



# Algorithms: COMP3121/3821/9101/9801

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TOPIC 1: RECURRENCES

# Asymptotic notation

- **“Big Oh” notation:**  $f(n) = O(g(n))$  is an abbreviation for:

*“There exist positive constants  $c$  and  $n_0$  such that  
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- Clearly, multiplying constants  $c$  of interest will be larger than 1, thus “enlarging”  $g(n)$ .

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- **“Theta” notation:**  $f(n) = \Theta(g(n))$  iff and only if  $f(n) = O(g(n))$  and  $f(n) = \Omega(g(n))$ ; thus,  $f(n)$  and  $g(n)$  have the same asymptotic growth rate.

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- Since Merge( $A, p, q, r$ ) runs in linear time, the runtime  $T(n)$  of Merge-Sort( $A, p, r$ ) satisfies

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

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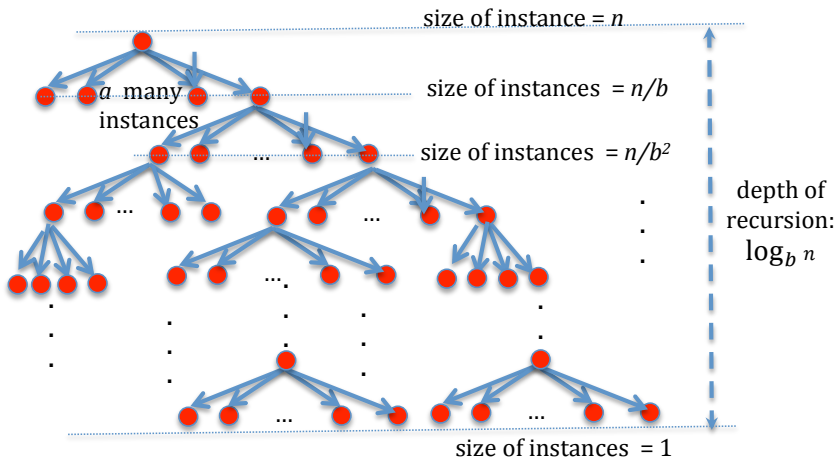
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but it can be shown that assuming that  $n$  is a power of  $b$  is OK, and that the estimate produced is still valid for all  $n$ .

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  - ② the **sizes of the constants** involved (more about that later)
- This is what the **Master Theorem** provides (when it is applicable).

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- 4 If none of these conditions hold, the Master Theorem is NOT applicable (in the form presented).

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- So whenever we have  $f = \Theta(g(n) \log n)$  we do not have to specify what base the log is - all bases produce equivalent asymptotic estimates.

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$$\text{thus } f(n) = cn = \Theta(n) = \Theta(n^{\log_2 2}).$$

Thus, condition of case 2 is satisfied; and so,

$$T(n) = \Theta(n^{\log_2 2} \log n) = \Theta(n \log n).$$

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  - Thus, in this case the Master Theorem does **not** apply!

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Note that so far we did not use any assumptions on  $f(n)$ ...

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**Case 1:**  $f(m) = O(m^{\log_b a - \varepsilon})$

$$\begin{aligned} \sum_{i=0}^{\lfloor \log_b n \rfloor - 1} a^i f\left(\frac{n}{b^i}\right) &= \sum_{i=0}^{\lfloor \log_b n \rfloor - 1} a^i O\left(\left(\frac{n}{b^i}\right)^{\log_b a - \varepsilon}\right) \\ &= O\left(\sum_{i=0}^{\lfloor \log_b n \rfloor - 1} a^i \left(\frac{n}{b^i}\right)^{\log_b a - \varepsilon}\right) = O\left(n^{\log_b a - \varepsilon} \sum_{i=0}^{\lfloor \log_b n \rfloor - 1} \left(\frac{a}{(b^i)^{\log_b a - \varepsilon}}\right)\right) \\ &= O\left(n^{\log_b a - \varepsilon} \sum_{i=0}^{\lfloor \log_b n \rfloor - 1} \left(\frac{a}{b^{\log_b a - \varepsilon}}\right)^i\right) = O\left(n^{\log_b a - \varepsilon} \sum_{i=0}^{\lfloor \log_b n \rfloor - 1} \left(\frac{a}{b^{\log_b a} b^{-\varepsilon}}\right)^i\right) \end{aligned}$$

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# Master Theorem Proof:

**Case 1 - continued:**

$$\sum_{i=0}^{\lfloor \log_b n \rfloor - 1} a^i f\left(\frac{n}{b^i}\right) = O\left(n^{\log_b a - \varepsilon} \frac{(b^\varepsilon)^{\lfloor \log_b n \rfloor} - 1}{b^\varepsilon - 1}\right)$$

# Master Theorem Proof:

**Case 1 - continued:**

$$\begin{aligned}\sum_{i=0}^{\lfloor \log_b n \rfloor - 1} a^i f\left(\frac{n}{b^i}\right) &= O\left(n^{\log_b a - \varepsilon} \frac{(b^\varepsilon)^{\lfloor \log_b n \rfloor} - 1}{b^\varepsilon - 1}\right) \\ &= O\left(n^{\log_b a - \varepsilon} \frac{\left(b^{\lfloor \log_b n \rfloor}\right)^\varepsilon - 1}{b^\varepsilon - 1}\right)\end{aligned}$$

# Master Theorem Proof:

**Case 1 - continued:**

$$\begin{aligned}\sum_{i=0}^{\lfloor \log_b n \rfloor - 1} a^i f\left(\frac{n}{b^i}\right) &= O\left(n^{\log_b a - \varepsilon} \frac{(b^\varepsilon)^{\lfloor \log_b n \rfloor} - 1}{b^\varepsilon - 1}\right) \\ &= O\left(n^{\log_b a - \varepsilon} \frac{\left(b^{\lfloor \log_b n \rfloor}\right)^\varepsilon - 1}{b^\varepsilon - 1}\right) \\ &= O\left(n^{\log_b a - \varepsilon} \frac{n^\varepsilon - 1}{b^\varepsilon - 1}\right)\end{aligned}$$

# Master Theorem Proof:

Case 1 - continued:

$$\begin{aligned}\sum_{i=0}^{\lfloor \log_b n \rfloor - 1} a^i f\left(\frac{n}{b^i}\right) &= O\left(n^{\log_b a - \varepsilon} \frac{(b^\varepsilon)^{\lfloor \log_b n \rfloor} - 1}{b^\varepsilon - 1}\right) \\ &= O\left(n^{\log_b a - \varepsilon} \frac{\left(b^{\lfloor \log_b n \rfloor}\right)^\varepsilon - 1}{b^\varepsilon - 1}\right) \\ &= O\left(n^{\log_b a - \varepsilon} \frac{n^\varepsilon - 1}{b^\varepsilon - 1}\right) \\ &= O\left(\frac{n^{\log_b a} - n^{\log_b a - \varepsilon}}{b^\varepsilon - 1}\right)\end{aligned}$$

# Master Theorem Proof:

Case 1 - continued:

$$\begin{aligned}\sum_{i=0}^{\lfloor \log_b n \rfloor - 1} a^i f\left(\frac{n}{b^i}\right) &= O\left(n^{\log_b a - \varepsilon} \frac{(b^\varepsilon)^{\lfloor \log_b n \rfloor} - 1}{b^\varepsilon - 1}\right) \\&= O\left(n^{\log_b a - \varepsilon} \frac{\left(b^{\lfloor \log_b n \rfloor}\right)^\varepsilon - 1}{b^\varepsilon - 1}\right) \\&= O\left(n^{\log_b a - \varepsilon} \frac{n^\varepsilon - 1}{b^\varepsilon - 1}\right) \\&= O\left(\frac{n^{\log_b a} - n^{\log_b a - \varepsilon}}{b^\varepsilon - 1}\right) \\&= O\left(n^{\log_b a}\right)\end{aligned}$$

# Master Theorem Proof:

## Case 1 - continued:

$$\begin{aligned}\sum_{i=0}^{\lfloor \log_b n \rfloor - 1} a^i f\left(\frac{n}{b^i}\right) &= O\left(n^{\log_b a - \varepsilon} \frac{(b^\varepsilon)^{\lfloor \log_b n \rfloor} - 1}{b^\varepsilon - 1}\right) \\ &= O\left(n^{\log_b a - \varepsilon} \frac{\left(b^{\lfloor \log_b n \rfloor}\right)^\varepsilon - 1}{b^\varepsilon - 1}\right) \\ &= O\left(n^{\log_b a - \varepsilon} \frac{n^\varepsilon - 1}{b^\varepsilon - 1}\right) \\ &= O\left(\frac{n^{\log_b a} - n^{\log_b a - \varepsilon}}{b^\varepsilon - 1}\right) \\ &= O\left(n^{\log_b a}\right)\end{aligned}$$

Since we had:  $T(n) \approx n^{\log_b a} T(1) + \sum_{i=0}^{\lfloor \log_b n \rfloor - 1} a^i f\left(\frac{n}{b^i}\right)$  we get:



# Master Theorem Proof:

## Case 1 - continued:

$$\begin{aligned}\sum_{i=0}^{\lfloor \log_b n \rfloor - 1} a^i f\left(\frac{n}{b^i}\right) &= O\left(n^{\log_b a - \varepsilon} \frac{(b^\varepsilon)^{\lfloor \log_b n \rfloor} - 1}{b^\varepsilon - 1}\right) \\&= O\left(n^{\log_b a - \varepsilon} \frac{\left(b^{\lfloor \log_b n \rfloor}\right)^\varepsilon - 1}{b^\varepsilon - 1}\right) \\&= O\left(n^{\log_b a - \varepsilon} \frac{n^\varepsilon - 1}{b^\varepsilon - 1}\right) \\&= O\left(\frac{n^{\log_b a} - n^{\log_b a - \varepsilon}}{b^\varepsilon - 1}\right) \\&= O\left(n^{\log_b a}\right)\end{aligned}$$

Since we had:  $T(n) \approx n^{\log_b a} T(1) + \sum_{i=0}^{\lfloor \log_b n \rfloor - 1} a^i f\left(\frac{n}{b^i}\right)$  we get:

$$\begin{aligned}T(n) &\approx n^{\log_b a} T(1) + O\left(n^{\log_b a}\right) \\&= \Theta\left(n^{\log_b a}\right)\end{aligned}$$

# Master Theorem Proof:

**Case 2:**  $f(m) = \Theta(m^{\log_b a})$

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$$\sum_{i=0}^{\lfloor \log_b n \rfloor - 1} a^i f\left(\frac{n}{b^i}\right) = \sum_{i=0}^{\lfloor \log_b n \rfloor - 1} a^i \Theta\left(\frac{n}{b^i}\right)^{\log_b a}$$

# Master Theorem Proof:

**Case 2:**  $f(m) = \Theta(m^{\log_b a})$

$$\begin{aligned}\sum_{i=0}^{\lfloor \log_b n \rfloor - 1} a^i f\left(\frac{n}{b^i}\right) &= \sum_{i=0}^{\lfloor \log_b n \rfloor - 1} a^i \Theta\left(\left(\frac{n}{b^i}\right)^{\log_b a}\right) \\ &= \Theta\left(\sum_{i=0}^{\lfloor \log_b n \rfloor - 1} a^i \left(\frac{n}{b^i}\right)^{\log_b a}\right)\end{aligned}$$

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**Case 2:**  $f(m) = \Theta(m^{\log_b a})$

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**Case 2:**  $f(m) = \Theta(m^{\log_b a})$

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# Master Theorem Proof:

**Case 2:**  $f(m) = \Theta(m^{\log_b a})$

$$\begin{aligned}\sum_{i=0}^{\lfloor \log_b n \rfloor - 1} a^i f\left(\frac{n}{b^i}\right) &= \sum_{i=0}^{\lfloor \log_b n \rfloor - 1} a^i \Theta\left(\left(\frac{n}{b^i}\right)^{\log_b a}\right) \\&= \Theta\left(\sum_{i=0}^{\lfloor \log_b n \rfloor - 1} a^i \left(\frac{n}{b^i}\right)^{\log_b a}\right) \\&= \Theta\left(n^{\log_b a} \sum_{i=0}^{\lfloor \log_b n \rfloor - 1} \left(\frac{a^i}{(b^i)^{\log_b a}}\right)\right) \\&= \Theta\left(n^{\log_b a} \sum_{i=0}^{\lfloor \log_b n \rfloor - 1} \left(\frac{a}{b^{\log_b a}}\right)^i\right) \\&= \Theta\left(n^{\log_b a} \sum_{i=0}^{\lfloor \log_b n \rfloor - 1} 1\right)\end{aligned}$$

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**Case 2:**  $f(m) = \Theta(m^{\log_b a})$

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# Master Theorem Proof:

## Case 2 (continued):

Thus,

$$\sum_{i=0}^{\lfloor \log_b n \rfloor - 1} a^i f\left(\frac{n}{b^i}\right) = \Theta\left(n^{\log_b a} \log_b n\right) = \Theta\left(n^{\log_b a} \log_2 n\right)$$

# Master Theorem Proof:

## Case 2 (continued):

Thus,

$$\sum_{i=0}^{\lfloor \log_b n \rfloor - 1} a^i f\left(\frac{n}{b^i}\right) = \Theta\left(n^{\log_b a} \log_b n\right) = \Theta\left(n^{\log_b a} \log_2 n\right)$$

because  $\log_b n = \log_2 n \cdot \log_b 2 = \Theta(\log_2 n)$ . Since we had (1):

$$T(n) \approx n^{\log_b a} T(1) + \sum_{i=0}^{\lfloor \log_b n \rfloor - 1} a^i f\left(\frac{n}{b^i}\right)$$

# Master Theorem Proof:

## Case 2 (continued):

Thus,

$$\sum_{i=0}^{\lfloor \log_b n \rfloor - 1} a^i f\left(\frac{n}{b^i}\right) = \Theta\left(n^{\log_b a} \log_b n\right) = \Theta\left(n^{\log_b a} \log_2 n\right)$$

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$$T(n) \approx n^{\log_b a} T(1) + \sum_{i=0}^{\lfloor \log_b n \rfloor - 1} a^i f\left(\frac{n}{b^i}\right)$$

we get:

$$\begin{aligned} T(n) &\approx n^{\log_b a} T(1) + \Theta\left(n^{\log_b a} \log_2 n\right) \\ &= \Theta\left(n^{\log_b a} \log_2 n\right) \end{aligned}$$

# Master Theorem Proof:

**Case 3:**  $f(m) = \Omega(m^{\log_b a + \varepsilon})$  and  $a f(n/b) \leq c f(n)$  for some  $0 < c < 1$ .

We get by substitution:

$$f(n/b) \leq \frac{c}{a} f(n)$$

$$f(n/b^2) \leq \frac{c}{a} f(n/b)$$

$$f(n/b^3) \leq \frac{c}{a} f(n/b^2)$$

$$\dots$$
$$f(n/b^i) \leq \frac{c}{a} f(n/b^{i-1})$$

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**Case 3:**  $f(m) = \Omega(m^{\log_b a + \varepsilon})$  and  $a f(n/b) \leq c f(n)$  for some  $0 < c < 1$ .

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By chaining these inequalities we get

$$\begin{aligned} f(n/b^2) &\leq \frac{c}{a} \underbrace{f(n/b)}_{\leq \frac{c}{a} f(n)} \leq \frac{c}{a} \cdot \frac{c}{a} f(n) = \frac{c^2}{a^2} f(n) \\ f(n/b^3) &\leq \frac{c}{a} \underbrace{f(n/b^2)}_{\leq \frac{c^2}{a^2} f(n)} \leq \frac{c}{a} \cdot \frac{c^2}{a^2} f(n) = \frac{c^3}{a^3} f(n) \\ &\dots \\ f(n/b^i) &\leq \frac{c}{a} \underbrace{f(n/b^{i-1})}_{\leq \frac{c^{i-1}}{a^{i-1}} f(n)} \leq \frac{c}{a} \cdot \frac{c^{i-1}}{a^{i-1}} f(n) = \frac{c^i}{a^i} f(n) \end{aligned}$$

# Master Theorem Proof:

## Case 3 (continued):

We got  $f(n/b^i) \leq \frac{c^i}{a^i} f(n)$

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$$\sum_{i=0}^{\lfloor \log_b n \rfloor - 1} a^i f\left(\frac{n}{b^i}\right) \leq \sum_{i=0}^{\lfloor \log_b n \rfloor - 1} a^i \frac{c^i}{a^i} f(n) < f(n) \sum_{i=0}^{\infty} c^i = \frac{f(n)}{1-c}$$

# Master Theorem Proof:

## Case 3 (continued):

We got  $f(n/b^i) \leq \frac{c^i}{a^i} f(n)$

Thus,

$$\sum_{i=0}^{\lfloor \log_b n \rfloor - 1} a^i f\left(\frac{n}{b^i}\right) \leq \sum_{i=0}^{\lfloor \log_b n \rfloor - 1} a^i \frac{c^i}{a^i} f(n) < f(n) \sum_{i=0}^{\infty} c^i = \frac{f(n)}{1-c}$$

Since we had (1):

$$T(n) \approx n^{\log_b a} T(1) + \sum_{i=0}^{\lfloor \log_b n \rfloor - 1} a^i f\left(\frac{n}{b^i}\right)$$



# Master Theorem Proof:

## Case 3 (continued):

We got 
$$f(n/b^i) \leq \frac{c^i}{a^i} f(n)$$

Thus,

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Since we had (1):

$$T(n) \approx n^{\log_b a} T(1) + \sum_{i=0}^{\lfloor \log_b n \rfloor - 1} a^i f\left(\frac{n}{b^i}\right)$$

and since  $f(n) = \Omega(n^{\log_b a + \epsilon})$  we get:

$$T(n) < n^{\log_b a} T(1) + O(f(n)) = O(f(n))$$

# Master Theorem Proof:

## Case 3 (continued):

We got 
$$f(n/b^i) \leq \frac{c^i}{a^i} f(n)$$

Thus,

$$\sum_{i=0}^{\lfloor \log_b n \rfloor - 1} a^i f\left(\frac{n}{b^i}\right) \leq \sum_{i=0}^{\lfloor \log_b n \rfloor - 1} a^i \frac{c^i}{a^i} f(n) < f(n) \sum_{i=0}^{\infty} c^i = \frac{f(n)}{1-c}$$

Since we had (1):

$$T(n) \approx n^{\log_b a} T(1) + \sum_{i=0}^{\lfloor \log_b n \rfloor - 1} a^i f\left(\frac{n}{b^i}\right)$$

and since  $f(n) = \Omega(n^{\log_b a + \epsilon})$  we get:

$$T(n) < n^{\log_b a} T(1) + O(f(n)) = O(f(n))$$

but we also have

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

# Master Theorem Proof:

## Case 3 (continued):

We got 
$$f(n/b^i) \leq \frac{c^i}{a^i} f(n)$$

Thus,

$$\sum_{i=0}^{\lfloor \log_b n \rfloor - 1} a^i f\left(\frac{n}{b^i}\right) \leq \sum_{i=0}^{\lfloor \log_b n \rfloor - 1} a^i \frac{c^i}{a^i} f(n) < f(n) \sum_{i=0}^{\infty} c^i = \frac{f(n)}{1-c}$$

Since we had (1):

$$T(n) \approx n^{\log_b a} T(1) + \sum_{i=0}^{\lfloor \log_b n \rfloor - 1} a^i f\left(\frac{n}{b^i}\right)$$

and since  $f(n) = \Omega(n^{\log_b a + \epsilon})$  we get:

$$T(n) < n^{\log_b a} T(1) + O(f(n)) = O(f(n))$$

but we also have

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

thus,

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

# Master Theorem Proof: Homework

**Exercise 1:** Show that condition

$$f(n) = \Omega(n^{\log_b a + \varepsilon})$$

follows from the condition

$$a f(n/b) \leq c f(n) \text{ for some } 0 < c < 1.$$

**Exercise 2:** Estimate  $T(n)$  for

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

**Note:** we have seen that the Master Theorem does **NOT** apply, but the technique used in its proof still works! Just unwind the recurrence and sum up the logarithmic overheads.