

CS146: Data Structures and Algorithms

Lecture 5



SOLVING RECURRENCE RELATIONS

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Recurrence Examples

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$$T(n) = \begin{cases} 1 & \text{if } n = 1, \\ T(n-1) + 1 & \text{if } n > 1. \end{cases}$$

Solution: $T(n) = n$.

$$T(n) = \begin{cases} 1 & \text{if } n = 1, \\ 2T(n/2) + n & \text{if } n \geq 2. \end{cases}$$

Solution: $T(n) = n \lg n + n$.

$$T(n) = \begin{cases} 0 & \text{if } n = 2, \\ T(\sqrt{n}) + 1 & \text{if } n > 2. \end{cases}$$

Solution: $T(n) = \lg \lg n$.

$$T(n) = \begin{cases} 1 & \text{if } n = 1, \\ T(n/3) + T(2n/3) + n & \text{if } n > 1. \end{cases}$$

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

Change of variables

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- $T(n) = T(\sqrt{n}) + 1$

Replace $m = \lg n$

- $T(2^m) = T(2^{m/2}) + 1$

Rename $S(m) = T(2^m)$

- $S(m) = S(m/2) + 1 = \lg m$

- $T(n) = T(2^m) = S(m) = \lg m = \lg \lg n$

Solving Recurrences

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1. Substitution method
2. Iteration method
3. Master method

Solving Recurrences

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- 1. The substitution method (CLR 4.1)
 - A.k.a. the “making a good guess method”
 - Guess the form of the answer, then use induction to find the constants and show that solution works
 - Examples:
 - ✦ $T(n) = 2T(n/2) + \Theta(n) \rightarrow T(n) = \Theta(n \lg n)$
 - ✦ $T(n) = 2T(\lfloor n/2 \rfloor) + n \rightarrow T(n) = \Theta(n \lg n)$
 - ✦ $T(n) = 2T(\lfloor n/2 \rfloor + 17) + n \rightarrow \Theta(n \lg n)$

Substitution method

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- Guess the form of the solution
- Use mathematical induction to find constants and show that your guess was correct

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

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- Upper bound of $T(n) \leq 2T(n/2) + cn$, $c \geq 0$
- Guess: $T(n) \leq dn \lg n$, constant $d \geq 0$
- Substitution:

$$\begin{aligned} T(n) &\leq 2T(n/2) + cn \\ &= 2 \left(d \frac{n}{2} \lg \frac{n}{2} \right) + cn \\ &= dn \lg \frac{n}{2} + cn \\ &= dn \lg n - dn + cn \\ &\leq dn \lg n \quad \text{if } \begin{array}{l} -dn + cn \leq 0, \\ d \geq c \end{array} \end{aligned}$$

- Therefore, $T(n) = O(n \lg n)$.

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

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- Lower bound of $T(n) \geq 2T(n/2) + cn$
- *Guess:* $T(n) \geq dn \lg n$, constant $d \geq 0$

- *Substitution:*

$$\begin{aligned} T(n) &\geq 2T(n/2) + cn \\ &= 2 \left(d \frac{n}{2} \lg \frac{n}{2} \right) + cn \\ &= dn \lg \frac{n}{2} + cn \\ &= dn \lg n - dn + cn \\ &\geq dn \lg n \quad \text{if } \begin{matrix} -dn + cn \geq 0, \\ d \leq c \end{matrix} \end{aligned}$$

- Therefore, $T(n) = \Omega(n \lg n)$.

Careful

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The false proof for the recurrence

$$T(n) = 4T(n/4) + n, \text{ that } T(n) = O(n):$$

$$\text{Proof: } T(n) \leq 4(c(n/4)) + n \leq cn + n = O(n)$$

wrong!

Why?

Because we haven't proven the *exact form* of our inductive hypothesis (which is that $T(n) \leq cn$), this proof is false.

Solving Recurrences

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- Another option is what the book calls the “iteration method”
 - Expand the recurrence
 - Work some algebra to express as a summation
 - Evaluate the summation
- We will show several examples

$$s(n) = \begin{cases} 0 & n = 0 \\ c + s(n-1) & n > 0 \end{cases}$$

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- $s(n) =$
 - $c + s(n-1)$
 - $c + c + s(n-2)$
 - $2c + s(n-2)$
 - $2c + c + s(n-3)$
 - $3c + s(n-3)$
 - ...
 - $kc + s(n-k) = ck + s(n-k)$

$$s(n) = \begin{cases} 0 & n = 0 \\ c + s(n-1) & n > 0 \end{cases}$$

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- So far for $n \geq k$ we have
 - $s(n) = ck + s(n-k)$
- What if $k = n$?
 - $s(n) = cn + s(0) = cn$

$$s(n) = \begin{cases} 0 & n = 0 \\ c + s(n-1) & n > 0 \end{cases}$$

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- So far for $n \geq k$ we have

- $s(n) = ck + s(n-k)$

- What if $k = n$?

- $s(n) = cn + s(0) = cn$

- So

- Thus in general

- $s(n) = cn$

$$s(n) = \begin{cases} 0 & n = 0 \\ c + s(n-1) & n > 0 \end{cases}$$

$$s(n) = \begin{cases} 0 & n = 0 \\ n + s(n-1) & n > 0 \end{cases}$$

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- $s(n)$

$$\begin{aligned}
 &= n + s(n-1) \\
 &= n + n-1 + s(n-2) \\
 &= n + n-1 + n-2 + s(n-3) \\
 &= n + n-1 + n-2 + n-3 + s(n-4) \\
 &= \dots \\
 &= n + n-1 + n-2 + n-3 + \dots + n-(k-1) + s(n-k)
 \end{aligned}$$

$$s(n) = \begin{cases} 0 & n = 0 \\ n + s(n-1) & n > 0 \end{cases}$$

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• $s(n)$

$$= n + s(n-1)$$

$$= n + n-1 + s(n-2)$$

$$= n + n-1 + n-2 + s(n-3)$$

$$= n + n-1 + n-2 + n-3 + s(n-4)$$

$$= \dots$$

$$= n + n-1 + n-2 + n-3 + \dots + n-(k-1) + s(n-k)$$

$$=$$

$$\sum_{i=n-k+1}^n i + s(n-k)$$

$$s(n) = \begin{cases} 0 & n = 0 \\ n + s(n-1) & n > 0 \end{cases}$$

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- So far for $n \geq k$ we have

$$\sum_{i=n-k+1}^n i + s(n-k)$$

$$s(n) = \begin{cases} 0 & n = 0 \\ n + s(n-1) & n > 0 \end{cases}$$

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- So far for $n \geq k$ we have

$$\sum_{i=n-k+1}^n i + s(n-k)$$

- What if $k = n$?

$$s(n) = \begin{cases} 0 & n = 0 \\ n + s(n-1) & n > 0 \end{cases}$$

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- So far for $n \geq k$ we have

$$\sum_{i=n-k+1}^n i + s(n-k)$$

- What if $k = n$?

$$\sum_{i=1}^n i + s(0) = \sum_{i=1}^n i + 0 = n \frac{n+1}{2}$$

$$s(n) = \begin{cases} 0 & n = 0 \\ n + s(n-1) & n > 0 \end{cases}$$

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- So far for $n \geq k$ we have

$$\sum_{i=n-k+1}^n i + s(n-k)$$

- What if $k = n$?

$$\sum_{i=1}^n i + s(0) = \sum_{i=1}^n i + 0 = n \frac{n+1}{2}$$

- Thus in general

$$s(n) = n \frac{n+1}{2}$$

- $T(n) =$
 $2T(n/2) + c$
 $2(2T(n/2/2) + c) + c$
 $2^2T(n/2^2) + 2c + c$
 $2^2(2T(n/2^2/2) + c) + 3c$
 $2^3T(n/2^3) + 4c + 3c$
 $2^3T(n/2^3) + 7c$
 $2^3(2T(n/2^3/2) + c) + 7c$
 $2^4T(n/2^4) + 15c$
...
 $2^kT(n/2^k) + (2^k - 1)c$

$$T(n) = \begin{cases} c & n = 1 \\ 2T\left(\frac{n}{2}\right) + c & n > 1 \end{cases}$$

- So far for $n > 2^k$ we have
 - $T(n) = 2^k T(n/2^k) + (2^k - 1)c$
- What if $k = \lg n$?
 - $T(n) = 2^{\lg n} T(n/2^{\lg n}) + (2^{\lg n} - 1)c$
 $= n T(n/n) + (n - 1)c$
 $= n T(1) + (n-1)c$
 $= nc + (n-1)c = (2n - 1)c$

$$T(n) = \begin{cases} c & n = 1 \\ 2T\left(\frac{n}{2}\right) + c & n > 1 \end{cases}$$

Solving Recurrences

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- The “iteration method”
 - Expand the recurrence
 - Work some algebra to express as a summation
 - Evaluate the summation

The Master Theorem

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Given: a *divide and conquer* algorithm

Algorithm divides the problem of size n into a subproblems, each of size n/b

The cost of each phase (i.e., time to divide the problem + combine solved subproblems) be described by the function $f(n)$

Then, the Master Theorem gives us a “cookbook” for the algorithm’s running time:

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

The Master Theorem

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

$$T(n) = \left\{ \begin{array}{ll} \Theta\left(n^{\log_b a}\right) & , \text{if } f(n) = O\left(n^{\log_b a - \varepsilon}\right) \\ \Theta\left(n^{\log_b a} \log n\right) & , \text{if } f(n) = \Theta\left(n^{\log_b a}\right) \\ \Theta\left(f(n)\right) & , \text{if } f(n) = \Omega\left(n^{\log_b a + \varepsilon}\right) \text{ AND} \\ & af(n/b) < cf(n) \text{ for large } n \end{array} \right\} \begin{array}{l} \varepsilon > 0 \\ c < 1 \end{array}$$

Using The Master Method

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$$T(n) = 9T(n/3) + n$$

$$a=9, b=3, f(n) = n$$

$$n^{\log_b a} = n^{\log_3 9} = n^2$$

Since $n = O(n^{\log_3 9 - \epsilon})$, where $\epsilon=1$, case 1 applies:

Thus the solution is $T(n) = \Theta(n^2)$

$$T(n)=T(2n/3)+1$$

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$$a=1, b=3/2, f(n)=1$$

$$\text{Case 2 } T(n)=\Theta(\lg n)$$

$$T(n)=3T(n/4)+n\log n$$

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$A=3, b=4,$

Case 3 $T(n)=\Theta(n\lg n)$

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

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$$A=2, b=2, f(n)=\lg n$$

Gap between case 2 and 3

So Master Theorem does not solve every $T(n) = aT(n/b) + f(n)$ ☹

Self test



What is the asymptotic complexity of

$$T(n) = 7T(n/2) + cn^2$$

(remember Strassen's Algorithm for Matrix Multiplication)

A. $T(n) = \Theta(n^{\log_2 7})$

B. $T(n) = \Theta(n^{\log_2 7} * \log_2 n)$

C. $T(n) = \Theta(n^2)$

D. $T(n) = \Theta(n \lg n)$

Self test

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What is the asymptotic complexity of

$$T(n) = 9T\left(\frac{n}{3}\right) + n^2:$$

- a. $\Theta(n^2 \lg n)$
- b. $\Theta((n^2)^2)$
- c. $\Theta(n^2)$
- d. None of the above

Example: Compare Algorithms

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- Algorithm A solves problems by dividing them into 2 subproblems of half the size, recursively solving each subproblem, and then combining the solutions in $O(\sqrt{n})$
- Algorithm B solves problems of size n by recursively solving one subproblem of size $n-1$ and additional operations take linear time
- Algorithm C solves problems of size n by dividing them into 8 subproblems of size $n/4$, recursively solving each subproblem, and then combining the solutions in $O(n^3)$ time.
- What are the running times of each of these algorithms (in big-O notation), and which would you choose?