

Intro

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Concerned with:

- design
- time taken to run - steps
 - computation steps for each logical step
- memory usage
 - larger data types increase this
- performance based on large n

The Fibonacci Series:

- Recursion
 - time - 1.6^n logical steps
 - from top to base
- pen and paper
 - store intermediate results in a table
 - from base to top
 - n logical steps
 - n logical RAM slots
- Iterative
 - fixed amount of RAM, only keep previous two values
 - larger integers mean RAM is actually proportional to n
 - from base to top
- Analytic
 - floating precision needs more bits as n increases
- Matrix
 - IMPORTANT - M^n takes $\log_2 n$ steps to compute
 - overhead piecing together results

Complexity Notation

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Notation	Pronunciation	... (approximately, proportionally)	Program takes
O		Less than	At most this long
Ω	Omega	Greater than	At least this long
Θ	Theta	Equal	Approximately this long

Theta notation

- approximately proportional
- **ignore constant factors**
- interested in **asymptotic behaviour**
 - large n
- **think for worst case**
 - has to be consistent for large n
 - e.g. if depends on even odd n - cannot give theta function

Best complexities:

Smaller

- Constant
- Logarithmic
- polynomial
- exponential
 - (factorial)

Bigger

A function $f(n)$ is $\Theta(g(n))$ if

there are constants $c_1 > 0$, $c_2 > 0$ and n_0 (starting n) such that for all $n \geq n_0$

$$0 \leq c_1 g(n) \leq f(n) \leq c_2 g(n)$$

- $f(n)$ sandwiched between two multiple of $g(n)$

A function $f(n)$ is $O(g(n))$ if

there are constants $c > 0$ and n_0 (starting n) such that when $n \geq n_0$

$$0 \leq f(n) \leq c g(n)$$

$$0 \leq f(n) < c g(n) - \text{small } o(g(n))$$

- $f(n)$ sandwiched between 0 and a multiple of $g(n)$
 - $f(n)$ less than a multiple of $g(n)$

A function $f(n)$ is $\Omega(g(n))$ if

there are constants $c > 0$ and n_0 (starting n) such that when $n \geq n_0$

$$0 \leq c g(n) \leq f(n)$$

$$0 \leq c g(n) < f(n) - \omega(g(n))$$

- $f(n)$ greater than a multiple of $g(n)$

Divide & Conquer

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subproblems - solve smaller - then recombine

- requires subproblems to be unrelated
- recombining has a cost
 - o increases as you divide further

E.g. $O(n^2)$

$$\text{new cost} = 2^k \left(\frac{n}{2^k} \right)^2 + nk = \frac{n^2}{2^k} + nk$$

- combine cost of $O(n)$

Subdivide to get to size of 1, $k = \log_2 n$

new cost = $n + n \log_2 n - O(n \log n)$

1. let $n = 2^k$

2. $2^k \left(\frac{T(n)}{2^k} \right)^2 + kO(n)$

Prove if $T(n)$ is O

- by induction
 - o assume true for all $m < n$
 - o then show true for n
- for $T(n) = O(\text{test})$
- start from $n = 1$ or 2 , get constraint on constant
- Start:
 - o $T(n) \leq 2T\left(\frac{n}{2}\right) + cn$
- $m = \frac{n}{2} < n$
- find $T\left(\frac{n}{2}\right)$
- place into Start
- constant constraint to show $P(n)$

Master Method:

- runtime of D&C algorithm
- don't use if you don't have a, b, d - then do by hand

$$T(n) = a T(n/b) + O(n^d) \quad \begin{cases} a & \text{Number of subcases} \\ n/b & \text{Size of each subcase} \\ O(n^d) & \text{How long it takes to combine} \end{cases}$$

for some $a > 0$, $b > 0$ and $d \geq 0$, then

$$T(n) = \begin{cases} O(n^d) & \text{if } d > \log_b a \\ O(n^d \log n) & \text{if } d = \log_b a \\ O(n^{\log_b a}) & \text{if } d < \log_b a \end{cases} = \tilde{O}\left(n^{\max(d, \log_b a)}\right)$$

Dynamic Programming

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divide into non-independent, overlapping subproblems

Optimal substructure - best possible solution built from best possible sub solutions

Once we know the optimal solutions for all the possible subproblems, we can choose the optimal way of combining them

Memoisation

- modify a function to store the result
- if the function is called again with same arguments, can retrieve result instead of re-computing
- easy to do with a hash table

DP with Memoisation:

- top of function, check if result already stored, if so retrieve and return the value - $O(1)$
- reconstruction
 - store partial results - save on memory use
 - build full solution at end

top-down vs bottom-up

generally bottom-up more efficient practically, but both same complexity wise

top-down:

- recursive function calls
- large stack size as n increases

can use bottom-up when,

- know the order of which results depends on others
- know you have to compute all the values to get final result

How-to:

- start computing results from lowest n
- look-back in data structure
 - use previous results to compute new one
- continue until you reach desired n