

# Analysis Tools for Data Structures and Algorithms

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March 24, 2020

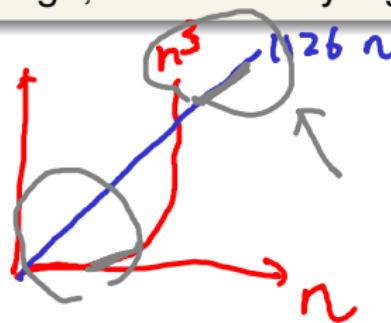
# Asymptotic Notation

# Representing “Rough” by Asymptotic Notation

- goal: rough rather than exact steps
- why rough? constant not matter much
  - when input size large

compare two complexity functions  $f(n)$  and  $g(n)$

growth of functions matters  
—when  $n$  large,  $n^3$  eventually bigger than  $1126n$



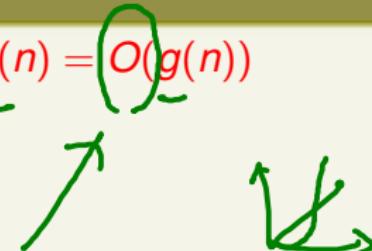
rough  $\Leftrightarrow$  asymptotic behavior

# Asymptotic Notations: Rough Upper Bound

big-O: rough upper bound

- $f(n)$  grows slower than or similar to  $g(n)$ :  $f(n) = O(g(n))$ 
  - $n$  grows slower than  $n^2$ :  $n = O(n^2)$
  - $3n$  grows similar to  $n$ :  $3n = O(n)$
- asymptotic intuition (rigorous math later):

$$\lim_{n \rightarrow \infty} \frac{f(n)}{g(n)} \leq c$$



$$f(n) = O(g(n))$$

big-O: arguably the most used “language” for complexity

# More Intuitions on Big-O

$$f(n) = O(g(n)) \Leftarrow \lim_{n \rightarrow \infty} \frac{f(n)}{g(n)} \leq c \quad (\text{not rigorously, yet})$$

*(126)*

- “ $= O(\cdot)$ ” more like “ $\in$ ”

- $n = O(n)$
- $n = O(10n)$
- $n = O(0.3n)$
- $n = O(n^5)$

$$\begin{aligned} n &= O(n^2) \\ n^2 &= O(n^2) \\ 0.1n^2 &= O(n^2) \\ 3n^2 &= O(n^2) \end{aligned}$$

- “ $= O(\cdot)$ ” also like “ $\leq$ ”

- $n = O(n^2)$
- $n^2 = O(n^{2.5})$
- $n = O(n^{2.5})$

- $1126n = O(n)$ : coefficient not matter

$n + \sqrt{n} + \log n = O(n)$ : lower-order term not matter

“exact”

intuitions (properties) to be proved later

## Formal Definition of Big-O

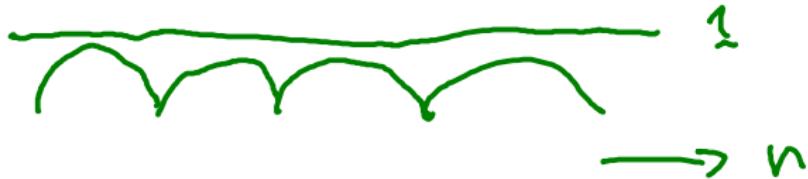
$$\lim \frac{f}{g} \leq c \quad \begin{array}{l} f(n) > 0 \\ g(n) > 0 \end{array}$$

Consider positive functions  $f(n)$  and  $g(n)$ ,

$f(n) = O(g(n))$ , iff exist  $c$  such that  $f(n) \leq c \cdot g(n)$  for all  $n \geq n_0$

- covers the  $\lim$  intuition if limit exists
- covers other situations without “limit” ↗  
e.g.  $|\sin(n)| = O(1)$

next: prove that  $\lim$  intuition  $\Rightarrow$  formal definition



# $\lim$ Intuition $\Rightarrow$ Formal Definition

$$\boxed{\begin{array}{l} f \leq c g \\ (c, n_0) \end{array}}$$



For positive functions  $f$  and  $g$ , if  $\lim_{n \rightarrow \infty} \frac{f(n)}{g(n)} \leq c$ , then  $f(n) = O(g(n))$ .

- with definition of limit, there exists  $\epsilon, n_0$  such that for all  $n \geq n_0$ ,  $\left| \frac{f(n)}{g(n)} - c \right| < \epsilon$ .
- That is, for all  $n \geq n_0$ ,  $\frac{f(n)}{g(n)} < c + \epsilon$ .
- Let  $c' = c + \epsilon$ ,  $n'_0 = n_0$ , big- $O$  definition satisfied with  $(c', n'_0)$ . QED.

important to not just have intuition (building),  
but know definition (building block)

## More on Asymptotic Notations

# Asymptotic Notations: Definitions

- $f(n)$  grows slower than or similar to  $g(n)$ : (" $\leq$ ")

$f(n) = O(g(n))$ , iff exist  $c, n_0$  such that  $f(n) \leq c \cdot g(n)$  for all  $n \geq n_0$

- $f(n)$  grows faster than or similar to  $g(n)$ : (" $\geq$ ")

$$c > 0$$

$f(n) = \Omega(g(n))$ , iff exist  $c, n_0$  such that  $f(n) \geq c \cdot g(n)$  for all  $n \geq n_0$

- $f(n)$  grows similar to  $g(n)$ : (" $\approx$ ")

$f(n) = \Theta(g(n))$ , iff  $f(n) = O(g(n))$  and  $f(n) = \Omega(g(n))$

let's see how to use them

$$\lim_{n \rightarrow \infty} \frac{f}{g}$$

$$\frac{\cancel{8+t}}{8} < \frac{f}{g} < \frac{\cancel{8+t}}{8} + \epsilon$$

# The Seven Functions as $g$

$$f(n) = O(1)$$

$$g(n) = ?$$



- 1: constant ✓
- $\log n$ : logarithmic (does base matter?)
- $n$ : linear ✓
- $n \log n$  ✓
- $n^2$ : square ✓
- $n^3$ : cubic .
- $2^n$ : exponential (does base matter?)

$$f(n) = O(\log n)$$

$$\log_2 n = \frac{\log_{10} n}{\log_{10} 2}$$

will often encounter them in future classes

# Analysis of Sequential Search

## Sequential Search

```
for i ← 0 to n – 1 do
    if list[i] == num
        return i
    end if
end for
return -1
```

- best case (e.g.  $num$  at 0): time  $\Theta(1)$
- worst case (e.g.  $num$  at last or not found): time  $\Theta(n)$

often just say  $O(n)$ -algorithm (linear complexity)

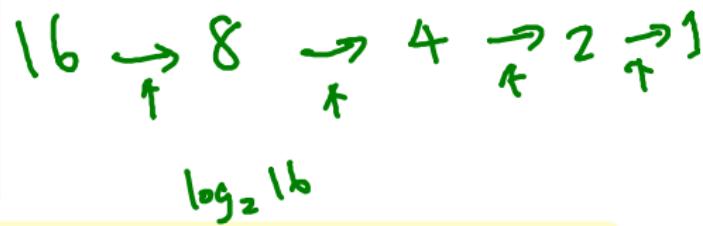
# Analysis of Binary Search

## Binary Search

```

left ← 0, right ← n – 1
while left ≤ right do
    mid ← floor((left + right)/2)
    if list[mid] > num
        left ← mid + 1
    else if list[mid] < num
        right ← mid – 1
    else
        return mid
    end if
end while
return –1
  
```

- best case (e.g. *num* at *mid*): time  $\Theta(1)$
- worst case (e.g. *num* not found): because range (*right* – *left*) halved in each WHILE, needs time  $\Theta(\log n)$  iterations to decrease range to 0



often just say  $O(\log n)$ -algorithm (logarithmic complexity)

# Sequential and Binary Search

- Input: **any** integer array *list* with size *n*, an integer *num*
- Output: if *num* not within *list*,  $-1$ ; otherwise,  $+1126$

**DIRECT-SEQ-SEARCH**  
 $(list, n, num)$

```

for  $i \leftarrow 0$  to  $n - 1$  do
    if  $list[i] == num$ 
        return  $+1126$ 
    end if
end for
return  $-1$ 

```

**SORT-AND-BIN-SEARCH**  
 $(list, n, num)$

```

SEL-SORT(list, n)
return

```

$\text{BIN-SEARCH}(list, n, num) \geq 0? + 1126 : -1$

- DIRECT-SEQ-SEARCH:  $O(n)$  time ✓
- SORT-AND-BIN-SEARCH:  $\overbrace{O(n^2)}$  time for SEL-SORT and  $\overbrace{O(\log n)}$  time for BIN-SEARCH ✓

next: operations for “combining” asymptotic complexity

# Properties of Asymptotic Notations

# Some Properties of Big-O I

## Theorem ( 封閉律 )

if  $f_1(n) = O(g_2(n))$ ,  $f_2(n) = O(g_2(n))$  then  $f_1(n) + f_2(n) = O(g_2(n))$

✓ • When  $n \geq n_1$ ,  $f_1(n) \leq c_1 g_2(n)$

✓ • When  $n \geq n_2$ ,  $f_2(n) \leq c_2 g_2(n)$

• So, when  $n \geq \max(n_1, n_2)$ ,  $f_1(n) + f_2(n) \leq (c_1 + c_2)g_2(n)$

QED

## Theorem ( 遷移律 )

if  $f_1(n) = O(g_1(n))$ ,  $g_1(n) = O(g_2(n))$  then  $f_1(n) = O(g_2(n))$

• When  $n \geq n_1$ ,  $f_1(n) \leq c_1 g_1(n)$

• When  $n \geq n_2$ ,  $g_1(n) \leq c_2 g_2(n)$

• So, when  $n \geq \max(n_1, n_2)$ ,  $f_1(n) \leq c_1 c_2 g_2(n)$

## Some Properties of Big-O II

sel-sort is  $O(n^2)$

bin-search is  $O(\log n)$

Theorem (併吞律)

if  $f_1(n) = O(g_1(n))$ ,  $f_2(n) = O(g_2(n))$  and  $g_1(n) = O(g_2(n))$  then  
 $f_1(n) + f_2(n) = O(g_2(n))$

Proof: use two theorems above.

$\log n$  is  $O(n^2)$

Theorem

If  $f(n) = a_m \underline{n^m} + \dots + a_1 n + a_0$ , then  $f(n) = O(n^m)$

Proof: use the theorem above.

similar proof for  $\Omega$  and  $\Theta$

$$\underline{f_1 + f_2} = O(n^2)$$

sel-sort-bin-search

# Some More on Big-O

$$\downarrow \quad \begin{matrix} \text{"}\leq\text{"} & 10 \\ \leq & 1126 \end{matrix}$$

RECURSIVE-BIN-SEARCH is  $O(\log n)$  time and  $O(\log n)$  space

- by 遞移律 , time also  $O(n)$
- time also  $O(n \log n)$   $\leq 5566$
- time also  $O(n^2)$
- also  $O(2^n)$   $\leq \dots$
- ...

prefer the tightest Big-O!

# Practical Complexity

some input sizes are time-wise **infeasible** for some algorithms

when 1-billion-steps-per-second

$n$	$n$	$n \log_2 n$	$n^2$	$n^3$	$n^4$	$n^{10}$	$2^n$
10	$0.01\mu s$	$0.03\mu s$	$0.1\mu s$	$1\mu s$	$10\mu s$	10s	$1\mu s$
20	$0.02\mu s$	$0.09\mu s$	$0.4\mu s$	$8\mu s$	$160\mu s$	$2.84h$	$1ms$
30	$0.03\mu s$	$0.15\mu s$	$0.9\mu s$	$27\mu s$	$810\mu s$	$6.83d$	$1s$
40	$0.04\mu s$	$0.21\mu s$	$1.6\mu s$	$64\mu s$	$2.56ms$	$121d$	$18m$
50	$0.05\mu s$	$0.28\mu s$	$2.5\mu s$	$125\mu s$	$6.25ms$	$3.1y$	$13d$
100	$0.10\mu s$	$0.66\mu s$	$10\mu s$	$1ms$	$100ms$	$3171y$	$4 \cdot 10^{15}y$
$10^3$	$1\mu s$	$9.96\mu s$	$1ms$	$1s$	$16.67m$	$3 \cdot 10^{13}y$	$3 \cdot 10^{284}y$
$10^4$	$10\mu s$	$130\mu s$	$100ms$	$1000s$	$115.7d$	$3 \cdot 10^{23}y$	
$10^5$	$100\mu s$	$1.66ms$	10s	$11.57d$	$3171y$	$3 \cdot 10^{33}y$	
$10^6$	1ms	19.92ms	16.67m	32y	$3 \cdot 10^7y$	$3 \cdot 10^{43}y$	

note: similar for space complexity,  
e.g. store an  $N$  by  $N$  double matrix when  $N = \underline{50000}$

