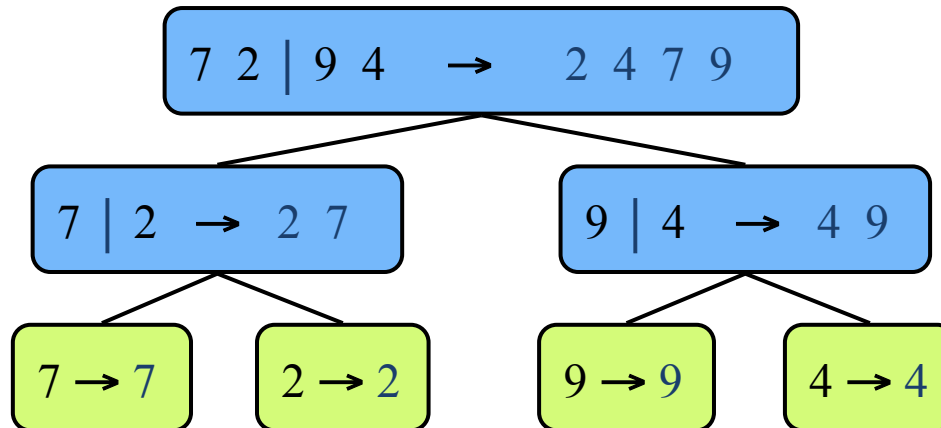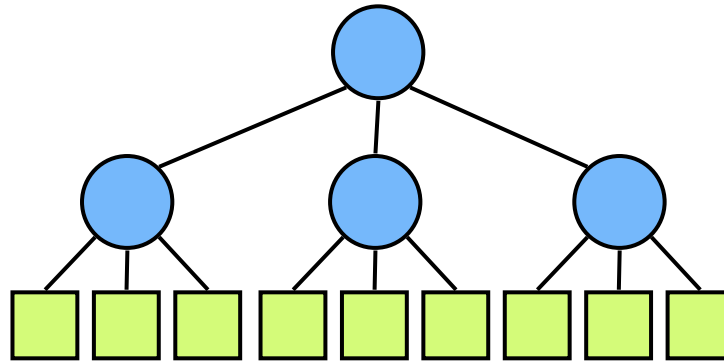# Divide and Conquer

Outline / Reading

- Divide-and-conquer paradigm (5.2)
- Review Merge-sort (4.1.1)
- Recurrence Equations (5.2.1)
  - Recursion trees
  - Induction
    - Iterative substitution
    - Guess-and-test
  - The master method
- Integer Multiplication (5.2.2)

Divide-and-Conquer

- Divide-and conquer is a general algorithm design paradigm:
  - Divide: divide the input data in two or more disjoint subsets $S_1, S_2, \dots$
  - Recur: solve the subproblems recursively
  - Conquer: combine the solutions for $S_1, S_2, \dots,$ into a solution for S
- The base case for the recursion are subproblems of constant size
- Analysis can be done using recurrence equations

Merge Sort Review

Merge-sort on an input sequence S with n elements consists of three steps:

- Divide: partition S into two sequences S_1 and S_2 of about $n/2$ elements each

- Recur: recursively sort S_1 and S_2

- Conquer: merge S_1 and S_2 into a unique sorted sequence

Algorithm *mergeSort(S, C)*
    Input sequence S with n elements, comparator C
    Output sequence S sorted according to C
    if *S.size*() > 1
        $(S_1, S_2) \leftarrow$ *partition(S, n/2)*
        mergeSort(S_1, C)
        mergeSort(S_2, C)
        $S \leftarrow$ *merge(S_1, S_2)*

Recurrence Equation Analysis

- The conquer step of merge-sort consists of merging two sorted sequences, each with n/2 elements and implemented by means of a doubly linked list, takes at most bn steps, for some constant b.

- Likewise, the basis case ($n < 2$) will take at most b steps.

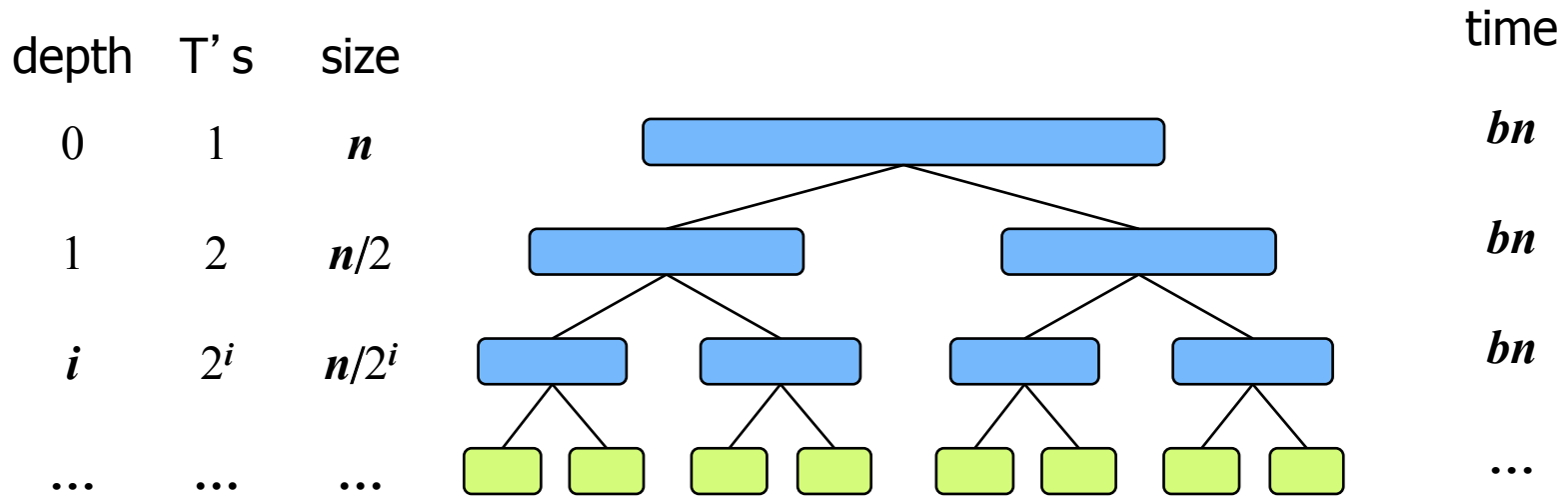- Therefore, if we let $T(n)$ denote the running time of merge-sort:

$$T(n) = \begin{cases} b & \text{if } n < 2 \\ 2T(n/2) + bn & \text{if } n \geq 2 \end{cases}$$

- We can analyze the running time of merge-sort by finding a closed form solution to the above equation.
  - That is, a solution that has $T(n)$ only on the left-hand side.

Recursion Tree

Draw the recursion tree for the recurrence relation and look for a pattern:

$$T(n) = \begin{cases} b & \text{if } n < 2 \\ 2T(n/2) + bn & \text{if } n \geq 2 \end{cases}$$

depth	T's	size		time
0	1	n		bn
1	2	$n/2$		bn
i	2^i	$n/2^i$		bn
…	…	…		…

Total time = bn + $bn \log n$

(last level plus all previous levels)

Iterative Substitution

In the iterative substitution, or "plug-and-chug," technique, we iteratively apply the recurrence equation to itself and see if we can find a pattern, then prove it is true by induction:

$$T(n) = 2T(n/2) + bn$$
$$= 2(2T(n/2^2)) + b(n/2)) + bn$$
$$= 2^2 T(n/2^2) + 2bn$$
$$= 2^3 T(n/2^3) + 3bn$$
$$= 2^4 T(n/2^4) + 4bn$$
$$= ...$$
$$= 2^i T(n/2^i) + ibn$$

- Note that the base case, $T(n) = b$, case occurs when $2^i = n$. That is, $i = \log n$. So we have: $T(n) = bn + bn \log n$
- Once we prove this by induction, then $T(n)$ is $O(n \log n)$.

Guess-and-Test Method

In the guess-and-test method, we guess a closed form solution and then try to prove it is true by induction:

$$T(n) = \begin{cases} b & \text{if } n < 2 \\ 2T(n/2) + bn\log n & \text{if } n \geq 2 \end{cases}$$

- Guess #1: $T(n) \leq cn\log n$.

$$T(n) = 2T(n/2) + bn\log n$$
$$\leq 2(c(n/2)\log(n/2)) + bn\log n$$
$$= cn(\log n - \log 2) + bn\log n$$
$$= cn\log n - cn + bn\log n$$

- Wrong: we cannot make this last line be less than $cn\log n$

Guess-and-Test Method (2)

Recall the recurrence equation:

$$T(n) = \begin{cases} b & \text{if } n < 2 \\ 2T(n/2) + bn\log n & \text{if } n \geq 2 \end{cases}$$

- <u>Guess #2</u>: $T(n) \leq cn\log^2 n$.

$$T(n) = 2T(n/2) + bn\log n$$

$$\leq 2(c(n/2)\log^2(n/2)) + bn\log n$$

$$= cn(\log n - \log 2)^2 + bn\log n$$

$$= cn\log^2 n - 2cn\log n + cn + bn\log n$$

$$\leq cn\log^2 n \qquad \text{if } c > b.$$

- So, $T(n)$ is $O(n\log^2 n)$.

In general, to use this method, you need to have a good guess.

Master Method

Many divide-and-conquer recurrence equations have the form:

$$T(n) = \begin{cases} c & \text{if } n < d \\ aT(n/b) + f(n) & \text{if } n \geq d \end{cases}$$

The Master Theorem:

1. if $f(n)$ is $O(n^{\log_b a - \varepsilon})$, then $T(n)$ is $\Theta(n^{\log_b a})$

2. if $f(n)$ is $\Theta(n^{\log_b a} \log^k n)$, then $T(n)$ is $\Theta(n^{\log_b a} \log^{k+1} n)$

3. if $f(n)$ is $\Omega(n^{\log_b a + \varepsilon})$, then $T(n)$ is $\Theta(f(n))$,

   provided $af(n/b) \leq \delta f(n)$ for some $\delta < 1$.

Master Method: Ex.1

The form:
$$T(n) = \begin{cases} c & \text{if } n < d \\ aT(n/b) + f(n) & \text{if } n \geq d \end{cases}$$

The Master Theorem:

1. if $f(n)$ is $O(n^{\log_b a - \varepsilon})$, then $T(n)$ is $\Theta(n^{\log_b a})$
2. if $f(n)$ is $\Theta(n^{\log_b a} \log^k n)$, then $T(n)$ is $\Theta(n^{\log_b a} \log^{k+1} n)$
3. if $f(n)$ is $\Omega(n^{\log_b a + \varepsilon})$, then $T(n)$ is $\Theta(f(n))$,
   provided $af(n/b) \leq \delta f(n)$ for some $\delta < 1$.

Example:
$$T(n) = 4T(n/2) + n$$

Solution: $\log_b a = 2$, so case 1 says T(n) is $\Theta(n^2)$.

Master Method: Ex. 2

The form:
$$T(n) = \begin{cases} c & \text{if } n < d \\ aT(n/b) + f(n) & \text{if } n \geq d \end{cases}$$

The Master Theorem:

1. if $f(n)$ is $O(n^{\log_b a - \varepsilon})$, then $T(n)$ is $\Theta(n^{\log_b a})$

2. if $f(n)$ is $\Theta(n^{\log_b a} \log^k n)$, then $T(n)$ is $\Theta(n^{\log_b a} \log^{k+1} n)$

3. if $f(n)$ is $\Omega(n^{\log_b a + \varepsilon})$, then $T(n)$ is $\Theta(f(n))$,

   provided $af(n/b) \leq \delta f(n)$ for some $\delta < 1$.

Example:
$$T(n) = 2T(n/2) + n \log n$$

Solution: $\log_b a = 1$, so case 2 says T(n) is $\Theta(n \log^2 n)$.

Master Method: Ex. 3

The form:
$$T(n) = \begin{cases} c & \text{if } n < d \\ aT(n/b) + f(n) & \text{if } n \geq d \end{cases}$$

The Master Theorem:

1. if $f(n)$ is $O(n^{\log_b a - \varepsilon})$, then $T(n)$ is $\Theta(n^{\log_b a})$

2. if $f(n)$ is $\Theta(n^{\log_b a} \log^k n)$, then $T(n)$ is $\Theta(n^{\log_b a} \log^{k+1} n)$

3. if $f(n)$ is $\Omega(n^{\log_b a + \varepsilon})$, then $T(n)$ is $\Theta(f(n))$,

   provided $af(n/b) \leq \delta f(n)$ for some $\delta < 1$.

Example:
$$T(n) = T(n/3) + n \log n$$

Solution: $\log_b a = 0$, so case 3 says T(n) is $\Theta(n \log n)$.

Master Method: Ex. 4

The form:
$$T(n) = \begin{cases} c & \text{if } n < d \\ aT(n/b) + f(n) & \text{if } n \geq d \end{cases}$$

The Master Theorem:

1. if $f(n)$ is $O(n^{\log_b a - \varepsilon})$, then $T(n)$ is $\Theta(n^{\log_b a})$

2. if $f(n)$ is $\Theta(n^{\log_b a} \log^k n)$, then $T(n)$ is $\Theta(n^{\log_b a} \log^{k+1} n)$

3. if $f(n)$ is $\Omega(n^{\log_b a + \varepsilon})$, then $T(n)$ is $\Theta(f(n))$,

   provided $af(n/b) \leq \delta f(n)$ for some $\delta < 1$.

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

Solution: $\log_b a = 3$, so case 1 says T(n) is $\Theta(n^3)$.

Master Method: Ex. 5

The form:
$$T(n) = \begin{cases} c & \text{if } n < d \\ aT(n/b) + f(n) & \text{if } n \geq d \end{cases}$$

The Master Theorem:

1. if $f(n)$ is $O(n^{\log_b a - \varepsilon})$, then $T(n)$ is $\Theta(n^{\log_b a})$

2. if $f(n)$ is $\Theta(n^{\log_b a} \log^k n)$, then $T(n)$ is $\Theta(n^{\log_b a} \log^{k+1} n)$

3. if $f(n)$ is $\Omega(n^{\log_b a + \varepsilon})$, then $T(n)$ is $\Theta(f(n))$,

provided $af(n/b) \leq \delta f(n)$ for some $\delta < 1$.

Example:
$$T(n) = 9T(n/3) + n^3$$

Solution: $\log_b a = 2$, so case 3 says T(n) is $\Theta(n^3)$.

Master Method: Ex. 6

The form:
$$T(n) = \begin{cases} c & \text{if } n < d \\ aT(n/b) + f(n) & \text{if } n \geq d \end{cases}$$

The Master Theorem:

1. if $f(n)$ is $O(n^{\log_b a - \varepsilon})$, then $T(n)$ is $\Theta(n^{\log_b a})$

2. if $f(n)$ is $\Theta(n^{\log_b a} \log^k n)$, then $T(n)$ is $\Theta(n^{\log_b a} \log^{k+1} n)$

3. if $f(n)$ is $\Omega(n^{\log_b a + \varepsilon})$, then $T(n)$ is $\Theta(f(n))$,

provided $af(n/b) \leq \delta f(n)$ for some $\delta < 1$.

Example:

$$T(n) = T(n/2) + 1 \quad \text{(binary search)}$$

Solution: $\log_b a = 0$, so case 2 says T(n) is $\Theta(\log n)$.

Master Method: Ex. 7

The form:
$$T(n) = \begin{cases} c & \text{if } n < d \\ aT(n/b) + f(n) & \text{if } n \geq d \end{cases}$$

The Master Theorem:

1. if $f(n)$ is $O(n^{\log_b a - \varepsilon})$, then $T(n)$ is $\Theta(n^{\log_b a})$

2. if $f(n)$ is $\Theta(n^{\log_b a} \log^k n)$, then $T(n)$ is $\Theta(n^{\log_b a} \log^{k+1} n)$

3. if $f(n)$ is $\Omega(n^{\log_b a + \varepsilon})$, then $T(n)$ is $\Theta(f(n))$,

   provided $af(n/b) \leq \delta f(n)$ for some $\delta < 1$.

Example:

$$T(n) = 2T(n/2) + \log n \qquad \text{(heap construction)}$$

Solution: $\log_b a = 1$, so case 1 says T(n) is $\Theta(n)$.

Iterative Justification of the Master Theorem

Use iterative substitution to find a pattern:

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

$$= a(aT(n/b^2)) + f(n/b)) + f(n)$$

$$= a^2 T(n/b^2) + af(n/b) + f(n)$$

$$= a^3 T(n/b^3) + a^2 f(n/b^2) + af(n/b) + f(n)$$

$$= \ldots$$

$$= a^{\log_b n} T(1) + \sum_{i=0}^{(\log_b n)-1} a^i f(n/b^i)$$

$$= n^{\log_b a} T(1) + \sum_{i=0}^{(\log_b n)-1} a^i f(n/b^i)$$

We then distinguish the three cases as
- Case 1: The first term is dominant
- Case 2: Each part of the summation is equally dominant
- Case 3: The second term is dominant

Integer Multiplication

Algorithm: Multiply two n-bit integers I and J.

- Divide step: Split I and J into high-order and low-order bits

$$I = I_h 2^{n/2} + I_l$$

$$J = J_h 2^{n/2} + J_l$$

- We can then define I*J by multiplying the parts and adding:

$$I * J = (I_h 2^{n/2} + I_l) * (J_h 2^{n/2} + J_l)$$

$$= I_h J_h 2^n + I_h J_l 2^{n/2} + I_l J_h 2^{n/2} + I_l J_l$$

- So, $T(n) = 4T(n/2) + n$, which implies $T(n)$ is $\Theta(n^2)$.
- But that is no better than the algorithm we learned in grade school.

Improved Integer Multiplication

Algorithm: Multiply two n-bit integers I and J.

- Divide step: Split I and J into high-order and low-order bits

$$I = I_h 2^{n/2} + I_l$$

$$J = J_h 2^{n/2} + J_l$$

- Observe that there is a different way to multiply parts:

$$I * J = I_h J_h 2^n + [(I_h - I_l)(J_l - J_h) + I_h J_h + I_l J_l] 2^{n/2} + I_l J_l$$

$$= I_h J_h 2^n + [(I_h J_l - I_l J_l - I_h J_h + I_l J_h) + I_h J_h + I_l J_l] 2^{n/2} + I_l J_l$$

$$= I_h J_h 2^n + (I_h J_l + I_l J_h) 2^{n/2} + I_l J_l$$

- So, $T(n) = 3T(n/2) + n$, which implies $T(n)$ is $\Theta(n^{\log_2 3})$.
- Thus, $T(n)$ is $O(n^{1.585})$.