CS 381 - Spring 2021

Week 2, Lecture 2
Part 1

Many recurrence relations arising from divide-and-conquer algorithms have the form:

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

where $a \ge 1$, b > 1 are constants and f is asymptotically positive

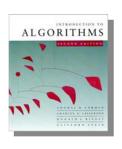
- There are **a** instances of the problem, each of size **n/b**
 - a is the branching factor
 - b is the reduction factor
- Setting up the problem instance before the recursive calls and combining subsolutions returned by the recursive calls takes f(n) work.

Master Theorem (4.5 CLRS)

• The Master Theorem (MS) is a method for solving many recurrences of the form

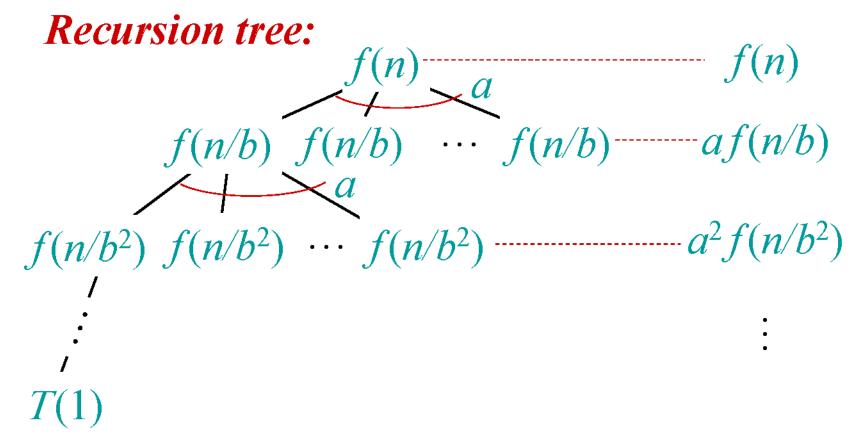
$$T(n) = aT(n/b) + f(n)$$

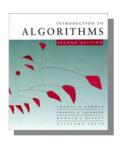
- There exist multiple versions of the Master Theorem
 - o All are based on the same idea, with three cases
 - Each with slightly different assumption about f(n); none cover all possibilities

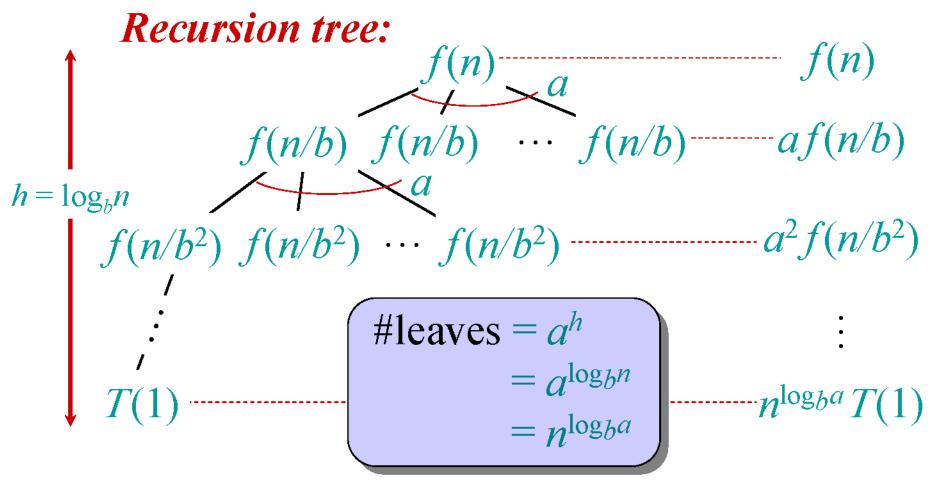


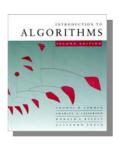
Recursion tree: $f(n/b^2)$ $f(n/b^2)$ ··· $f(n/b^2)$

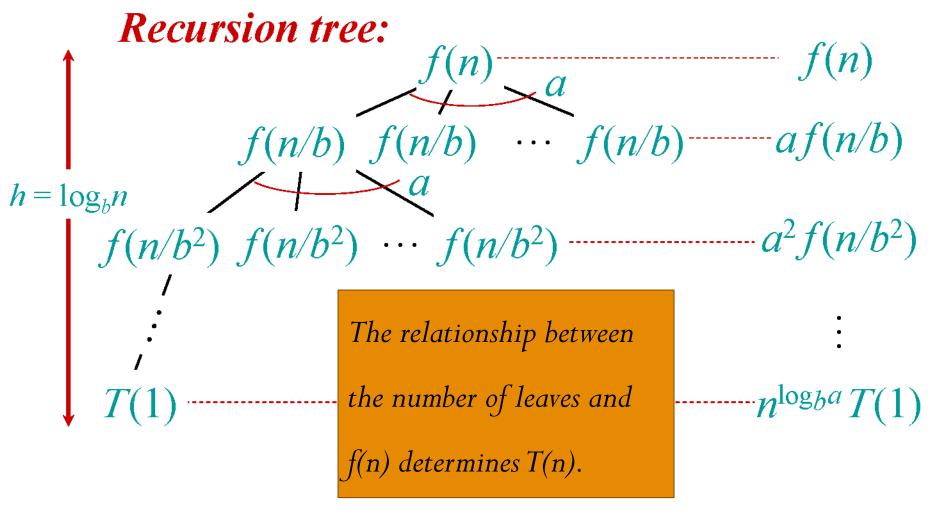












$$T(n) = aT(n/b) + f(n)$$

- Height of recursion tree: log_b n
- Number of leaves: $n^{\log_b a}$
- Total number of nodes in the recursion tree:

$$\sum_{i=0}^{(\log_b n) - 1} a^i = \frac{a^{\log_b n} - 1}{a - 1}$$

Reminder:
$$\sum_{i=0}^{k} x^i = \frac{x^{k+1}-1}{x-1}$$

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

Matches
$$T(n) = a T(n/b) + f(n)$$
 with $a = 4$, $b = 2$, $f(n) = n$.

- Number of levels in recursion tree: $\log_2 n$
- Number of leaves: $n^{log_ba} = nlog^{24} = n^2$
- Work done for a problem of size m: f(m) = O(m)

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

Total work done:

$$n + 4\frac{n}{2} + 4^{2}\frac{n}{2^{2}} + 4^{3}\frac{n}{2^{3}} + \dots + n^{2}$$

$$= n + 2n + 4n + 8n + \dots + n2^{\log n}$$

$$= n\sum_{i=0}^{\log n} 2^{i} = n\left(2^{(\log n)+1} - 1\right) = n(2n-1)$$

$$= O(n^{2})$$

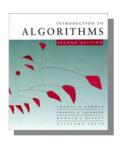
Master Theorem

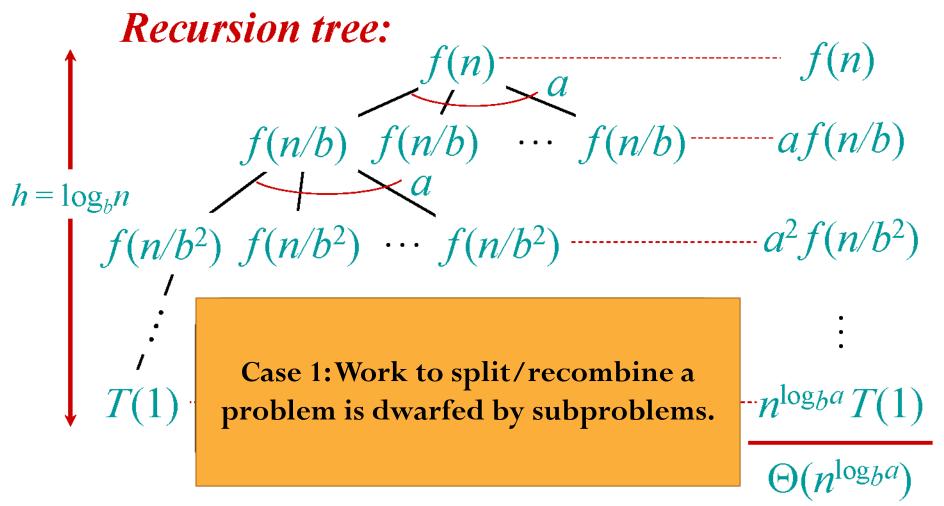
Let $a \ge 1$ and b > 1 be constants. Let f(n) be a function, and T(n) be

defined on the nonnegative integers by
$$T(n) = a \cdot T(\frac{n}{b}) + f(n)$$
,

where we interpret n/b to mean either $\lfloor n/b \rfloor$ or $\lceil n/b \rceil$. Then T(n) has the following asymptotic bounds:

- 1. If $f(n) = O(n^{\log_b a \epsilon})$ for a constant $\epsilon > 0$, then $T(n) = \Theta(n^{\log_b a})$.
- 2. If $f(n) = \Theta(n^{\log_b a})$, then $T(n) = \Theta(n^{\log_b a} \cdot \log n)$.
- 3. If $f(n) = \Omega(n^{\log_b a + \epsilon})$ for a constant $\epsilon > 0$, and if $a \cdot f(\frac{n}{b}) \le cf(n)$
- for some constant c > 1 and all large enough n, then $T(n) = \Theta(f(n))$.





Case 1:
$$f(n) = O(n^{\log_b(a) - \varepsilon})$$
, for a constant $\varepsilon > 0$.

This means the leaves do a fraction of the total work (number of nodes dominate the time, not the work done at the nodes).

Then
$$T(n) = \Theta(n^{\log_b a})$$
.

Master Theorem:
$$T(n) = aT(n/b) + f(n)$$

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What is $T(n)$?

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Example:
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 $a=4, b=2, f(n) = n$
 $n^{\log_b a} = n^2 \text{ versus } f(n) = O(n) \text{ [set } \epsilon = 1\text{]}$
Hence, $T(n) = \Theta(n^{\log_b a}) = \Theta(n^2)$

Another example: $T(n) = 5T(n/2) + n^2$

What is T(n)?

Another example: $T(n) = 5T(n/2) + n^2$

- a = 5, b = 2
- $f(n) = n^2$

Number of levels: $\log_2 n$

Number of leaves: $n^{\log_b a} = n^{\log_2 5} \approx n^{2.32}$

Does n^2 grow polynomially slower than $n^{2.32}$? Yes, by $n^{0.3}$

$$T(n) = \Theta(n^{\log_2 5})$$

f(n) grows polynomially slower than g(n)

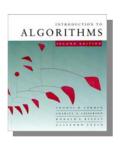
Does a polynomial n^{ε} separate f(n) and g(n)?

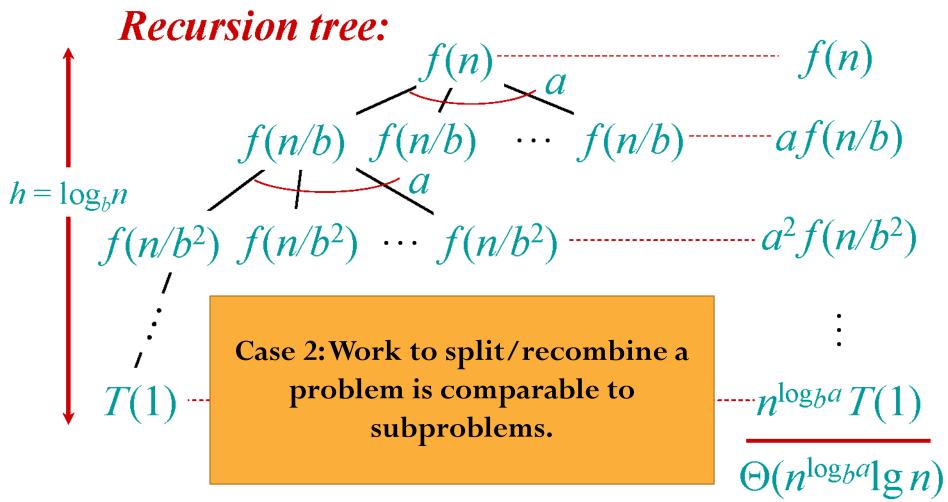
f(n)	g(n)
n	n^2
O(1)	n log n
log^8n	$n^{1.3}$
log n	\sqrt{n}
n	n log n
log n	$(\log n)^3$
n^5	2 ⁿ

f(n) grows polynomially slower than g(n)

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f(n)	g(n)
n	n^2
O(1)	n log n
log ⁸ n	$n^{1.3}$
log n	\sqrt{n}
n	n log n not true
log n	$(\log n)^3$ not true
n^5	2 ⁿ





Case 2: $f(n) = \theta(n^{\log_b a})$. This means f(n) and $n^{\log_b a}$ grow at the same rate, so total work done at every level is about the same.

Then, $T(n) = \Theta(n^{\log_b a} \log n)$.

Master Theorem:
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Example:

$$T(n) = 2T(n/2) + cn.$$

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Then,
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Example:

$$T(n) = 2T(n/2) + cn = \theta (n \log n)$$

$$[a=b=2, n^{\log_b a} = n = f(n)]$$

Case 2: $f(n) = \theta (n^{\log_b a})$. This means f(n) and $n^{\log_b a}$ grow at the same rate, i.e., total work done at every level is about the same.

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More
$$T(n) = T(n/2) + c$$

Examples: What is T(n)?

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More
$$T(n) = T(n/2) + c = \theta (\log n)$$

Examples: $a=1, b=2, f(n) = O(1) = n^{\log_2 1} = O(1)$

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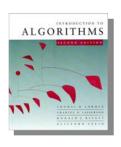
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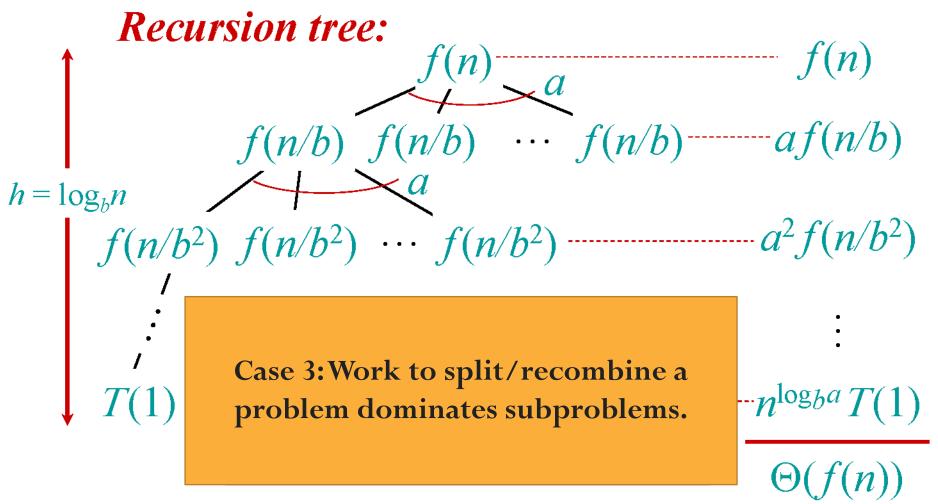
More
$$T(n) = T(n/2) + c = \theta (\log n)$$

Examples: $a=1, b=2, f(n) = O(1) = n^{\log_2 1} = O(1)$

$$T(n) = 4T(n/2) + n^2 = \theta (n^2 \log n)$$

 $a=4, b=2, f(n) = n^2 = n^{\log_2 4} = n^2$





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

Case 3: f(n) grows polynomially faster than $n^{\log_b a}$; i.e., $f(n) = \Omega(n^{\log_b a})$ and a regularity condition is satisfied:

$$a \cdot f\left(\frac{n}{b}\right) \leq c \cdot f(n)$$
 for some constant $c < 1$

Then,
$$T(n) = \Theta(f(n))$$
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$$T(n) = aT(n/b) + f(n)$$

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E.g.:
$$T(n) = T(n/2) + n \log n$$
.
What is $T(n)$?

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

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E.g.:
$$T(n) = T(n/2) + n \log n = \theta (n \log n)$$

- $a = 1, b = 2, n^{\log_b a} = O(1), f(n) = n \log n$
- Regularity condition: $1 * \frac{n}{2} * \log \frac{n}{2} < \frac{n}{2} \log n = \frac{1}{2} n \log n$
- We have $c = \frac{1}{2} < 1$