CSE 332

JUNE 30TH - AMORTIZED ANALYSIS

Tokens

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 - 3 tokens

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 - Opportunity to redo an exercise

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 - One late day on a project

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- P1 Due Wednesday now



Recurrences

TODAY

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- Master Theorem

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- Amortized Analysis

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- Amortized Analysis
- Project checkpoint

- Algorithm Analysis
 - Asymptotic behavior

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- Loops and iterations

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- Recursive functions

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- Loops and iterations
- Recursive functions
 - Recurrence relations



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 - Roll out the recurrence and produce the closed form
 - Upper-bound the closed form with bigO notation



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- We can derive the pattern this way, but it isn't necessarily intuitive



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- Each recursive call is a node in a tree
- Helpful for logarithmic patterns and when each run calls itself more than once



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- Therefore, if you can produce a recurrence, there is actually a procedural way to produce solutions
- If T(n) = a*T(n/b)+n^c for n > n₀ and if the base case is a constant
 - Case 1: $\log_{b}(a) < c$: T(n) = O(n^c)
 - Case 2: $\log_{b}(a) = c$: T(n) = O(n^c Ig n)
 - Case 3: $\log_{b}(a) > c$: $T(n) = O(n^{\log a})$

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- Verify with merge sort: a = 2, b = 2, c = 1



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- Usually for worst-case analysis





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 - Resizing is the costly O(n) operation
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 - Do these types of operations really slow down the function?

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 - Doubling the array

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 - What if we only add some constant number to the array?
 - Let's resize and add 10,000 elements every time
 - How long does it take to add *n* elements?
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 - What if we only add some constant number to the array?
 - Let's resize and add 10,000 elements every time
 - How long does it take to add *n* elements?
 - $n-n/10,000*O(1) + n/10,000*O(n) = O(n^2)$
 - This is for any constant, regardless of how large

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- Once one of us has talked with you, you're free to go



• Dictionaries



- Dictionaries
 - Binary Search Trees
 - Balancing