

Divide and Conquer: Recursion Trees

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Programming, Data Structures and Algorithms using Python

Week 8

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- Is there a uniform way to compute the asymptotic expression for $T(n)$?

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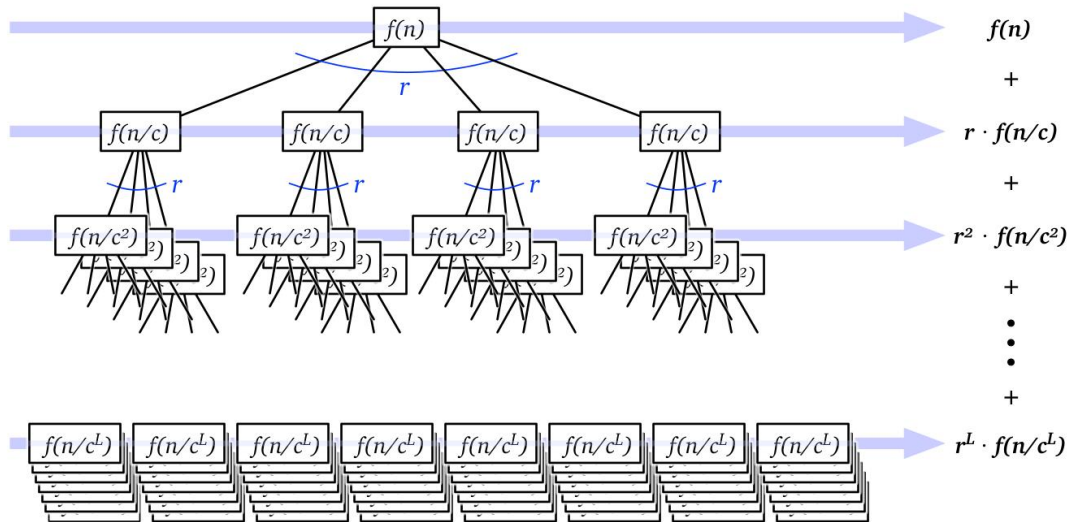
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- Root has r children, each (recursively) the root of a tree for $T(n/c)$
- Each node at level d has value $f(n/c^d)$
 - Assume, for simplicity, that n was a power of c

Recursion tree for $T(n) = rT(n/c) + f(n)$



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- Number of leaves is r^L
 - Last term in the level by level sum is $r^L \cdot f(1) = r^{\log_c n} \cdot 1 = n^{\log_c r}$
 - Recall that $a^{\log_b c} = c^{\log_b a}$

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 - $T(n) = O(f(n) \cdot L) = O(f(n) \log n)$ — $\log_c n$ is asymptotically same as $\log n$

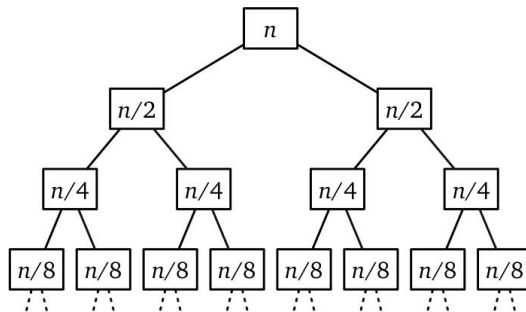
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- **Increasing** Series grows exponentially, each term a constant factor larger than previous term
 - Leaves dominate the sum, $T(n) = O(n^{\log_c r})$

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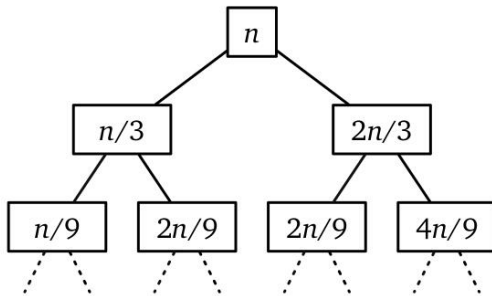
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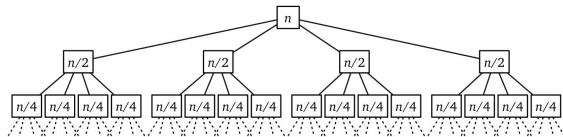
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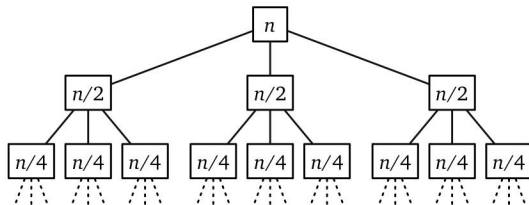
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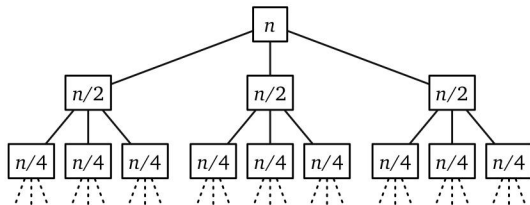
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- Acknowledgment

Illustrations from
Algorithms by Jeff Erickson,
<https://jeffe.cs.illinois.edu/teaching/algorithms/>