

FUNCTIONS' GROWTH

Asymptotic Efficiency

- Asymptotic efficiency refers to the analysis of how the performance of an algorithm grows as the size of the input data increases (towards infinity)
- To describe asymptotic efficiency, we use asymptotic notations:
 - Big O notation: upper-bound, worst-case scenario
 - Big Ω notation: lower-bound, best-case scenario
 - Big Θ notation: tight-bound, where both upper and lower are defined.

Comparing 2 algorithms asymptotic efficiency

Consider 2 sorting algorithms A and B on the same set of data of size n . Denote $f(n)$ and $g(n)$ to be the upper bounds of A and B respectively. Which is the better upper bound?

We can compare by solving

$$L = \lim_{n \rightarrow \infty} \frac{f(n)}{g(n)}$$

The result can either be:

- $L > 0$: $f(n)$ and $g(n)$ grows at the same rate

$$\text{or } L < \infty \Leftrightarrow \left\{ \begin{array}{l} f(n) \text{ is } \Theta(g(n)) \\ f(n) \text{ is } O(g(n)) \\ f(n) \text{ is } \Omega(g(n)) \end{array} \right. \text{ or } \left\{ \begin{array}{l} g(n) \text{ is } \Theta(f(n)) \\ g(n) \text{ is } O(f(n)) \\ g(n) \text{ is } \Omega(f(n)) \end{array} \right.$$

\Rightarrow both functions are tightly bound to each other

- $L = 0$: $f(n)$ grows significantly slower than $g(n)$
 $\Leftrightarrow f(n) \text{ is } o(g(n)) \text{ or } g(n) \text{ is } \omega(f(n))$
 $f(n)$ is upper-bounded by $g(n)$ $g(n)$ is lower-bounded by $f(n)$

\Leftrightarrow algorithm A is more efficient than B

• $L = \infty$: $f(n)$ grows significantly faster than $g(n)$
 $\Leftrightarrow g(n)$ is $o(f(n))$ or $f(n)$ is $\omega(g(n))$
 $g(n)$ is upper-bounded by $f(n)$ $f(n)$ is lower-bounded by $g(n)$

\Rightarrow algorithm B is more efficient than A

Big O

We can write: $f(n) = O(g(n))$

if there exist $n_0 > 0$ and $c > 0$ such that:

$$f(n) \leq c \cdot g(n), \quad n \geq n_0$$

We say $g(n)$ is the "fuzzy" upper-bound of $f(n)$. "Fuzzy" because there is a possibility that $f(n)$ grows the same rate as $g(n)$

Little O

We can write: $f(n) = o(g(n))$

if there exist $n_0 > 0$ and $c > 0$ such that

$$f(n) < c \cdot g(n), \quad n \geq n_0$$

The only difference between big O and little O is the "strictness". In little O, there is no possibility of $f(n)$ ever match the grow rate of $g(n)$.

Big Omega

We can write: $f(n) = \Omega(g(n))$

If there exist $n_0 > 0$ and $c > 0$ such that:

$$f(n) \geq c \cdot g(n), \quad n \geq n_0$$

Little Omega

definition can

be derived using same logic as Big O / Little O

Big Theta

We can write: $f(n) = \Theta(g(n))$

If there exist $n_0 > 0$ and $c_1, c_2 > 0$ such that:

$$c_1 \cdot g(n) \leq f(n) \leq c_2 \cdot g(n), \quad n \geq n_0$$

$$f(n) = \Theta(g(n)) \Leftrightarrow g(n) = \Theta(f(n))$$

Proof:

$$f(n) = \Theta(g(n)) \Rightarrow \begin{cases} c_1 \cdot g(n) \leq f(n) \\ f(n) \leq c_2 \cdot g(n) \end{cases}$$

$$\Leftrightarrow \begin{cases} g(n) \geq \frac{1}{c_1} f(n) \\ \frac{1}{c_2} f(n) \geq g(n) \end{cases} \Rightarrow \frac{1}{c_1} f \leq g \leq \frac{1}{c_2} f$$

$$\Rightarrow g(n) = \Theta(f(n))$$

The " \sim " symbol

When we say: $f(n) \sim g(n)$

$f(n)$ is asymptotic equivalence to $g(n)$

$f(n) \sim g(n)$ when:

$$\lim_{n \rightarrow \infty} \frac{f(n)}{g(n)} = 1$$

Can think of " \sim " symbol as a "stricter" form of Theta Θ notation, similar to how Big O / Little o, Big Omega / Little omega works.

$$f(n) \sim g(n) \Rightarrow f(n) = (1 + o(1)) \cdot g(n)$$

Proof:

$$f(n) = (1 + o(1)) \cdot g(n)$$

$$\Leftrightarrow \frac{f(n)}{g(n)} = 1 + o(1) \quad (1)$$

Because $o(1)$ refers to a function that approaches 0 as $n \rightarrow \infty$.

In other words, if $h(n) = o(1)$, then:

$$\lim_{n \rightarrow \infty} h(n) = 0$$

Denote $k(n) = 1 + h(n)$, then as $\lim_{n \rightarrow \infty} h(n) = 0$:

$$\lim_{n \rightarrow \infty} k(n) = \lim_{n \rightarrow \infty} (1 + h(n)) = 1$$

Substitute $k(n) = 1 + h(n)$ back to equation (1), we can say that:

$$\lim_{n \rightarrow \infty} k(n) = \lim_{n \rightarrow \infty} 1 + h(n)$$

$$= \lim_{n \rightarrow \infty} \frac{f(n)}{g(n)} = 1$$

↳ Definition of $f(n) \sim g(n)$

Example:

The Door-in-Wall Puzzle

You are facing a wall that extends infinitely in both directions. There is a gap somewhere in the wall in one of the direction. Comes up with an algorithm that guarantee to find the gap within a finite number of steps. In other words, what is Θ -bound on the worst case number of steps taken by this algorithm?

Solution:

◦ Algorithm:

```

for i : 1 → ∞ :    # number of steps
    for each direction:
        for pos : 0 → i :
            if see gap
                return pos
    
```

◦ Θ -bound on worst case number of steps:

◦ Let $T(n)$ describe time complexity of the algorithm, where n is distance from starting point to the gap

◦ Total steps taken after k iterations is:

$$\begin{aligned} T(k) &= 2(1 + 2 + \dots + k) \\ &= k^2 + k \end{aligned}$$

◦ If gap is located at step n , then it will takes $k = n$ of exploration, substitute this in $T(k)$ we have:

$$T(n) = n^2 + n \sim n^2$$

Conclusion: $T(n) = O(n^2)$

Better Solution:

- Algorithm:

```
for i: 1 → ∞:  
  for each direction:  
    for pos: 0 → 2i:  
      if see gap  
        return pos
```

- Θ-bound worst case number of steps
- Let $T(n)$ describe the time complexity of the algorithm
- Total steps taken after k iterations:

$$\begin{aligned} T(k) &= 2(2^0 + 2^1 + 2^2 + \dots + 2^k) \\ &= 2 \left(\frac{2^{k+1} - 1}{2 - 1} \right) \\ &= 2(2^{k+1} - 1) \\ &= 2^{k+2} - 2 \end{aligned}$$

- If gap is located at step n , then it will take $k = \log_2 n$ of exploration. Substitute this in $T(k)$ we have:

$$\begin{aligned} T(n) &= 2^{\log_2 n + 2} - 2 \\ &\sim 2^{\log_2 n + 2} \\ &= 2^{\log_2 n} \cdot 2^2 \\ &= n \cdot 2^2 < a^{\log_a b} = b > \\ &= 4n \end{aligned}$$

Conclusion: $T(n) = O(n)$

⇒ Better than $O(n^2)$

Recap on logarithmic properties

Definition: $\log_a b = k$ <divides b by a k times to reach 1>
 $\Leftrightarrow a^k = b$ < a times itself k times to reach b >

Another definition:

$$a^{\log_a b} = b \quad \text{or} \quad b^{\frac{1}{\log_a b}} = a$$

\Rightarrow Interpret as "taking $\log_a b$ steps in base a to get to b ".

Important properties:

• Product property:

$$\log_a (mn) = \log_a (m) + \log_a (n)$$

• Quotient property:

$$\log_a \left(\frac{m}{n} \right) = \log_a (m) - \log_a (n)$$

• Power property:

$$\log_a (m^n) = n \cdot \log_a (m)$$

• Change of Base formula:

$$\log_a b = \frac{\log_k b}{\log_k a}$$

• Special values:

$$\log_a 1 = 0$$

$$\log_a a = 1$$

$$\log_a a = 1 \quad \text{for } \begin{cases} \forall a > 0 \\ a \neq 1 \end{cases}$$

• Cancel out:

$$\log_b b^a = a \quad \text{if } b > 0 \text{ and } b \neq 1$$

• Monotonicity:

The logarithm function is monotonically increasing. If:

$$a < b \quad \text{for any } a, b \geq 0$$

$$\text{Then: } \log(a) < \log(b)$$

• Inequality:

$$\text{If } a \geq 2^b, \text{ then:}$$
$$b \leq \log_2 a$$

Recap on exponent properties

- Positive number expression:

$$2 = e^{\ln(2)}$$

or more generally, $a > 0$:

$$a = e^{\log_a(a)}$$

- Product: $a^m \cdot a^n = a^{(m+n)}$

- Quotient: $\frac{a^m}{a^n} = a^{(m-n)}$

- Power of power: $(a^m)^n = a^{m \cdot n}$

- Power of product: $(ab)^n = a^n \cdot b^n$

- Power of quotient: $\left(\frac{a}{b}\right)^n = \frac{a^n}{b^n}$

- Negative exponent: $a^{-n} = \frac{1}{a^n}$