Lecture 2: Divide and Conquer & Recurrences

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Overview

- Divide-and-Conquer Paradigm
- Solving Recurrences
- Optional: Maximum Subarray Sum
- Acknowledgements

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Examples:

- Sorting: merge sort
- 2 Searching: binary search
- Matrix Multiplication
- Olynomial Multiplication
- many more, (see [CLRS 2009])

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- Conquer: recursively solve instances I₁,..., I_a, obtaining solutions S₁,..., S_a
- **Solution:** Solutions $S_1, \ldots, S_a \mapsto$ solution S to instance I
- "Recursion for running time:"

$$T(I) = T(I_1) + \cdots + T(I_a) + \text{ time to combine}$$

Example: Merge Sort

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sort(A[\alpha, \beta]):

1 If \beta - \alpha < 10, then trivially sort array and return.

2 B = \text{sort}(A[\alpha, \lfloor (\alpha + \beta)/2 \rfloor]), C = \text{sort}(A[\lfloor (\alpha + \beta)/2 \rfloor + 1, \beta]))

3 return merge(B, C)
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• Merging algorithm: (input arrays sorted in increasing order)

merge(B, C):

- Let D = [] be an empty array, and let i, j be two pointers, indexing position on arrays B, C, initialized at 1.
- 2 Until we are done scanning both B, C:
 - If $B[i] \leq C[j]$, then D.append(B[i]) and $i \leftarrow i + 1$
 - Else, D.append(C[j]) and $j \leftarrow j+1$

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- Can also "guess and check" the answer

 $T(n) = cn \log n$ (guess) $T(n) = 2 \cdot \left(c \cdot \frac{n}{2} \log(n/2)\right) + cn$ $= cn(\log n - 1) + cn = cn \log n$ • Divide-and-Conquer Paradigm

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- Mergesort recurrence was easy to analyze.

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Theorem (Master Theorem (simple))

Given recurrence

$$T(n) = aT(n/b) + \Theta(n^c)$$

with T(1), $a \ge 1, b > 1, c \ge 0$ (constants), then

$$T(n) = \begin{cases} \Theta(n^c), & \text{if } c > \log_b a \\ \Theta(n^c \log n), & \text{if } c = \log_b a \\ \Theta(n^{\log_b a}), & \text{if } c < \log_b a \end{cases}$$

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 If c > log_b a, then top level dominates decreasing geometric sequence, ratio a/b^c < 1
 If c = log_b a, then every layer same, and θ(log n) layers
 If c < log_b a, then bottom level dominates *increasing* geometric sequence, ratio a/b^c > 1

General Master Theorem

Theorem (Master Theorem)

Given recurrence

$$T(n) = aT(n/b) + f(n)$$

with $T(1), f(1), a \ge 1, b > 1$ (constants), then

$$T(n) = \begin{cases} \Theta(n^{\log_b a}), & \text{if } f(n) = O(n^{\log_b a - \varepsilon}), \text{ for some } \varepsilon > 0\\ \Theta(n^{\log_b a} \log n), & \text{if } f(n) = \Theta(n^{\log_b a})\\ \Theta(f(n)), & \text{if } f(n) = \Omega(n^{\log_b a + \varepsilon}), \text{ for some } \varepsilon > 0\\ & \text{and if } af(n/b) \le cf(n) \text{ for some } 0 < c < 1 \end{cases}$$

• Same proof

Imbalanced trees:

•
$$T(n) = T(n/3) + T(2n/3) + c \cdot n$$
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at level *i*, subproblem of size n^2

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• Exponential time recurrences:

•
$$T(n) = n \cdot T(n-1) + 1$$

 $T(n) = O(n!)$

• Fibonacci: T(n) = T(n-1) + T(n-2)

$$T(n) = O(n!)$$
$$T(n) = O(\phi^n)$$

$$\phi = \frac{1 + \sqrt{5}}{2}$$

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Maximum Subarray Sum

- Input: array $A = (a_1, \ldots, a_n)$ where each a_i is an integer
- **Output:** indices $1 \le i \le j \le n$ and s such that

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, and $s = \max_{\alpha \leq \beta} \sum_{k=\alpha}^{\beta} a_k$

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- for more details, see [CLRS 2009, Chapter 4.1]

Acknowledgement

Based on Prof Lau's lecture

https://cs.uwaterloo.ca/~lapchi/cs341/notes/L02.pdf

References I



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