac{1}{2}n^2 + 3n$ . Which of the following statements are true? (There might be more than one correct answer.)

- a) T(n) = O(n)
- b)  $T(n) = \Omega(n)$
- c)  $T(n) = \Theta(n^2)$
- d)  $T(n)={\cal O}(n^3)$



• True or False?

If f(n) = O(g(n)) and g(n) = O(h(n)), then  $h(n) = \Omega(f(n))$ 

If f(n) = O(g(n)) and g(n) = O(f(n)) then f(n) = g(n)

