

Insertion Sort $\mathcal{O}(n^2) = cn^2$

$$2 \times \frac{10^7 \times 10^7}{10^{10}} \frac{\text{data}}{\text{ins/sec}} = 2 \times 10^4 \text{ sec} \quad (5.5 \text{ hrs.})$$

Merge Sort $\mathcal{O}(n \log n) = c \cdot n \cdot \log n$

$$\frac{50 \times 10^7 \times \log(10^7)}{10^7 \text{ ins/sec}} = 50 \times 7 \text{ sec} \quad (20 \text{ mins})$$

↗
1000x slower computer, still faster.

Constraint

1. Speed (main concern)
2. Memory
3. Quality
 - 1) ML
 - 2) Data Driven Algorithm

* Synthetically Standardize.

* Save memory, batch process

Assignment

Hand Gesture

Gesture x Orientation → Different Meaning.

Holistic Measure

Mahan / Manhattan distance.

DDW

$\log n \sqrt{n} n n \log n^2 n^3 \underline{2^n n!}$

avoid

* n^c - polynomial

* 2^n - exponent

* $n!$ - all possible combination, brute force

"Bruteforce is not an algorithm"

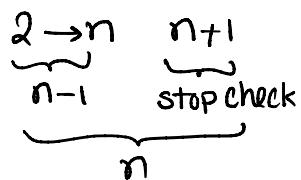
#not realistically solvable.

Insertion Sort

In place sorting

Every iteration \rightarrow array is sorted. (loop invariant)

Line 1



itr + boundary cond.

$$\sum_{j=2}^n t_j$$

\uparrow because of $A[i] > \text{key}$
based on j

* $t_j = 1$

Best case $\Theta(n)$ Already sorted. ($t_j = 1$)

Worst case $\Theta(n^2)$ Reverse sorted. $t_j = j$

Avg case:

$$t_j = \frac{j}{2}$$

Chapter 3

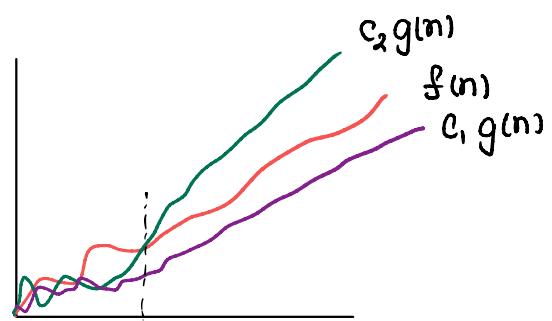
Average Case

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

$$c_1 g(n) < f(n) < c_2 g(n)$$

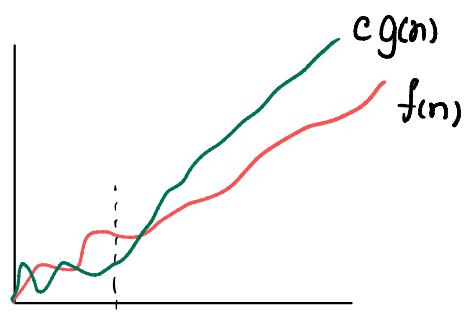
Upper & Lower Bound.

Tight bound



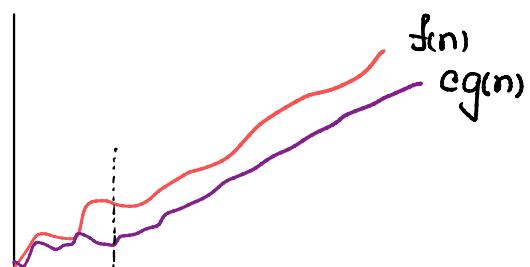
$$f(n) = O(g(n))$$

Upper Bound



$$f(n) = \Omega(g(n))$$

Lower Bound.



$O \rightarrow$ upper bound

but not tight

$$2n^2 = O(n^2) \text{ tight}$$

$$2n = O(n^2) \text{ not tight}$$

$$\frac{n^3}{2} = \omega(n)$$

$$\frac{n^3}{2} \neq \omega(n^2)$$

$$\lim_{n \rightarrow \infty} \frac{f(n)}{g(n)} = 0 \quad g(n) \gg f(n) \quad \text{small } o$$

$$\lim_{n \rightarrow \infty} \frac{f(n)}{g(n)} = \infty \quad f(n) \gg g(n) \quad w$$

Chapter 4

Divide & Conquer

$$\text{Divide Cost} = D(n)$$

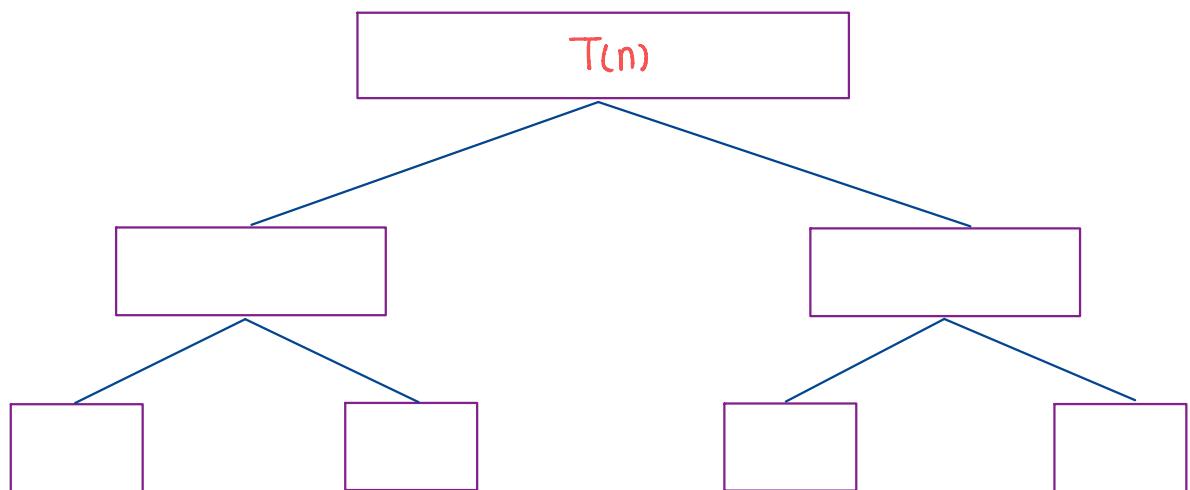
$D(1)$ (half)

$$\text{Conquer Cost} = C(n) \quad \{ \text{Merging cost} \}$$

$\Theta(n)$

$$\text{Calculation Cost} = f(n) \quad \{ \text{fixed cost} \}$$

$$T(n) = D(n) + C(n) + f(n)$$



Recursion: Solving a problem with same function but different dataset.

Example : Binary Search.

* Sorting two sorted arrays take n iterations.

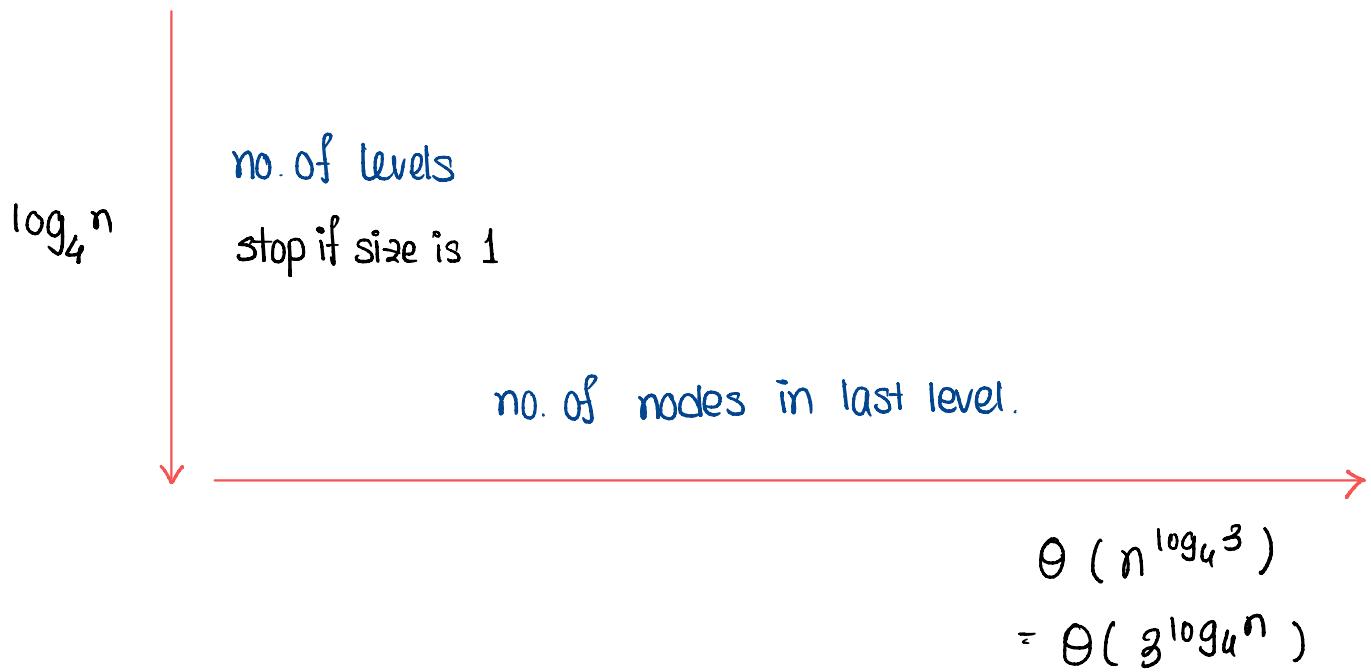
$$T(n) = 2T(\frac{n}{2}) + \Theta(n) + \Theta(1)$$

$$\begin{array}{c}
 D \quad C \quad f \\
 \underbrace{\qquad\qquad\qquad}_{f(n)}
 \end{array}$$

$$T(n) = 2T(n/2) + f(n)$$

Master's Method :

$$\# T(n) = 3 T\left(\frac{n}{4}\right) + n^2$$



$\log_{(\text{division})} n$ Upper bound $O(n^2)$

div ↑ depth ↓

No. of problems in last level factor i (3^i)

"See things you didn't see"

$$T(n) = a T(\frac{n}{3}) + b n^2$$

$$T(n) = T(n/3) + T(\frac{2n}{3}) + \Theta(n)$$

$\frac{2}{3}$ longer than $\frac{1}{3}$

depth using $b = \frac{3}{2}$

$$\log_{\frac{3}{2}} b \quad O(n \log n)$$

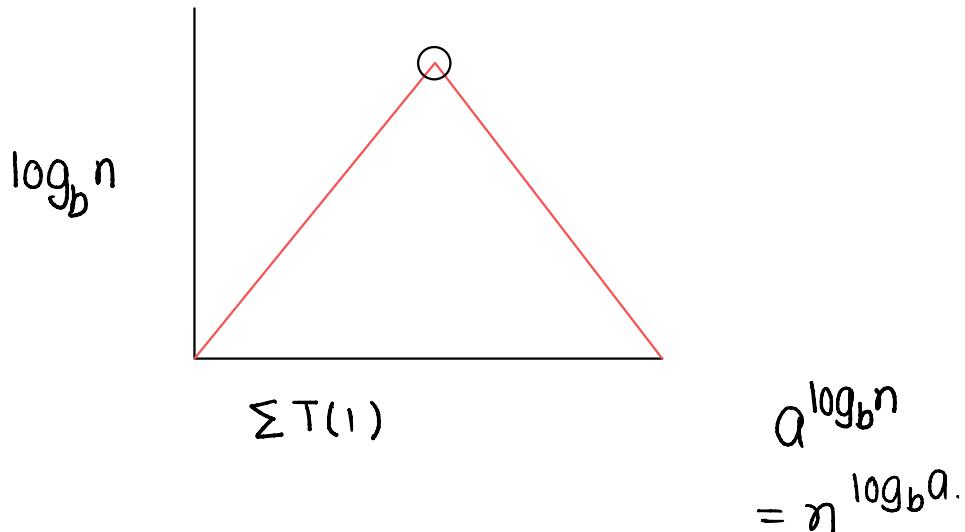
Merge sort

$$\log_2 n \quad b = 2$$

$$\begin{aligned} \text{Last depth} \quad & 2^i \\ & = 2^{\log_2 n} \\ & = n \end{aligned}$$

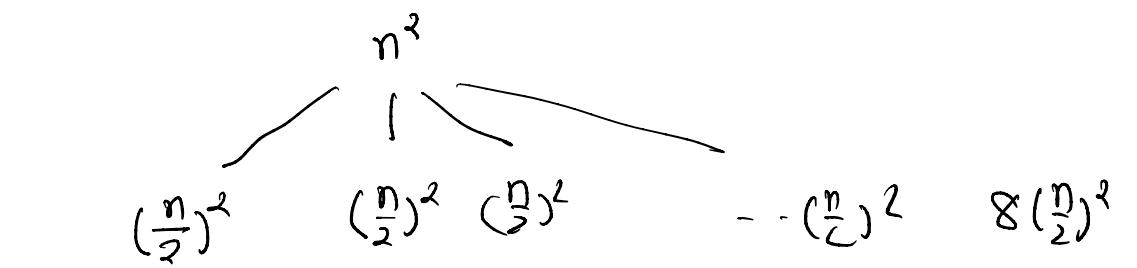
Every Recursion can be represented by

$$T(n) = a \cdot T(n/2) + f(n)$$



* Bottom level cost \gg Top level cost

$$T(n) = 8T(n/2) + n^2$$



$\therefore n^2 + 2n^2 + 4n^2 + 16n^2 + \dots$ last level cost will dominate
 (increasing)

$$① f(n) = O(n^{\log_b a - \epsilon})$$

↑
cost of top level

cost of bottom level
 Subtracting ϵ is still bigger
 polynomially bigger.

Bottom level determines cost

$$② f(n) = \Theta(n^{\log_b a}) \quad 3^{rd} \text{ clause of masters method}$$

$$T(n) = \Theta(f(n) \cdot \log_2 n)$$

$$③ f(n) = \Omega(n^{\log_b a + \epsilon})$$

$$T(n) = \Theta(f(n))$$

- * Cost determined by top
- * Cost has to monotonically decrease.

$$af\left(\frac{n}{b}\right) < cf(n)$$

↑ Top cost

cost of the
layer immediate
below top. (2nd)

* decreasing cost of
level

Assignment : Sheet. 15 Marks

Explaining these.

29/01/24
Monday

Divide & Conquer

Binary Search

"Any multiplication can't be reduced"

$$\begin{array}{r} \underline{\begin{array}{cccc} 1 & 2 & 3 & 4 \\ 5 & 6 & 7 & 8 \end{array}} x \end{array} \quad n^2 \text{ multiplication} \quad (nm)$$

4 X 4 Multiplications

- Claimed by Russian Mathematician.
 - Proved wrong by Japanese Student Karabatsu just after 15 days.

$a_L a_R$	A	n digits
$b_L b_R$	B	m digits

$$10^n a_L + a_R$$

b, be

$$a_R b_R + \underline{a_L b_R + a_R b_L} + a_L b_L$$

still not reduced.
same property

$$a_L b_L + a_R b_R + \frac{(a_L + a_R)}{P} \left(\frac{b_L + b_R}{Q} \right) - a_L b_L - a_R b_R$$

sum,

$$a_L b_L + a_R b_R + P \emptyset - a_L b_L - a_R b_R$$

We need 3
Multiplications

$$T(n) = 3 T(\frac{n}{2}) + \Theta(n)$$

↑
Addition

Half size, Three multiplication.

$$O(n^{\log_2 3}) = O(n^{1.58})$$

better than $O(n^2)$

Strassen's Algorithm

7 Eqⁿ

} Self Study

$$T(n) = 7 T(\frac{n}{2}) + n^2$$

Karabatsu → Overhead of shift (10^n), addition

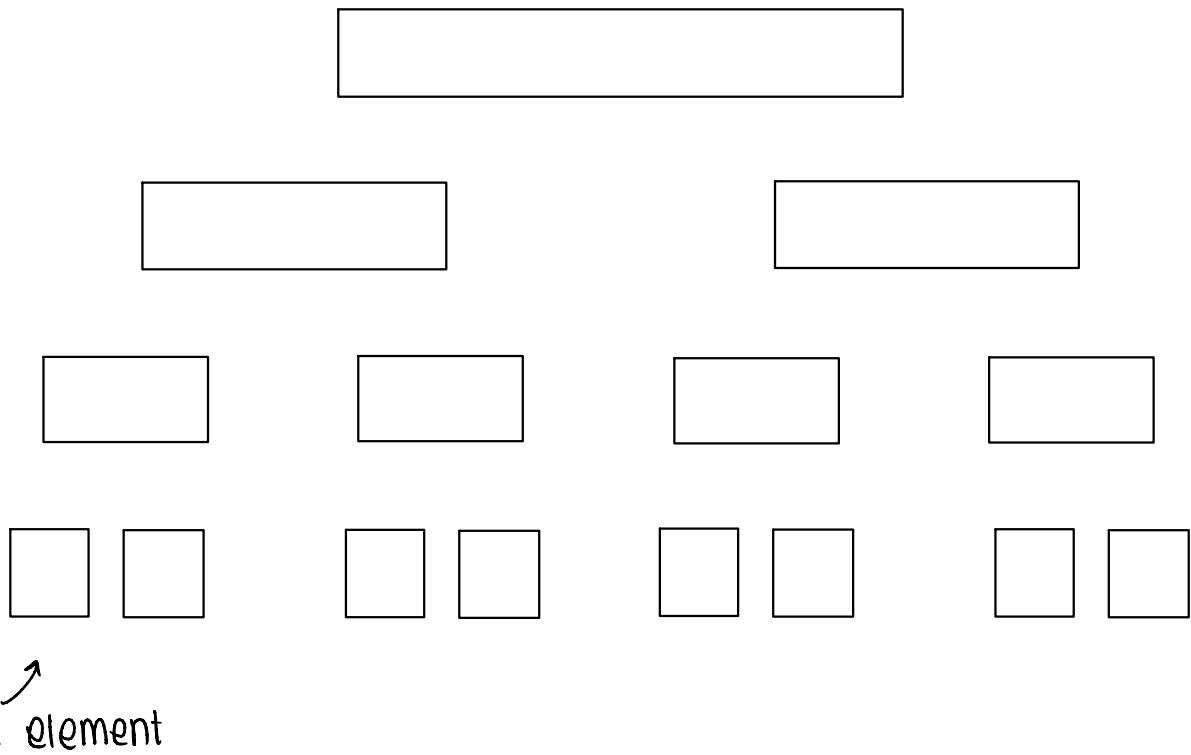
Not ideal for multiplication of fewer digits
 ↳ Slower in terms of speed $\approx O(n^3)$

Digits need to be multiplication of 2 / Power of 2.
 Zero padding required.

Just theoretical approach → Introduction of divide & conquer

"Karabatsu"

Merge Sort



Sorting task not reduced. (Again sort 2,4,8,16 elements)

Save time → this time sub-arrays are sorted.

Merge two sorted arrays - $\Theta(n)$

Merge (A,B) - Proof of exam.

Two markers, compare and add lower.

$i=0, j=0, k=0$

if $A[i] < B[j]$,

$Arr[k] = A[i]$

$k++, i++$

else $Arr[k] = B[j]$

$k++, j++$

Compose a single element.

Copy remaining

"There's no magic"

- K-H on basics of an optical mouse.

Quick Sort

Partition and calling

Only division, no merging / conquer

Quicksort (A, p, r)

p - start index

if $p < r$

q - last index

$q = \text{Partition}(A, p, r)$

Quicksort ($A, p, q-1$)

} q dropped.

Quicksort ($A, q+1, r$)

↳ That's why merging is not necessary

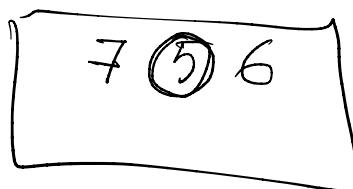
q is in the right position.

pivot → with whom I compare everybody

1 7 5 6 ③
pivot



③



□ 5 □ 7, 6

□ 6 □ 7

No merging

Division is not cheap.

Compare with pivot.

$$T(n) = T(q-1) + T(n-q) + D(n) + C(n)$$

$q-1+n-q = n-1$

Divide Cost Conquer Cost
= Position Cost O (None)

Quicksort

$$T(n) = T(q-1) + T(n-q) + \Theta(n)$$

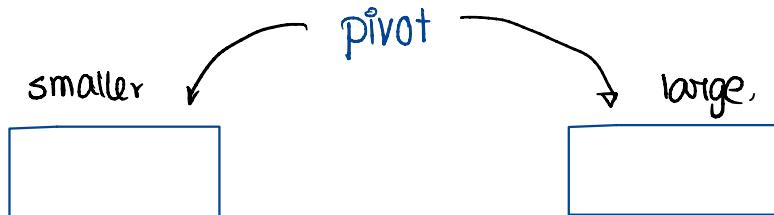
Clustering → Optimized divide and conquer
Expectation Maximization

2 divide & conquer in your research domain
& Dynamic Programming

2 Algo in area of research. or Dynamic Programming
Recent / Most used Tools.

Assignment : Due 6th week.

Max sub-array → DNC or greedy $\xrightarrow{\text{better}}$ $(\sin \text{ variation})$
 Sum of max sub.array



Worst case already sorted. $O(n^2)$ \approx Insertion

Best case , middle partition $O(n \log n)$ \approx Merge

Average case, 1 vs all $O(n \log n)$

$$\text{Avg Case : } T(n) = T\left(\frac{n}{10}\right) + T\left(\frac{9n}{10}\right) + \Theta(n)$$

$\xrightarrow{\text{finish quickly}}$ \uparrow longer tree.

$$= T\left(\frac{n}{10}\right) + T\left(\frac{n}{10}\right) + \Theta(n)$$

$$\therefore \text{Max level} = \log_{\frac{1}{2}} n$$

$$\therefore O(n \log n)$$

Best and Worst case doesn't happen regularly.

Practically quick-sort is very 'stable'.

Insertion sort - Small data

Quicksort - $(n \log n)$ for any size of data.

Master's Theorem

$$T(n) = aT\left(\frac{n}{b}\right) + f(n)$$

||

$$D(n) + C(n)$$

No. of nodes in last level $a^{\log_b n} = n^{\log_b a}$.

$$\text{Total} = \Theta(n^{\log_b a}) + \sum_{j=0}^{\log_b n - 1} a^j f\left(\frac{n}{b^j}\right)$$

1. Bottom level cost > Top Level Cost

$$f(n) = O\left(\frac{n^{\log_b a - \epsilon}}{\text{bottom level cost}}\right) \quad g(n) = O(n^{\log_b a})$$

$\xrightarrow{\text{upper bound}}$

bottom level cost \downarrow polynomially big

2. Equally distributed.

$$f(n) = \Theta(n^{\log_b a}) \quad g(n) = \Theta(n^{\log_b a}, \log n)$$

3. Bottom level cost < Top level Cost (monotonically decreasing from top)

$$af\left(\frac{n}{b}\right) \leq c f(n) \quad g(n) = \Theta(c f(n))$$

$$c < 1, \Sigma \neq 1$$

3 \rightarrow Top dominated.

Proof:

Case 1

$$\begin{aligned} g(n) &= O\left(\sum_{j=0}^{\log_b a - 1} a^j \left(\frac{n}{b^j}\right)^{\log_b a - \varepsilon}\right) \\ &= O\left(n^{\log_b a - \varepsilon} \cdot \sum_{j=0}^{\log_b a - 1} \left(\frac{a}{b^{\log_b a - \varepsilon}}\right)^j\right) \\ &= O\left(n^{\log_b a - \varepsilon} \cdot \sum_{j=0}^{\log_b a - 1} \left(\frac{a}{a \cdot b^{-\varepsilon}}\right)^j\right) \\ &= O\left(\log_b a^{-\varepsilon} \cdot \sum_{j=0}^{\log_b a - 1} b^{\varepsilon j}\right) \\ &= O\left[n^{\log_b a - \varepsilon} \cdot \frac{(b^\varepsilon)^{\log_b a} - 1}{b^\varepsilon - 1}\right] \\ &= O\left[n^{\log_b a - \varepsilon} \cdot \frac{n^\varepsilon - 1}{b^\varepsilon - 1}\right] \quad \text{keep, other's constant} \\ &= O(n^{\log_b a}) \end{aligned}$$

\nwarrow

$$T(n) = \Theta(n^{\log_b a}) + g(n)$$

Case II

$$\begin{aligned}g(n) &= O\left(\sum_{j=0}^{\log_b - 1} a^j \left(\frac{n}{b^j}\right)^{\log_b a}\right) \\&= O\left(n^{\log_b a} \cdot \sum_{j=0}^{\log_b a - 1} \left(\frac{a}{b^{\log_b a}}\right)^j\right) \\&= O\left(n^{\log_b a} \cdot \sum_{j=0}^{\log_b a - 1} \left(\frac{a}{a}\right)^j\right) \\&= O\left(n^{\log_b a} \cdot \sum_{j=0}^{\log_b a - 1} 1\right) \\&= O(n^{\log_b a} \cdot \log_b n)\end{aligned}$$

$$\begin{aligned}g(n) &= \Theta(n^{\log_b a} \cdot \log_b n) \\&= \Theta(n^{\log_b a} \cdot \log_b n)\end{aligned}$$

Case III

$$a f\left(\frac{n}{b}\right) < c f(n) \longrightarrow \frac{a}{c} f\left(\frac{n}{b^2}\right) < f\left(\frac{n}{b}\right)$$

$$\Rightarrow \frac{a}{c} f\left(\frac{n}{b}\right) < f(n) \quad \text{replacing } n \text{ by } \frac{n}{b}$$

$$\Rightarrow \frac{a^2}{c^2} f\left(\frac{n}{b^2}\right) < f(n)$$

$$\vdots \qquad \vdots$$

$$\left(\frac{a}{c}\right)^j f\left(\frac{n}{b^j}\right) < f(n)$$

$$\Rightarrow a^j f\left(\frac{n}{b^j}\right) < c^j f(n)$$

$$\begin{aligned} g(n) &= \sum_{j=0}^{\log_b n - 1} a^j f\left(\frac{n}{b^j}\right) \\ &\leq \sum_{j=0}^{\log_b n - 1} c^j f(n) + O(1) \\ &\leq f(n) \sum_{j=0}^{\log_b n - 1} c^j + O(1) \\ &= f(n) \cdot \frac{1}{1 - c} + O(1) \\ &= O(f(n)) \end{aligned}$$

Dynamic Programming (DP)

- sub-problems
- reuse of sub-problems. (not done in D&C)
- Restricted vs AI (more options, explore, path finding)
- optimization problem → Gives a single solution min cost, max value.
- Single objective (single goal / factor / constraint)
 - (Time / Path / Cost / Quality but not together)
 - (Can't get best of all features if they aren't aligned) → Minimum things

Fibonacci Number

$$F(n) = F(n-1) + F(n-2)$$

$$F(n) = \underline{F(n-1)} + F(n-2)$$

$$\text{Subproblem} = F(n-2) + F(n-3) + F(n-3) + F(n-4)$$

Not optimization → Divide and Conquer.

Not entirely DP → Reuse subproblem but doesn't optimize.

Characterize the problem

i. Divide and Conquer

ii. Recursive

iii. Reuse subproblem

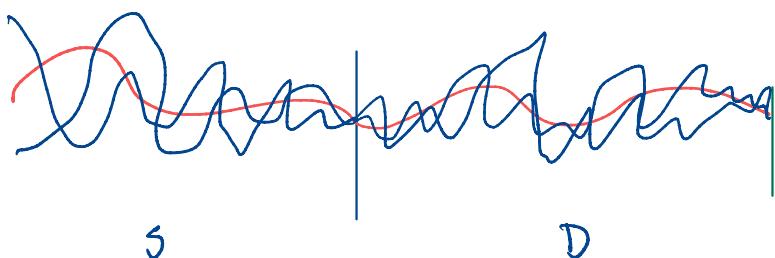
* (Optimal substructure)

* Tries all combination (BF) picks best

* DP doesn't remember all combinations/paths, gives best single output.

Airlines Examples

$$(S)_{\text{best}} + (D)_{\text{best}}$$



$$P_n = \max_{1 \leq i \leq n} (P_i + P_{n-i})$$



Optimal substructure Eqⁿ

$$T(n) = 1 + \sum_{j=0}^{n-1} T(j) \quad O(2^n)$$

Kinda bruteforce

Memoization

Recursion + DP bad

Bottom up \rightarrow DP , no recursion required.

Combination problem minimized, Overall best \leftarrow best of all combination

DP \rightarrow Memory vs Time

Possible within the substructure.

Dynamic Programming

Combining subproblem

Optimal Substructure

* Longest Simple path

After combining -

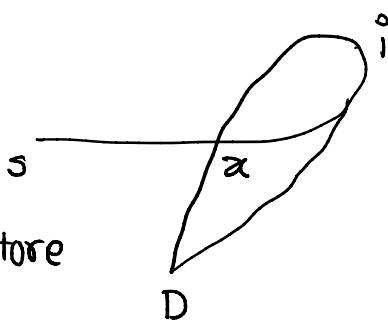
longest but not simple

All combinations not possible to store

* loops

Optimal substructure fails

DP is hard.



Matrix Chain Multiplication / Parenthesis

Sequence important

Based on dimension the number of dimension is determined.

A_0

$P_0 \times P_1$

A_1

$P_1 \times P_2$

$$C = P_0 \times P_1 \times P_2$$

Combinatorial problem

$$A_1 A_2 A_3 - (A_1 A_2) A_3, A_1 (A_2 A_3)$$

$$A_1 A_2 A_3 A_4 - A_1 (A_2 A_3 A_4), (A_1 A_2) (A_3 A_4), (A_1 A_2 A_3) A_4$$

$$\underbrace{\hspace{1cm} \quad \quad \quad \quad}_{\text{2}} \quad \quad \quad \underbrace{\hspace{1cm} \quad \quad \quad}_{\text{1}} \quad \quad \quad \underbrace{\hspace{1cm} \quad \quad \quad}_{\text{2}}$$

5

"Combination is hard to understand"

$$A_1 A_2 A_3 A_4 A_5 - A_1 (A_2 A_3 A_4 A_5), (A_1 A_2) (A_3 A_4 A_5), (A_1 A_2 A_3) (A_4 A_5),$$

$$\underbrace{\hspace{1cm} \quad \quad \quad}_{\text{5}} \quad \quad \quad \underbrace{\hspace{1cm} \quad \quad \quad}_{\text{2}} \quad \quad \quad \underbrace{\hspace{1cm} \quad \quad \quad}_{\text{2}}$$

$$(A_1 A_2 A_3 A_4 A_5) A_5 = 14$$

Exponential problem - grows quickly

Catalan Number ✓

Catalan Number

All possible combination.

$$\sum_{k=1}^{n-1} P(k) P(n-k) \quad n \geq 2$$

Grows exponentially - not easily tractable.

Cut all position k , multiplications needed - $P_{i-1} P_k P_j$

Subproblems already calculated.

We don't do combination.

Complexity of problem.

Change problem - It gets hard.

DP v Combination x Same time

Cost Matrix & Solution Matrix

$$A_1 (A_2 A_3) = 0 + 2625 + 30 \times 35 \times 5$$

$$(A_1 A_2) A_3 = 15,750 + 0 + 30 \times 15 \times 5$$

Algo isn't a theory, its a technique

LCS Edit Distance ✓

BLAST ✗

Interpretation of Table

DTW from Internet (Dynamic Time Warping)

0/1 Knapsack Move & Match

GPU Computer Doesn't help DP

Quasi-Polynomial $O(\text{item no} \times \text{sack size})$
 $\times 2^n$

0/1 Knapsack - hard problem

but weak, easy to solve.

Knapsack problem - hard (0/1)

Fractional Knapsack problem is easy

All or nothing

Taking or not taking that element.

Within capacity

capacity \ component	1	2	3	4	5
i ₁					
i ₂					
i ₃					
i ₄					
i ₅					

Depend on data size, not input size / value.

Good algo depend on input size

0/1 Knapsack - Input capacity

DP - Doesn't depend on input size.

Sequential process, can't be parallel.

Longest Common Subsequence (LCS)

First algo in bio-informatics, then BLAST.

EDITH Distance Algo

Divide & Conquer Problem

Match from x or y - $\max(c[i,j-1], c[i-1,j])$

Proof - if you want

Computer representation - 2 tables (data, direction)

Sequence consecutive match

Table is important, follow sequence

Signal matching - Warping & Matching

Sequential matching

$$dtw(i,j) = cost(i,j)$$

medium - an intuitive approach to DTW

Diagonally \rightarrow Progressive Match (most diagonal match)

Horizontal/Vertical \rightarrow Single Match - element (not good)

Will not always produce good match.

$O(mn)$ \rightarrow expensive

DTW allows matching betⁿ any dimension (big, small)

Use fast DTW - Saves time, but quality not ensured

Longer sequence zipped down.

Complexity $O(n)$

Interpolate to match - Bad result

Constant DTW - Skip matching beyond diagonal,
No interpolation for match
Progressive sequence
Matching skipped - Faster
Good.

LSTM >> DTW

CTC : ML alternative of HMM
tweaking needed, not good

FFT \rightarrow Divide & Conquer , skip for now

DP

Rod

Matrix

LCS Edith

DTW

0/1 Knapsack

Algo depend on sack capacity, can't skip - bad
not input size of sack.

Quasi-Polynomial - Hard but close to sol'n

Quicksort

Complete analysis

Randomized Quicksort - Randomized pivot

Instead of last element, switch last with another element, then new last element as pivot

Randomized pivot - 7.1

Max - best

Assumption

Indicator random variable - spike

Uniform probability of pivot.

left & Right side is not overlapped.

Quicksort - Reasonably well, Stable

$O(n \log n)$

Partition

Ch-9

Median order statistics (9.1)

Median in linear time.

Exaggerated assumption

9.1 ~ 9.2

CH - 2

7

DNC , Quicksort - 6, 7

2

CH 9

9

15

Text, Diagram

Explain