Data Structures and Algorithms (CS210A) Semester I – 2014-15

Lecture 15:

• Solving recurrences that occur frequently in the analysis of algorithms.

Commonly occurring recurrences

 $T(n) = \frac{n!}{2} \frac{1}{2} \frac{1}$

Methods for solving Common Recurrences in algorithm analysis

Methods for solving common Recurrences

- Unfolding the recurrence.
- **Guessing** the solution and then <u>proving by induction</u>.
- A General solution for <u>a large class</u> of recurrences (Master theorem)

Solving a recurrence by unfolding

Let **T**(1) = 1,

T(n) = c n + 4 T(n/2) for n > 1, where c is some positive constant

Solving the recurrence for **T**(*n*) by **unfolding** (expanding)

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

= $cn + 2cn + 4^2 T(n/2^2)$
= $cn + 2cn + 4cn + 4^3 T(n/2^3)$
= $cn + 2 cn + 4cn + 8cn + ... + 4^{\log_2 n}$
= $cn + 2 cn + 4cn + 8cn + ... + n^2$

A geometric increasing series with log *n* terms and common ratio 2

Solving a recurrence by guessing and then proving by induction



Solving a recurrence by guessing and then proving by induction

Key points:

- You have to make a <u>right guess</u> (past experience may help)
- What if your guess is too loose ?
- Be <u>careful</u> in the **induction step**.

Solving a recurrence by guessing and then proving by induction

Exercise: Find error in the following reasoning. For the recurrence $T(1) = c_1$, and $T(n) = 2T(n/2) + c_2 n$,

one guesses T(n) = O(n)

Proposed (wrong)proof by induction:

Induction hypothesis: $T(k) \le ak$ for all k < n $T(n) = 2T(n/2) + c_2 n$ $\le 2(a\frac{n}{2}) + c_2 n //$ by induction hypothesis $= an + c_2 n$ = O(n)

A General Method for solving a large class of Recurrences

Solving a large class of recurrences

T(1) = 1, T(n) = f(n) + a T(n/b)Where

- a and b are constants and b >1
- **f**(*n*) is a *multiplicative* function:

 $\mathbf{f}(xy) = \mathbf{f}(x)\mathbf{f}(y)$

AIM : To solve T(n) for $n = b^k$

Warm-up



Question: Can you express $a^{\log_b c}$ as power of c? Answer: $= c^{\log_b a}$

Solving a slightly general class of recurrences

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

= f(n) + a f(n/b) + a²T(n/b²)
= f(n) + a f(n/b) + a²f(n/b²) + a³T(n/b³)
= ...
= f(n) + a f(n/b) + ... + aⁱf(n/bⁱ) + ... + a^{k-1}f(n/b^{k-1}) + a^kT(1)
= $\left(\sum_{i=0}^{k-1} a^{i}f(n/b^{i})\right) + a^{k}$
... after rearranging ...
= $a^{k} + \sum_{i=0}^{k-1} a^{i}f(n/b^{i})$

... continued to the next page ...

 $T(n) = a^{k} + \sum_{i=0}^{k-1} a^{i} f(n/b^{i})$ (since f is multiplicative) $= a^{k} + \sum_{i=0}^{k-1} a^{i} f(n) / f(b^{i})$ $= a^{k} + \sum_{i=0}^{k-1} a^{i} f(n) / (f(b))^{i}$ $= a^{k} + f(n) \sum_{i=0}^{k-1} a^{i} / (f(b))^{i}$ $= a^{k} + f(n) \sum_{i=0}^{k-1} (a/f(b))^{i}$ A geometric series $= a^{k} + (\mathbf{f}(b))^{k} \sum_{i=0}^{k-1} (a/\mathbf{f}(b))^{i}$

Case 1: a = f(b), $T(n) = \begin{bmatrix} a^k(k+1) \end{bmatrix} = O(a^{\log_b n} \log_b n) \end{bmatrix} = O(n^{\log_b a} \log_b n)$

$$T(n) = a^{k} + \sum_{i=0}^{k-1} a^{i} f(n/b^{i})$$
(since f is multiplicative)

$$= a^{k} + \sum_{i=0}^{k-1} a^{i} f(n) / f(b^{i})$$

$$= a^{k} + \sum_{i=0}^{k-1} a^{i} f(n) / (f(b))^{i}$$

$$= a^{k} + f(n) \sum_{i=0}^{k-1} a^{i} / (f(b))^{i}$$
For $a < f(b)$, the sum of this series is bounded by

$$= a^{k} + f(n) \sum_{i=0}^{k-1} (a/f(b))^{i}$$

$$= a^{k} + (f(b))^{k} \sum_{i=0}^{k-1} (a/f(b))^{i}$$
Case 2: $a < f(b)$, $T(n) = a^{k} + (f(b))^{k} \cdot O(1) = O((f(b))^{k}) = O(f(n))$

$$T(n) = a^{k} + \sum_{i=0}^{k-1} a^{i} f(n/b^{i})$$
(since f is multiplicative)
$$= a^{k} + \sum_{i=0}^{k-1} a^{i} f(n) / f(b^{i})$$

$$= a^{k} + \sum_{i=0}^{k-1} a^{i} f(n) / (f(b))^{i}$$

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$$= a^{k} + f(n) \sum_{i=0}^{k-1} (a/f(b))^{i}$$

$$= a^{k} + (f(b))^{k} \sum_{i=0}^{k-1} (a/f(b))^{i}$$
Case 3: $a > f(b)$, $T(n) = a^{k} + O(a^{k}) = O(n^{\log_{b} a})$

Three cases

 $T(n) = a^{k} + (f(b))^{k} \sum_{i=0}^{k-1} (a/f(b))^{i}$

Case 1: a = f(b), $T(n) = n^{\log_b a} \log_b n$

Case 2: a < f(b), T(n) = O(f(n))

Case 3: a > f(b), $T(n) = O(n^{\log_{b} a})$

T(1) = 1,

T(n) = f(n) + a T(n/b) where f is *multiplicative*.

There are the following solutions

Case 1: a = f(b), $T(n) = n^{\log_{b} a} \log_{b} n$ Case 2: a < f(b), T(n) = O(f(n))Case 3: a > f(b), $T(n) = O(n^{\log_{b} a})$

Examples

If T(1) = 1, and T(n) = f(n) + a T(n/b) where f is *multiplicative*, then there are the following solutions Case 1: a = f(b), $T(n) = n^{\log_b a} \log_b n$ Case 2: a < f(b), T(n) = O(f(n))Case 3: a > f(b), $T(n) = O(n^{\log_b a})$

Example 1: T(n) = n + 4 T(n/2)



Solution: $T(n) = 0(n^2)$

If T(1) = 1, and T(n) = f(n) + a T(n/b) where f is *multiplicative*, then there are the following solutions Case 1: a = f(b), $T(n) = n^{\log_b a} \log_b n$ Case 2: a < f(b), T(n) = O(f(n))Case 3: a > f(b), $T(n) = O(n^{\log_b a})$

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



Solution: $\mathbf{T}(n) = \mathbf{O}(n^2 \log_2 n)$

If T(1) = 1, and T(n) = f(n) + a T(n/b) where f is *multiplicative*, then there are the following solutions Case 1: a = f(b), $T(n) = n^{\log_b a} \log_b n$ Case 2: a < f(b), T(n) = O(f(n))Case 3: a > f(b), $T(n) = O(n^{\log_b a})$

Example 3: $T(n) = n^3 + 4 T(n/2)$



Solution: T(n) =

O(n³)

If T(1) = 1, and T(n) = f(n) + a T(n / b) where f is *multiplicative*, then there are the following solutions Case 1: a = f(b), $T(n) = n^{\log_b a} \log_b n$ Case 2: a < f(b), T(n) = O(f(n))

Case 3: a > f(b), $T(n) = O(n^{\log_{b} a})$

Example 4: $T(n) = 2 n^{1.5} + 3 T(n/2)$

Solution: T(n) =

We can not apply master theorem directly since $f(n) = 2 n^{1.5}$ is not multiplicative.

If T(1) = 1, and T(n) = f(n) + a T(n/b) where f is *multiplicative*, then there are the following solutions Case 1: a = f(b), $T(n) = n^{\log_b a} \log_b n$ Case 2: a < f(b), T(n) = O(f(n))Case 3: a > f(b), $T(n) = O(n^{\log_b a})$

Example 4: $T(n) = 2 n^{1.5} + 3 T(n/2)$ Solution: G(n) = T(n)/2 $\Rightarrow G(n) = n^{1.5} + 3 G(n/2)$ $\Rightarrow G(n) = O(n^{\log_2 3}) = O(n^{1.58})$ $\Rightarrow T(n) = O(n^{1.58}).$



If T(1) = 1, and T(n) = f(n) + a T(n/b) where f is *multiplicative*, then there are the following solutions Case 1: a = f(b), $T(n) = n^{\log_b a} \log_b n$ Case 2: a < f(b), T(n) = O(f(n))Case 3: a > f(b), $T(n) = O(n^{\log_b a})$

Example 6: $T(n) = T(\sqrt{n}) + c n$

Solution: **T**(*n*)=

We can not apply master theorem directly since $T(\sqrt{n}) \ll T(n/b)$ for any constant *b*.

Solving $T(n) = T(\sqrt{n}) + c n$ using the method of unfolding



A series which is decreasing at a rate faster than any geometric series



= **O**(*n*)

If T(1) = 1, and T(n) = f(n) + a T(n/b) where f is *multiplicative*, then there are the following solutions Case 1: a = f(b), $T(n) = n^{\log_b a} \log_b n$ Case 2: a < f(b), T(n) = O(f(n))Case 3: a > f(b), $T(n) = O(n^{\log_b a})$

Example 5: $T(n) = n (\log n)^2 + 2 T(n/2)$

Solution: **T**(*n***)=**

We **can not** apply master theorem since $f(n) = n (\log n)^2$ is **not** *multiplicative*. Using the method of "unfolding", it can be shown that $T(n) = O(n (\log n)^3)$.

Homework

Solve the following recurrences <u>systematically</u> (if possible by various methods). Assume that T(1) = 1 for all these recurrences.

- T(n) = 1 + 2 T(n/2)
- $T(n) = n^3 + 2 T(n/2)$
- $T(n) = n^2 + 7 T(n/3)$
- $T(n) = n/\log n + 2T(n/2)$
- T(n) = 1 + T(n/5)
- $T(n) = \sqrt{n} + 2 T(n/4)$
- $T(n) = 1 + T(\sqrt{n})$
- T(n) = n + T(9 n/10)
- $T(n) = \log n + T(n/4)$

Next 2 classes

