



# DATA STRUCTURES

WENYE LI  
CUHK-SZ

# ALGORITHM

- What is an algorithm?
  - An algorithm is a finite set of precise instructions for performing a computation or for solving a problem.
  - This is a rather vague definition.
- But this one is good enough for now...

# CHARACTERISTICS

- **Input** from a specified set,
- **Output** from a specified set (solution),
- **Definiteness** of every step in the computation,
- **Correctness** of output for every possible input,
- **Finiteness** of the number of calculation steps,
- **Effectiveness** of each calculation step and
- **Generality** for a class of problems.

# EXAMPLE

- We will use a pseudocode to specify algorithms, which slightly reminds us of Basic and Pascal.
- Example: an algorithm that finds the maximum element in a finite sequence

**procedure** max( $a_1, a_2, \dots, a_n$ : integers)

max :=  $a_1$

**for** i := 2 **to** n

**if** max <  $a_i$  **then** max :=  $a_i$

{max is the largest element}

# EXAMPLE

- Example: a linear search algorithm, that is, an algorithm that linearly searches a sequence for a particular element.

**procedure** linear\_search( $x$ : integer;  $a_1, a_2, \dots, a_n$ : integers)

$i := 1$

**while** ( $i \leq n$  and  $x \neq a_i$ )

$i := i + 1$

**if**  $i \leq n$  **then** location :=  $i$

**else** location := 0

{location is the subscript of the term that equals  $x$ , or is zero if  $x$  is not found}

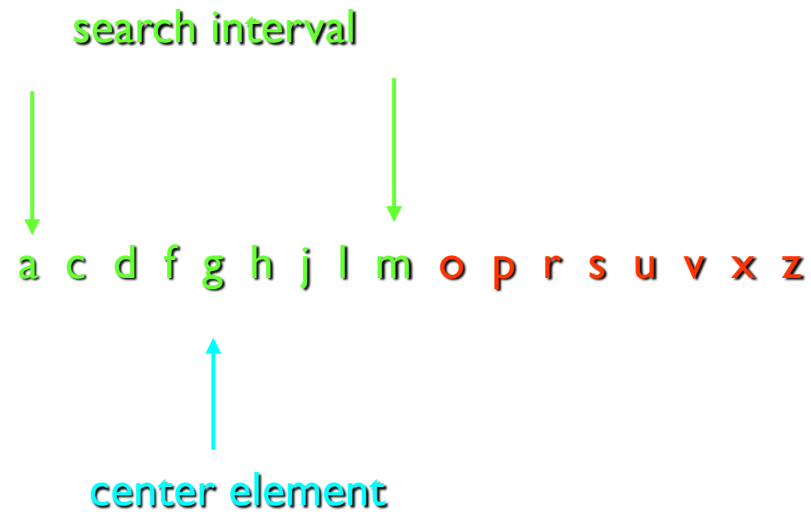
# EXAMPLE

- If the terms in a sequence are ordered, a binary search algorithm is more efficient than linear search.
- The binary search algorithm iteratively restricts the relevant search interval until it closes in on the position of the element to be located.

## binary search for the letter 'j'



## binary search for the letter 'j'





## binary search for the letter 'j'

search interval

a c d f g h j l m o p r s u v x z

center element



## binary search for the letter 'j'

search interval

a c d f g h j l m o p r s u v x z

center element

## binary search for the letter 'j'

search interval



a c d f g h j l m o p r s u v x z



center element

**found !**

# EXAMPLE

**procedure** binary\_search(x: integer;  $a_1, a_2, \dots, a_n$ : integers)

$i := 1$  {i is left endpoint of search interval}

$j := n$  {j is right endpoint of search interval}

**while** ( $i < j$ )

**Begin**

$m := \lfloor (i + j)/2 \rfloor$

**if**  $x > a_m$  **then**  $i := m + 1$

**else**  $j := m$

**end**

**if**  $x = a_i$  **then** location := i

**else** location := 0

{location is the subscript of the term that equals x, or is zero if x is not found}

# COMPLEXITY

- In general, we are not so much interested in the time and space complexity for small inputs.
- For example, while the difference in time complexity between linear and binary search is meaningless for a sequence with  $n = 10$ , it is gigantic for  $n = 2^{30}$ .

# COMPLEXITY

- Assume two algorithms A and B that solve the same class of problems.
- The time complexity of A is  $5,000n$ , the one for B is  $\lceil 1.1^n \rceil$  for an input with  $n$  elements.
- For  $n = 10$ , A requires 50,000 steps, but B only 3, so B seems to be superior to A.
- For  $n = 1000$ , however, A requires 5,000,000 steps, while B requires  $2.5 \cdot 10^{41}$  steps.
- Algorithm B cannot be used for large inputs, while algorithm A is feasible.
- What is important is the **growth** of the complexity functions.
- The growth of time and space complexity with increasing input size  $n$  is a suitable measure for the comparison of algorithms.

# COMPARISON OF COMPLEXITY

Input Size	Algorithm A	Algorithm B
$n$	$5,000n$	$\lceil 1.1^n \rceil$
10	50,000	3
100	500,000	13,781
1,000	5,000,000	$2.5 \cdot 10^{41}$
1,000,000	$5 \cdot 10^9$	$4.8 \cdot 10^{41392}$

# GROWTH OF FUNCTION

- The growth of functions is usually described using the **big-O** notation.
- **Definition:** Let  $f$  and  $g$  be functions from the integers or the real numbers to the real numbers. We say that  $f(x)$  is  $O(g(x))$  if there are constants  $C$  and  $k$  such that

$$|f(x)| \leq C|g(x)|, \text{ whenever } x > k.$$

- When we analyze the growth of complexity functions,  $f(x)$  and  $g(x)$  are always positive.
- Therefore, we can simplify the big-O requirement to

$$f(x) \leq C \cdot g(x) \text{ whenever } x > k.$$

- If we want to show that  $f(x)$  is  $O(g(x))$ , we only need to find one pair  $(C, k)$ .



# GROWTH OF FUNCTION

- The idea behind the big-O notation is to establish an **upper boundary** for the growth of a function  $f(x)$  for large  $x$ . This boundary is specified by a function  $g(x)$  that is usually much **simpler** than  $f(x)$ .
- We accept the constant  $C$  in the requirement
$$f(x) \leq C \cdot g(x) \text{ whenever } x > k,$$
because  **$C$  does not grow with  $x$ .**
- We are only interested in large  $x$ , so it is OK if  $f(x) > C \cdot g(x)$  for  $x \leq k$ .

# GROWTH OF FUNCTION EXAMPLE

Show that  $f(x) = x^2 + 2x + 1$  is  $O(x^2)$ .

For  $x > 1$  we have:

$$x^2 + 2x + 1 \leq x^2 + 2x^2 + x^2$$

$$\Rightarrow x^2 + 2x + 1 \leq 4x^2$$

Therefore, for  $C = 4$  and  $k = 1$ :

$$f(x) \leq Cx^2 \text{ whenever } x > k.$$

$$\Rightarrow f(x) \text{ is } O(x^2).$$

# GROWTH OF FUNCTION EXAMPLE

Question: If  $f(x)$  is  $O(x^2)$ , is it also  $O(x^3)$ ?

**Yes.**  $x^3$  grows faster than  $x^2$ , so  $x^3$  grows also faster than  $f(x)$ .

We are always interested in the **smallest** simple function  $g(x)$  for which  $f(x)$  is  $O(g(x))$ .

- “Popular” functions  $g(n)$  are  $n \log n$ ,  $1$ ,  $2^n$ ,  $n^2$ ,  $n!$ ,  $n$ ,  $n^3$ ,  $\log n$
- Listed from slowest to fastest growth:
  - $1 < \log n < n < n \log n < n^2 < n^3 < 2^n < n!$

# TRACTABLE, INTRACTABLE, UNSOLVABLE

- A problem that can be solved with polynomial worst-case complexity is called **tractable**.
- Problems of higher complexity are called **intractable**.
- Problems that no algorithm can solve are called **unsolvable**.
- More details can be found in the study of Computability and Complexity.

# USEFUL RULES OF BIG-O

- For any polynomial  $f(x) = a_n x^n + a_{n-1} x^{n-1} + \dots + a_0$ , where  $a_0, a_1, \dots, a_n$  are real numbers,  $f(x)$  is  $O(x^n)$ .

If  $f_1(x)$  is  $O(g_1(x))$  and  $f_2(x)$  is  $O(g_2(x))$ , then  $(f_1 + f_2)(x)$  is  $O(\max(g_1(x), g_2(x)))$ .

If  $f_1(x)$  is  $O(g(x))$  and  $f_2(x)$  is  $O(g(x))$ , then  $(f_1 + f_2)(x)$  is  $O(g(x))$ .

If  $f_1(x)$  is  $O(g_1(x))$  and  $f_2(x)$  is  $O(g_2(x))$ , then  $(f_1 f_2)(x)$  is  $O(g_1(x) g_2(x))$ .

# EXAMPLE

- What does the following algorithm compute?

```
procedure who_knows( $a_1, a_2, \dots, a_n$ : integers)
```

```
   $m := 0$ 
```

```
  for  $i := 1$  to  $n-1$ 
```

```
    for  $j := i + 1$  to  $n$ 
```

```
      if  $|a_i - a_j| > m$  then  $m := |a_i - a_j|$ 
```

```
{ $m$  is the maximum difference between any two numbers in the input sequence}
```

Comparisons:  $n-1 + n-2 + n-3 + \dots + 1 = (n-1)n/2 = 0.5n^2 - 0.5n$

Time complexity is  $O(n^2)$ .

# EXAMPLE

- Another algorithm solving the same problem:

```
procedure max_diff( $a_1, a_2, \dots, a_n$ : integers)
```

```
  min :=  $a_1$ 
```

```
  max :=  $a_1$ 
```

```
  for  $i$  := 2 to  $n$ 
```

```
    if  $a_i < \text{min}$  then min :=  $a_i$ 
```

```
    else if  $a_i > \text{max}$  then max :=  $a_i$ 
```

```
  m := max - min
```

Comparisons:  $2n - 2$

Time complexity is  $O(n)$ .



THANKS