

Cost of Algorithms

Inputs: parameterized by an integer n , called the size

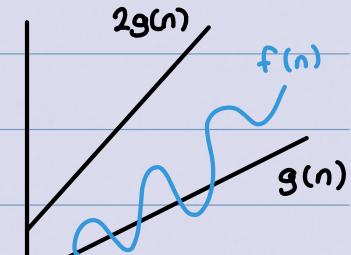
$T(I)$ = runtimes on input $I \Rightarrow$ runtime of a particular instance

$T_{\text{Worst}}(n) = \max_{I \text{ of size } n} (T(I)) \Rightarrow$ worst-case runtime (default)

$T_{\text{best}}(n) = \min_{I \text{ of size } n} (T(I)) \Rightarrow$ best-case runtime, not used much

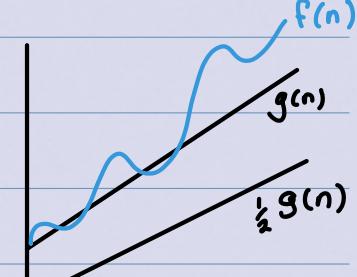
Asymptotic Notation - consider 2 functions $f(n)$ and $g(n)$ with values in $\mathbb{R}_{>0}$

big-O: we say that $f(n) \in O(g(n))$ if there exists a $C > 0$ and n_0 such that for $n \geq n_0$, $f(n) \leq C g(n)$



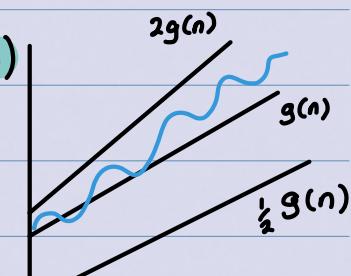
big- Ω : we say that $f(n) \in \Omega(g(n))$ if there exists a $C > 0$ and n_0 such that for $n \geq n_0$, $f(n) \geq C g(n)$

\Rightarrow equivalent to $g(n) \in O(f(n))$



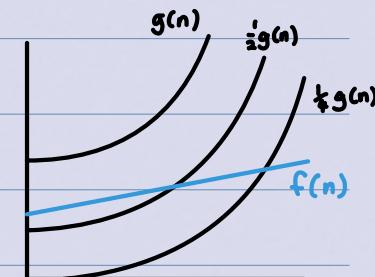
Θ : we say that $f(n) \in \Theta(g(n))$ if $f(n) \in O(g(n))$ and $f(n) \in \Omega(g(n))$.

\Rightarrow in particular true if $\lim_{n \rightarrow \infty} \frac{f(n)}{g(n)} = C$ for some $0 < C < \infty$



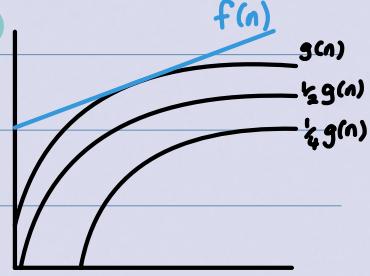
little-O: we say that $f(n) \in o(g(n))$ if for all $C > 0$, there exists an n_0 such that for $n \geq n_0$, $f(n) \leq C g(n)$

\Rightarrow equivalent to $\lim_{n \rightarrow \infty} \frac{f(n)}{g(n)} = 0$



little- ω : we say that $f(n) \in \omega(g(n))$ if for all $c > 0$, there exists an n_0 such that for $n \geq n_0$, $f(n) \geq c g(n)$

\Rightarrow equivalent to $\lim_{n \rightarrow \infty} \frac{f(n)}{g(n)} = \infty$



Examples

a) $n^k + C_{k-1} n^{k-1} + \dots + C_0 \in \Theta(n^k)$

b) $2^{n-1} \notin \Theta(2^n)$

c) $(n-1)! \in \Theta(n!)$

Definitions for Several Parameters

consider two functions $f(n, m)$, $g(n, m)$ with values in $\mathbb{R}_{>0}$

$f(n, m)$ is in $O(g(n, m))$ if there exist C, n_0, m_0 such that

$f(n, m) \leq C g(n, m)$ for $n \geq n_0$ or $m \geq m_0$

Case study: maximum subarray

Given an array $A[0, \dots, n]$, find a contiguous subarray $A[i, \dots, j]$

that maximises the sum $A[i] + \dots + A[j]$.

Example: given $A = [10, -5, 4, 3, -5, 6, -1, -1]$, the subarray $A[0, \dots, 5] = [10, -5, 4, 3, -5, 6]$ has sum $10 - 5 + 4 + 3 - 5 + 6 = 13$ is the max.

Brute Force algorithm:

runtime is $\Theta(n^3)$

but, we can improve on this!

idea: we recompute the same

sum many times in the j loop

BruteForce (A)

1. $opt = 0$
2. for ($i = 0 \rightarrow n$) {
3. for ($j = i \rightarrow n$) {
4. $Sum = 0$
5. for ($k = i \rightarrow j$) {
6. $Sum += A[k]$

BetterBruteForce (A)

```
1. opt = 0  
2. for (i=0→n) {  
3.     sum = 0  
4.     for (j=1→n) {  
5.         sum += A[j]  
6.         if (sum > opt) {  
7.             opt = sum  
8.         }  
9.     }  
10.    }  
11. return opt
```

```
7.     }  
8.     if (sum > opt) {  
9.         opt = sum  
10.    }  
11.    }  
12.    }  
13. return opt
```

→ runtime $\Theta(n^2)$

but, we can still do better using a **divide-and-conquer approach**:

idea: solve the problem twice in size $n/2$ (assuming n is a power of 2). Then, the optimal subarray (if not empty):

1. is completely in the left half $A[0, \dots, n/2]$
2. or is completely in the right half $A[n/2+1, \dots, n]$
3. or contains both $A[n/2]$ and $A[n/2+1]$

⇒ the three cases are mutually exclusive

to find the optimal subarray in case 3, we have:

$$A[i] + \dots + A[n/2] + A[n/2+1] + \dots + A[j]$$

more abstractly, we have $F(i, j) = f(i) + g(j)$, for $i \in [0, \dots, n/2]$ and $j \in [n/2+1, \dots, n]$.

To maximise $F(i, j)$, we maximise $f(i)$ and $g(j)$ independently!

Maximise Lower Half (A)

```
1. opt = A[n/2]
```

Maximise Upper Half (A)

```
1. opt = A[n/2+1]
```

```

2. sum = A[n/2]
3. for (i=n/2-1 → 0) {
4.   sum += A[i]
5.   if (sum > opt) {
6.     opt = sum
7.   }
8. }
9. return opt

```

```

2. sum = A[n/2 + 1]
3. for (i=n/2+1 → n) {
4.   sum += A[i]
5.   if (sum > opt) {
6.     opt = sum
7.   }
8. }
9. return opt

```

↳ runtimes are $\Theta(n)$! ↵

So, final divide and conquer algorithm:

Divide And Conquer Maximum Subarray ($A[0, \dots, n]$)

1. if ($n == 1$) return max($A[0]$, 0)
2. opt_low = DivideAndConquerMaximumSubarray ($A[0, \dots, n/2]$)
3. opt_high = DivideAndConquerMaximumSubarray ($A[n/2+1, \dots, n]$)
4. opt_mid = MaximiseLowerHalf(A) + MaximiseUpperHalf(A)
5. return max(opt_low, opt_mid, opt_high)

⇒ runtime: $T(n) = 2T(n/2) + \Theta(n) \in \Theta(n\log n)$