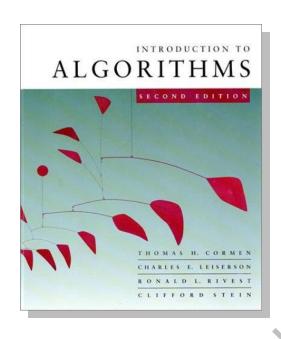
Algorithms



LECTURE 2

Asymptotic Notation

• O-, Ω -, and Θ -notation

Recurrences

- Substitution method
- Iterating the recurrence
- Recursion tree
- Master method

Professor Ashok Subramanian



O-notation (upper bounds):

```
We write f(n) = O(g(n)) if there exist constants c > 0, n_0 > 0 such that 0 \le f(n) \le cg(n) for all n \ge n_0.
```



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EXAMPLE:
$$2n^2 = O(n^3)$$
 $(c = 1, n_0 = 2)$



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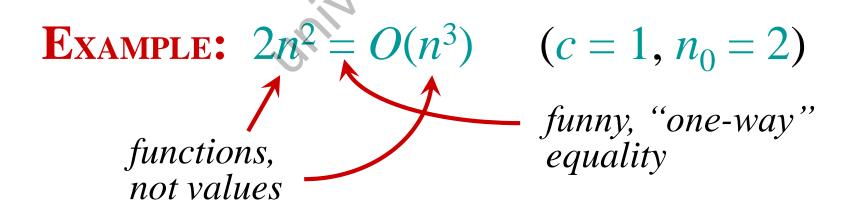
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Example:
$$2n^2 = O(n^3)$$
 $(c = 1, n_0 = 2)$ functions, not values



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We write f(n) = O(g(n)) if there exist constants c > 0, $n_0 > 0$ such that $0 \le f(n) \le cg(n)$ for all $n \ge n_0$.





Set definition of O-notation

```
O(g(n)) = \{ f(n) : \text{there exist constants} 

c > 0, n_0 > 0 \text{ such} 

\text{that } 0 \le f(n) \le cg(n) 

\text{for all } n \ge n_0 \}
```



Set definition of O-notation

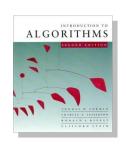
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EXAMPLE:
$$2n^2 \in O(n^3)$$



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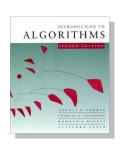
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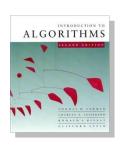
EXAMPLE: $2n^2 \in O(n^3)$

(Logicians: $\lambda n.2n^2 \in O(\lambda n.n^3)$, but it's convenient to be sloppy, as long as we understand what's *really* going on.)



Macro substitution

Convention: A set in a formula represents an anonymous function in the set.



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```
Example: f(n) = n^3 + O(n^2)

means
f(n) = n^3 + h(n)
for some h(n) \in O(n^2).
```



Macro substitution

Convention: A set in a formula represents an anonymous function in the set.

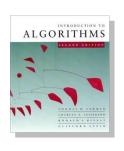
```
Example: n^2 + O(n) = O(n^2) means for any f(n) \in O(n): n^2 + f(n) = h(n) for some h(n) \in O(n^2).
```



Ω -notation (lower bounds)

O-notation is an *upper-bound* notation. It makes no sense to say f(n) is at least $O(n^2)$.

Algorithms L2.12



Ω-notation (lower bounds)

O-notation is an *upper-bound* notation. It makes no sense to say f(n) is at least $O(n^2)$.

```
\Omega(g(n)) = \{ f(n) : \text{there exist constants} \}
c > 0, n_0 > 0 \text{ such}
\text{that } 0 \le cg(n) \le f(n)
\text{for all } n \ge n_0 \}
```



Ω -notation (lower bounds)

O-notation is an *upper-bound* notation. It makes no sense to say f(n) is at least $O(n^2)$.

$$\Omega(g(n)) = \{ f(n) : \text{there exist constants} \}$$
 $c > 0, n_0 > 0 \text{ such}$
 $\text{that } 0 \le cg(n) \le f(n)$
 $\text{for all } n \ge n_0 \}$

EXAMPLE:
$$\sqrt{n} = \Omega(\lg n)$$
 $(c = 1, n_0 = 16)$



Θ-notation (tight bounds)

$$\Theta(g(n)) = O(g(n)) \cap \Omega(g(n))$$

Algorithms



Θ-notation (tight bounds)

$$\Theta(g(n)) = O(g(n)) \cap \Omega(g(n))$$

Example:
$$\frac{1}{2}n^2 - 2n = \Theta(n^2)$$



o-notation and ω-notation

O-notation and Ω -notation are like \leq and \geq . *o*-notation and ω -notation are like < and >.

$$o(g(n)) = \{ f(n) : \text{ for any constant } c > 0, \\ \text{there is a constant } n_0 > 0 \\ \text{such that } 0 \le f(n) < cg(n) \\ \text{for all } n \ge n_0 \}$$

EXAMPLE:
$$2n^2 = o(n^3)$$
 $(n_0 = 2/c)$

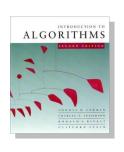


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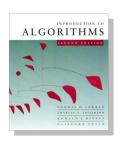
$$\omega(g(n)) = \{ f(n) : \text{ for any constant } c > 0, \\ \text{there is a constant } n_0 > 0 \\ \text{such that } 0 \le cg(n) < f(n) \\ \text{for all } n \ge n_0 \}$$

EXAMPLE:
$$\sqrt{n} = \omega(1gn)$$
 $(n_0 = 1 + 1/c)$



Solving recurrences

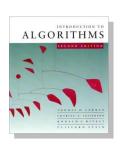
- The analysis of merge sort from *Lecture 1* required us to solve a recurrence.
- Recurrences are like solving integrals, differential equations, etc.
 - Learn a few tricks.
- Lecture 3: Applications of recurrences to divide-and-conquer algorithms.



Substitution method

The most general method:

- 1. Guess the form of the solution.
- 2. Verify by induction.
- 3. Solve for constants.

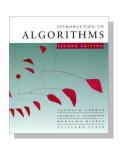


$$T(n) = 2T(\lfloor n/2 \rfloor) + n ,$$

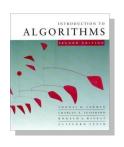


 $T(n) = O(n \lg n)$. The substitution method requires us to prove that $T(n) \le cn \lg n$ for an appropriate choice of the constant c > 0. We start by assuming that this bound holds for all positive m < n, in particular for $m = \lfloor n/2 \rfloor$, yielding $T(\lfloor n/2 \rfloor) \le c \lfloor n/2 \rfloor \lg(\lfloor n/2 \rfloor)$. Substituting into the recurrence yields

Algorithms L2.22



$T(n) \leq 2(c \lfloor n/2 \rfloor \lg(\lfloor n/2 \rfloor)) + n$ $\leq cn \lg(n/2) + n$ $= cn \lg n + cn \lg 2 + n$ $= cn \lg n + cn + n$ $\leq cn \lg n,$



Substitution method

The most general method:

- 1. Guess the form of the solution.
- 2. Verify by induction.
- 3. Solve for constants.

EXAMPLE: T(n) = 4T(n/2) + n

- [Assume that $T(1) = \Theta(1)$.]
- Guess $O(n^3)$. (Prove O and Ω separately.)
- Assume that $T(k) \le ck^3$ for k < n.
- Prove $T(n) \le cn^3$ by induction.



Example of substitution

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

$$\leq 4c(n/2)^3 + n$$

$$= (c/2)n^3 + n$$

$$= cn^3 - ((c/2)n^3 + n) \leftarrow desired - residual$$

$$\leq cn^3 \leftarrow desired$$
whenever $(c/2)n^3 - n \geq 0$, for example, if $c \geq 2$ and $n \geq 1$.
$$residual$$



Example (continued)

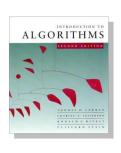
- We must also handle the initial conditions, that is, ground the induction with base cases.
- **Base:** $T(n) = \Theta(1)$ for all $n < n_0$, where n_0 is a suitable constant.
- For $1 \le n < n_0$, we have " $\Theta(1)$ " $\le cn^3$, if we pick c big enough.



Example (continued)

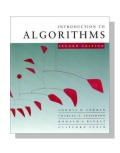
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This bound is not tight!



We shall prove that $T(n) = O(n^2)$.

Algorithms



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Assume that $T(k) \le ck^2$ for k < n:

Tissume that
$$T(n) = cn$$
 for $T(n) = 4T(n/2) + n$

$$\leq 4c(n/2)^2 + n$$

$$= cn^2 + n$$

$$= O(n^2)$$

Algorithms



We shall prove that $T(n) = O(n^2)$.

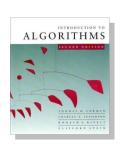
Assume that $T(k) \le ck^2$ for $k \ge n$:

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

$$\leq 4c(n/2)^{2} + n$$

$$= cn^{2} + n$$

= cn + n= (m + n)= (m + n)Wrong! We must prove the I.H.



We shall prove that $T(n) = O(n^2)$.

Assume that $T(k) \le ck^2$ for k < n:

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

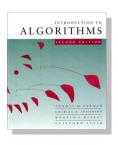
$$\leq 4c(n/2)^{2} + nc$$

$$= cn^{2} + n$$

= Wrong! We must prove the I.H.

$$=cn^2-(-n)$$
 [desired – residual]

 $\leq cn^2$ for **no** choice of c > 0. Lose!



IDEA: Strengthen the inductive hypothesis.

• Subtract a low-order term.

Inductive hypothesis: $T(k) \le c_1 k^2 - c_2 k$ for k < n.

Algorithms L2.32



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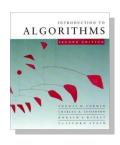
$$T(n) = 4T(n/2) + n$$

$$= 4(c_1(n/2)^2 - c_2(n/2)) + n$$

$$= c_1n^2 - 2c_2n + n$$

$$= c_1n^2 - c_2n - (c_2n - n)$$

$$\leq c_1n^2 - c_2n \quad \text{if } c_2 \geq 1.$$



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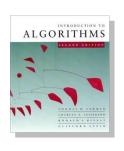
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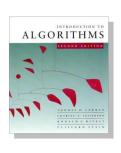
$$\leq c_1n^2 - c_2n \quad \text{if } c_2 \geq 1.$$

Pick c_1 big enough to handle the initial conditions.



Recursion-tree method

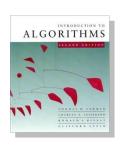
- A recursion tree models the costs (time) of a recursive execution of an algorithm.
- The recursion-tree method can be unreliable, just like any method that uses ellipses (...).
- The recursion-tree method promotes intuition, however.
- The recursion tree method is good for generating guesses for the substitution method.



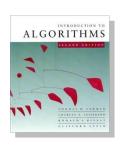
Example of recursion tree

Solve
$$T(n) = T(n/4) + T(n/2) + n^2$$
.

Algorithms

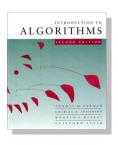


Solve
$$T(n) = T(n/4) + T(n/2) + n^2$$
.
$$T(n)$$



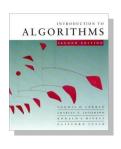
Solve
$$T(n) = T(n/4) + T(n/2) + n^2$$
:
$$T(n/4)$$

$$T(n/2)$$



Solve
$$T(n) = T(n/4) + T(n/2) + n^2$$
:
$$(n/4)^2 \qquad (n/2)^2$$

$$T(n/16) \qquad T(n/8) \qquad T(n/8) \qquad T(n/4)$$

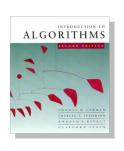


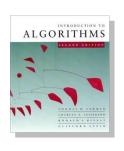
Solve
$$T(n) = T(n/4) + T(n/2) + n^2$$
:
$$(n/4)^2 \qquad (n/2)^2$$

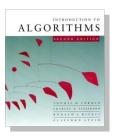
$$(n/16)^2 \qquad (n/8)^2 \qquad (n/8)^2 \qquad (n/4)^2$$

$$\vdots$$

$$\Theta(1)$$



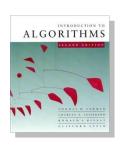




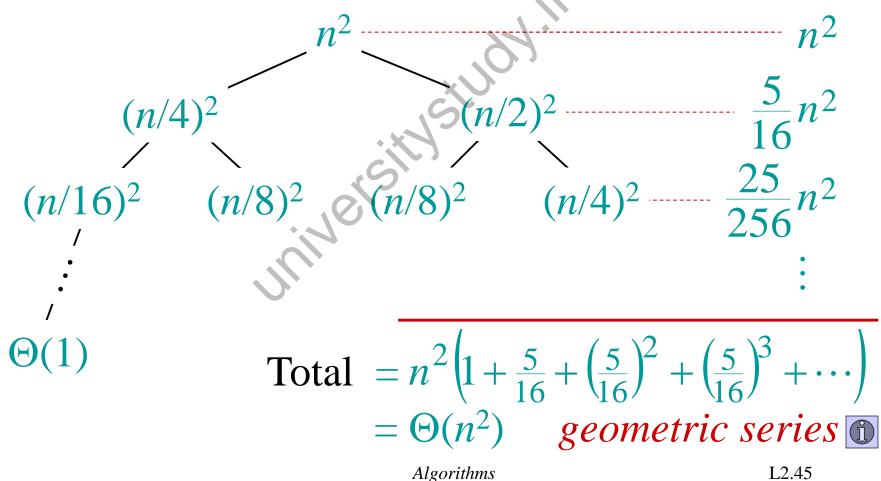


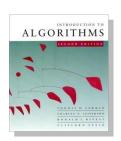
Recursion Tree

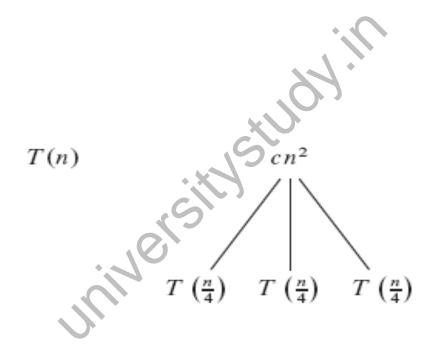
$$T(n) = 3T(n/4) + cn^2.$$



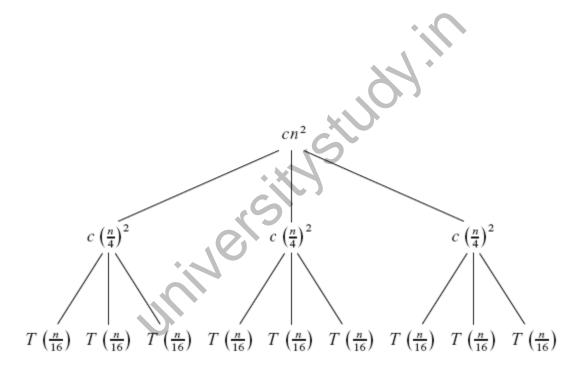
Solve
$$T(n) = T(n/4) + T(n/2) + n^2$$
:

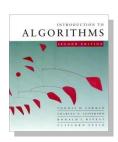


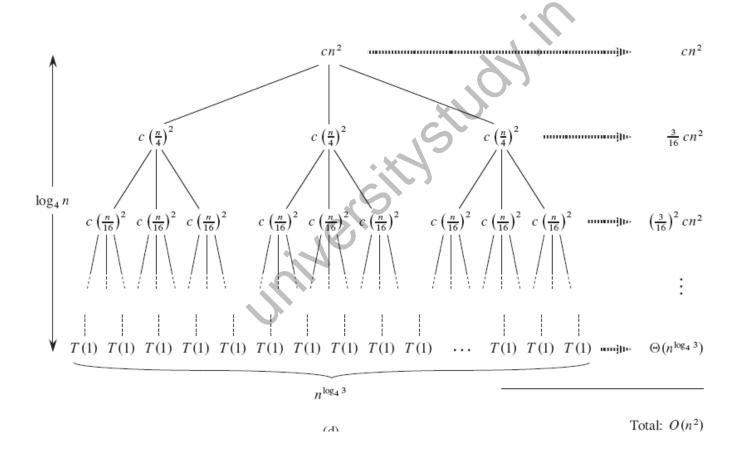




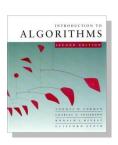




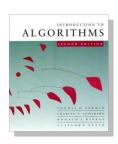




Algorithms

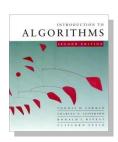


Because subproblem sizes decrease by a factor of 4 each time we go down one level, we eventually must reach a boundary condition. How far from the root do we reach one? The subproblem size for a node at depth i is $n/4^i$. Thus, the subproblem size hits n = 1 when $n/4^i = 1$ or, equivalently, when $i = \log_4 n$. Thus, the tree has $\log_4 n + 1$ levels (at depths $0, 1, 2, \ldots, \log_4 n$).

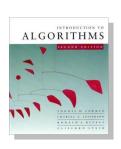


Next we determine the cost at each level of the tree. Each level has three times more nodes than the level above, and so the number of nodes at depth i is 3^{i} .

Algorithms L2.50



Because subproblem sizes reduce by a factor of 4 for each level we go down from the root, each node at depth i, for $i=0,1,2,\ldots,\log_4 n-1$, has a cost of $c(n/4^i)^2$. Multiplying, we see that the total cost over all nodes at depth i, for $i=0,1,2,\ldots,\log_4 n-1$, is $3^i c(n/4^i)^2=(3/16)^i cn^2$. The bottom level, at depth $\log_4 n$, has $3^{\log_4 n}=n^{\log_4 3}$ nodes, each contributing cost T(1), for a total cost of $n^{\log_4 3}T(1)$, which is $\Theta(n^{\log_4 3})$, since we assume that T(1) is a constant.



$$T(n) = cn^{2} + \frac{3}{16}cn^{2} + \left(\frac{3}{16}\right)^{2}cn^{2} + \dots + \left(\frac{3}{16}\right)^{\log_{4}n - 1}cn^{2} + \Theta(n^{\log_{4}3})$$

$$= \sum_{i=0}^{\log_{4}n - 1} \left(\frac{3}{16}\right)^{i}cn^{2} + \Theta(n^{\log_{4}3})$$

$$= \frac{(3/16)^{\log_{4}n} - 1}{(3/16) - 1}cn^{2} + \Theta(n^{\log_{4}3}) \qquad \text{(by equation (A.5))}.$$



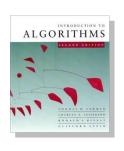
$$T(n) = \sum_{i=0}^{\log_4 n - 1} \left(\frac{3}{16}\right)^i cn^2 + \Theta(n^{\log_4 3})$$

$$< \sum_{i=0}^{\infty} \left(\frac{3}{16}\right)^i cn^2 + \Theta(n^{\log_4 3})$$

$$= \frac{1}{1 - (3/16)} cn^2 + \Theta(n^{\log_4 3})$$

$$= \frac{16}{13} cn^2 + \Theta(n^{\log_4 3})$$

$$= O(n^2).$$



The master method

The master method applies to recurrences of the form

$$T(n) = a T(n/b) + f(n) ,$$

T(n) = a T(n/b) + f(n), where $a \ge 1$, b > 1, and f is asymptotically positive.



Three common cases

Compare f(n) with $n^{\log ba}$:

- 1. $f(n) = O(n^{\log_b a \varepsilon})$ for some constant $\varepsilon > 0$.
 - f(n) grows polynomially slower than $n^{\log_b a}$ (by an n^{ε} factor). **Solution:** $T(n) = \Theta(n^{\log_b a})$.



Three common cases

Compare f(n) with $n^{\log_b a}$:

- 1. $f(n) = O(n^{\log_b a \varepsilon})$ for some constant $\varepsilon > 0$.
 - f(n) grows polynomially slower than $n^{\log ba}$ (by an n^{ϵ} factor).

```
Solution: T(n) = \Theta(n^{\log_b a}).
```

- 2. $f(n) = \Theta(n^{\log_b a} \lg^k n)$ for some constant $k \ge 0$.
 - f(n) and $n^{\log_b a}$ grow at similar rates.

Solution:
$$T(n) = \Theta(n^{\log_b a} \lg^{k+1} n)$$
.



Three common cases (cont.)

Compare f(n) with $n^{\log_b a}$:

- 3. $f(n) = \Omega(n^{\log_b a + \varepsilon})$ for some constant $\varepsilon > 0$.
 - f(n) grows polynomially faster than $n^{\log_b a}$ (by an n^{ϵ} factor),

and f(n) satisfies the regularity condition that $af(n/b) \le cf(n)$ for some constant c < 1.

Solution: $T(n) = \Theta(f(n))$.

```
Ex. T(n) = 4T(n/2) + n

a = 4, b = 2 \Rightarrow n^{\log ba} = n^2; f(n) = n.

CASE 1: f(n) = O(n^{2-\epsilon}) for \epsilon = 1.

\therefore T(n) = \Theta(n^2).
```

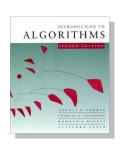


Ex.
$$T(n) = 4T(n/2) + n$$

 $a = 4, b = 2 \Rightarrow n^{\log ba} = n^2; f(n) = n.$
Case 1: $f(n) = O(n^{2-\epsilon})$ for $\epsilon = 1.$
 $\therefore T(n) = \Theta(n^2).$

Ex.
$$T(n) = 4T(n/2) + n^2$$

 $a = 4, b = 2 \Rightarrow n^{\log_b a} = n^2; f(n) = n^2.$
Case 2: $f(n) = \Theta(n^2 \lg^0 n)$, that is, $k = 0$.
 $\therefore T(n) = \Theta(n^2 \lg n)$.



```
Ex. T(n) = 4T(n/2) + n^3

a = 4, b = 2 \Rightarrow n^{\log_b a} = n^2; f(n) = n^3.

CASE 3: f(n) = \Omega(n^{2+\epsilon}) for \epsilon = 1

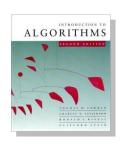
and 4(n/2)^3 \le cn^3 (reg. cond.) for c = 1/2.

\therefore T(n) = \Theta(n^3).
```



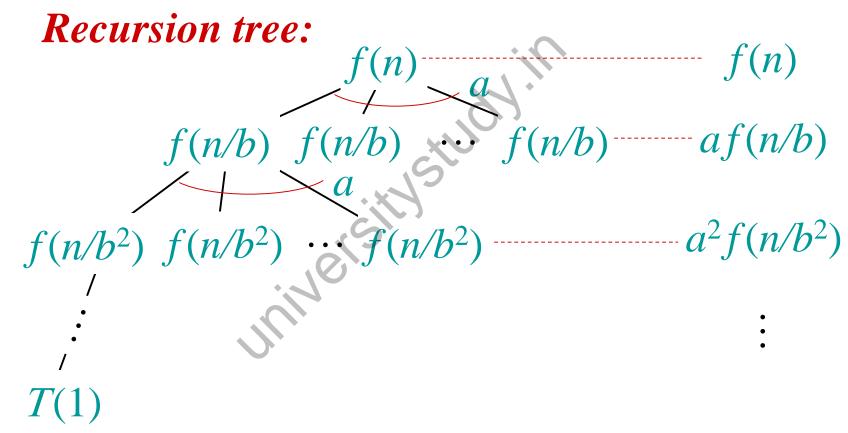
Ex. $T(n) = 4T(n/2) + n^3$ $a = 4, b = 2 \Rightarrow n^{\log ba} = n^2; f(n) = n^3.$ CASE 3: $f(n) = \Omega(n^{2+\epsilon})$ for $\epsilon = 1$ and $4(n/2)^3 \le cn^3$ (reg. cond.) for c = 1/2. $\therefore T(n) = \Theta(n^3).$

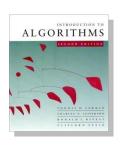
Ex. $T(n) = 4T(n/2) + n^2/\lg n$ $a = 4, b = 2 \Rightarrow n^{\log_b a} = n^2; f(n) = n^2/\lg n.$ Master method does not apply. In particular, for every constant $\varepsilon > 0$, we have $n^{\varepsilon} = \omega(\lg n)$.

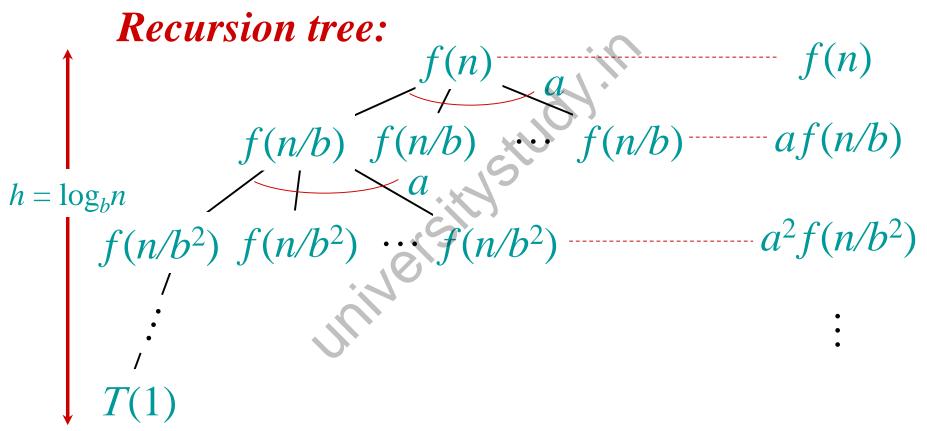


Recursion tree:

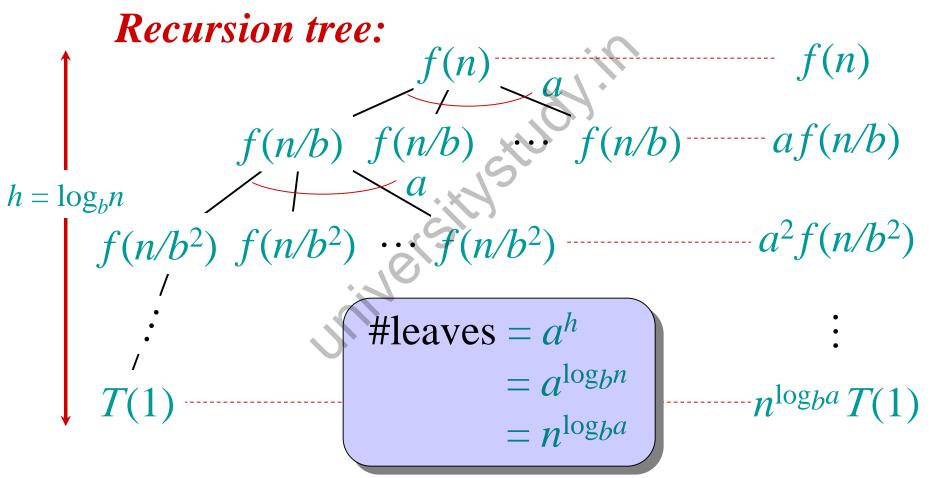




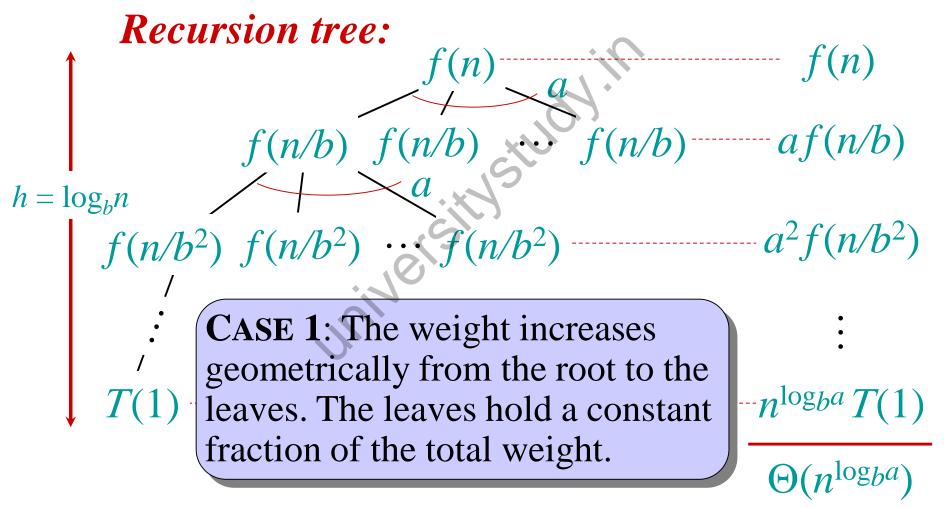




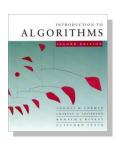


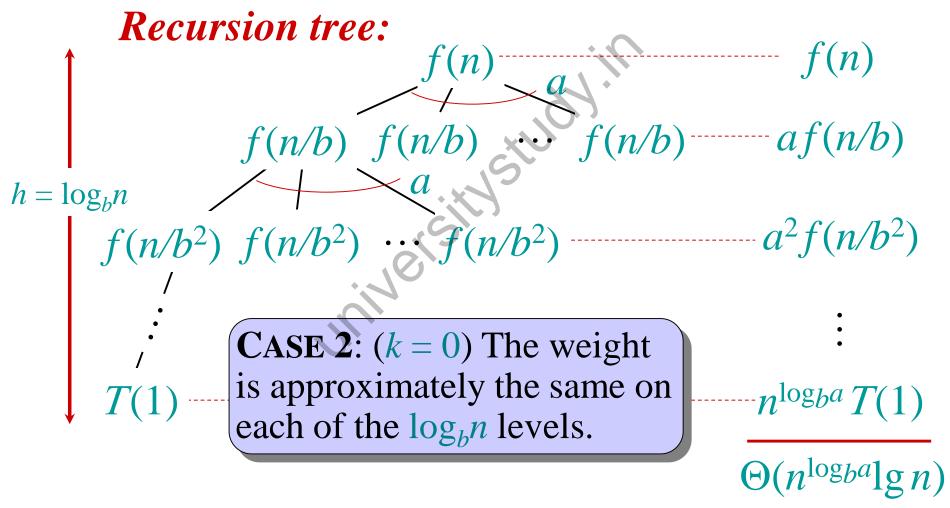






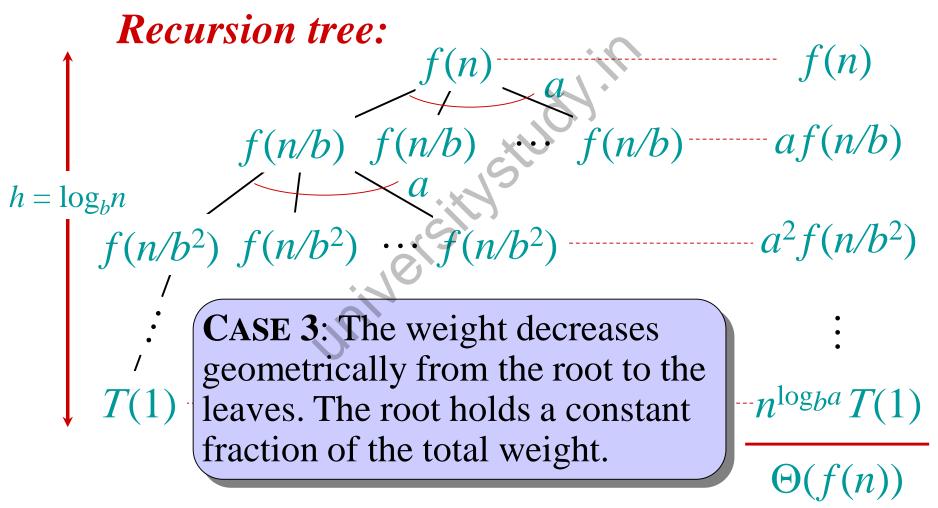
L2.66





Algorithms L2.67





L2.68