

# Course Name: Analysis and Design of Algorithms

# Topics to be covered

- Algorithms
  - What is an Algorithm?
  - Characteristics
  - Complexity

# Algorithms

- 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. You will get to know a more precise and mathematically useful definition when you attend CS420.
- But this one is good enough for now...

# Algorithms

- Properties of algorithms:
- **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.

# Algorithm Examples

- 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)
- $\text{max} := a_1$
- **for**  $i := 2$  **to**  $n$
- **if**  $\text{max} < a_i$  **then**  $\text{max} := a_i$
- {max is the largest element}

# Algorithm Examples

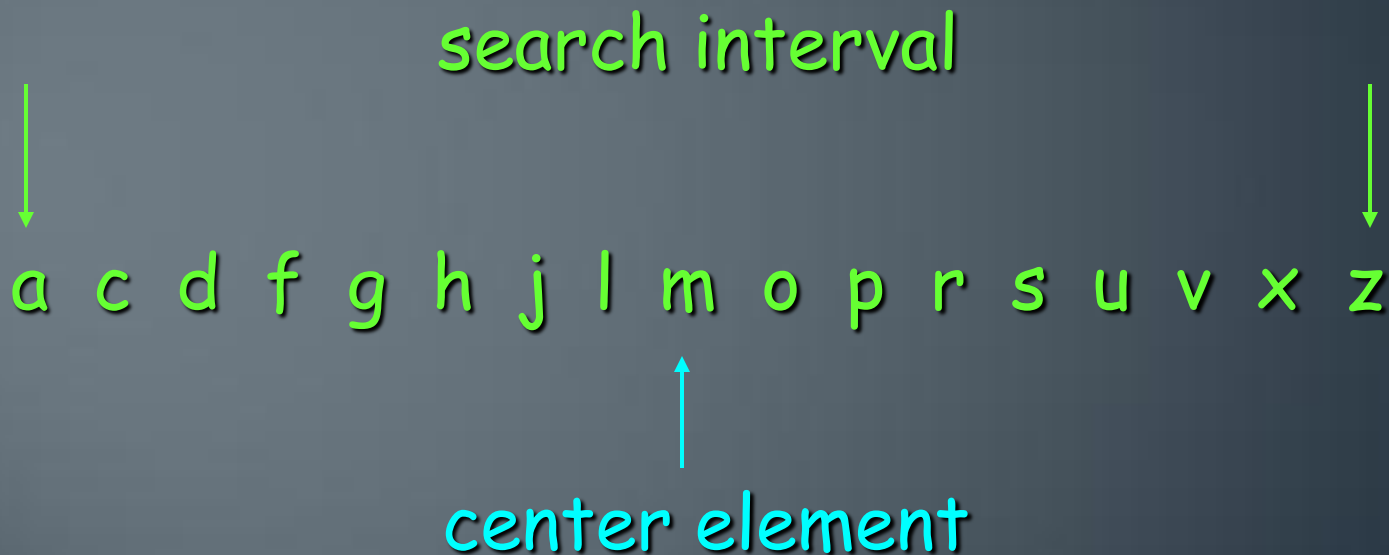
- **Another example:** a linear search algorithm, that is, an algorithm that linearly searches a sequence for a particular element.
- **procedure** linear\_search( $x$ : integer;  $a_1, a_2, \dots, a_n$ : integers)
  - $i := 1$
  - **while** ( $i \leq n$  and  $x \neq a_i$ )
    - $i := i + 1$
  - **if**  $i \leq n$  **then** location :=  $i$
  - **else** location := 0
  - {location is the subscript of the term that equals  $x$ , or is zero if  $x$  is not found}

# Algorithm Examples

- 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.

# Algorithm Examples

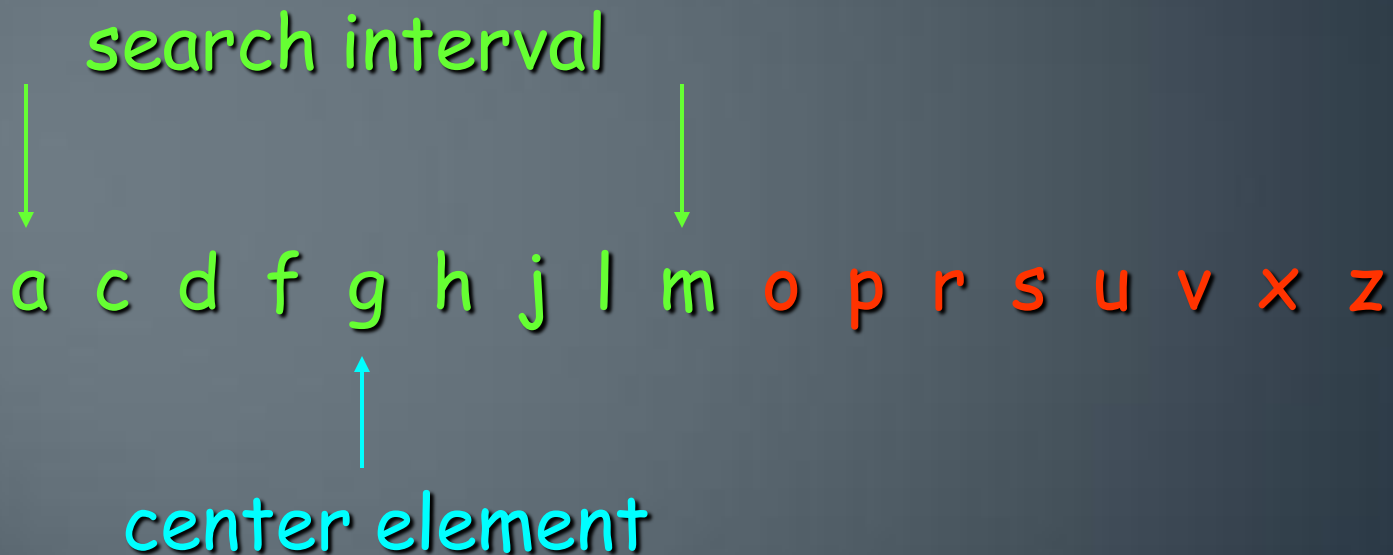
binary search for the letter 'j'





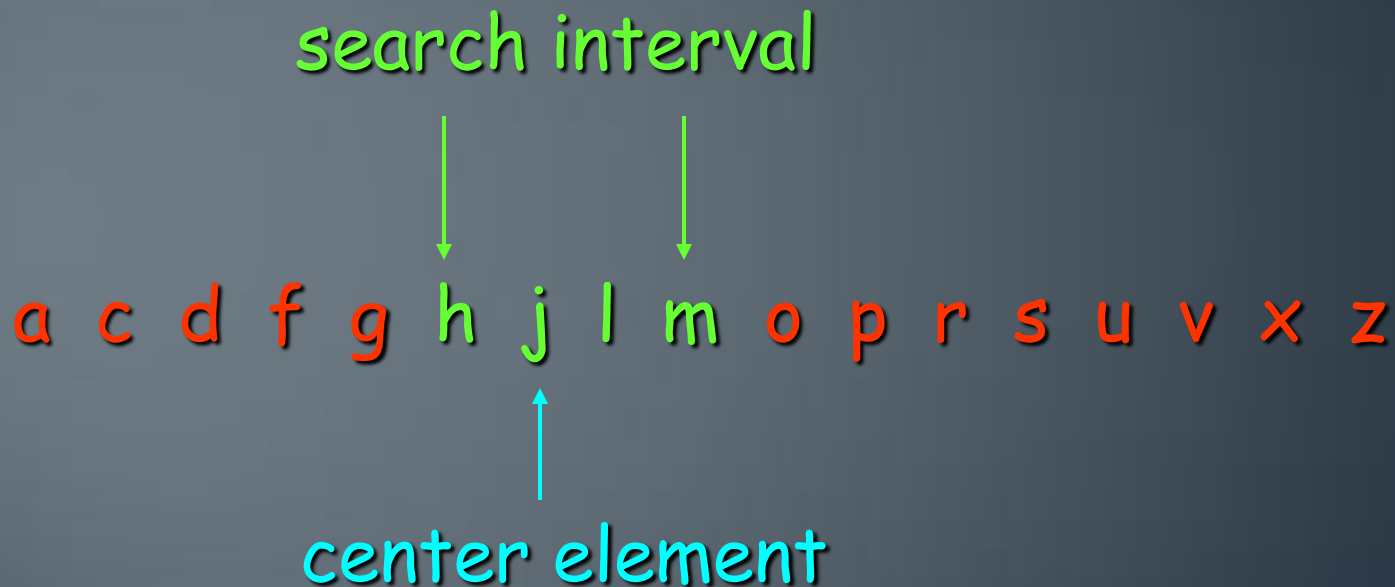
# Algorithm Examples

binary search for the letter 'j'



# Algorithm Examples

binary search for the letter 'j'



# Algorithm Examples

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

# Algorithm Examples

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 !

# Algorithm Examples

- **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

- For example, let us 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.

# Complexity

- This means that algorithm B cannot be used for large inputs, while algorithm A is still feasible.
- So 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.



# Complexity

- **Comparison:** time complexity of algorithms A and B

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	$5 \cdot 10^9$	$4.8 \cdot 10^{41392}$

# Complexity

- This means that algorithm B cannot be used for large inputs, while running algorithm A is still feasible.
- So 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.

# The Growth of Functions

- 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
  - $|f(x)| \leq C|g(x)|$
  - whenever  $x > k$ .

# The Growth of Functions

- 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
- $f(x) \leq C \cdot g(x)$  whenever  $x > k$ .
- If we want to show that  $f(x)$  is  $O(g(x))$ , we only need to find **one** pair  $(C, k)$  (which is never unique).

# The Growth of Functions

- 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
- $f(x) \leq C \cdot g(x)$  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  $x \leq k$ .

# The Growth of Functions

- 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  $k = 1$ :
- $f(x) \leq Cx^2$  whenever  $x > k$ .
- $\Rightarrow f(x)$  is  $O(x^2)$ .

# The Growth of Functions

- 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  $f(x)$ .
- Therefore, we always have to find the **smallest** simple function  $g(x)$  for which  $f(x)$  is  $O(g(x))$ .

# The Growth of Functions

- “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:
  - $1$
  - $\log n$
  - $n$
  - $n \log n$
  - $n^2$
  - $n^3$
  - $2^n$
  - $n!$



# The Growth of Functions

- 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**.
- You will find out more about this in CS420.

# Useful Rules for 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  $O(g_1(x) g_2(x))$ .

# Complexity Examples

- 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  $O(n^2)$ .

# Complexity Examples

- 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  $O(n)$ .