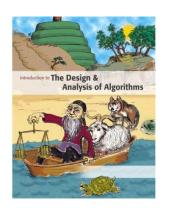




Introduction to

Algorithm Design and Analysis

[3] Recursion



Yu Huang

http://cs.nju.edu.cn/yuhuang Institute of Computer Software Nanjing University



In the Last Class ...

- Asymptotic growth rate
 - \circ O, Ω , Θ
 - ο ο, ω
- Brute force algorithms
 - o By iteration
 - o By recursion



Recursion

- Recursion in algorithm design
 - o The divide and conquer strategy
 - o Proving the correctness of recursive procedures
- Solving recurrence equations
 - o Some elementary techniques
 - o Master theorem



Recursion in Algorithm Design

- Computing n! with Fac(n)
 - o if n=1 then return 1 else return Fac(n-1)*n

M(1)=0 and M(n)=M(n-1)+1 for n>0 (critical operation: multiplication)

Hanoi Tower

o if n=1 then move d(1) to peg3 else Hanoi(n-1, peg1, peg2); move d(n) to peg3; Hanoi(n-1, peg2, peg3)

M(1)=1 and M(n)=2M(n-1)+1 for n>1 (critical operation: move)



Recursion in Algorithm Design

Counting the Number of Bits

- o Input: a positive decimal integer *n*
- o Output: the number of binary digits in *n*'s binary representation

Int BitCounting (int n)

- 1. If(n==1) return 1;
- 2. Else
- 3. return BitCounting(n div 2) +1;

$$T(n) = \begin{cases} 0 & n = 1 \\ T(\lfloor n/2 \rfloor) + 1 & n > 1 \end{cases}$$

Divide and Conquer

Divide

o Divide the "big" problem to smaller ones

Conquer

o Solve the "small" problems by recursion

Combine

o Combine results of small problems, and solve the original problem



Divide and Conquer

```
The general pattern
solve(I)
   n=size(I);
   if (n≤smallSize)
       solution=directlySolve(I);
   else
       divide I into I_1, \dots I_k;
       for each i \in \{1, ..., k\}
          S_i = \mathbf{solve}(I_i);
       solution=combine(S_1, \ldots, S_L);
   return solution
```

T(n)=B(n) for $n \le small Size$

$$T(n)=D(n)+\sum_{i=1}^{k}T(size(I_i))+C(n)$$

for n>smallSize

Divide Conquer

The BF recursion

- o Problem size: often decreases linearly
 - "n, n-1, n-2, ..."

The D&C recursion

- o Problem size: often decrease exponentially
 - "n, n/2, n/4, n/8, ..."



Examples

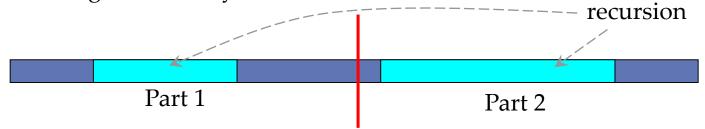
Max sum subsequence

$$T(n) = 2T\left(\frac{n}{2}\right) + n$$

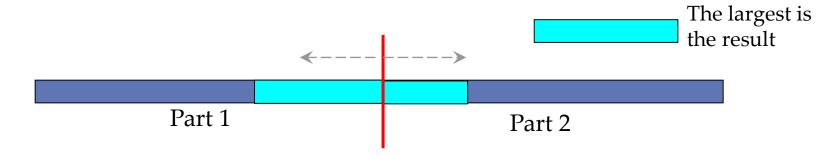
Part 1

Part 2

the sub with largest sum may be in:



or:



Examples

- Maxima
- Frequent element
- Multiplication
 - o Integer
 - o Matrix
- Nearest point pair

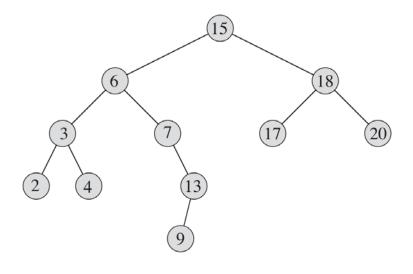


Examples

Arrays

3 5 7 8 9 12 15

• Trees



Workhorse

"Hard division, easy combination"

"Easy division, hard combination"

Usually, the "real work" is in one part.



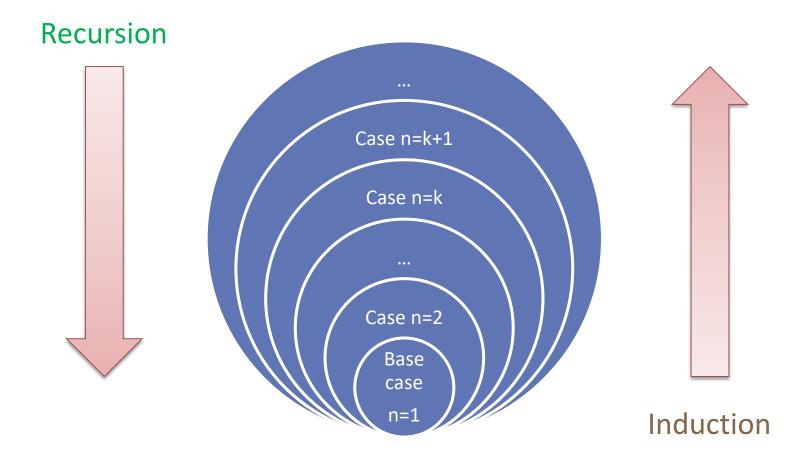
More Applications of D&C

The simplest, most important tool for reducing complexity is the divide-and-conquer technique: analyze or design the system as a collection of interacting subsystems, called *modules*. The power of this technique lies primarily in being able to consider interactions among the components within a module without simultaneously thinking about the components that are inside other modules.

J. Saltzer et al., Principles of Computer System Design, Chap. 1.3.1.



Correctness of Recursion





Analysis of Recursion

Solving recurrence equations

- E.g., Bit counting
 - o Critical operation: add
 - o The recurrence relation

$$T(n) = \begin{cases} 0 & n = 1 \\ T(\lfloor n/2 \rfloor) + 1 & n > 1 \end{cases}$$



Analysis of Recursion

Backward substitutions

By the recursion equation : $T(n) = T\left(\left\lfloor \frac{n}{2} \right\rfloor\right) + 1$

For simplicity, let $n = 2^k (k \text{ is a nonnegative integer})$, that is, $k = \log n$

$$T(n) = T\left(\frac{n}{2}\right) + 1 = T\left(\frac{n}{4}\right) + 1 + 1 = T\left(\frac{n}{8}\right) + 1 + 1 + 1 = \dots$$

$$T(n) = T\left(\frac{n}{2^k}\right) + \log n = \log n \quad (T(1)=0)$$



Smooth Functions

- f(n)
 - Nonnegative eventually non-decreasing function defined on the set of natural numbers
- f(n) is called smooth
 - \circ If $f(2n) \in \mathcal{O}(f(n))$.

- Examples of smooth functions
 - o $\log n$, n, $n \log n$ and n^{α} ($\alpha \ge 0$)
 - E.g., $2n\log 2n = 2n(\log n + \log 2) \in \Theta(n\log n)$



Even Smoother

- Let f(n) be a smooth function, then for any fixed integer $b \ge 2$, $f(bn) \in \Theta(f(n))$.
 - o That is, there exist positive constants c_b and d_b and a nonnegative integer n_0 such that

$$d_b f(n) \le f(bn) \le c_b f(n)$$
 for $n \ge n_0$.

It is easy to prove that the result holds for $b = 2^k$, for the second inequality:

$$f(2^k n) \le c_2^k f(n)$$
 for $k = 1,2,3...$ and $n \ge n_0$.

For an arbitrary integer $b \ge 2, 2^{k-1} \le b \le 2^k$

Then, $f(bn) \leq f(2^k n) \leq c_2^k f(n)$, we can use c_2^k as c_b .



Smoothness Rule

- If $T(n) \in \mathcal{O}(f(n))$ for values of n that are powers of $b(b \ge 2)$, then $T(n) \in \mathcal{O}(f(n))$.
 - Let T(n) be an eventually non-decreasing function and f(n) be a smooth function.

```
Just proving the big - Oh part:
```

By the hypothsis: $T(b^k) \leq cf(b^k)$ for $b^k \geq n_0$.

By the prior result: $f(bn) \leq c_b f(n)$ for $n \geq n_0$.

Let
$$n_0 \leq b^k \leq n \leq b^{k+1}$$
,

$$T(n) \leq T(b^{k+1}) \leq cf(b^{k+1}) = cf(bb^k) \leq cc_b f(b^k) \leq cc_b f(n)$$



Smoothness Rule

- If $T(n) \in \Theta(f(n))$ for values of n that are **powers of** $b(b \ge 2)$, then $T(n) \in \Theta(f(n))$.
 - \circ Let T(n) be an eventually non-decreasing function and f(n) be a smooth function.

By the recursion equation : $T(n) = T\left(\left|\frac{n}{2}\right|\right) + 1$

For simplicity, let $n = 2^k (k \text{ is a nonnegative integer}),$

that is,
$$k = \log n$$

$$T(n) = T\left(\frac{n}{2}\right) + 1 = T\left(\frac{n}{4}\right) + 1 + 1 = T\left(\frac{n}{8}\right) + 1 + 1 + 1 = \dots$$

$$T(n) = T\left(\frac{n}{2^k}\right) + \log n = \log n \quad (T(1)=0)$$

$$T(n) = T\left(\frac{n}{2^k}\right) + \log n = \log n \quad (T(1)=0)$$



Guess and Prove

- Example: $T(n)=2T(\lfloor n/2 \rfloor) + n$
- Guess
 - $\circ T(n) \in O(n)$?
 - $T(n) \le cn$, to be pro-
 - $\circ T(n) \in O(n^2)$?
 - $T(n) \le cn^2$, to be prove
 - \circ **Or maybe**, $T(n) \in O(n \log n)$
 - $T(n) \le cn \log n$, to be prove
- Prove
 - o by substitution

Try to prove $T(n) \le cn$:

HOLLOW.

However:

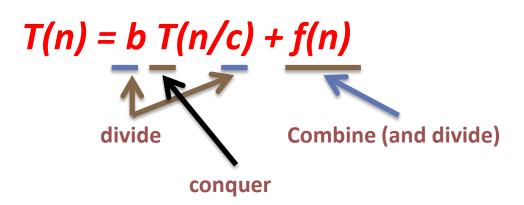
$$T(n) = 2T(\lfloor n/2 \rfloor) + n$$

$$\leq 2(c \lfloor n/2 \rfloor \log (\lfloor n/2 \rfloor)) + n$$

- \leq *cn*log (*n*/2)+*n*
- $= cn \log n cn \log 2 + n$
- $= cn \log n cn + n$
- $\leq cn \log n \text{ for } c \geq 1$

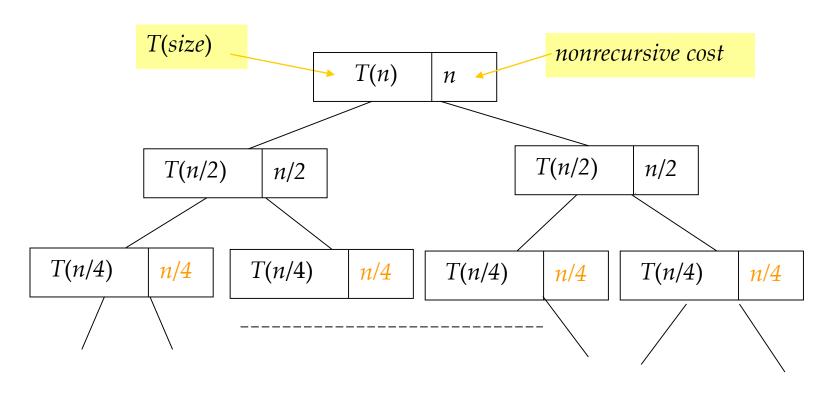
Divide and Conquer Recursions

- Divide and conquer
 - o Divide the "big" problem to smaller ones
 - o Conquer the "small" problems by recursion
 - Combine results of small problems, and solve the original problem
- Divide and conquer recursion





Recursion Tree



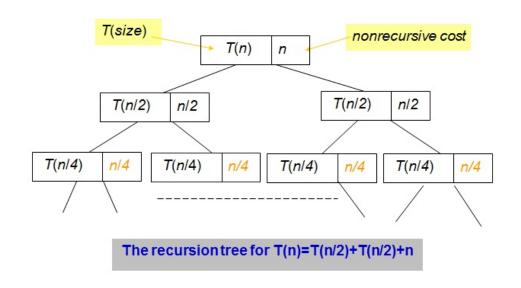
The recursion tree for T(n) = 2T(n/2) + n



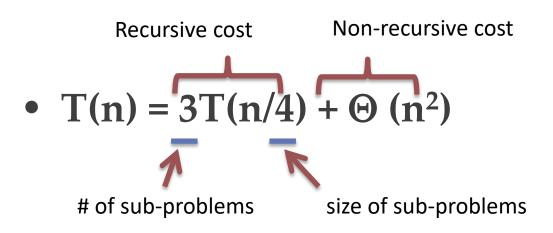
Recursion Tree

Node

- o Non-leaf
 - Non-recursive cost
 - Recursive cost
- o Leaf
 - Base case
- Edge
 - o Recursion

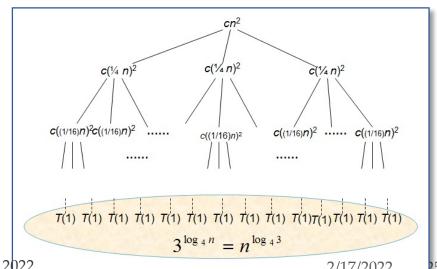


Recursion Tree



Total cost

Sum of row sums



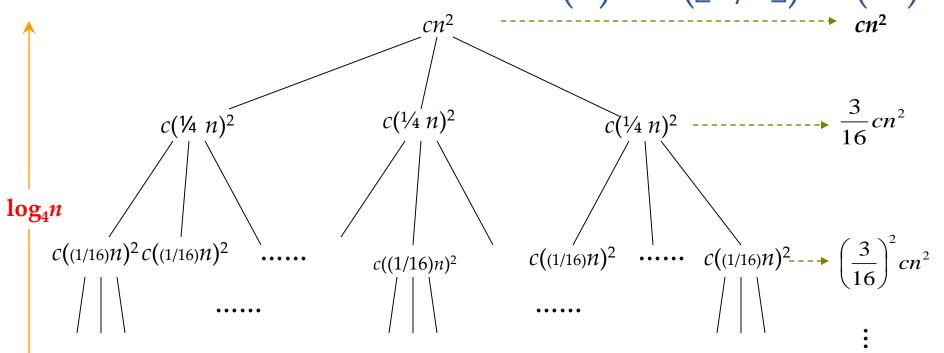


Lectures on Algorithm Design and Analysis (LADA), Spring 2022

2/17/2022

Sum of Row-sums





T(1) T(1)



Note: $3^{\log_4 n} = n^{\log_4 3}$

Total: $O(n^2)$

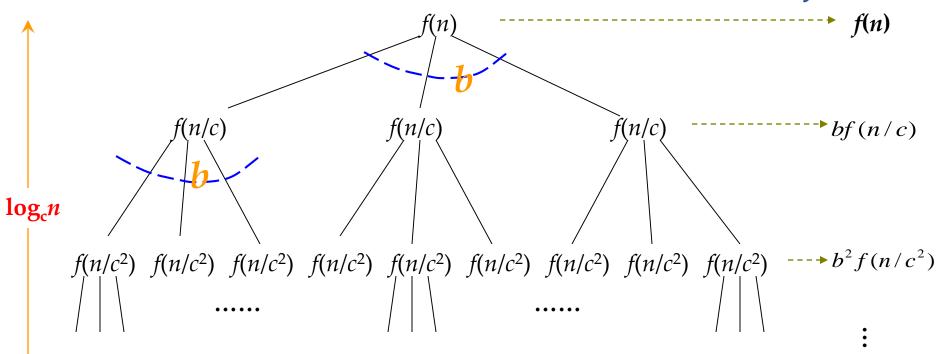
Solving the Divide-and-Conquer Recurrence

- The recursion equation for divide-and-conquer, the general case: T(n)=bT(n/c)+f(n)
- Observations:
 - o Let base-cases occur at depth D(leaf), then $n/c^D=1$, that is $D=\log(n)/\log(c)$
 - o Let the number of leaves of the tree be L, then $L=b^D$, that is $L=b^{(\log(n)/\log(c))}$.
 - o By a little algebra: $L=n^E$, where $E=\log(b)/\log(c)$, called *critical exponent*.



Recursion Tree for

$$T(n)=bT(n/c)+f(n)$$



T(1) ... T(1) T(1) T(1) T(1) T(1)



Note: $b^{\log_c n} = n^{\log_c b}$ Lectures on Algorithm Design and Analysis (LADA), Spring 2022

Total?

Divide-and-Conquer - the Solution

- The solution of divide-and-conquer equation is the non-recursive costs of all nodes in the tree, which is the sum of the row-sums
 - o The recursion tree has depth $D=\log(n)/\log(c)$, so there are about that many row-sums.
- The 0th row-sum
 - \circ is f(n), the nonrecursive cost of the root.
- The *D*th row-sum
 - o is n^E , assuming base cases cost 1, or $\Theta(n^E)$ in any event.



Solution by Row-sums

- [Little Master Theorem] Row-sums decide the solution of the equation for divide-and-conquer:
 - o Increasing geometric series: $T(n) \in \Theta(n^E)$
 - Constant: $T(n) \in \Theta(f(n) \log n)$
 - o Decreasing geometric series: $T(n) \in \Theta(f(n))$

This can be generalized to get a result not using explicitly row-sums.



Master Theorem

• Loosening the restrictions on f(n)

- o Case 1: $f(n) \in O(n^{E-\varepsilon})$, $(\varepsilon>0)$, then: $T(n) \in \Theta(n^E)$
- Case 2: $f(n) \in \Theta(n^E)$, as all node depth contribute about equally:

$$T(n) \in \Theta(f(n)\log(n))$$

o case 3: $f(n) \in \Omega(n^{E+\varepsilon})$, ($\varepsilon > 0$), and if $bf(n/c) \le \theta f(n)$ for some constant $\theta < 1$ and all sufficiently large n, then:

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

The positive ε is critical, resulting gaps between cases as well



Using Master Theorem

- Example 1: $T(n) = 9T(\frac{n}{3}) + n$ $b = 9, c = 3, E = 2, f(n) = n = O(n^{E-1})$ Case 1 applies: $T(n) = \Theta(n^2)$
- Example 2: $T(n) = T(\frac{2}{3}n) + 1$ $b = 1, c = \frac{3}{2}, E = 0, f(n) = 1 = \Theta(n^E)$ Case 2 applies: $T(n) = \Theta(\log n)$
- Example 3: $T(n) = 3T(\frac{n}{4}) + n \log n$ $b = 3, c = 4, E = \log_4 3, f(n) = \Omega(n^{E+\epsilon})$ $bf(\frac{n}{4}) = \frac{3}{4}n \log n - \frac{3}{2}n$ Case 3 applies: $T(n) = \Theta(n \log n)$



Using Master Theorem

- T(n) = 2T(n/2) + nlogn
 - o Does Case 3 apply? Why?
- $T(n)=\sqrt{n} T(\sqrt{n}) + n$

- The gap between the 3 cases
 - o Often, none of the 3 cases apply
 - o Your task: design more non-solvable recursions



Thank you!

Q & A

Yu Huang

yuhuang@nju.edu.cn http://cs.nju.edu.cn/yuhuang

