

Lecture 5: Master Method and Quick-Sort

(CLRS 4.3-4.4 (read this note instead), 7.1-7.2)

May 22nd, 2002

1 Master Method (recurrences)

- We have solved several recurrences using *substitution* and *iteration*.
- Last time we solved several recurrences of the form $T(n) = aT(n/b) + n^c$ ($T(1) = 1$).
 - Strassen's algorithm $\Rightarrow T(n) = 7T(n/2) + n^2$ ($a = 7, b = 2$, and $c = 2$)
 - Merge-sort $\Rightarrow T(n) = 2T(n/2) + n$ ($a = 2, b = 2$, and $c = 1$).
- It would be nice to have a general solution to the recurrence $T(n) = aT(n/b) + n^c$.
- We do!

$$\boxed{\begin{array}{l} T(n) = aT\left(\frac{n}{b}\right) + n^c \quad a \geq 1, b \geq 1, c > 0 \\ \Downarrow \\ T(n) = \begin{cases} \Theta(n^{\log_b a}) & a > b^c \\ \Theta(n^c \log_b n) & a = b^c \\ \Theta(n^c) & a < b^c \end{cases} \end{array}}$$

Proof (Iteration method)

$$\begin{aligned} T(n) &= aT\left(\frac{n}{b}\right) + n^c \\ &= n^c + a\left(\left(\frac{n}{b}\right)^c + aT\left(\frac{n}{b^2}\right)\right) \\ &= n^c + \left(\frac{a}{b^c}\right)n^c + a^2T\left(\frac{n}{b^2}\right) \\ &= n^c + \left(\frac{a}{b^c}\right)n^c + a^2\left(\left(\frac{n}{b^2}\right)^c + aT\left(\frac{n}{b^3}\right)\right) \\ &= n^c + \left(\frac{a}{b^c}\right)n^c + \left(\frac{a}{b^c}\right)^2n^c + a^3T\left(\frac{n}{b^3}\right) \\ &= \dots \\ &= n^c + \left(\frac{a}{b^c}\right)n^c + \left(\frac{a}{b^c}\right)^2n^c + \left(\frac{a}{b^c}\right)^3n^c + \left(\frac{a}{b^c}\right)^4n^c + \dots + \left(\frac{a}{b^c}\right)^{\log_b n - 1}n^c + a^{\log_b n}T(1) \\ &= n^c \sum_{k=0}^{\log_b n - 1} \left(\frac{a}{b^c}\right)^k + a^{\log_b n} \\ &= n^c \sum_{k=0}^{\log_b n - 1} \left(\frac{a}{b^c}\right)^k + n^{\log_b a} \end{aligned}$$

Recall geometric sum $\sum_{k=0}^n x^k = \frac{x^{n+1} - 1}{x - 1} = \Theta(x^n)$

- $a < b^c$

$$a < b^c \Leftrightarrow \frac{a}{b^c} < 1 \Rightarrow \sum_{k=0}^{\log_b n - 1} \left(\frac{a}{b^c}\right)^k \leq \sum_{k=0}^{+\infty} \left(\frac{a}{b^c}\right)^k = \frac{1}{1 - \left(\frac{a}{b^c}\right)} = \Theta(1)$$

$$a < b^c \Leftrightarrow \log_b a < \log_b b^c = c$$

$$\begin{aligned} T(n) &= n^c \sum_{k=0}^{\log_b n - 1} \left(\frac{a}{b^c}\right)^k + n^{\log_b a} \\ &= n^c \cdot \Theta(1) + n^{\log_b a} \\ &= \Theta(n^c) \end{aligned}$$

- $a = b^c$

$$a = b^c \Leftrightarrow \frac{a}{b^c} = 1 \Rightarrow \sum_{k=0}^{\log_b n-1} \left(\frac{a}{b^c}\right)^k = \sum_{k=0}^{\log_b n-1} 1 = \Theta(\log_b n)$$

$$a = b^c \Leftrightarrow \log_b a = \log_b b^c = c$$

$$\begin{aligned} T(n) &= \sum_{k=0}^{\log_b n-1} \left(\frac{a}{b^c}\right)^k + n^{\log_b a} \\ &= n^c \Theta(\log_b n) + n^{\log_b a} \\ &= \Theta(n^c \log_b n) \end{aligned}$$

- $a > b^c$

$$a > b^c \Leftrightarrow \frac{a}{b^c} > 1 \Rightarrow \sum_{k=0}^{\log_b n-1} \left(\frac{a}{b^c}\right)^k = \Theta\left(\left(\frac{a}{b^c}\right)^{\log_b n}\right) = \Theta\left(\frac{a^{\log_b n}}{(b^c)^{\log_b n}}\right) = \Theta\left(\frac{a^{\log_b n}}{n^c}\right)$$

$$\begin{aligned} T(n) &= n^c \cdot \Theta\left(\frac{a^{\log_b n}}{n^c}\right) + n^{\log_b a} \\ &= \Theta(n^{\log_b a}) + n^{\log_b a} \\ &= \Theta(n^{\log_b a}) \end{aligned}$$

- Note: Book states and proves the result slightly differently (don't read it).

1.1 Other recurrences

Some important/typical bounds on recurrences not covered by master method:

- Logarithmic: $\Theta(\log n)$
 - Recurrence: $T(n) = 1 + T(n/2)$
 - Typical example: Recurse on half the input (and throw half away)
 - Variations: $T(n) = 1 + T(99n/100)$
- Linear: $\Theta(N)$
 - Recurrence: $T(n) = 1 + T(n-1)$
 - Typical example: Single loop
 - Variations: $T(n) = 1 + 2T(n/2)$, $T(n) = n + T(n/2)$, $T(n) = T(n/5) + T(7n/10 + 6) + n$
- Quadratic: $\Theta(n^2)$
 - Recurrence: $T(n) = n + T(n-1)$
 - Typical example: Nested loops
- Exponential: $\Theta(2^n)$
 - Recurrence: $T(n) = 2T(n-1)$

2 Quick-sort

- We previously saw how divide-and-conquer can be used to design sorting algorithm—Merge-sort
 - Partition n elements array A into two subarrays of $n/2$ elements each
 - Sort the two subarrays recursively
 - Merge the two subarrays

Running time: $T(n) = 2T(n/2) + \Theta(n) \Rightarrow T(n) = \Theta(n \log n)$

- Another possibility is to use the “opposite” version of divide-and-conquer—Quick-sort
 - Partition $A[1..n]$ into subarrays $A' = A[1..q]$ and $A'' = A[q+1..n]$ such that all elements in A'' are larger than all elements in A' .
 - Recursively sort A' and A'' .
 - (nothing to combine/merge. A already sorted after sorting A' and A'')

If $q = n/2$ and we divide in $\Theta(n)$ time, we again get the recurrence $T(n) = 2T(n/2) + \Theta(n)$ for the running time $\Rightarrow T(n) = \Theta(n \log n)$

The problem is that it is hard to develop partition algorithm which always divide A in two halves

- Pseudo code for Quick-sort:

```

QUICKSORT( $A, p, r$ )
IF  $p < r$  THEN
     $q = \text{PARTITION}(A, p, r)$ 
    QUICKSORT( $A, p, q - 1$ )
    QUICKSORT( $A, q + 1, r$ )
FI
  
```

Sort using QUICKSORT($A, 1, n$)

```

PARTITION( $A, p, r$ )
 $x = A[r]$ 
 $i = p - 1$ 
FOR  $j = p$  TO  $r - 1$  DO
    IF  $A[j] \leq x$  THEN
         $i = i + 1$ 
        Exchange  $A[i]$  and  $A[j]$ 
    FI
OD
Exchange  $A[i + 1]$  and  $A[r]$ 
RETURN  $i + 1$ 
  
```

- PARTITION runs in time $\Theta(n)$

- Correctness:

- Clear if PARTITION divides correctly

- Example:

2	8	7	1	3	5	6	4	i=0, j=1
2	8	7	1	3	5	6	4	i=1, j=2
2	8	7	1	3	5	6	4	i=1, j=3
2	8	7	1	3	5	6	4	i=1, j=4
2	1	7	8	3	5	6	4	i=2, j=5
2	1	3	8	7	5	6	4	i=3, j=6
2	1	3	8	7	5	6	4	i=3, j=7
2	1	3	8	7	5	6	4	i=3, j=8
2	1	3	4	7	5	6	8	q=4

- PARTITION can be proved correct (by induction) using the loop invariant:

- * $A[k] \leq x$ for $p \leq k \leq i$
- * $A[k] > x$ for $i + 1 \leq k \leq j - 1$
- * $A[k] = x$ for $k = r$

- Running time depends on how well PARTITION divides A .

- In the example it does reasonably well.

- In the worst case q is always p and the running time becomes $T(n) = \Theta(n) + T(1) + T(n - 1) \Rightarrow T(n) = \Theta(n^2)$.

- * and what is maybe even worse, the worst case is when A is already sorted.

- So why is it called "quick"-sort? Because it "often" performs very well—can we theoretically justify this?

- Even if all the splits are relatively bad, we get $\Theta(n \log n)$ time:

- * Example: Split is $\frac{9}{10}n, \frac{1}{10}n$.
- $T(n) = T(\frac{9}{10}n) + T(\frac{1}{10}n) + n$
- Solution?
- Guess: $T(n) \leq cn \log n$
- Induction

$$\begin{aligned}
 T(n) &= T\left(\frac{9}{10}n\right) + T\left(\frac{1}{10}n\right) + n \\
 &\leq \frac{9cn}{10} \log\left(\frac{9n}{10}\right) + \frac{cn}{10} \log\left(\frac{n}{10}\right) + n \\
 &\leq \frac{9cn}{10} \log n + \frac{9cn}{10} \log\left(\frac{9}{10}\right) + \frac{cn}{10} \log n + \frac{cn}{10} \log\left(\frac{1}{10}\right) + n \\
 &\leq cn \log n + \frac{9cn}{10} \log 9 - \frac{9cn}{10} \log 10 - \frac{cn}{10} \log 10 + n \\
 &\leq cn \log n - n\left(c \log 10 - \frac{9c}{10} \log 9 - 1\right)
 \end{aligned}$$

$T(n) \leq cn \log n$ if $c \log 10 - \frac{9c}{10} \log 9 - 1 > 0$ which is definitely true if $c > \frac{10}{\log 10}$

- So, in other words, if just the splits happen at a constant fraction of n we get $\Theta(n \lg n)$ —or, its almost never bad!
- Next time we will further justify the good practical performance by looking at average case running time.