DSC 40B
Lecture 9:
Recurrences

Recurrence Relations



Recurrence Relations

Last Lecture: We found

$$T(n) = \begin{cases} T(n/2) + \Theta(1), & n \ge 2 \\ \Theta(1), & n = 1 \end{cases}$$

• This is a recurrence relation.



Solving Recurrences

- We want simple, non-recursive formula for T(n) so we can see how fast T(n) grows.
 - Is it $\Theta(n)$? $\Theta(n^2)$? Something else?
- Obtaining a simple formula is called solving the recurrence.

Example: Getting Rich

- Suppose on day 1 of job, you are paid \$3.
- Each day thereafter, your pay is doubled.
- Let S(n) be your pay on day n:

$$S(n) = \begin{cases} 2 \cdot S(n-1), & n \ge 2 \\ 3, & n = 1 \end{cases}$$

Example: Unrolling

$$S(n) = \begin{cases} 2 \cdot S(n-1), & n \ge 2 \\ 3, & n = 1 \end{cases}$$

- How much are you paid on day 4?
- $S(4) = 2 \cdot S(3)$

$$= 2 \cdot 2 \cdot S(2)$$

$$= 2 \cdot 2 \cdot 2 \cdot S(1)$$

$$= 2 \cdot 2 \cdot 2 \cdot 3$$

$$S(n) = 2^{n-1} \cdot 3$$



Solving Recurrences in general

We'll use a **four-step** process to solve recurrences:

- 1. "Unroll" several times to find a pattern.
- 2. Write general **formula** for kth unroll.
- 3. Solve for # of unrolls needed to reach base case.
- 4. Plug this number into general formula.

$$S(n) = 2 \cdot S(n-1)$$



$$S(n) = 2 \cdot S(n-1)$$

$$= 2 \cdot 2 \cdot S(n-2)$$



$$S(n) = 2 \cdot S(n-1)$$

$$= 2 \cdot 2 \cdot S(n-2)$$

$$= 2 \cdot 2 \cdot 2 \cdot S(n-3)$$

$$S(n) = 2 \cdot S(n-1)$$

$$= 2 \cdot 2 \cdot S(n-2)$$

$$= 2 \cdot 2 \cdot 2 \cdot S(n-3)$$

$$= 2 \cdot 2 \cdot 2 \cdot 2 \cdot S(n-4)$$

.



$$S(n) = 2 \cdot S(n-1)$$
 #**k=1**

$$= 2 \cdot 2 \cdot S(n-2)$$
 #**k**=2

$$= 2 \cdot 2 \cdot 2 \cdot S(n-3)$$
 #**k=3**

$$= 2 \cdot 2 \cdot 2 \cdot 2 \cdot S(n-4)$$

On step k:

$$S(n) = 2 \cdot S(n-1)$$
 #**k=1**

$$= 2 \cdot 2 \cdot S(n-2)$$
 #**k**=2

$$= 2 \cdot 2 \cdot 2 \cdot S(n-3)$$
 #**k=3**

=
$$2 \cdot 2 \cdot 2 \cdot 2 \cdot S(n-4) # k = 4$$

On step k:

$$S(n) = 2^k \cdot S(n-k)$$



- On step k, $S(n) = 2^k \cdot S(n-k)$.
- When do we see S(1)?

- On step k, $S(n) = 2^k \cdot S(n k)$.
- When do we see S(1)?
- When $\mathbf{n} \mathbf{k} = 1$

- On step k, $S(n) = 2^k \cdot S(n k)$.
- When do we see S(1)?
- When n k = 1 = > k = n 1

- From **step 2**: $S(n) = 2^k \cdot S(n-k)$.
- From **step 3**: Base case of S(1) reached when k = n 1.
- So

- From step 2: $S(n) = 2^k \cdot S(n-k)$.
- From step 3: Base case of S(1) reached when k = n 1.
- So $S(n) = 2^{n-1} \cdot S(n (n-1))$

- From step 2: $S(n) = 2^k \cdot S(n-k)$.
- From step 3: Base case of S(1) reached when k = n 1.

• So
$$S(n) = 2^{n-1} \cdot S(n - (n-1))$$

= $2^{n-1} \cdot S(1)$

- From step 2: $S(n) = 2^k \cdot S(n-k)$.
- From step 3: Base case of S(1) reached when k = n 1.

• So
$$S(n) = 2^{n-1} \cdot S(n - (n-1))$$

$$= 2^{n-1} \cdot S(1)$$

$$= 2^{n-1} \cdot 3$$

$$S(n) = \begin{cases} 2 \cdot S(n-1), & n \ge 2 \\ 3, & n = 1 \end{cases}$$



Solving the Recurrence

- We have solved the recurrence: $S(n) = 3 \cdot 2^{n-1}$
- This is the **exact** solution. The **asymptotic** solution is

$$S(n) = \Theta(2^n).$$

- We'll call this method "solving by unrolling".
- Take the job? Yes! On day 20 you will get ~ 1.5 mill.\$

Binary Search Recurrence



Binary Search

- What is the time complexity of binary_search?
- Best case: $\Theta(1)$.
- Worst case:

$$T(n) = \begin{cases} T(n/2) + \Theta(1), & n \ge 2 \\ \Theta(1), & n = 1 \end{cases}$$



Simplification

• When solving, we can **replace** $\Theta(f(n))$ with f(n):

$$T(n) = \begin{cases} T(n/2) + 1, & n \ge 2 \\ 1, & n = 1 \end{cases}$$

• As long as we state **final answer** using Θ notation!



Another Simplification

• When solving, we can assume n is a power of 2.



$$T(n) = \begin{cases} T(n/2) + 1, & n \ge 2 \\ 1, & n = 1 \end{cases}$$

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



$$T(n) = \begin{cases} T(n/2) + 1, & n \ge 2 \\ 1, & n = 1 \end{cases}$$

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$$T(n) = \begin{cases} T(n/2) + 1, & n \ge 2 \\ 1, & n = 1 \end{cases}$$

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

$$= [T(n/4) + 1] + 1 = T(n/4) + 2$$

$$T(n) = \begin{cases} T(n/2) + 1, & n \ge 2 \\ 1, & n = 1 \end{cases}$$

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

$$= [T(n/4) + 1] + 1 = T(n/4) + 2$$

$$= [T(n/8) + 1] + 2 = T(n/8) + 3$$

On step k:

$$T(n) = T(n/2) + 1 #k=1$$

= T(n/4) + 2 # k = 2

$$= T(n/8) + 3 \# k = 3$$

$$T(n) = T(n/2) + 1 #k=1$$

$$= T(n/4) + 2 #k=2$$

$$= T(n/8) + 3 \# k = 3$$

On step k:

$$T(n) = ? + k$$

$$T(n) = T(n/2) + 1 #k=1$$

$$= T(n/4) + 2 \# k = 2$$

$$= T(n/8) + 3 \# k = 3$$

On step k:

$$T(n) = T(\frac{n}{2^k}) + k$$



$$T(n) = \begin{cases} T(n/2) + 1, & n \ge 2 \\ 1, & n = 1 \end{cases}$$

- On step k, $T(n) = T(\frac{n}{2^k}) + k$
- When do we see T(1)?



$$T(n) = \begin{cases} T(n/2) + 1, & n \ge 2 \\ 1, & n = 1 \end{cases}$$

- On step k, $T(n) = T(\frac{n}{2^k})$ When do we see T(1)2

Step 3: Find step # of base case $T(n) = \begin{cases} T(n/2) + 1, & n \ge 2 \\ 1, & n = 1 \end{cases}$

- On step k, $T(n) = T(\frac{n}{2^k}) + k$
- When do we see T(1)?

$$\frac{n}{2^{k}} = 1$$

Step 3: Find step # of base case $T(n) = \begin{cases} T(n/2) + 1, & n \ge 2 \\ 1, & n = 1 \end{cases}$

- On step k, $T(n) = T(\frac{n}{2^k}) + k$
- When do we see T(1)?

$$\frac{n}{2^k} = 1$$

$$n = 2^k$$

Step 3: Find step # of base case

$$T(n) = \begin{cases} T(n/2) + 1, & n \ge 2 \\ 1, & n = 1 \end{cases}$$

- On step k, $T(n) = T(\frac{n}{2^k}) + k$
- When do we see T(1)?

$$\frac{n}{2^k} = 1$$

$$n = 2^k \longrightarrow k = \log_2 n$$



$$\bullet \quad T(n) = T(\frac{n}{2^k}) + k$$



$$\bullet \quad T(n) = T(\frac{n}{2^k}) + k$$

$$T(n) = T(\frac{n}{2^{\log_2 n}}) + \log_2 n$$



$$\bullet \quad T(n) = T(\frac{n}{2^k}) + k$$

$$T(n) = T(\frac{n}{2^{\log_2 n}}) + \log_2 n$$

$$T(n) = T(1) + \log_2 n$$

$$T(n) = \begin{cases} T(n/2) + 1, & n \ge 2 \\ 1, & n = 1 \end{cases}$$

$$\bullet \quad T(n) = T(\frac{n}{2^k}) + k$$

$$T(n) = T(\frac{n}{2^{\log_2 n}}) + \log_2 n$$

$$T(n) = T(1) + \log_2 n$$

$$T(n) = 1 + \log_2 n$$

$$T(n) = \begin{cases} T(n/2) + 1, & n \ge 2 \\ 1, & n = 1 \end{cases}$$

$$\bullet T(n) = T(\frac{n}{2^k}) + k$$

$$T(n) = T(\frac{n}{2^{\log_2 n}}) + \log_2 n$$

$$T(n) = T(1) + \log_2 n$$

$$T(n) = 1 + \log_2 n = \Theta(\log n)$$



Reminder

$$log_a n = \frac{log_c n}{log_c a} = \frac{1}{log_c a} log_c n$$

Reminder

$$log_a n = \frac{log_c n}{log_c a} = \frac{1}{log_c a} log_c n$$

Constant

Reminder

$$log_a n = \frac{log_c n}{log_c a} = \left(\frac{1}{log_c a}\right) log_c n$$

Constant

- So we **don't** write $\Theta(\log_2 n)$
- Instead, just: $\Theta(\log n)$



Time Complexity of Binary Search

- Best case: Θ(1)
- Worst case: $\Theta(\log n)$



Is binary search fast?

- Suppose all 10¹⁹ grains of sand are assigned a unique number, sorted from least to greatest.
- Goal: find a particular grain.
- Assume one basic operation takes 1 nanosecond.



Is binary search fast?

- Suppose all 10¹⁹ grains of sand are assigned a unique number, sorted from least to greatest.
- Goal: find a particular grain.
- Assume one basic operation takes 1 nanosecond.
- Linear search: ?



Is binary search fast?

- Suppose all 10¹⁹ grains of sand are assigned a unique number, sorted from least to greatest.
- Goal: find a particular grain.
- Assume one basic operation takes 1 nanosecond.
- Linear search: 317 years.
- Binary search: ≈ 60 nanoseconds.



Think!

Binary search seems so much faster than linear search.

What's the caveat?

Caveat

- The array must be sorted.
- This takes $\Omega(n)$ time.



Why use binary search?

- If data is **not sorted**, sorting + binary search **takes longer** than linear search.
- But if doing multiple queries, looking for nearby elements, sort once and use binary search after.



Theoretical Lower Bounds

- A tight lower bound for searching a sorted list is $\Omega(\log n)$.
- This means that binary search has **optimal** worst case time complexity.

Thank you!

Do you have any questions?

CampusWire!